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Modeling Property Prices Using Neural Network Model for Hong Kong

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This paper develops a forecasting model of residential property prices for Hong Kong using an artificial neural network approach. Quarterly time-series data are applied for testing and the empirical results suggest that property price index, lagged one period, rental index, and the number of agreements for sales and purchases of units are the major determinants of the residential property price performance in Hong Kong. The results also suggest that the neural network methodology has the ability to learn, generalize, and converge time series.

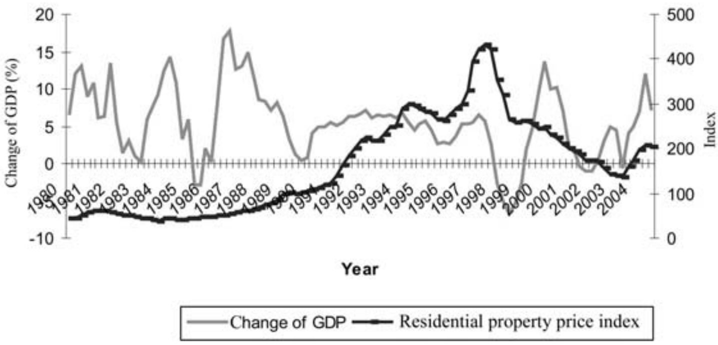
Keywords

residential property prices, artificial neural network (ANN), property price determinants, forecasting models, Hong Kong

Introduction

Property price volatility can have a significant impact on the economy as a whole. Hong Kong experienced deflation in the property market from November 1998 until July 2004. The Price Index fell by about 66.9% from the peak reached in October1997 to mid-2003 (Bank of China Group, 2003). As a result, a large number of properties become negative assets for families. The property prices have now rebounded by 40% from that lower base. With a strong economic performance during the first half of 1997, Hong Kong's GDP recorded HK$309,483 million in the third quarter of 1997; which fell to HK$275,427 million in the first quarter of 1998 (constant 2000 prices). Recently, the GDP has reached to HK$380,751 million in the third quarter of 2004 (Census and Statistics Department, 2004). Figure 1 depicts GDP and property prices that demonstrate a strong relationship after 90s in Hong Kong. The volatile economy indicators and property prices had social costs in terms of increased repossessions (Wilson et al., 2002), created unemployment and stimulated unsound banking practices (Chan, et al., 2001), impaired consumers' confidence in the government, and led to an unstable economy. Accurate measures of the price trend are crucial for understanding the behavior of the real estate market (Berg, 2005). It is desirable to develop price forecasting models for both consumers and the government. Consumers would then be able to make informed property purchasing and selling decisions and the government would benefit in its housing policy formulation.

Figure 1: Relationship between GDP and residential property price index in Hong Kong



(Source: Census and Statistic Department, HK Government)

Volumes of theoretical and empirical studies have been conducted in the property price forecasting field. Forecasting is estimating an unknown future on the basis of related past and current information (Wilson, et al., 2002). Prior research and expert domain knowledge are used to specify relationships between a variable to be forecast and explanatory variables. Econometric methods such as multiple regression analysis are commonly used for forecasting. Other methods such as rule-based forecasting, artificial neural network, and quantitative analogies are also used.

The aim of this paper is to develop a forecasting model of residential property prices for Hong Kong using the artificial neural network approach. This enables an investigation of main determinants of housing prices and assesses the forecasting accuracy of the selected model. The paper is divided into three sections. The first section reviews briefly reduced-form models for property price forecasting. The second section studies the theory, learning rules and applications of artificial neural network model (ANN). The third section contains an empirical study that includes an overview for the data provided, estimates property price formation using an ANN model, and discusses of result followed by conclusions.

Reduced-Form Models for Property Price Forecasting

To study housing price behaviour, many researchers have used reduced-form equations (Reichert, 1990) and applied them to different aspects. A reduced-form equation for the price function is formulated based on supply and demand functions for owner-occupied housing, and the housing price is derived from the supply and demand functions under an equilibrium assumption (DiPasquale and Wheaton, 1994).

Regression analysis is commonly used to estimate model coefficients such that they are consistent with prior knowledge (Ho & Ganesan, 1998). Many variables impact on property prices. Also, current property prices will be positively related to recent past prices (DiPasquale & Wheaton, 1994). Thus, multiple regression analysis (MRA) and time series have been applied for property price forecasting. Autoregressive process is a term to represent the process of time series. The equation is shown as

$$\mathrm{HP}_t = \theta \mathrm{HP}_{t-1} + \varepsilon_t \qquad \text{where } \varepsilon_t \sim \mathrm{WN}(0, \sigma^2) \tag{1}$$

Where HP_t and HP_{t-1} are property price at time t and t–1. ε_t is the autoregressive error and θ is a coefficient.

