**Predicting Indonesian Financial Crises using**

**the Artificial Neural Network Model****[[1]](#footnote-1)**

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**Abstract**

This study offered a method for predicting crises in Indonesia using an artificial neural network (ANN) model. The empirical findings indicated that an ANN model would have performed well in predicting crises from 1971:1 to 1995:12 (in-sample) and from 1996:1 to 1998:12 (out-of-sample), namely the Asian Financial Crisis, which hit Indonesia in 1997--1998. The empirical results indicated that financial crises can be predicted and the application of the ANN model in predicting Indonesian financial crises is promising. Thus, the government can develop an ANN model to predict recurrent financial crises and use it to provide an early warning system.

***Keywords:*** *financial crises, artificial neural network model, early warning system model, Indonesian economy*.

**Introduction**

The costs of financial crises are huge. According to Hutchison and Noy (2002), currency crises can lead to average growth reductions by between 5 and 8 per cent, and the decline from banking crises is on average about 8 to 10 per cent. Other works that examined emerging economies claim that the effects of currency crises can reduce economic growth by 2 to 3 per cent and the effect of sudden-stop crises is 6 to 8 per cent, and a combination of both can reduce growth by 13 to 15 per cent. Laeven and Valencia (2008) indicated that the average fiscal cost of resolving a financial crisis is about 16 per cent of GDP. The cost of a currency crisis that occurs simultaneously with a banking crisis (a twin crisis) (Kaminsky and Reinhart, 1999) is enormous and can have a devastating effect on an economy. As well as causing financial chaos and disruption, a financial crisis can also have adverse social effects, such as increasing the number of people forced into poverty and unemployment.

Given the huge cost of these crises, and to help avoid their recurrence, many studies have been focusing on explaining the causes of these crises. However, since the 1990s, these studies have been extended by the development of what are known as early warning system (EWS) models. Previous studies mostly used two standard EWS models; the signal model and the probit/logit model (Kaminsky *et al*., 1998; Kaminsky, 1998; Edison, 2000; Zhuang and Dowling, 2002; Eichengreen *et al*., 1996; Kamin and Babson, 1999; Kamin *et al*., 2007; and Goldstein *et al*., 2000). Even though these models have been successful in identifying economic vulnerability, their results were mixed and not robust, particularly in predicting Indonesian financial crisis of 1997--1998 (Edison, 2000; Goldstein *et al*., 2000; Kaminsky, 1998; Kaminsky and Reinhart, 1998), either because of the limitations of their models (Nag and Mitra, 1999; Yu *et al*., 2006) or because of unobserved data sets (Syaifullah, 2011), that is, the lack of indicators to capture the contagion effect (Goldstein *et al*., 2000; Kaminsky, 1998; Kaminsky and Reinhart, 1998). At this stage, these models cannot substitute for the instinctive judgment that has been widely practised by policy-makers (Bussière and Fratzscher, 2002; Zhuang and Dowling, 2002). For this reason, many economists and scholars have attempted to find other models to predict crises (Edison, 2000; Kaminsky *et al*., 1998). Accordingly, this study developed an alternative EWS model to predict Indonesian financial crises using an artificial neural network (ANN) model.

The ANN model also has some drawbacks, especially because it requires large computational analysis and has a tendency to over-fit. In addition, the ANN model is a black-box model, which means it cannot explain the causal relation between input and output (Braspenning *et al*., 1995).

