PREDICTING THE GDP OF THE NEW ECONOMY BASED ON THE HUMAN CAPITAL USING NEURAL NETWORK APPROACH

Mohd Zukime Mat Junoh[1], Fadzilah Siraj[2], Arman Hadi Abdul Manaf[3], Mohd Suberi Ab. Halim[4], Muhammad Safizal Abdullah[5]

[1,4,5]School of Business Innovation and Technopreneurship, Universiti Malaysia Perlis;
[2]School of Information Technology, Universiti Utara Malaysia, MALAYSIA;
[3]Faculty of Business Administration, Kanagawa University, JAPAN.

[1]mohd.zukime@gmail.com, [2]fad173@webmail.uum.edu.my, [3]armanhadi.abdulmanaf@gmail.com, [4]suberi@unimap.edu.my, [5]safizal@unimap.edu.my

ABSTRACT

Human capital has become important because knowledge is a critical ingredient for gaining competitive advantages, particularly in the New Economy era. It has been described as becoming the preeminent resource for creating economic wealth. To date, several studies have been conducted to determine the relationship between human capital and company performance. The relationship between human capital and economic growth has been explored. However, past literature reveals that artificial intelligence techniques have not been utilized in understanding the effect of human capital on economic growth. Artificial intelligence techniques such as neural networks have been successfully applied to business and financial problems. To this end, the neural networks approach was used to determine the impact of human capital on the New Economy. This paper discusses the results of the exploratory study for predicting demand for human capital. Data from 1971 to 1996 was collected for this study. The variables used for the prediction were based on Canadian's Human Capital Measurement as suggested by Laroche and Merrette (2000). The exploratory study indicated that neural network is a potential approach for predicting the GDP based on human capital. In conjunction with neural network approach, statistical methods were also used to explain the relationships between variables in the study.

Keywords: Neural Network, GDP, Prediction, Human Capital, New Economy

INTRODUCTION

A neural network may be envisioned as a highly-interconnected structure of processing elements that attempt to mimic the parallel computational ability of the biological brain. Its structure consists of highly interconnected computational units called neurons, nodes, or perceptrons. In general, a neural network is characterized by the network's topology, the computational characteristics of its elements, and the training rule. Neural networks are efficient at analyzing problems of prediction rather than explanation, comparatively robust and fault tolerant (DeTienne and Joshi, 1999; McMillen and Henley, 2001; Ladstätter, Garrosa, Badea and Moreno, 2010).

A number of forecasting models have been developed over the past several years, with many of them finding their ways into regular use by practical forecasters (Kou, 1996; Kou and Sobel, 2004). Conventional models rely on historical data and use it to project variables of interest. Models assume that the future will be exactly like the past, except for those variables specifically used by the model to develop a forecast. Artificial intelligence techniques, particularly neural networks have the most commercial applications, including forecasting (Kou, 1996; Azen, Xiang, Lapuerta, Ryutow and Buckley, 2000; Swales and Yoon, 1992; Hutchinson, Lo and Poggio, 1994; Shaaf and Ahmadi, 1999; Shaaf, 2000; Zhang, 2004).

Previous research indicated that neural networks offer potential advantages in time series models in addressing nonlinear data problems. Furthermore, their performance is at par with, or occasionally superior to, that of statistical models (Swales and Yoon, 1992; Hutchinson et al., 1994; Shaaf and Ahmadi, 1999; Azen et al., 2000; Shaaf, 2000). Neural networks are highly versatile and do not require formal model specifications. In addition, neural networks can tolerate chaotic components, a critical ability when dealing with time series data (Hansen, McDonald and Nelson, 1999).

Human capital is generally believed to be essential in the process of economic growth. [Hers, 1998] concludes that human capital exerts a positive significant effect to economic growth. This study explores a new approach in determining the GDP of the New Economy by considering the human capital as the input to the prediction model. The New Economy can be described as an economy that is increasingly producing digital embodiments of ideas rather than physical entities (Gundlach, 2001). It is an industry that generates earnings without the need for physical products and/or uses intelligence and innovation as its raw materials (Simpson, 2000). The economy that was based on old economy industries has paved the way for the New Economy by investing in education and electronic infrastructures. The primary source of wealth for the New Economy is based on the intellectual capital rather than material resources. Considering that the New Economy is also based on the development of electronic global multimedia networks, the profits of intellectual capital could dramatically improve in a networked economy.

