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PREDICTING GDP GROWTH IN MALAYSIA USING KNOWLEDGE-BASED ECONOMY INDICATORS: A COMPARISON BETWEEN NEURAL NETWORK AND ECONOMETRIC APPROACHES

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ABSTRACT

In recent years, neural network techniques have been increasingly used for a wide variety of applications where statistical methods had been traditionally employed. Neural network techniques, for example, have been applied to problems like chemical process control, seismic signals interpretation, machines diagnostic, target marketing, economic forecasting, financial modelling, market share prediction, stock market prediction, and risk management. In contrast, traditional econometric approaches have continued to be used for prediction models in almost all the above areas. This paper proposes the extension of neural network techniques to include prediction models because of two obvious advantages. First, it does not require any assumptions about underlying population distribution; second, it is especially useful in cases where inputs are highly correlated or are missing, or where the systems are nonlinear. This paper presents a comparative case study between neural network and econometric approaches to predict GDP growth in Malaysia using knowledge based economy indicators based on time series data collected from 1995–2000. The findings indicate that the neural network technique has an increased potential to predict GDP growth based on knowledge based economy indicators compared to the traditional econometric approach.

Key words: GDP growth, knowledge based economy, artificial neural networks.

INTRODUCTION

In recent years, neural networks have been used for a wide variety of applications where statistical methods were traditionally employed. The neural network technique with its forecasting ability has been used successfully in various economic studies including investment, economic and financial forecast, (Hsieh, 1993; Swales and Yoon, 1992; Hutchinson, Lo and Poggio, 1994) and exports growth as the source of economic growth (Shaaf and Ahmadi, 1999; Shaaf, 2000). Initially neural networks were developed as simulation models of the brain and the terminology used is still a reminder of this origin. This physiological context, widely used to handle complex data, may have contributed considerably to the diffusion and implementation of neural network models in economics and econometrics (Hecht-Nielson, 1990; Hercht, Gallant and White, 1989; White, 1992; Swanson and Halbert, 1997).

But in spite of a growing application of neural networks to a wide variety of problems, traditional econometric approaches continue to be used for prediction models in almost all the above areas. By means of a case study, this paper proposes that the neural network techniques may successfully be extended to include prediction models because of two obvious advantages. First, it does not require any assumptions about underlying population

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distribution; second, it is especially useful in cases where inputs are highly correlated or are missing, or where the systems are nonlinear. This exploratory study, therefore, presents a comparison between neural network and econometric approaches to predict GDP growth using k-economy indicators in Malaysia based on time series data collected from 1995–2000. Finally, the paper proposes modifications to the neural network model in order to improve prediction accuracy.

KNOWLEDGE-BASED ECONOMY

A Knowledge-Based Economy (k-economy) is shaped not only by the development and diffusion of computer hardware and software, but also by cheaper and rapidly increasing electronic connectivity (Daley, 2000). The use of open systems, the development of software and supporting technology, and particularly the use of the Internet accelerate the information technology (IT) revolution. In economic terms, the main feature of the IT revolution is the ability to manipulate, store and transmit large quantities of information at a very low cost (Houghton and Sheehan, 2000). Because of its low manipulation, storage and transmission cost, information flow across the Internet and, consequently, the application of knowledge to all aspects of the economy are greatly facilitated.

A reduction of tariff and non-tariff barriers, the floating of currencies, the reduction of barriers to foreign direct investment and the deregulation of product markets in many countries have accompanied the globalization of economic activities. Various observers describe today's global economy as one in transition to a "knowledge economy," or an "information society." But the rules and practices that determined success in the industrial economy of the twentieth century need to be re-written in an interconnected world where resources such as "know-how" are more critical than other economic resources.

Productivity growth is one of the most important indicators of economic health (Montes, 2000). Advancements in IT are the driving forces behind this acceleration in productivity. Because of faster productivity growth, the U.S economy for example, can now sustain a higher growth rate of Gross Domestic Product (GDP). In order to boost productivity growth, Blinder (2000) suggests doing one or more of these three things: (1) improve the quality of the workforce through education and training, (2) equip the workers with more and better capital such as computers, and (3) improve technology, so that the given input produces greater output.

