# GDP Estimation and Slow Down Signal Model for Indonesia: An Artificial Neural Network Approach

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*The purpose of this paper is to develop a model estimation of Gross Domestic Product (GDP) and economic slowdown signal models with an artificial neural network approach. This approach is as an alternative or complement to other approaches that are widely used such as regression model. An artificial neural network model is inspired from the biological sciences such as the working of the human brain in solving problems. In this study, external sectors have substantial role in influencing the growth of GDP. Almost 90 percent of leading indicators of external factors contributing the fluctuation of Indonesian GDP. Major trading partner of Indonesian manufactured goods such as China, South Korea, US and Japan to some extents, however, affect GDP fluctuation. The diversification of trading partners and commodities to be exported is one of the most important policies to reduce external shocks. Based on the model developed, the performance model is adequate in predicting the samples – in and outside – in terms of a lower error. This model, however, is still experimental in nature. Therefore, it needs to be further developed by using different topology and adding observations.*

*Keywords: forecasting GDP, business cycles, artificial neural network.*

## INTRODUCTION

The purpose of this paper is to develop a forecasting model of Gross Domestic Product (GDP) and signal recession model with artificial neural network approach. This model is an experimental in nature. Therefore, this approach can be used as an alternative or complement to other approaches that have been widely used such as regression. Economic development always has fluctuation. Due to the increasing integration of the Indonesian economy to the global economy, the Indonesia economy is strongly influenced by the global economy.

Many academicians have tried to model the economic fluctuation or more often called the business cycle model in order to make the policy anticipation. With the an appropriate pre-emptive policy action, it is expected that recession or slow down of economy will not last long, because it has been detected earlier so that the proper policy in order to make soft landing could be made easily. The pioneers in the business cycle model were Kydlan and Prescot (1982). Generally, the business cycle model developed by Kydland and Prescot based micro-economic theory. The production function affects economic fluctuation. Thus, the source of economic growth based on productivity growth. This approach is known as supply-side economics. However, there is also demand-side economics or Keynesian economics that tries to contribute in the framework of the period of expansion and recession with the role of government and policy as the focus of analysis. For example, Wen (2007) which tries to identify a causal relationship between consumption, investment and output, and found that consumption causes the growth of GDP and GDP growth led to the growth of investment and not vice versa. The article further explains the model of business cycles in the context of general equilibrium with demand shocks.

In Indonesia, to the best of authors' knowledge, only the BPS and BI tried to develop a model of business cycles. The current study uses a relatively new approach to detect fluctuation of Indonesian economy, namely artificial neural network approach. There are a few articles that try to predict GDP growth with artificial neural network approach (see Tkacz and Hu, 1999; Teräsvirta and van Dijk, 2003; Ao and Tang, 2009; Shi, Chen and Xie, 2006; Qi, 2006). The approach that has been widely used to predict GDP or business cycle is a regression analysis. The advantage of artificial neural network approach is that this model can capture the relationship of non linear, especially if the economy is very volatile, the artificial neural network model to be superior in the forecast for chaotic data (see Tkacz and Hu, 1999).

The Indonesian economic growth is around 5-6%. However, various external disturbances frequently affect Indonesia's economic growth as the global financial crisis triggered by the sub-prime mortgage crisis in the U.S. in 2007, and then lately is the financial crisis in Greece beginning in 2010. By modeling a simulation, it is expected that the factors determined can be identified.

## LITERATURE REVIEW

Best (2010) argued that the Austrian Theory of Business Cycles might be the best for explaining business cycle. Austrian business cycle is based primarily on the period of credit expansion and contraction of central bank credit. Therefore, it is concluded that the Austrian theory tends to the approach of supply shocks. Meanwhile, after the Second World War, the business cycle approach on the basis of fluctuations in output and employment was mainly due to the variations in aggregate demand (The Royal Swedish Academy of Sciences, 2004). So after the Second World War period, Keynes's theory is much more dominant in explaining the business cycle, so that where the government intervened with fiscal policy needed in anticipation of the business cycle. But until the mid-1970s, the golden period of Keynes's theory began to be seen to fail in explaining the occurrence of macro-economic fluctuations in which the new phenomenon is the occurrence of stagnation and unemployment. Thus, this phenomenon can be explained by supply shocks approach. The fluctuation of supply is related to supply-side theory that rising oil prices and declining growth in productivity (The Royal Swedish Academy of Sciences, 2004).

In general, the development of this business cycle theory can be divided into two main branches. *First,* the model based on Keynes's theory of the business cycle is related to the demand shocks, so that the macro-economic management is needed for government intervention in influencing the business cycle. *Second,* the model based on micro approach, namely the existence of supply shocks, so that the productivity slowdown affects the business cycle. By looking at this cycle, then the business world to halt production by spending inventory. This second approach is based on minimizing the role of government, because the cycle is due to the disturbance in the field of technology and production factors. The approach recognizes that economic grows through total factor productivity.

The business cycle is also quite dependent on the main trading partner countries. Allegret and Essaadi (2009) showed that there is a synchronization of the turmoil in East Asian countries which are generally driven by external factors. Although countries in East Asia have a strong trade relationship with each others, they remain vulnerable to the turmoil that occurred in developed countries. Pensieroso (2007) distinguished business cycle theory in explaining fluctuations in the cycle of income and employment by two basic fundamental hypotheses of namely equilibrium hypothesis and the hypothesis of exogenous shocks. However, in subsequent development, business cycles model is much more based on the data alone without the support of micro-economic theory *per se*. Modelers turned to how to predict GDP growth through macroeconomic data without such micro-economic theory based on business cycle theory when it was originally developed. Therefore, a model to predict GDP is also done by looking at the various macroeconomic indicators both monetary and other sectors. This development became forecasting by using leading indicators. This leading indicator was used to forecast GDP growth.