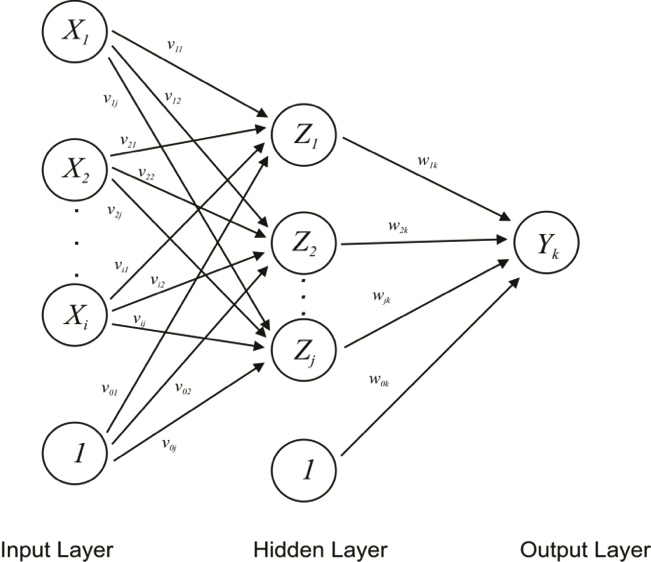
This paper is organised as follows: section 2 explains the proposed model and data set; section 3 presents an application of an ANN model for Indonesia; and the conclusion is in section 4.

**Research method**

*Specifications and architecture of the ANN model*

Basically, an artificial neural network mimics the operation of a biological neural network. The biological neural system consists of a simple structure that performs three basic functions: receiving signals (input) from other neurons; processing these signals; and then sending them to other neurons. As shown in Figure 1, the architecture of the ANN model also can be divided into three layers: an input layer, a hidden layer and an output layer.

Like those of human brain, all neurons in these layers are fully connected to other neurons in the next layer but there are no connections between neurons within each layer and each connection is given a weight. Basically, in the feed-forward neural network, all neurons including the bias neuron will send all signals to other neurons in the next layer in a forward direction.



**Figure 1.** Architecture of the ANN model.

Sources: Braspenning *et al*., 1995

*Input layer*

In developing a neural network model, the first step was to select the appropriate indicators for input variables to ensure the precision of the prediction of output; even the type or the number of neurons in the input layer were determined by researchers in relation to their research objectives. However, the selection of potential independent variables is important (Walczak and Cerpa, 1999; Zhang *et al*., 1998). This is because, for a supervised learning neural network, the more relevant explanatory variables with the output variable will reduce the model’s learning time. A more detailed discussion about the selection of input neurons is in the section on empirical findings.

*Hidden layers*

In Figure 1, the next layer or any intermediate layers between input and output layers were hidden layers. Several issues arose from hidden layers, such as the appropriate number of hidden layers and the number of neurons for each layer. Regarding the number of the hidden layers, in a neural network model, using more than one hidden layer was also possible. In addition, if there was more than one hidden layer in the network, the signals from the first hidden layer would be distributed to the next hidden layer before reaching the output layer, and this would increase the learning time for the model to converge.

Another issue was related to the appropriate number of neurons in a hidden layer. There was a trade-off between putting too many or too few neurons in this layer. Using too many neurons will affect to a longer learning period for the model, sometimes lead to the model being over-fitted with data, which causes it to perform poorly when adding new data because it starts to model the noise in the data set (Svozil *et al*., 1997; Walczak and Cerpa, 1999). On the other hand, if the number of neurons in the hidden layer is too small, the neural network will have a problem dealing with a complex data set (Zhan *et al*., 1998; Walczak and Cerpa, 1999). So, the optimal number of hidden layers and hidden neurons can be chosen at the point where the model has the smallest training error.

*Output layer*

The last layer in Figure 1 is the output layer. The output neuron in the output layer corresponds to the predicted variable. In this study, there was only one expected output neuron or variable, namely the probability of a financial crisis in Indonesia having a value in the range of 0 to 1. In this model, to guarantee that the output neuron fell into this range, the logistic activation function was utilised. To train this model in the supervised learning neural network, this output neuron was compared with the target.