The declining prices of IT goods and services have worked, directly and indirectly, to reduce the overall inflation in the U.S. economy. Nevertheless, because of the extraordinary growth of IT industries in the period 1995 to 1999, they accounted for an average 30 percent of total real U.S. economic growth (Dalton, 2000). Dumagan (2000) also confirmed that based on macroeconomic and firm-level evidence, IT contributed significantly to productivity growth in the U.S.

Haltiwanger and Jarmin (1999) suggested five major areas to measure the digital economy. These included IT infrastructure, e-commerce, firm and industry market structure, demographic and worker characteristics, and price behaviour. However, more than 50 percent of GDP in the major OECD economies is now based on the production and distribution of knowledge (Ernst and Young, 1999). The growth of the Internet and other related new technology has become the catalyst for the creation of the knowledge economy.

Because of these facts, this exploratory study focused on IT infrastructures as inputs to the neural network model.

THE CASE OF MALAYSIA

A k-economy is one where the generation and utilization of knowledge contribute significantly to economic growth and wealth creation. Thus, the economy must be characterized by knowledge-based activities and high-tech industries accounting for a significant share of GDP growth. In Malaysia, the k-economy proposes to provide the platform to sustain a rapid rate of economic growth. The national economy has already achieved positive GDP growth after the recovery from the Asian financial crisis. The expected GDP growth for 2003 is from 6.0 to 6.5 per cent compared to 4.0 to 5.0 per cent for 2002, (Post-Budget 2003 Report). Malaysia, having spent 5.2 percent of its GDP (US$5.3 billion) on Information and Communication Technology (ICT) in 2001, is in a relatively better position compared to many other countries in the matter of ICT spending (Table 1). Table 2 shows personal computers and phone lines per 1,000 persons in Asian countries.

Table 1. Information and Communication Technology Spending, 2001

Country	% GDP	(Billion US$)
New Zealand	10.5	6.5
United States	8.9	761.9
Australia	8.9	36.8
Hong Kong	8.3	12.8
Singapore	7.7	8.0
Vietnam	7.4	1.7
Japan	7.1	362.0
Malaysia	**5.2**	**5.3**
China	4.9	47.9
Taiwan	4.8	16.0
South Korea	4.4	24.4
India	3.5	15.5
Philippines	2.7	2.5
Thailand	2.1	3.9
Indonesia	1.4	2.9

Source: Asiaweek, June 29, 2001, p. 48.

THE VARIABLES AND DATA SOURCES

Knowledge based economy indicators are selected based on k-economy Development Index (KDI) (Table 3), including four independent variables, namely:

1. Mobile telephone subscribers per 1,000 population (*MP*)

2. Internet subscribers per 1,000 population (*IS*)
3. Number of computers per 1,000 population (*NPC*)
4. Personal computer installation per 1,000 population (*PCI*)

Table 2. Personal Computers and Phone Lines (Per 1,000 People)

Country	Personal Computers	Telephone Lines
Singapore	485.3	486.6
Hong Kong	346.1	578.7
Malaysia	**104.7**	**210.3**
Thailand	23.5	83.2
Philippines	19.6	39.7
China	16.1	121.1
India	4.6	32.3

Source: Asiaweek, June 29, 2001, p. 49.

The choice of independent variables is to test if the IT infrastructures contribute to GDP growth in the knowledge economy era. The real GDP growth is used as dependent variable or output target. In addition, the interaction between the variables is explored to determine if there is an uncertainty regarding the proper functional relationship between the input and output variables (Delurgio, 1998). This research used the data that were collected from 1995 to 2000. All the data were obtained from the economic reports 1999/2000 (Ministry of Finance, 2000) and the Eighth Malaysian Plan, 2001–2005.