Pioneer the use of leading indicators are Mitchell and Burns (1938, 1946). When this model introduced, the model has a lot of attention from politicians and business community (Marcellino, 2006). However, economists and econometric experts have diverse views and initiated by Koopmans (1947) that he criticized Burns and Mitchell's writings, and he argued that calculation experiment has no theoretical foundation. After that, the development of leading indicators model has been developed by various groups to predict GDP growth. In general, the methodology often used in the prediction of business cycles is the econometric and time series model. But recently, artificial neural network (ANN) became very popular for prediction GDP. For example, there are a lot of studies in many countries using ANN for GDP prediction, such as Tkacz and Hu (1999), Tkacz (2001) for the Canadian economy, Swanson and White (1995), and Qi (2001) for the U.S. economy, Shi, Chen and Xie (2006); Ao and Tang (2009) for China's economy, Hj Mat Junoh (2004) for Malaysia's economy.

Zhuang and Zhang (2001) developed a model of the business cycle based on periods of expansion and contraction of the economy. They were developed for the Philippines and Malaysia. This model was developed to create composite leading indicator (CLI). Indonesian business cycle model was done by Bank Indonesia and Central Bureau of Statistics (Sutomo and Irawan, 2005). Tkacz and Hu (1999) used artificial neural networks to forecast the Gross Domestic Product of Canada. The model they developed showed that the artificial neural network approach has better performance than linear regression as indicated by 17% of more accurate. Gonzalez (2000) also found that artificial neural networks are superior in terms of accuracy compared with linear regression. This model has a higher accuracy of about 13-25% better than linear regression model for both the sample and outside the sample (Gonzalez, 2000). Qi (2001) also tries to predict a recession in the United States by using early indicators (leading indicators) by artificial neural network model. According to Qi, the business cycle is asymmetric and cannot be accommodated by the linear model. Thus, artificial neural network model can accommodate non-linear model. Ao and Tang (2009) compares the various models with artificial neural network for forecasting GDP in China and found that artificial neural network method was better than chaos forecasting methods. Meanwhile, Hj Mat Junoh (2004) also found the same thing that the artificial neural network method is more accurate than that the econometric model. Similarly, Shi, Chen and Xie (2006) showed that artificial neural network method is very promising for macro-economic forecasting.

The present paper tries some experiments to integrate for estimating GDP and develop signaling model to detect slow down and expansion of GDP by using artificial neural network. The slow down term is used rather than recession, because Indonesia as emerging market experienced positive GDP growth except on some years.

**Neural Network Model Description**

Artificial neural network model, inspired from the biological sciences such as the workings of the human nervous in solving problems. This model can calculate or predict on the basis of the information and identification of patterns processed by the artificial neural network (Tan, 1997). Initially, McCulloch and Pitts used artificial neural networks and presented in biological neural models (McCulloch and Pitts, 1943 quoted from Tan, 1997). They can solve logic problems in parallel neural network model.

Krose and van der Smagt (1996) suggested that the artificial neural network model is a computational model with some characteristics such as the ability to learn, to generalize and classification and categorization. The calculation is performed on artificial neural network models are parallel. *Jain et. al* (1998) suggested that the artificial neural network model is generally used for pattern recognition, data clustering, function approximation, forecasting, optimization and controls. In the financial sector, this model has been widely used to predict the stock, currency exchange rates or the potential bankruptcy of the company (see Tan and Diharjo, 1999; Vanstone, Finnie and Tan, 2005). There are also several recent studies that use these models to predict financial crises (such as Franck and Schmied, 2003; Peltonen, 2002; Babutsidze, 2005; Imansyah and Kusdarjito, 2009; Peltonen, 2006).

The first generation of artificial neural network model starts from the work of McCulloh and Pitts in 1943. The model developed is a simplification of how the neural network. Nevertheless, the development of artificial neural network model was stagnant since 1969, after Minsky and Papert showed a weakness on artificial neural network models, namely the inability of artificial neural network model (which is named as perceptron) to make generalizations on the case of XOR (exclusive OR). The development of artificial neural network model regained momentum in the early 1980s along with the progressive development of computer hardware and discovery algorithms that can overcome the problems raised by Minsky and Papert with the emergence of a back propagation error method. The existence of error back propagation algorithm allows the application of artificial neural network model that consists of several layers. In addition, the use of multi-layer artificial neural network model allows the prediction functions perform non-linear (Jain *et al*, 1998).

Multi-layer model generally consists of input layer, hidden layer and output layer. Because the input layer does not perform a calculation process, an artificial neural network model that consists of input layer, one hidden layer and output layer is called the model of one-layer artificial neural network (Krose and van der Smagt, 1996,

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Sima, 1998). Figure 1 shows an artificial neural network models which are common with one hidden layers.

The process of preparation of artificial neural network model involves three stages: (1) determination of the structure, the architecture or the shape (topology) artificial neural network model, (2) encoding, the method used to change the weight value, for example back propagation or Hebbian learning, and (3) Recall, that the recall process information from an artificial neural network model if the artificial neural network model is given a certain input values (Krose and van der Smagt, 1996). Furthermore, Krose and van der Smagt, (1996) suggested that the artificial neural network models generally consist of a set of processing units (neurons, cell); unit output, which shows the level of activation for each unit Yk; connections between units that connect neurons. In general, the connection is denoted by the symbol Wjk, which showed the effects of signal from unit j to unit k; propagation rules that serves to determine the effective input value sk; function that determines the level of activation Fk new activation level based on the value of effective input sk (t) and current activation condition Yk (t); external input (also known as bias or offset) $\theta$ for each unit; and methods of learning that shows how the information is processed by artificial neural network model.

## METHODOLOGY AND DATA

### Artificial Neural Network Methodology[1]

This artificial neural network carries out the calculation based on patterns that can be identified by the model. The calculation process of the artificial neural network is similar with linear regression when only one neuron available, where Y is the dependent variable, and X is the independent variable.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \quad (1)$$

or

$$Y = \sum_{n=1}^{n} \beta_n X_n \quad (2)$$

Equation 2 states that Y is the sum of Xn.