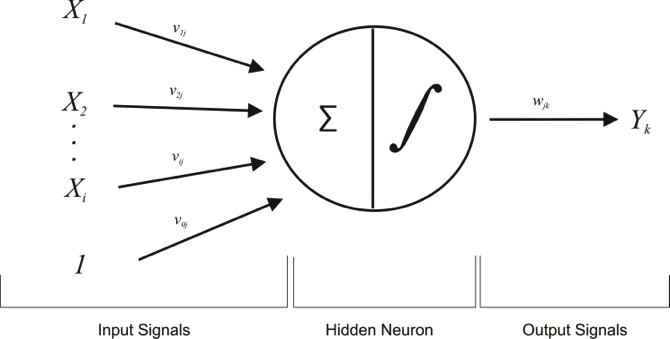
*The learning algorithm*

As mentioned earlier, like a human brain, this ANN model can be trained to make its prediction more accurate and powerful. There are many supervised learning algorithms available, such as the radial basis function neural network, the probabilistic neural network, and the generalised regression neural network, but the most popular and commonly used is the back-propagation method (Werbos, 1974; Wong *et al*., 2000). More than 95 per cent of the applications of neural networks in business apply this learning algorithm (Wong *et al*., 2000). As already mentioned, all neurons from the input to output layer were connected, and each connection had a connection weight, and this weight was initially set randomly with it. In this supervised learning, as with back-propagation, the objective of the training process was to discover the appropriate weight for every connection among neurons in all layers.

According to Fausett (1994), training a neural network using the back-propagation method can be done in three steps, as follows.

Step 1: Feed-forward

In this step, all signals travel from the input to the output layer. Using the feed-forward mechanisms, all the signals from all neurons in the input layer (*Xi*), together with one bias neuron, are sent to the neurons in the hidden layer, their initial weights (*vij*) being set to small random values. In the hidden neuron, two processes apply (see Figure 2).



**Figure 2.** A single hidden neuron.

Sources: Fausett, 1994

First, all the incoming signals from input neurons were summed using the following equation:

Because the preference output of the neural network model is the probability of crisis, which has a value in a range between 0 for ‘no crisis’ and 1 for ‘crisis’, this study applied a logistic sigmoid activation function to keep this value within the range of 0 to 1. Therefore, for consistency, the second step was to convert the value of the hidden layer to be within the range of 0 to 1, using the logistic sigmoid activation function, before sending it to the output layer, using the following equation:

For simplicity, this study used one hidden layer only; hence these activation signals (*Zj*) were sent to the next layer, the output layer. In this output neuron (*Yk*), a similar process with a hidden neuron was also applied. First, all incoming signals from hidden neurons were summed using the following equation:

Then, to make the value of the model’s output or *yk* be in the range of 0 to 1, this summation value would be transformed using a logistic sigmoid activation function, as follows:

Step 2: Back-propagation of error

In this step, the network’s output (*Yk*) was compared with the target (*Ok*) and all the errors from this comparison were back-propagated from the output to the input layer via a hidden layer.

*Step 3: Adjusting the associated weights*

Finally, the associated weight involved in each connection among neurons in all layers was gradually adjusted. As already mentioned, using the back-propagation mechanism, the error would be adjusted gradually in a backward direction.

This learning process was continued until the network met one condition; when the net output of the model converged to its target, or the minimum threshold of the error was achieved. However, if the neural network never converged to its target, setting the maximum number of iterations could stop this learning process. Therefore, even though this model fails to achieve its target, that is, the minimum error, this learning process would stop whenever the maximum number of iterations was achieved. The application of this model to predict the Indonesian financial crises would be discussed in the next section.

**The application of the ANN EWS model for predicting Indonesian financial crises**

**Constructing the ANN model**

For predicting financial crises in Indonesia, this study constructed an ANN model based on the training parameters in Table 1. In developing an early warning system model, particularly an ANN model, the first step was to select the episode of financial crisis as the target or output of this model. This output can be used to train the ANN model.

**Table 1.** The training parameter for ANN models.

|  |  |  |
| --- | --- | --- |
| **No.** | **Description** | **Training Information** |
| 1 | Type of network | Multi-layer perception |
| 2 | No of layers | 3 |
| 3 | No of hidden layer | 1 |
| 4 | No of input neurons | 10 |
| 5 | No of hidden neurons | 10 |
| 6 | No of output neurons | 1 |
| 7 | Activation functions | Logistic |
| 8 | Performance function | Mean squared error |
| 9 | Training algorithm | Back-propagation |
| 10 | Starting weights and biases | Random |
| 11 | Number of iterations | 30,000 |
| 12 | Training error | 0.3847 |
| 13 | Learning rate (*α*) | 0.010 |
| 14 | Momentum factor (*β*) | 0.800 |