Intellectual capital comprises three areas. The first area is human capital, which includes the capabilities of individuals to provide solutions to customers. The second is structural capital, which refers to the capability of the organization to meet market requirements. The third area is customer capital, which is the penetration, width, loyalty and profitability of the organization's relationship with all its customers (Saint-Onge, 1997). However, Gary Becker contends that the chief source of wealth of an organization is contributed by human capital. He further emphasized that human capital is the most important type of wealth in the U.S. and other modern nations. Human capital is estimated to be three to four times the value of stocks, bonds, housing, and other assets. Thus, the vast wealth associated with human capital gives competitive advantage as well as value added in accelerating economic growth. The market capitalization of an organization will depend on the quality of its human capital such as skill, agility, competence, and experienced workers. As Siebert (2000), indicated that the New Economy implies a further shift in relative demand in favor of qualified labor and the disadvantage of less qualified labor.

Human Capital is defined as "… the capabilities of the individuals in an organization what are required to provide solutions to customers". Individual capabilities are composed of attributes, competencies, and mindsets. Human capital represents the individual knowledge of all employees in an organization (Solow, 1956). Most knowledge is contained in the skills and expertise of so-called expert employees. The human capital embedded in these employees is important because it is a source of innovation and strategic renewal. Human capital also refers to productive capabilities of human beings as income-producing agents in the economy, whereas human resource development is associated with investment in humans and their development as a creative and productive resource (Ghosh, 1998; Galor and Moav, 2004).

Considering that human capital will replace physical capital as the crucial factor of production, improving the qualifications of the labor force is essential to successfully address the challenges of the New Economy in the labor market (Klodt, 2001). Hence, the New Economy has long been predicted to generate a substantial increase in aggregate productivity growth (Gundlach, 2001). The strong increase in US labor productivity growth provides the most convincing evidence in favor of the emergence of a New Economy. If the diffusion of information technology improves business practices, generates sectoral spillovers, and raises productivity, average labor productivity growth could be substantially higher in the future than in the past (Gundlach, 2001; Partridge, 2005). The presence of qualified people to develop the New Economy is particularly important (Bassanini and Scarpetta, 2001; Coppel, 2000; OECD, 2000; Engel, 1999). Human capital formation, therefore, is the core of economic policy in the New Economy. The organization of educational systems for the young, the dual system of schooling and training on the job as in some European countries, the organization of the universities and of basic research are the key policy parameters to participate in the benefits of the New Economy.

This study predicts human capital based on economic growth using educational attainment as a proxy to human capital stock in Canada (Laroche and Merrette, 2000; Tallman and Wang, 1994). In addition, the relationship between human capital and economic growth is presented.

HUMAN CAPITAL AND ECONOMIC GROWTH

Human capital is known to have an impact on economic growth. However, its relative importance in stimulating economic growth and the mechanisms by which human capital stimulates growth remain unclear. Certain studies have confirmed the importance of education in explaining growth. As Florides (1991) indicated that investment in human capital increases productivity. Most studies conclude that human capital exerts a positive and significant effect on growth (Hers, 1998). A study conducted by Bassanini, Scarpetta and Visco (2000), indicates that a positive and significant impact of human capital accumulation to output per capita growth.

The first theories of economic growth were formalized in the 1950s and 1960s. The early models are known as the neoclassical approach to growth theory. These models have several weaknesses; one of which is that they assumed the technological change (and hence productivity growth) was driven entirely by factors beyond our control. Hence, these models did not provide a good representation of the real world (Kerr, 2001).

New growth theories appeared in the beginning of the 1980s. Based on these new theories, two schools of thought were established. The first emphasized the stock of human capital as an important determinant of economic growth. On the other hand, the second school of thought emphasized on the incentives that firms have to generate new ideas, as Kerr (2001) indicated that these models provide a more useful benchmark for thinking about the role of education in economic growth and the design of education policies.