Figure 3 shows the feed-forward neural network with n = 4 input nerve, k = 3 hidden nerve, one hidden layer, and a neural output. It is called feed-forward model because Xn affect Y, and not vice versa (because for some models of artificial neural networks, one can model the changes that will affect the change of Y X). Strength of the relationship $\alpha$k, k = 1,2,3, ..., associated with hidden neuron against Y; strength of the relationship $\beta$nk, n = 1,2,3,4, and k = 1,2,3, associated with input neuron to the hidden neuron. Analytically, it can be shown to function as follows:

$$Y = h\left(\sum_{k=1}^{k} \alpha_k g\left(\sum \beta_{nk} X_n\right)\right) \quad (3)$$

Apparently the strength of the relationship $\alpha$kg (.) is the sum and filter through the activation function h (.) For practical purposes, g (.) and h (.) are considered equal. The difference of a single hidden layer of the neuron between the inputs and outputs do not seem the same at this time. However, if hidden neuron is sufficient, equation (5) will estimate the various forms of non-linear function with reasonable accuracy. It is known in the artificial neural network as the nature of the approach. Such an approach is not possible without a hidden layer (see White, 1992 as cited by Tkacz and Hu, 1999). Estimation of $\alpha$k and

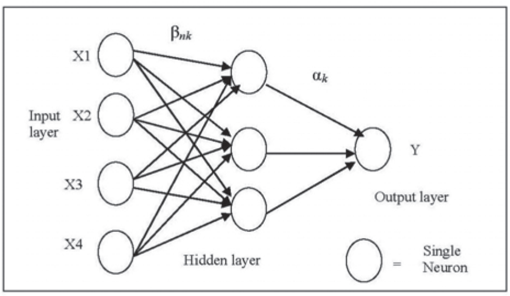
[1] This methodology section is summarized from Tkacz and Hu (1999).

ânk in equation (3) which is a learning process is direct, i.e. find the number of minimum deviation (sum squared deviation), between output and the network.

$$\min \alpha_k, \beta_n SSD = \left[ \sum_{t=1}^{T} Y_t - h\left( \sum_{k=1}^{K} \alpha_k g\left( \sum_{n=1}^{N} \beta_{nk} X_{nt} \right) \right) \right]^2 \quad (4)$$

The equation above is obtained by adjusting αk and reached the level pre-specification βnk until reaching convergence. Various numerical algorithms can be used to obtain these results although back propagation method is used. Search to find the value that adjusts the appropriate weight in order to minimize errors.

**Figure 1. Feed-forward Artificial Neural Network with Single Hidden Layer**




Artificial neural network equation (4) is sufficient for a wide range of economic application. For example, it can be used with a hidden layer more and more output as well. In general, artificial neural network requires three different sets of data. *First*, the data is required to exercise in order to make initial estimates of parameters. *Second*, the data samples for testing to verify the accuracy of the model forecasting exercise. If the testing sample forecast is not good, it is necessary to practice again with strict or relax convergence criteria. The training model is then tested again its accuracy. *Third,* forecasting sample is needed in which models can be used to predict.

The methodology incorporating signal model in order to detect slow down (recession) and expansion uses framework of Kaminsky, Lizondo and Reinhart (1998) signal model. This model assumes that if there is crisis in certain period (for example if window period is 24 months, the dependent variable (indicator) will be valued of 1 during 24 months before the onset of the slow down). Therefore, output nodes are 3 nodes containing GDP growth, slow down signal and expansion signal. Meanwhile, input nodes covers 19 indicators for the first group and the 16 input nodes for the second groups

The duration of expansion period of GDP on average is 11.4 months and the duration of slow down period is 17.25 months. The present authors set the assumptions for window period of slow down signal, 10 months (lower than that the actual of expansion period) and the expansion signal, 18 months (higher than that the actual slow down period). The reason of such assumption is that when the expansion hit the peak during 10 months (shorter than the fact due to risk averse), the economy will slow down. Therefore, the signal for slowdown of GDP is 10 months. Conversely, the signal for expansion of GDP is 18 months.

**Strength and Weakness of Artificial Neural Networks**

One of the advantages of artificial neural networks (ANN) is easy to make without having to make a model specifications. Furthermore, it can handle large irregular data. Another advantage of ANN is that this model can solve the problem of non-linear. So this model is well suited to data when is very volatile, erratic and incomplete (Tan, 1997). The use of artificial neural network is actually relatively simple.

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Some experts stated that artificial neural network is a special case of statistics model so many special restrictions in statistics also applied in the artificial neural network (Tan, 1997). In addition, the availability of software for artificial neural network allows users not need to know in depth the process of learning in artificial neural network model. The weakness of this model is the character of black box. So, it is difficult to interpret network weight estimation as well as to find the global minimum (Gonzalez, 2000). The construction of appropriate network architecture may be time consuming (Gonzalez, 2000).

**Data**

In applying artificial neural network approach, the authors make the selection data set of economic indicators that are theoretically affect economic growth both in terms of macro and micro approaches. Data indicators are converted in the form of annual growth and to eliminate seasonal effects if data influenced by seasonal effect. Otherwise, data on level will be used. Then examine the data whether it affects economic growth with the identification through Granger causality where their lag can be identified with the best lag for each indicator. Having identified the best lag among these indicators, the new data are restructured based on their lag to do calculations with artificial neural network model. Detailed process of determining indicators can be seen in Figure 2.

Meanwhile, the detailed network architecture (topology) of models is shown in Tables 1 and 2.

**Table 1. Topology of 19 Indicators**

| | Number of Imput | Number of Hidden Layer | Number of the First Hidden Layer Node | Number of the Second Hidden Layer Node | Number of Output |
|---|---|---|---|---|---|
| Case 0 | 19 | 1 | 9 | | 3 |
| Case 1 | 19 | 1 | 7 | | 3 |
| Case 2 | 19 | 1 | 5 | | 3 |
| Case 3 | 19 | 1 | 3 | | 3 |
| Case 4 | 19 | 2 | 9 | 3 | 3 |