Sources: Author, 2013

*Defining financial crisis as an output neuron*

This study followed Kaminsky *et al*. (1998) in determining the financial crises as an output neuron. According to Kaminsky *et al*. (1998), a financial crisis is a situation where an attack on the currency leads to sharp currency depreciation, a large decline in international reserves, or a combination of the two. If so, this financial crisis (*ct*) can be measured as 1 whenever the exchange market pressure index (*EMPI*) is greater than its threshold of 3 *EMPI*s standard deviation (*σ*) above the index’s mean (*μ*) or otherwise 0 for no crisis, which is calculated as follows:

This definition encompasses successful and unsuccessful attacks on the currency, which may be managed in a fixed exchange rate regime or other exchange rate regimes. The *EMPI* was defined in this way so that it would exceed its threshold eight times during November 1978, April 1983, September 1986, August 1997, December 1997, January 1998, May 1998 and June 1998 (see Figure 3).

**Figure 3.** EMPI and thresholds.

Sources: Author calculation, 2013

*Input neurons*

As mentioned in Table 1, this model used 10 input neurons in predicting the Indonesian financial crises and the list of input neurons is in Table 2. These 10 input neurons were selected from 55 indicators using the noise-to-signal ratio, which were commonly used in signal models for selecting the best leading indicators. For a more detail explanation, interested readers can go to the works of Kaminsky *et al*. (1998), Edison (2000), Syaifullah (2011), Goldstein *et al*. (2000) and others.

**Table 2.** List of input neurons.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Input neurons** | **NSR** | **Source** |
| 01 | Real USD:JPY exchange ratea | 0.03 | IFS |
| 02 | Short-term capital flows to GDP | 0.03 | IFS |
| 03 | US annual growth rate | 0.06 | US Bureau of Economic Analysis |
| 04 | US real interest ratec | 0.09 | IFS |
| 05 | US real interest rate | 0.13 |
| 06 | Loans to depositsc | 0.23 | IFS |
| 07 | M1 to GDPc | 0.23 | IFS |
| 08 | Real effective exchange ratea | 0.24 | Bloomberg |
| 09 | Exportsb | 0.29 | IFS line 70 |
| 10 | M1 to GDP | 0.32 | IFS |

Notes: a. deviation from trend-HP filter; b. 12 months percentage change; c. 12 months change

Sources: Kaminsky *et al*. (1998), Edison (2000), Syaifullah (2011), Goldstein *et al*. (2000)

Before putting these variables as input neurons in the input layer, all data would be normalised to keep values in the range -1 to 1 (Hall *et al*., 2009), using the following equation:

The connection weights for this model were initially set randomly and then, during the training process, they were adjusted gradually until the model’s output came close to its target value, or the error became smallest or, if not smallest, then until the maximum number of iterations (30,000) was reached.

Similar to the parametric approach (probit/logit model), and based on the results of the training done, this model can show the average contribution of each input neuron to the output neuron that is the probability of financial crises in Indonesia. However, it should be noted, unlike the parametric model, that with the ANN model, there are still many other factors apart from the input neurons that might affect or determine the output of this model, such as the number of hidden layers and hidden neurons, the value of the momentum and learning rates, and the number of iterations.

As shown in Table 3, this model indicated the US real interest rate to be the main contributor to the probability of financial crises in Indonesia. Increases in world interest rates, especially US real interest rates, lead to an increase in the likelihood of a crisis by causing capital outflows from developing countries, such as Indonesia (Zhuang and Dowling, 2002; Kamin *et al*., 2007).