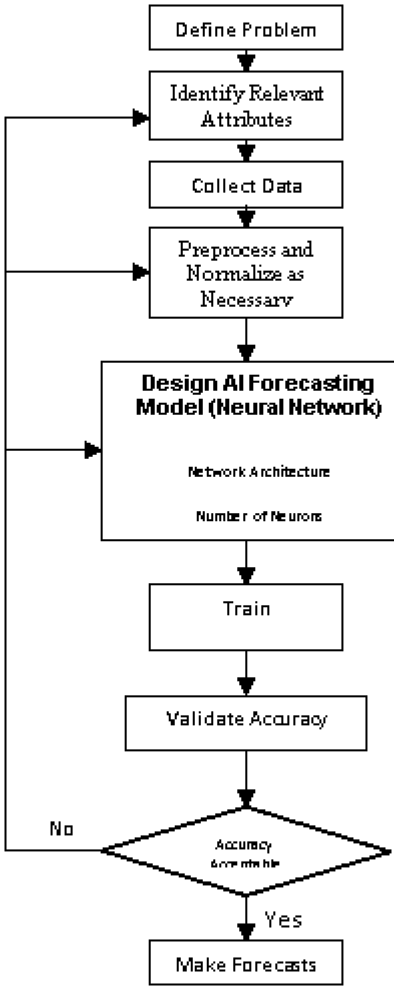
The improvement in human capital seems to be a common factor behind growth in recent decades in all OECD country (OECD, 2001). The increase in human capital particularly in Greece, Ireland, Italy, and Spain accounted for more than half an extra percentage point of growth in the 1990s compared with the previous decade.

APPROACH AND MODEL

Laroche and Merrette (2000) indicated that three main approaches have been used in the economic literature to measure the stock and the contribution of human capital to economic growth. The first approach is known as the cost-based approach, which estimates human capital stock by summing direct expenditures in schools and other items defined as human capital investments. The second approach is referred to as the output-based approach, which measures the output of the educational system. The third approach is called the income-based approach, which considers the returns individuals receive from the labor market for their investment in education. For the purpose of this study, the output-based approach has been employed.

Apart from education and training, other factors such as religion have been found to influence the human capital (Florides, 1991; Lehrer,2009). However, for this exploratory study, we only focus on the effect of qualification on the economic growth because we assume that the major factor influencing the level of human capital is the degree of investment in education and training.

Figure 1: Forecasting using Neural Network Models



The application of neural network technology in economy remains in its infancy. Neural networks techniques, with their forecasting ability, have been used successfully in various economic studies, including investment, economic and financial forecast (Florides, 1991; Swales and Yoon, 1992; Hsieh, 1993; Hutchinson et al., 1994), as well as export growth as the source of economic growth (Shaaf and Ahmadi, 1999; Shaaf, 2000; Kou, 1996). Artificial Neural Network (ANN) model is a mathematical model inspired by the function of the human brain and its use is mainly motivated by capability approximating measurable

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function to any degree of accuracy (Rech and Neuve, 2002; Hsiao-Tein, 2008). The neural network model has been applied in this study and the outline of acquiring such a model is illustrated in Figure 1.

From Figure 1, the forecasting process involves several steps:

Firstly, the dependent and independent variables will be identified, and the data will be collected. In the Second phase, the data will be pre-processed and normalized whenever necessary.

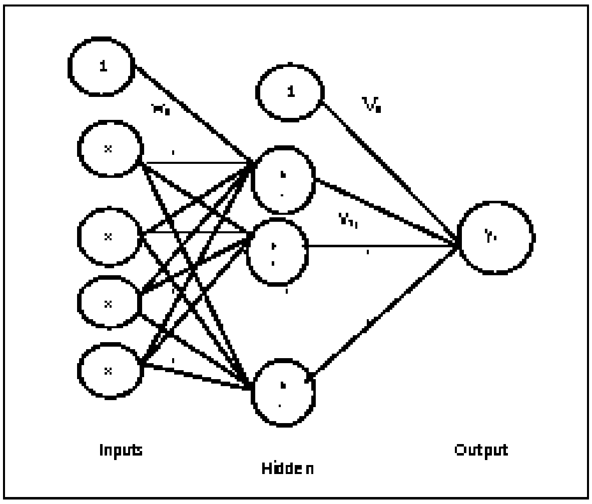
At this junction, Back Propagation learning has been chosen to be incorporated in the forecasting model. The third phase involves choosing the suitable neural network model. The network architecture, number of neurons, the activation function, learning rate, momentum, and training tolerance will be determined.