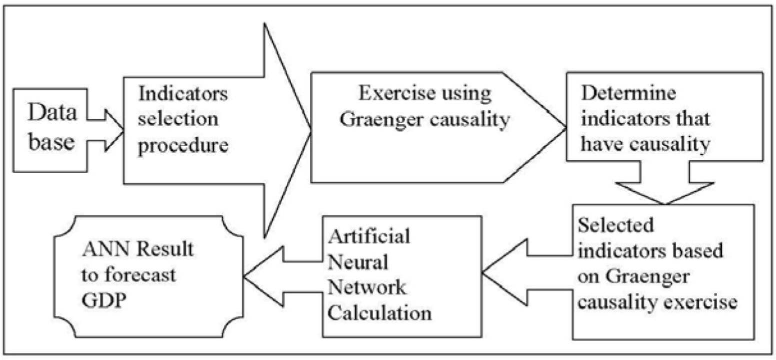
Source: Authors' Calculation

**Table 2. Topology of 16 Indicators**

| | Number of Imput | Number of Hidden Layer | Number of the First Hidden Layer Node | Number of Output |
|---|---|---|---|---|
| Case 0 | 16 | 1 | 8 | 3 |
| Case 1 | 16 | 1 | 6 | 3 |
| Case 2 | 16 | 1 | 5 | 3 |
| Case 3 | 16 | 1 | 5 | 3 |

Source: Authors' Calculation

**Figure 2. Flowchart for the prediction of GDP**




Monthly data are used, otherwise quarterly data are interpolated by using the data in that quarter to fill the rest of the month within the quarter. The purpose of using these monthly data to predict economic growth is much faster, so it can be used for policy-making, because most of data are generally available on monthly basis.

After the selection of data from those process, nineteen indicators were selected that are theoretically and its direction affects GDP growth using Granger causality method. The data used comes from Bank Indonesia, Central Bureau of Statistics, Motor Vehicle Manufacturers Association and Mundi commodity index. The model was developed using data from January 2000 until December 2008. Meanwhile, to make the simulation outside the sample, the data used is January 2009 through December 2010.

Nineteen leading indicators were used to carry-out simulations with various forms of networks to search for the best performance in-sample and out-sample. In addition, it is also made of 16 leading indicators by eliminating the lowest contribution to GDP prediction based on 19 leading model. Various models are simulated and then evaluated its performance based on MSE (Mean Squared Error). The lowest MSE is assumed to be the best model.

## ESTIMATION AND SIMULATION RESULTS

In 2002, GDP experienced a slowdown and later became a turning point with the growing trend though with fluctuations. The global economic crisis triggered by sub-prime mortgage crisis in the U.S. in mid-2007 affected Indonesian economy in mid 2008 in Indonesia (See Figure 3). Since mid 2008, there was a slowdown in economic growth by nearly 4% in the third quarter of 2009. This slowdown is expected to have reached the lower limit so that in future there will be accelerated back up to above 5% for each quarter.

Selected leading indicator can be seen in Table 3. These indicators represent indicators in the financial sector such as 1-month SBI interest rate, stock price index (JSX). Meanwhile, the real sector is represented by motorcycle sales growth. In the external sectors are export growth, import growth, the growth of non-oil exports, growth in imports of consumer goods, raw materials import growth, GDP growth in U.S. GDP growth in South Korea. In addition, international prices of export commodities were also elected as leading indicators. The business tendency and consumer tendency indices are used as leading indicators to represent the level of consumer confidence and the business sentiment.


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**Figure 3. Indonesian GDP Growth 2000-2010**

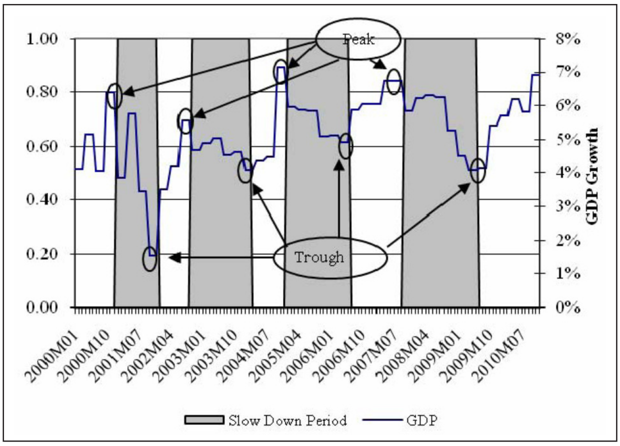


**Table 3. Selected Indicators**

| No. | Indicators | Code | *Lead* in months |
|---|---|---|---|
| 1 | Capital Expenditure (growth yoy) | CAPEX | **5** |
| 2 | International Rubber Price (level) | RUBBERPRICE | **4** |
| 3 | International Copper Price (level) | COPPERPRICE | **3** |
| 4 | Brent Oil Price (growth yoy) | BRENTPRICE | **3** |
| 5 | International Nickel Price (level) | NIKELPRICE | **2** |
| 6 | Import of Raw Materials (growth yoy) | GBBIMPR | **2** |
| 7 | Import of Consumption Goods (growth yoy) | GCONSIMP | **3** |
| 8 | Hard Sandwood (growth yoy) | GHARDWOD | **2** |
| 9 | International Aluminium Price (growth yoy) | GALUMINIUM | **3** |
| 10 | Jakarta Stock Price Index (growth yoy) | GIHSG | **3** |
| 11 | Imports (growth yoy) | GIMPRT | **2** |
| 12 | Exports (growth yoy) | GINDEXPRT | **3** |
| 13 | Non Oil and Gas Exports (growth yoy) | GINDEXPRTNMIGAS | **3** |
| 14 | Business Tendency Index (growth yoy) | GITB | **10** |
| 15 | Motorcycle Sales (growth yoy) | GMTR | **3** |
| 16 | Consumer Tendency Index (level) | ITK | **1** |
| 17 | South Korean GDP (growth yoy) | GPDBSKOR | **4** |
| 18 | US GDP (growth yoy) | GPDBUS | **4** |
| 19 | Central Bank Interest Rate 1 month (SBI) | SBI | **2** |

Source: Author Calculation Results

Business cycles in countries like South Korea and the United States which are the main trading partner seem to affect the domestic business cycle as well. Especially, these countries are the major non oil and gas (manufactured goods) exports. Therefore, the expansion of export destination countries will influence business cycles in the domestic economy. In the meantime, various international commodity prices, which are the main commodities of Indonesian exports, also affected Indonesia's GDP. These commodities include copper, nickel, petroleum, etc.