Table 3. Components of the Knowledge Based Economy Development Index (KDI)

Computer Infrastructure

- Share of worldwide computers in use
- Computers per 1,000 population
- Share of total worldwide millions of instructions per second (MIPS)
- Computer power per capita
- Connections to the Internet

Infostructure

- Investment in telecommunication
- Main telephones in use per 1,000 population
- Cellular mobile telephone subscribers per 1,000 population
- Television sets per 1,000 population
- Radios per 1,000 population
- Fax machines per 1,000 population
- International call cost
- Newspaper circulation

Table 3 (continued)

Education and Training

- Total expenditure on education per capita
- Literacy rate
- Student-teacher ratio (primary)
- Student teacher ratio (secondary)
- Secondary enrolment
- Higher education enrolment

Research and Development (R and D) and Technology

- High-technology exports as a proportion of manufacturing exports
- Number of scientists and engineers in R and D
- Total expenditure on R and D personnel nationwide per capita
- Total expenditure on R and D as a percentage of GDP
- Average annual number of patents granted to residents
- Business expenditure on R and D per capita

Source: Malaysia: Third Outline Perspective Plan Report, (OPPT3, 2001–2005), p. 129.

PREDICTION MODELS

In this study, two forecasting models were employed to forecast the GDP growth using k-economy indicators: the neural network model and the econometric model.

Neural Network Model

Neural networks are a form of multiprocessor computer system, with simple processing elements, a high degree of interconnection, simple scalar messages and adaptive interaction between elements. The neural network system consists of neurons (cells), neural interconnections (internal links) and connections with the outer world (Figure 1). This network is connected to the outer world by the first or input layer and by the last or output layer. Between input and output layer, one can have a hidden layer that is used to solve non-linear problems. The network is "fully connected," that is, all nodes are linked in adjacent layers. These links are weights that can be strong or weak depending on their values. The weights are adjusted to minimize of the mean square error, which is the objective function.

This study uses the most popular neural network model termed "Back Propagation." Back Propagation is a learning algorithm by which multi-layer networks are set for pattern recognition using time series data as the external teacher. As in the econometric method, Back Propagation employs an optimisation technique to find optimum values of the weights as parameters.

To explain the mathematical equation of the neural networks, assume that x represents the independent variables, h represents hidden nodes in the hidden layer, and y represents output nodes in the output layer. Accordingly, Back Propagation computes the summation of multiplication of independent variables (x_i), with their corresponding weights (input to hidden layer), and adds bias weights (intercept) to produce a signal that goes into h_k (Figure 1).