The learning rate factor is used to adjust the internal connection strengths (weights) of the network to bring the training pattern and the network output patterns closer. The momentum factor determines the proportion of the last weight change that is added to the new weight change. The training tolerance factor specifies the precision used in comparing network output patterns with training patterns.

The final phase, involves training and testing processes. The network performance will be measured based on its prediction accuracy.

To explain the mathematical equation of the neural networks, we assume that ***x*** represents the number of 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 as illustrated in Figure 2.

Figure 2: Neural Network Model



In Neural Network, the signal that goes into h_k can be calculated as:

$$h_{k\_in} = w_0 + \sum_{k=1}^{m}\sum_{i=1}^{n} x_i w_{ik} \text{ ……………… [1]}$$

By considering $x_0 = 1$, equation [1] can be simplified as the following:

$$h_{k\_in} = \sum_{k=1}^{m}\sum_{i=0}^{n} x_i w_{ik} \ldots\ldots\ldots\ldots\ldots\ldots [\ 2]$$

Equation [1] states that h_{k_in} is a weight sum of the x_i. This relationship is shown in Figure 2 with i = n, where each x_i is linked to h_k by the input weights w_{ik} are the weights from the input i to hidden node k.

Equation [2] is generalized by the introduction of non-linearities into relationship. The weight summations, y_j, 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

$$g(u) = \frac{1}{1+e^{-u}} \ldots\ldots\ldots\ldots\ldots\ldots [\ 3]$$

where e is the base of natural logarithms.

Hence, to allow for non-linear relationship between the weighted inputs and the output, the equation [3] can be applied to equation [2], yielding:

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

More generally, the hidden units (intermediate variable) in neural networks need not be identified in order to forecast y_j; they can simply be considered as unknown. Tkacz (1999) explain 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 k to output neuron y_j. The neural networks computation can be represented as

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

or

$$y_{j\_in} = \sum_{k=0}^{p}\sum_{j=1}^{m} h_k v_{kj} \ldots\ldots\ldots\ldots\ldots\ldots [\ 6]$$

Consequently, the connection link v_{kj} are accumulated and filtered by another activation function h(r) viz:

$$h(r) = \frac{1}{1+e^{-r}} \ldots\ldots\ldots\ldots\ldots\ldots [\ 7]$$

The output from neural network model can be calculated as

$$y_j = h(y_{j\_in}) \ldots\ldots\ldots\ldots\ldots\ldots [\ 8]$$

If a sufficient number of hidden neurons are present, equation (6) can approximate any non-linear function to an arbitrary degree of accuracy. According to White (1989), this is known

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as the universal approximation property of neural networks, and such approximation is not possible in the absence of the hidden layer.

The error (a function of the weights to be minimized is

$$E = \frac{1}{2}\sum\left[t_j - y_j\right]^2 \ldots\ldots\ldots\ldots. [9]$$

This is succeeded by adjusting the weight v_k and β_{ik} until the desired pre-specified level of convergence is achieved. The neural network (6) is practicable for most economic applications.

RESULTS

The economic growth is determined by two key variables: the physical capital stock and the quality of labor. The emergence of the endogenous growth literature with the seminal papers of Romer (1996) and Lucas Jr. (1988) has re-emphasized the importance of human capital as a source of progress and economic growth. Recent studies have been conducted to look at the relationship between human capital and economic growth. It aims at channels by which human capital can enhance economic growth. Among them is the stimulus to domestic activities related to technological creation, invention, and innovation. Human capital also greatly facilitates the absorption and imitation of new technology originating from abroad. As a factor of economic growth, the accumulation of human capital may be of even greater importance than the accumulation of physical capital.

As the human capital is claimed to have a positive impact on economic growth, this study explores its impact by using neural network approach and multiple regression model. For the purpose of this exploratory study, we use Canada's human capital stock from 1976 to 1996 based on the completion levels and the number of years of working experience (Laroche and Merrette, 2000). Although school and university enrollment were insufficient to explain the impact of human capital on economic growth, the trend of the enrollment is illustrated in Figure 3.