**Table 4. Period of Business Cycle in Indonesia**

| Trough | | Peak | |
|---|---|---|---|
| **Slowing Down Period** | **Duration** | **Expansion Period** | **Duration** |
| Jan 2001 - Dec 2001 | 12 months | Jan 2000- Dec 2000 | 12 months |
| Sep 2002 - Mar 2004 | 18 months | Jan 2002 - Sep 2002 | 9 months |
| Jan 2005 - Jun 2006 | 18 months | May 2004 - Dec 2004 | 9 months |
| Oct 2007 - Jun 2009 | 21 months | Jul 2006 - Sep 2007 | 15 months |
| | | Jul 2009 - Jun 2010 | 12 months |
| Mean | 17.25 months | Mean | 11.4 months |

Source: Authors' calculation

Two number groups of indicator were used. The first group is the 19 indicators with 5 models. The second group consists of 16 indicators with 4 models. The reduction of leading indicators from 19 indicators to 16 indicators based on their contribution to estimate GDP growth. The contribution of each indicator is shown in Table 4 for 19 leading indicators (Model of 19-case 2). The indicators that have a major contribution in forecasting economic growth in the artificial neural network model are non-oil and gas exports, international nickel prices, international rubber prices, international copper prices and non-oil exports. It appears that the international economy, as reflected by the large contribution of international commodity prices, significantly affected the national economic growth. In addition, non-oil export in the form of manufactured products also affected domestic economic growth. This means that Indonesian economy is very exposed to the international economy. Almost 90 per cent of leading indicators of the international economy affected the domestic economy. Meanwhile, contribution of leading indicator of the domestic economy is only about 10 percent. If 16 leading indicators (model 16-case 0) were selected, the phenomenon is very similar as well. Thus, the Indonesian economy is very vulnerable to international economic upheavals that transmitted through various international commodity prices. International commodities as well as manufactured goods are the main Indonesian exports.

The contribution of leading indicator of the domestic financial sector, the level of 1-month SBI interest rate is only 5.10 per cent. Meanwhile, capital expenditure contributed to 2.66 per cent to estimation of GDP. The real sector confidence indicator is 3.01 per cent. Leading indicators of domestic policy variable is Bank Indonesia interest rate (SBI one-month). If leading indicator is not a


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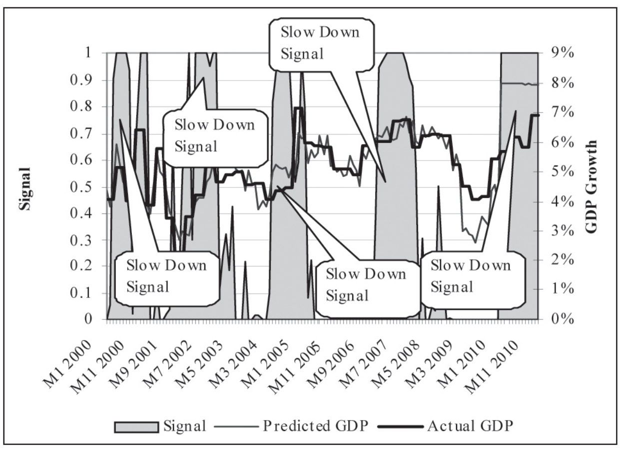
policy variable, to some extent, however, it can be affected indirectly through an appropriate government policy. For example, the consumer tendency index, this is related to the consumer confidence over the future economic prospects. This means that if the government makes policies in line with consumer expectation, then this index will increase. The consequences of increasing consumer demand will drive business prospect as well in the future. In the meantime, another government policy that may affect indirectly on the indicator of capital expenditure is a government policy to facilitate the investment climate so that capital expenditure or investment will increase. An improvement of infrastructure and appropriate fiscal policies will create investment climate.

Forecasting results of model 19 indicators and 16 indicators can be seen in Figure 4-7. These models were selected based on the performance of the lowest mean square error (MSE)[2]. The performance of the model can be measured by the mean square error (MSE). This artificial neural network models can be regarded as non-parametric model, hence statistical tool is not available to test it. The formula used to measure the deviation with the MSE is as follows:

$$MSE(t) = \frac{1}{n}\sum_{i=1}^{k}(P_n - R_n)^2 \qquad (5)$$

P= Predicted GDP growth
R= Actual GDP growth

**Figure 4. Forecasting GDP growth and Slowdown Signal 2000 - December 2010 (Model 19 Indicators-case 2)**




2 Due to limited space for this journal, anyone, interested in detailed calculation results, can request to the authors.

**Figure 5. Forecasting GDP growth and Expansion Signal 2000 - December 2010 (Model 19 Indicators-case 2)**

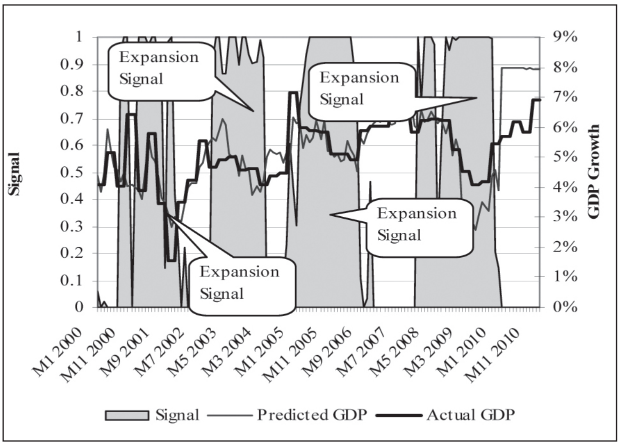



**Figure 6. Forecasting GDP growth and Slowdown Signal 2000 - December 2010 (Model 16 Indicators-case 0)**

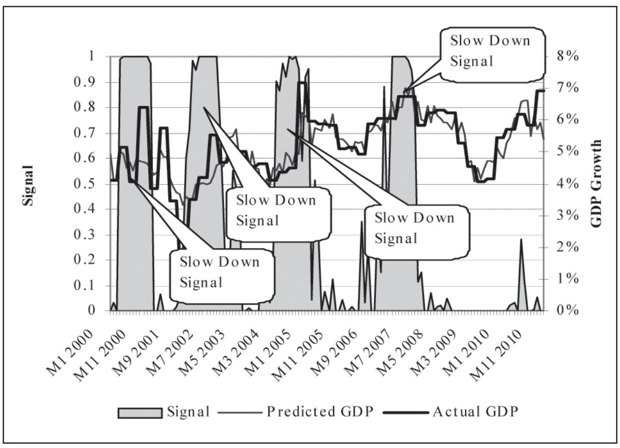
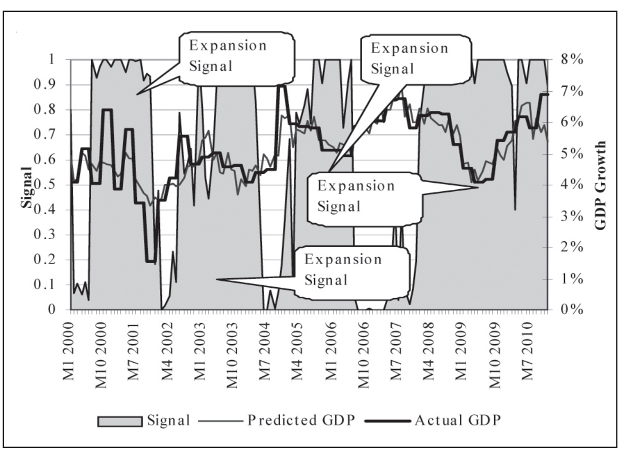



**Figure 7. Forecasting GDP growth and Expansion Signal 2000 - December 2010 (Model 16 Indicators-case 0)**

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The Figure 4 and 5 shows the predicted GDP growth of model 19-case 2. The signal of slowdown economy can be seen as well. This signal is very useful to predict the economic condition in the next 10 months whether there is a possible slow down or still expansion. Therefore, the model estimates not only the magnitude of GDP growth, but it can send a signal of possible slow down or expansion of GDP as well in 10 months earlier for slow down and 18 months earlier for expansion. Therefore, government has time make policy options to anticipate the condition. Meanwhile, model of 16 indicators case 0 also shows similar pattern for GDP growth. However, the signal pattern is slightly different especially for slow down signal. The model for 16 indicators case 0 shows a more optimistic than that of 19 leading case 0 model for slow down signal. This is very important for policy maker to make an appropriate policy. On the other hand, an expansion signal is important for business community to anticipate production and stock policy in their business.

Signal forecasting performance can be measured by measuring the mean square deviation (mean squared error), the quadratic probability score (QPS) Meanwhile, to measure the forecasting accuracy of calibration is also measured by the global squared bias (GSB).

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(P_t - R_t)^2 \quad (6)$$

Where:
P=Forecasting
R=Realization
T=period
QPS has a range from 0 to 2, if score = 0 reflects very accurately.

Meanwhile, the calibration of probability forecasting accuracy is associated with forecasting signal and observed relative frequency. Calibration compares the forecasting signal average of the average realization. The formula is as follows:

$$GSB = 2(\overline{P} - \overline{R})^2 \quad (7)$$

$$\text{Where } \overline{P} = \frac{1}{T}\sum_{t=1}^{T} Pt \quad \text{and} \quad \overline{R} = \frac{1}{T}\sum_{t=1}^{T} Rt \quad (8)$$

GSB value ranges from 0 to 2 with a value score = 0 reflects perfect calibration.

**Table 5. Indicators in Forecasting GDP Contribution (19 Indicator- Model 2)**

| No. | Indicators | Contribution (%) |
|---|---|---|
| 1 | Non Oil and Gas Exports (growth yoy) | 9.06 |
| 2 | Import of Raw Materials (growth yoy) | 8.06 |
| 3 | International Nickel Price (level) | 7.61 |
| 4 | Capital Expenditure (growth yoy) | 5.17 |
| 5 | Imports (growth yoy) | 4.86 |
| 6 | Import of Consumption Goods(growth yoy) | 4.49 |
| 7 | Consumer Tendency Index (level) | 3.59 |
| 8 | Central Bank Certificate Deposit Rate 1 month | 3.35 |
| 9 | Hard Sandwood (growth yoy) | 3.31 |
| 10 | International Rubber Price (level) | 3.10 |

| | | |
|---|---|---|
| 11 | Brent Oil Price (growth yoy) | 2.60 |
| 12 | International Aluminium Price (growth yoy) | 2.47 |
| 13 | Exports (growth yoy) | 2.14 |
| 14 | International Copper Price (level) | 2.08 |
| 15 | Motorcycle Sales (growth yoy) | 1.96 |
| 16 | South Korean GDP (growth yoy) | 1.89 |
| 17 | Business Tendency Index (growth yoy) | 1.76 |
| 18 | Jakarta Stock Price Index (growth yoy) | 1.29 |
| 19 | US GDP (growth yoy) | 1.22 |

Source: Authors'calculation

Comparing both models, one should take caution, because there are many aspects to be considered. The smaller the number of indicators with the better results is more preferred A larger indicator demands more effort to collect those data. Based on the performance of GDP estimation of both model, it appears that the model of 19 leading indicators case 2 is much better performance for GDP estimation and signal estimation than that of model of 16 leading indicators case 0[3].

Based on model of 19 leading indicators, there will be a possible slowdown as signal sends this alarm. In fact, infrastructure constraint will hamper the possible expansion of GDP in this case. This is the worst case or pessimistic case. On the other hand, an optimistic case, it looks like that the economic growth stay at the current level and it is hard to increase more than 7 per cent per year in the current infrastructure and economic policy except any break trough of the current economic policy. A policy maker should act as risk averse rather than a risk taker. Therefore, policy should take into account of this possible slowing down economic activity.

**Table 5. Indicators in Forecasting GDP Contribution (16 Indicator- Model 0)**

| No. | Indicators | Contribution (%) |
|---|---|---|
| 1 | Exports (growth yoy) | 18.19 |
| 2 | Brent Oil Price (growth yoy) | 11.59 |
| 3 | International Copper Price (level) | 8.18 |
| 4 | International Aluminium Price (growth yoy) | 7.88 |
| 5 | Imports (growth yoy) | 6.89 |
| 6 | Import of Raw Materials (growth yoy) | 6.69 |
| 7 | International Nickel Price (level) | 5.50 |

[3] Due to limited space for this journal, detailed calculation results are available upon request.