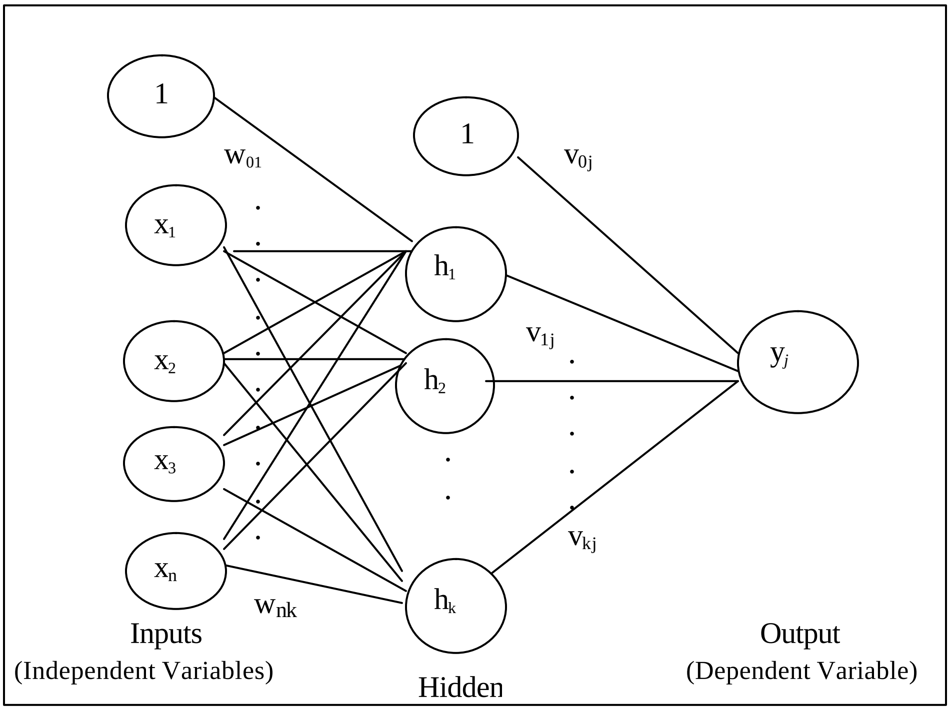

Figure 1. A neural network approach

In a neural network, the signal that goes into h_k can be calculated as

$$h_{k\_in} = w_0 + \sum_{\substack{i=1 \\ k=1}}^{\substack{m \\ n}} x_i w_{ik} \tag{1}$$

By considering $x_0 = 1$, equation (1) can be simplified as follows:

$$h_{k\_in} = \sum_{\substack{i=0 \\ k=1}}^{\substack{m \\ n}} x_i w_{ik} \tag{2}$$

In words, equation (1) states that h_{k_in} is a weighted sum of the x_i. This relationship is shown in Figure 1 with $i = n$, where each x_i is linked to h_k by the input weights w_{ik}. Now, equation (2) is generalized by the introduction of nonlinearities. The weight summations, h_{k_in} in equation (2), are then transformed by a transfer function in the hidden layer. In this study, the sigmoid transfer function such as logistic function is defined as

$$g(u) = \frac{1}{1+e^{-u}}. \tag{3}$$

where e is the base of natural logarithms.

Hence, to allow for a nonlinear relationship between the weighted input and the output, equation (3) can be applied to equation (2), yielding:

$$h_k = \mathrm{g}(h_{k\_in})$$

The value of h_k is determined by the following condition.

$$h_k = 1 \text{ if } h_{k\_in} \geq 0$$
$$h_k = 0 \text{ if } h_{k\_in} < 0$$

More generally, the hidden units (intermediate variable) in a neural network need not be identified in order to forecast y_j; they can simply be considered as unknown. Tkacz (1999) explains that proceeding with the hypothetical example, if an intermediate variable can be thought of as representing investment, then the neural network model can allocate larger weights for investment levels that have proportionately larger effects on output growth.

The connection link v_{kj} links the hidden neuron h_k to output neuron y_j. The neural network computation can be represented as

$$y_{j\_in} = v_{0j} + \sum_{\substack{k=1 \\ j=1}}^{\substack{p \\ m}} h_k v_{kj} \tag{5}$$

or as

$$y_{j\_in} = \sum_{\substack{k=0 \\ j=1}}^{\substack{p \\ m}} h_k v_{kj} \tag{6}$$

Consequently, it is seen that the connection link v_{kj} is accumulated and filtered through another activation function $h(r)$ viz:

$$h(r) = \frac{1}{1+e^{-r}}. \tag{7}$$

The output from the neural network model can be calculated as

$$y_j = h(y_{j\_in}) \tag{8}$$

If there are sufficient numbers of hidden neurons, equation (6) can approximate any nonlinear function to an arbitrary degree of accuracy. According to White (1992), this is known as the universal approximation property of neural networks, and such an approximation is not possible in the absence of the hidden layer.

The error function of the weights to be minimized is

$$E = (½)\sum (t_j - y_j)^2 \qquad (9)$$

The last layer contains the output unit, denoted by t_j (training values). In statistical nomenclature these units are known as the dependent or response variables. This is the sum of the squared difference between the predicted response (output values) and the observed response averaged over all outputs and observations (pattern). This is done by adjusting the weights v_{kj} and w_{ik} until the desired level of convergence is achieved.

Econometric Model

An econometric model can be configured as a perceptron to predict GDP growth using knowledge based economy indicators (Figure 2). However, the activation function used with Multilayer Perceptron (MLP) is a sigmoid function. Therefore, a similar econometric model will be a regression model (Sarle, 1994). Figure 2 illustrates an economic model.