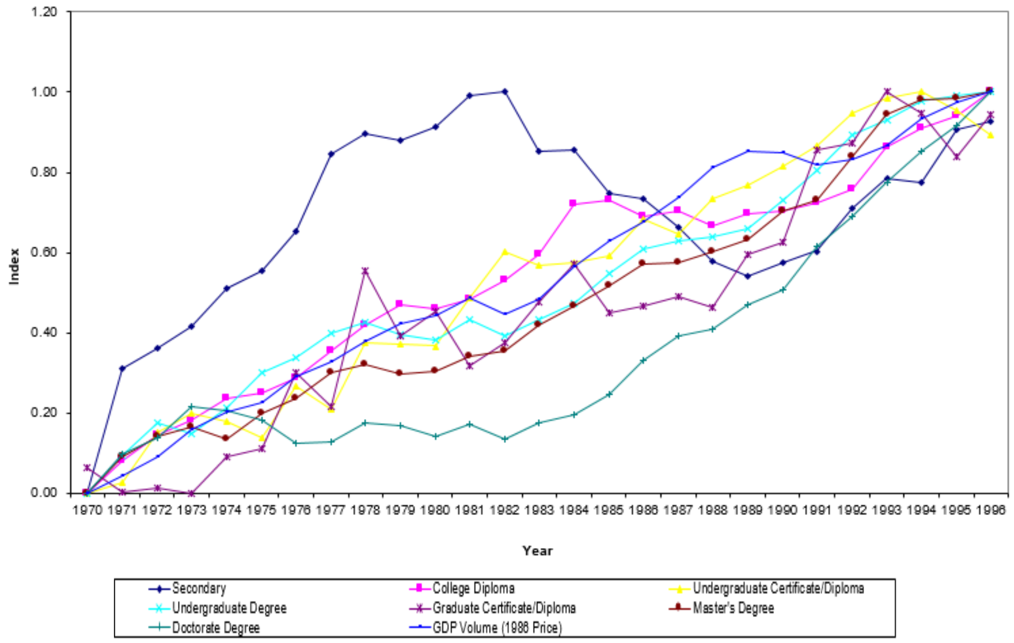

Figure 3: The school and university enrollments

Figure 3 reveals that the number of enrollment increases steadily from the year 1971 to 1996. However, from 1972 to 1982, the highest enrollment was from the secondary school. The number starts to decrease from 1983 to 1991.

The prediction of human capital on the economic growth was performed using neural network technique. The generalization result obtained in this study is 98.40 percent. For comparison purposes, the multiple regression was also applied to the same set of data. The result exhibited in Table 1 indicates that multiple regression merely achieved 82.07 percent.

Table 1. The Performance of Neural Network and Multiple Regression

	NN Model	MR Model
Percentage Of Correctness	98.40 %	82.07 %

Both generalization results were further analyzed to determine the prediction ability of neural network and multiple regression based on the level of education pertaining to economic growth (see Figure 4). The results displayed in Figure 4 reveal that for every level of education, the neural network outperforms the multiple regression. This indicates that neural network delivers higher predictive results when compared with multiple regression.