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| | | |
|---|---|---|
| 8 | International Rubber Price (level) | 5.47 |
| 9 | Import of Consumption Goods(growth yoy) | 5.27 |
| 10 | South Korean GDP (growth yoy) | 5.13 |
| 11 | Central Bank Certificate Deposit Rate 1 month | 5.10 |
| 12 | Non Oil and Gas Exports (growth yoy) | 3.22 |
| 13 | Consumer Tendency Index (level) | 3.01 |
| 14 | Capital Expenditure (growth yoy) | 2.66 |
| 15 | Hard Sandwood (growth yoy) | 2.64 |
| 16 | Motorcycle Sales (growth yoy) | 2.59 |

Source: Authors'calculation

## CONCLUSIONS AND POLICY IMPLICATIONS

The model identified some indicators that played a major role in influencing GDP growth. Most of those indicators are largely from external factors. This means that Indonesia's economy is highly vulnerable to external shocks. Therefore, the government must be more careful to monitor the global economic fluctuation. Thus, if the indicators are listed as a leading indicator with a sufficient period of time, 3 months or 6 months, it will provide an opportunity for policy makers to devise appropriate counter-cyclical policy. In addition, the role of each indicator is also important to look at the impact on GDP growth, such as business tendency index. Business confidence is closely related to the way of economic management and policies issued by the Government. An improvement of infrastructure and appropriate fiscal policies will create investment climate.

External sectors have substantial role in influencing the growth of GDP. Almost 90 per cent of leading indicators of external factors contributed to the fluctuation of Indonesian GDP. The implication of this finding is that international trade affected Indonesian economy. Major trading partner of Indonesian manufactured goods such as China, South Korea, US and Japan to some extent, however, influence GDP fluctuation. Likewise, the various international prices of commodities, which are the main of Indonesian exports such as copper, rubber and nickel, affected the domestic economy fluctuation as well. Therefore, in order to reduce the vulnerability of Indonesian economy against external shocks, the diversification of trading partners and commodities to be exported is one of the most important policies in the future.

Based on the model developed, the performance model is adequate in predicting in the sample and outside the sample. However, this model is still experimental in nature. Therefore it needs to be further developed by using different topology and adding observations for example by increasing the years of observation from the 1980s or even 1970s so it is expected to have a better predictive power.

## REFERENCES

Albu, Lucian-Liviu (2008), A Model to Estimate The Composite Index of Economic Activity in Romania –IIE-RO, *Romanian Journal of Forecasting*, 2/ 2008.

Allegret , Jean-Pierre, Essahbi Essaad (2009), *Synchronization in Business Cycle of East Asian Economy: Evidence from Time Varying Coherence Study,* at http://www.gate.cnrs.fr/perso/allegret/JPA_EE_May%2009.pdf

Andreev, Yuriy (2005), *Predicting Financial Distress Of Spanish Companies*, at http://webs2002.uab.es/dep-economia-empresa/Jornadas/Papers/2006/Andreev.pdf

Ao, Shan and Tang *Shou (2009), Chaos Forecasting Model for GDP Based on Neural Networks Error-Correction*, at http://www.seiofbluemountain.com/upload/product/200910/2007glhy-14a9.pdf

Babutsidze, Zakaria (2005), On *the Predictability of Currency Crises,* Working Paper Central European University, February 2005.

Berg, A. dan Pattillo, C.. (1999). Are Currency Crises Predictable? A Test. *IMF Staff*

Best, Ben (2010), *An Austrian Theory of Business Cycles,* http://www.benbest.com/polecon/buscycle.html

Carpio, K J E and Hermosilla, A Y (2000) *On Multicolliniearity and Artificial Neural Network* Manila: Dept of Mathematics, University of Philipines.

Carpio, K J E dan Hermosilla, A Y (2000) *On Multicolliniearity and Artificial Neural Network* Manila: Dept of Mathematics, University of Philipines.

Cobourn , W G , Dolcine, L, French, M and Hubbard, M C (2000) A Comparison of Nonlinear Regression and Neural Network Models for Ground-Level Ozone Forecasting *Journal of the Air & Waste Management Association 50:* 1999-2009. Sima, J (1998) *Introduction to Neural Networks Technical Report No. V-755* Prague: Institute of Computer Science, Academy of Sciences of the Czech Republic.

Gonzalez, Steven, (2000), Neural Networks for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models, Working Paper 2000-07, at http://dsp-psd.pwgsc.gc.ca/Collection/F21-8-2000-7E.pdf

Hj Mat Junoh, Mohd Zukime (2003), Predicting GDP Growth In Malaysia Using Knowledge-Based Economy Indicators: A Comparison Between Neural Network And Econometric Approaches in *Sunway College Journal 1, 39–50*.

Franck , Raphael  and Aurelien Schmied (2004), Predicting Currency Crisis Contagion from East Asia to Russia and Brazil: An Artificial Neural Network Approach, at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=535402.

Imansyah,  M. Handry dan Kusdarjito, Cungki (2009), Meramalkan Potensi Risiko Krisis atau Instabilitas di Sektor Keuangan: Pendekatan Jaringan Saraf Buatan dalam *Kajian Stabilitas Keuangan,* no 13 September 2009, Bank Indonesia.

Jain, A K, Mao, J dan Mohiudin, K (1998) *Artificial Neural Network: A Tutorial* Michigan: Michigan State University.

Kaminsky, G.L., Lizondo, S., dan Reinhart, C.M. (1998), *Leading indicators of currency crisis*, IMF Staff Papers 45/1, International Monetary Fund, Washington D.C.

Khurshid M. Kiani, Prasad V. Bidarkota,Terry L. Kastens (2005), Forecast performance of neural networks and business cycle asymmetries, *Applied Financial Economics Letters*, 2005, vol. 1, issue 4, pages 205-210.