**Table 3.** Average contribution of input nodes to output node.

|  |  |  |
| --- | --- | --- |
| **No.** | **Description** | **Average contribution** |
| **1** | Short-term capital flows to GDP | 6.90% |
| **2** | Exportsb | 5.19% |
| **3** | Real effective exchange ratea | 8.79% |
| **4** | M1 to GDP | 6.06% |
| **5** | M1 to GDPc | 10.25% |
| **6** | Loans to depositsc | 12.11% |
| **7** | US real interest rate | 16.57% |
| **8** | US real interest ratec | 11.06% |
| **9** | US annual growth rate | 14.95% |
| **10** | Real USD:JPY exchange ratea | 8.12% |
|  | Total | 100% |

Notes: a. deviation from trend-HP filter; b. 12 months percentage change  
c 12 months change

Sources: Zhuang and Dowling, 2002; Kamin *et al*., 2007

*Predicting Indonesian financial crises*

The in-sample forecasting results of this model are presented in Figure 4, and Figure 5 displays the out-of-sample forecasting results. Furthermore, the in-sample and the out-of-sample performance assessment results are recorded in Table 4.

*In-sample prediction (1971--1995)*

Figure 4 shows that this model can predict all in-sample financial crises accurately, because its probability of crisis rose throughout the entire 12-month pre-crisis periods (these being marked as grey areas).

**Figure 4.** The ANN model: in-sample prediction.

Sources: Author calculation, 2013

In addition, Figure 4 shows this model sent fewer false alarms, thus increasing its accuracy in capturing the tranquil periods. The model also has an increased ability to capture the whole observation for crisis and for tranquil periods.

*Out-of-sample predictions*

An attempt was made to test the ability of this model to predict the out-of-sample crises, particularly the Asian financial crisis that affected Indonesia during the period 1997--1998. The prediction of this model can be seen in Figure 5. Based on this figure, it was found that this model could predict Indonesian financial crisis because its probability of crisis increased in the yellow shaded areas, which represented the 12-month pre-crisis periods.

With regard to the timing of the signals transmitted, Figure 5 shows that this model was capable of sending warning signals from early 1996, or eight months before their prediction horizon. However these signals could be classified as false alarms because no financial crises occurred within the crisis windows (Goldstein *et al*., 2000). However, based on this figure, although a bit late or three months after the 12-month pre-crisis periods, this model was capable of sending warning signals from January 1997, with the probability of a crisis reaching 100 per cent, but dropping to 12 per cent in November 1997 before rising again to 100 per cent in January 1998.

**Figure 5.** The ANN model: out-of-sample prediction.

Sources: Author calculation, 2013

Apart from the ability to predict crises, Figure 5 also shows that after the Asian financial crisis in 1997--1998 and until the end of 2008, this model still sent many warning signals of impending crises in Indonesia. However, as previously stated, based on equation 5 and Figure 3, no financial crises were found in Indonesia during this period (1998--2008). Actually, during the periods 1998 to 1999 and 2001 to 2002, there was the political transition from the ‘new order regime’ to the ‘reform regime’ and the transition from the fourth to the fifth president of the Republic of Indonesia and these signals during these periods could be classified as false alarms. It can also be pointed out as one limitation of this model that it could not distinguish financial crises from other economic vulnerabilities.

*Robustness test*

As discussed earlier, this study aimed at developing an early warning system (EWS) model capable of predicting financial crises rather than tranquil periods, and it has set a 50 per cent cut-off-probability as a threshold. Thus, the model will indicate a crisis date if its probability of crisis is greater than its cut-off probability. Moreover, in evaluating the performance of this EWS model in predicting financial crises in Indonesia for in-sample and for out-of-sample periods, then following Berg and Pattillo (1999), the performance of this ANN model can be evaluated using six assessment methods, such as the percentage of observations correctly called, the percentage of pre-crisis periods correctly called, the percentage of tranquil periods correctly called, noise-to-signal ratio (NSR), and Diebold and Rudebusch’s (1989) quadratic probability score (QPS) and global score bias (GSB). A more detailed explanation of these methods is in the appendix.

The good performance of this model in predicting the in-sample financial crises was also supported by the percentage of the pre-crises period correctly called in Table 4, which indicated that all models were able to predict 100 per cent of the 12-month pre-crisis periods for the 50 per cent cut-off probabilities. Furthermore, Table 4 records that their QPS and GSB scores were close to zero, which indicated that the accuracy and calibration of these models was almost perfect.