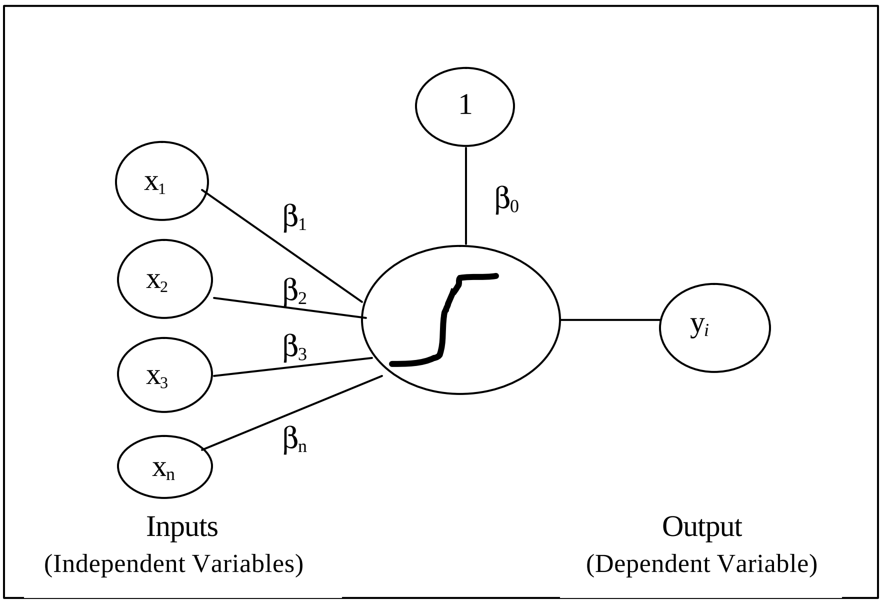

Figure 2. Econometric Model configured as a Neural Network Model

The mathematical equation that represents the econometric model is

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i + e_i \tag{10}$$

It is assumed that the random component has a normal distribution with mean zero and variance σ^2. Equation (10) can be simplified as

$$y_{i\,(X)} = \beta_0 + \sum_{i=1}^{n} b_i x_i + e_i \tag{11}$$

where $e_i \sim N(0, \sigma^2)$. The objective of this regression problem is to find the coefficients β_i that minimize the sum of squared errors,

$$E = \frac{1}{2} \sum_{i=1}^{I} \left[y_i - \sum_{i=0}^{N} b_i x_i \right]^2 \tag{12}$$

To find the coefficients for the model, a data set that includes the independent variables and associated known values of the dependent variable is needed. The regression model used is as follows:

$$y_i = \beta_0 + \beta_1\, IS_t + \beta_2 MP_t + \beta_3\, NPC_t + \beta_4\, PCI_t + e_I$$

where y_i is real GDP growth, and β_0, β_1, β_2, β_3, and β_4 are the parameters of the equation. Each exogenous variable has a significant effect on GDP growth (t-statistic: IS = 0.643, MP = 0.667 and NPC = 0.896 respectively) as shown in Table 4.

Table 4. The Estimated Result of Regression

Independent Variables	Estimated Coefficient	Standard Error	t-statistic
Constant	0.927	46.3311	0.0200
IS	5.100	7.9300	0.6429**
MP	0.009	0.0141	0.6679**
NPC	1.171	1.3061	0.8966***
PCI	–84.169	75.2116	–1.1191

R-squared: 62.47. Adjusted R-squared: 87.63. Note: *, **, and *** denote significance at the 1 percent, 5 percent and 10 percent levels.

EMPIRICAL RESULTS

In this study, the Back Propagation technique, a delta-learning rule and a sigmoid transfer function are considered appropriate for learning and pattern recognition. The delta rule measures the error and changes the weight for each observation. Most neural network models accept only numeric data in the range of 0 to 1 or –1 to +1. The first step that should be taken in data processing is eliminating redundancy, since it can seriously reduce the network performance (Bigus, 1996). The data normalization of this study is in the range of 0 to 1 for the neural network model. Most problems such as those with a small number of inputs and one single output can be solved with a single hidden layer. Therefore, a set of hidden nodes or units are tested in this study by using tria l and error testing as suggested by Tsoukalas and Uhrig (1997).