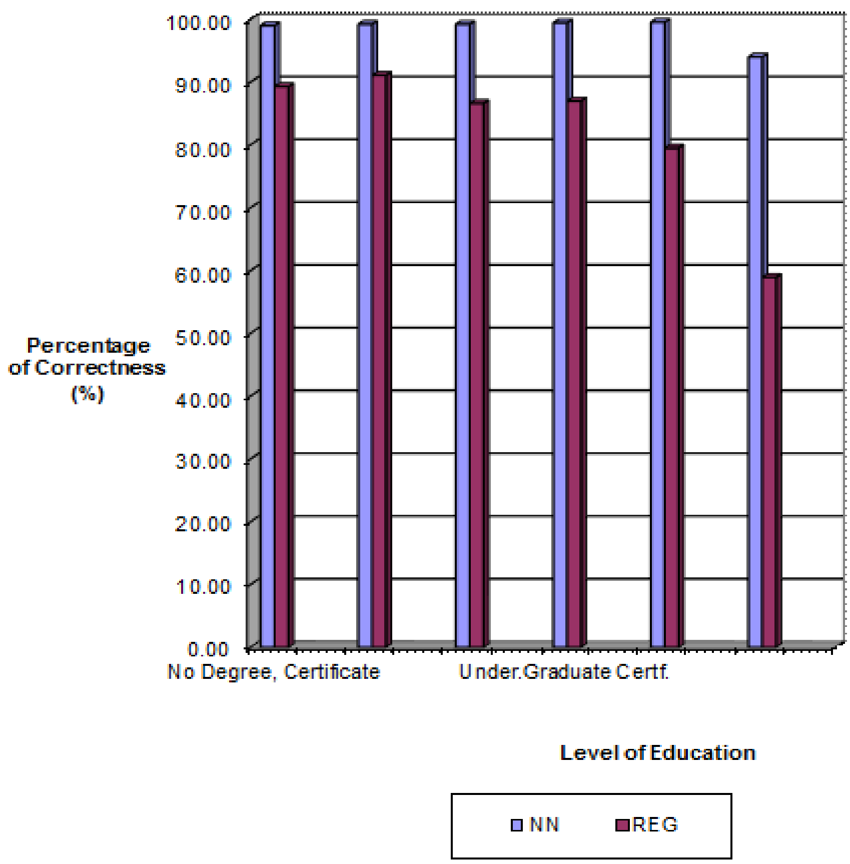

Figure 4. The evaluation performance of neural networks and regression model by level of education

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Further analysis on the levels of education reveal that diploma, degree and master degree holders are the most significant contributors to the prediction model at 5% significance level ($p = 0.002$, $p = 0.004$, $p = 0.032$). The correlation analysis indicates that other variables such as graduate certificate/diploma and doctorate degrees have strong contribution to the economic growth. However, those with secondary graduation diplomas shows a low correlation at 5% significance level with economic growth. Hence, due to this fact, the secondary graduation diploma was removed from the set of data to be used for neural network training. Furthermore, level of age's proxy as a human capital experience indicates that the variables secondary certificate, diploma, undergraduate degree, and graduate degree have a significant contribution to the economy growth at 5 per cent level. The strong significant contribution to the economic growth at 25 to 34 levels of ages compares with other level of ages.

Further, figures 5 and 6 show that the actual and predicted graphs for both no degree and certificate, as well as the college diploma, lie on the same lines. The predicted graph for the secondary school certificate differs slightly from the actual graph. This may have some relationship with the secondary school enrollment as illustrated in Figure 3. The actual and predicted graphs for the undergraduate certificate, undergraduate degree and the graduate degree do not exhibit considerable difference. Therefore, the findings indicate that neural network is an effective tool for predicting human capital based on economic growth. As a result, the model obtained in this study can be used to predict human capital in the New Economy.