**Table 4.** In-sample and out-of-sample evaluation at 50 per cent cut-off probability.

|  |  |  |  |
| --- | --- | --- | --- |
| **Assessment methods** | **In-sample** | **Out-of-sample** | |
| *1971--1995* | *1996--1998* | *1996--2008* |
| Percentage of observations correctly called | 100.00% | 52.78% | 73.86% |
| Percentage of pre-crisis periods correctly called | 100.00% | 68.18% | 68.18% |
| Percentage of tranquil periods correctly called | 100.00% | 28.57% | 74.81% |
| Percentage of false alarms to total alarms | 0.00% | 40.00% | 68.75% |
| QPS | 0.0000 | 0.9444 | 0.5229 |
| GSB | 0.0000 | 0.0139 | 0.0578 |

Sources: Author calculation, 2013

However, the model performed less well in predicting the out-of-sample financial crises compared to the in-sample prediction; it was only able to predict about 68 per cent at *Pr\**=50 per cent. Table 4 also indicates that the ability of the model to capture the tranquil periods tended to decline with an increase in the prediction horizons. It still sent many false alarms even though no financial crises occurred during this period.

**Conclusions**

The application of the ANN model as an alternative EWS model to predict financial crises, particularly for Indonesia, is promising because it is able to predict almost 12 months before the in-sample financial crises in Indonesia. However, even though the prediction results for the out-of-sample financial crises were not as good as the in-sample prediction, the ANN model was also able to predict the 12 months prior to the out-of-sample Indonesian financial crises. This finding also supports the idea that financial crises can be predicted.

This study also indicated that the 12-month percentage change of the US real interest rate contributes significantly in determining Indonesian financial crises because increasing world interest rates could trigger capital outflows from developing countries, including Indonesia.

Even though this model was able to predict Indonesian financial crises, it also sent lots of false alarms, this being particularly noticeable during the political transition period from 1999 to 2001. It indicates a possible weakness of this model: it cannot distinguish financial crises from other vulnerabilities, including political distress. This might require further investigation; some researchers have suggested there is a close link between political instability and financial crises (Mei and Guo, 2004; Vaaler *et al*., 2005).

**Policy recommendation**

The empirical results indicate that financial crises can be predicted and the application of the ANN model as another EWS model for predicting Indonesia’s financial crises is promising. Thus, the government can develop EWS models, including the ANN model, to predict crises. By doing that, the government can avoid the recurrence of crises or at least it can reduce the negative effects if the crisis cannot be avoided.

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**Appendix**

In evaluating this EWS model, this study set a 50 per cent cut-off probability as a threshold. The model’s predicted crises will be defined if the model’s probabilities of crisis pass its threshold. Then, this crisis signal was divided into four categories, depending on their capability to predict the crisis within the crisis window, such as ‘A’, ‘B’, ‘C’ and ‘D’. Basically, with the first three methods, the higher value of these indicators, the more powerful was the model in predicting a crisis. In contrast, with the last three methods, the lower the value of these indicators, the more powerful was the model in predicting a crisis.

* Percentage of observations correctly called
* Percentage of pre-crisis periods correctly called
* Percentage of tranquil periods correctly called
* Quadratic probability score or , and
* Global score bias or .

In the last two methods, the model’s predicted crisis (*P*) will be compared to the actual crisis (*R*). The score of *QPS* and *GSB* ranged from 0 to 2 and zero corresponded to perfect accuracy or calibration.

The signal approach selected the set of independent variables based on their performance in predicting past crises. The performance of an indicator in predicting a crisis can be shown in the value of its noise-to-signal ratio (*NSR*). Basically, the NSR was based on the ability of an indicator to send more good signals, but at the same time to eschew bad signals. This ratio can be obtained by taking the ratio of the percentage of bad signals over the percentage of good signals (Kaminsky *et al*., 1998) or

1. This paper is modified from my PhD thesis and my previous work in Syaifullah (2011). [↑](#footnote-ref-1)