The best network model obtained consists of 4 input units (IS, MP, NPC and PCI), one hidden layer with one hidden unit, and one output unit (real GDP growth). The learning rate for the last hidden layer must be twice that of the output layer. In general, the normalized cumulative delta rule works well. In this study, the learning rate is set to 0.1, the normalized cumulative delta rule with an epoch of 15 is considered appropriate.

Table 5. Performance of Neural Network Model versus Econometric Model

Output Measurement Criteria	Neural Network Model	Econometric Model
Root Mean Square Error (RMSE)	0.578	3.504
Mean Absolute Error (MAE)	0.334	3.068
Percentage of Correctness (%)	83.33	62.47

The forecasting performances obtained by the neural network and econometric models are shown in Table 5. The results indicate that the neural network model achieved higher performance compared to the econometric model using standard statistical measurement criteria. At all final stages, the forecast errors of all horizons are calculated and used to produce two summaries criteria which are Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The results for the neural network model show that RMSE and MAE are better than those generated by the econometric model.

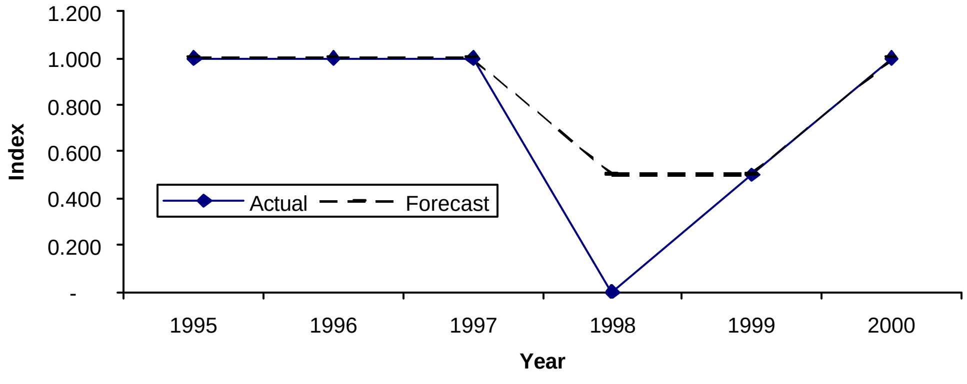

Figure 3. Knowledge-based economy on GDP growth

The results imply that the neural network model is a better alternative approach to predict GDP growth using knowledge based economy indicators. The actual and predicted knowledge based economy on GDP growth is illustrated in Figure 3. The results of the study indicate that IT infrastructure plays a crucial role in GDP growth in the knowledge economy.

The predicted GDP growth produced by the neural network model is the same as the actual GDP growth for the years 1995 to 1997 and 1999 to 2000. The neural network model predicted a GDP growth slightly higher than the actual GDP growth for the year 1998. The difference between the actual and the forecast GDP growth is due to the recession that affected the global economy. On the whole, the neural network model has demonstrated a great potential to predict GDP growth using knowledge based economy indicators.

CONCLUSION AND FURTHER RESEARCH

The findings of this study show that it is possible to use a neural network to predict the GDP growth using knowledge based economy indicators. To improve the prediction accuracy, one possible way is to include other factors such as firm and industry market structure, demography and worker characteristics and price behaviours as suggested by Haltiwanger and Jarmin (1999).

The extensive use of other microeconomic and macroeconomic variables can also improve the findings of this study. In addition, longer time series and even higher-frequency data might improve the prediction result. This approach can be used to test the effects of other micro and macro variables. Finally, the neural network developed for this research can be modified in terms of neural network type, topology, and learning rules. Integrating the neural network with statistical techniques, genetic algorithms (Goldberg 1989), fuzzy logic (Cox 1992), and expert systems (Watkins & Eliot, 1993) is a research direction where high payoffs can be expected.

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