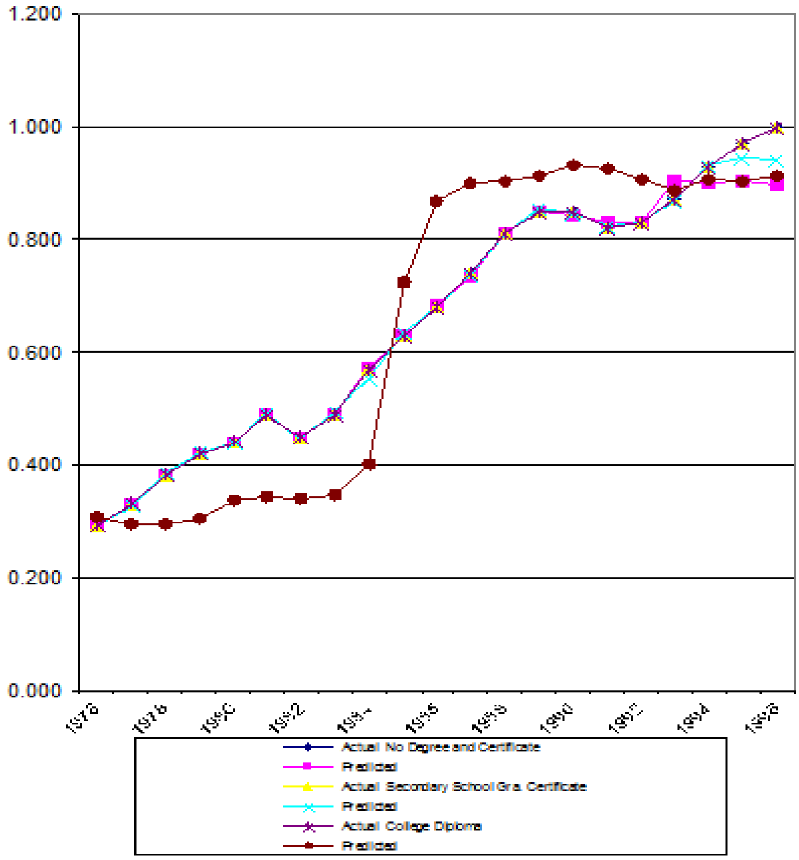

Figure 5. The actual and predicted impact of human capital stock (no degree and certificate, secondary school and college diploma) on economic growth

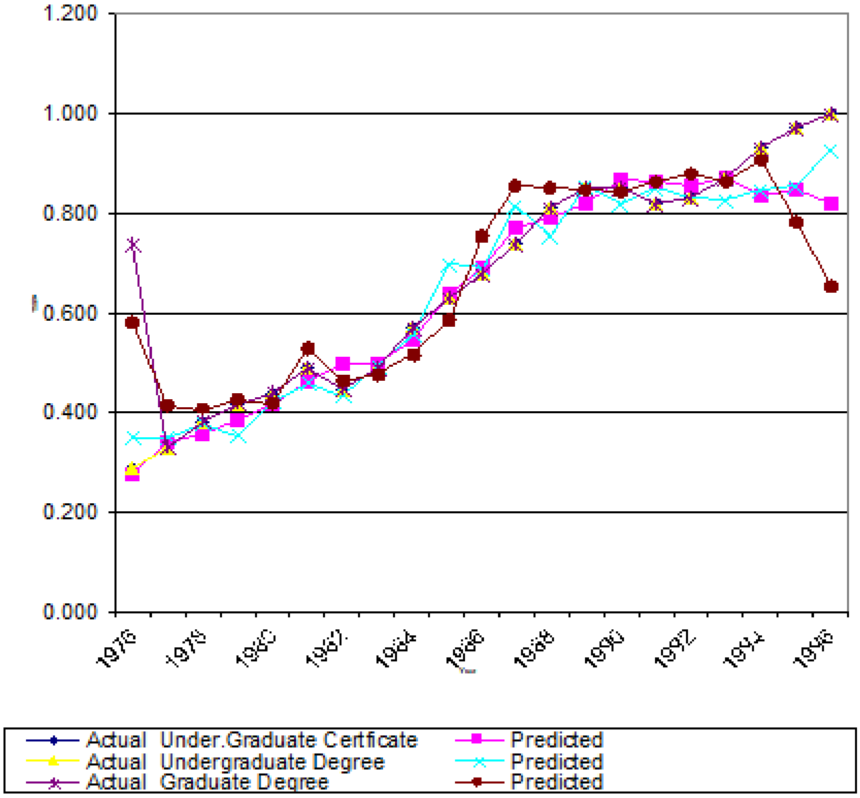

Figure 6. The actual and predicted impact of human capital stock (undergraduate certificate, undergraduate degree and graduate degree) on economic growth

CONCLUSION

An economy can reach a higher growth path by increasing investment in human capital formation because human capital is an important policy variable (Hers, 1998; Beach, 2009). As Florides (1991) suggested that investment in human capital may be analyzed by a more "scientific" approach. By considering the contribution of the human capital to the economy growth, we are able to arrive at certain conclusions as to the profitability of investing in education. This study explores the use of neural network approach to predict the impact of human capital on economic growth. The studies conclude that neural network proved to be an effective predictor, and thus, future work will involve the use of this model for predicting the effect of human capital on economic growth, particularly the New Economy in Malaysia.

The main policy implication of these findings is that the human capital formulation stimulates economic growth. Empirical evidence shows that worker's productivity, and hence the wage, depends on education and experience (Laroche and Merrette, 2000; Kulvisaechana, 2006). Labor force quality has been shown to have a strong impact on economic growth (Kerr, 2001; Wobmann, 2003). As the quality of labor force depends on educational attainment, the quality of education must be emphasized. Increasing school and university enrollment is simply insufficient. The policy framework must provide good incentives for the generation of ideas and knowledge and the diffusion of technology in the New Economy.

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