Khurshid M. Kiani, 2005, Detecting Business Cycle Asymmetries Using Artificial Neural Networks and Time Series Models, *Journal Computational Econo-*

*mics*. Springer, vol. 26(1), pp. 65-89, August.

Koopmans, Tjalling C. (1947), Measurement Without Theory, *The Review of Economic Statistics*, Vol. 29, No. 3 (Aug., 1947), p. 161-172.

Krose, B and van der Smagt, P (1996) *An Introduction to Neural Network* Amsterdam: Faculty of Mathematics and Computer Science, University of Amsterdam.

Krose, B dan van der Smagt, P (1996) *An Introduction to Neural Network* Amsterdam: Faculty of Mathematics and Computer Science, University of Amsterdam.

Kusdarjito, C (2002) *Model Saraf Buatan* Yogyakarta: FP-UJB.

Kydlan, Finn E. and Prescott, Edward C (1982), Time to Build and Aggregate Fluctuations in *Economterica* November 1982.

Li, S, Wunsch, D, O'Hair, E and Gieselmann, M G (2001) Comparative Analysis of Regression and Artificial Neural Network Models for Wind Turbine Power Curve Estimation *Journal of Solar Energy Engineering* 123:327-332.

Lucas, R.E. Jr. (1977), Understanding Business Cycles, in Lucas R.E. Jr (1981), *Studies in Business Cycle Theory*, MIT Press, Cambridge, MA, 1983.

Marcelino, Massimiliano (2006), Leading Indicators, in Elliott, G., Granger, C.W.J. and Timmermann, A. (eds), *Handbook of Economic Forecasts*, Chapter 16, Amsterdam: Elsevier. At http://www.eui.eu/Personal/Marcellino/13.pdf

Min Qi, (2001), Predicting US recessions with leading indicators via neural network models, *International Journal of Forecasting, Volume 17, Issue 3*, July-September 2001, Pages 383-401.

Mirbagher, Mirnaser (2010), Fuzzy-logic and Neural network Fuzzy forecasting of Iran GDP Growth, African Journal of Business Management, Vol. 4(6), pp. 925-929 at htpp://www.academic-journas.org/ajbm

Mitchell , Wesley C. and Burns , Arthur F. (1939), Statistical Indicators Of Cyclical Revivals, National Bureauof Economic Research, *Bulletin 69*, May 28, 1938.

Peltonen, Tuomas A (2006), *Are Emerging Market Currency Crises Predictable? A Test*, Working Paper Series no. 571 / January 2006, European Central Bank.

Peltonen,T.(2002*),* Are Currency Crises Predictable?An Application of Panel Estimation Methods and Artificial Neural Networks*, European University Institute, Department of Economics, Florence, mimeo.*

Pensieroso, Luca (2007), Real Business Cycle Models of the Great Depression: a Critical Survey, *Journal of Economic Survey*, Vol. 21, 1(2), pp. 110-142.

Shi , Pengyi, Zhuo Chen, and Guangming Xie (2006), *Using artifcial neural network trained with genetic algorithm to model GDP prediction,* http://www.mech.pku.-edu.cn/robot/fourleg/members/shi-pengyi/Using_artificial%20_eural_-network_trained_with_GA_to_model_-GDP.pdf

Sima, J (1998) *Introduction to Neural Networks Technical Report No. V-755* Prague: Institute of Computer Science, Academy of Sciences of the Czech Republic.

Slamet, Sutomo and Puguh B. Irawan (tanpa tahun), Development of Composite Leading Indicators (CLIs) in Indonesia, http://www.oecd.org/data-oecd/54/49/34898123.pdf.

Solow, R.M. (1956), A Contribution to the Theory of Economic Gorwth, *Quarterly Journal of Economics*, Vol. 70, pp. 65-94.

Tan, Clarence (1997), *An Artificial Neural*

*Networks Primer with Financial Applications Examples in Financial Distress Predictions and Foreign Exchange Hybrid Trading System*, Bond University.

Tan, Clarence, and Herlina Diharjo (1999), *A Study on Using Artificial Neural Networks to Develop An Early Warning Predictor for Credit Union Financial Distress with Comparison to the Probit Model*. http://www.it.bond.edu.au/publications/00TR/00-07.PDF.

Teräsvirta, Timo, Dick van Dijky and Marcelo C. Medeirosz, (2003), *Smooth transition autoregressions, neural networks, and linear models in forecasting macroeconomic time series: A re-examination,* at http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.130.3608&rep=rep1&type=pdf

The Royal Swedish Academy of Sciences*, Finn Kydland and Edward Prescott's Contribution to Dynamic Macroeconomics: The Time Consistency of Economic Policy and the Driving Forces Behind Business Cycle*, at http://nobelprize.org/nobel_prizes/economics/laureates/2004/ecoadv.pdf

Tkacz, Greg and Sarah Hu (1999), Forecasting GDP Growth Using Artificial Neural Networks, Working Paper 1999-3, Bank of Canada, at http://www.bankofcanada.ca/wp-content/uploads/2010/05/wp99-3.pdf

Tkacz, Greg (2001), Neural Network Forecasting of Canadian GDP Growth, International Journal of Forecasting, 17, pp. 57-69.

Vanstone, Bruce J, Finnie, Gavin R and Tan, Clarence N W (2005), *Evaluating The Application Of Neural Networks And Fundamental Analysis In The Australian Stockmarket.* School of Information Technology, Information Technology papers, Bond University.

Wen, Yi (2007), Graenger Causality and Equilibrium Business Cycle Theory*, Federal Reserve Bank of St. Louis Review*, May/June 2007, pp. 195-205.

Zhang, G. Peter and Min Qi (2005), Neural network forecasting for seasonal and trend time, *European Journal of Operational Research,* Volume 160, Issue 2, 16 January 2005, Pages 501-514 series.

Zhang, Wenda and Juzhong Zhuang, (2001), Leading Indicators of Business Cycles in Malaysia and the Philippines, ERD Working Paper Series No. 32, Economics And Research Department, Asian Development Bank, at http://www.adb.org/Documents/ERD/Working_Papers/wp032.pdf

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