The MRA method works well on linear relationships between dependent and independent variables. The problem with the MRA method is that it involves judgment because it relies on functional assumptions to ascribe a form to fit the relationships of the variables. It is difficult to map multi-attribute nonlinear relationships using regression analysis. Artificial neural networks (ANN) could overcome these problems because they have the ability to learn by themselves, to generalize solutions, and to respond adequately to highly correlated, incomplete, or previously unknown data (Shaw, 1992). The following section studies theory, learning rules, and applications of ANN.

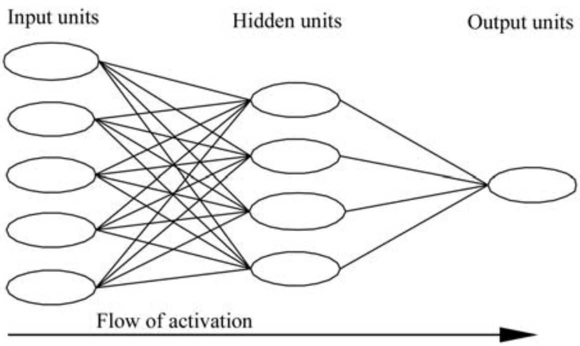
Artificial Neural Network Model

Faster computers with greater data handling capabilities, in conjunction with multivariate analysis, have provided the ability to study complex non-linear relationship between property price and the supply and demand for houses. Neural networks are suited to handle non-linear problems because of their adaptability due to their structure; i.e., non-linear activation functions. It has been demonstrated that any arbitrarily irregular patterns can be mapped by artificial networks (Widrow et al., 1994). Neural networks are simpler and faster to apply. There is no requirement for the selection of forecasting functions at any time. The latent function is located by the network in the course of its automatic self-learning from the training set of behaviours on input variables.

Back propagation (BP) models have been the most popular and widely implemented of all neural network paradigms. A BP network is a method for computing the gradient of the case-wise error function for a forward-feeding network, an application of the chain rule of elementary calculus (Werbos, 1994). It is called a fully connected feed forward network, which means activation travels in a direction from the input layer to the output layer, and the units in one layer are connected to every other unit in the next layer up (Callan, 1999). A multilayer feed-forward neural network consists of a series of simple interconnected neurons, or nodes, between input and output vectors. The nodes are connected by weights and output signals, which are functions of the sum of the inputs to the node modified by an activation function. The output of a node is scaled by the connecting weight and fed forward to be an input to the nodes in the next layer of the network (Ge et al. 2002).

A key element in the BP paradigm is the existence of a hidden layer of nodes. The network is fully connected, every node in layer $n-1$ connected to every node in layer n. The typical topography of a BP network is a three-layered network: an input layer, an output layer, and a hidden layer of neurons. However, a BP network can contain a greater number of hidden layers. The first layer receives the inputs to the network, every input being connected without modification to every neuron in the layer. The number of inputs depends on the number of characteristics being modelled (McCluskey et al., 1996). In the second and subsequent layers, each neuron takes in as inputs the outputs of all the neurons in the preceding layer, modified by the connection weights. The interconnection weights between nodes at a lower (i-th) layer and those at the next upward (j-th) layer are randomly set at the start of the training process. As a result of this randomness, the actual output vector y (issued by the output nodes) will generally be at variance from the target vector. The output values of the neurons in the last layer act as the outputs of the neural network. A typical topology of three-layer BP is illustrated in Figure 2.

Figure 2: Three-layer BP network



The theory

In Figure 2, the input layer has n nodes and a bias node that represents noise data. The collection of nodes in a layer is called a vector. There are m hidden nodes and a bias node in the hidden layer. All nodes in adjacent layers are fully interconnected. The inputs and outputs of the neurons in the first layer can be expressed as

$$I_i^F = O_i^I = X_i \qquad (i = 1, 2, \ldots. n) \tag{2}$$

$$O_i^F = f(I_i^F) = f(X_i) \qquad (F = \text{the first layer}) \tag{3}$$

The interconnections between the input layer and the hidden layer are synapses that are weighted. That is, when the i-th neuron of a layer sends a signal to the j-th neuron of another layer, that signal is multiplied by the weighting on the i,j synapse. This weighting can be symbolised as W_{ij}. If the output of the i-th neuron is designated as O_i, then the input to the j-th neuron from the i-th neuron is O_iW_{ij}. Summing the weighted inputs to the j-th neuron:

$$I_j^H = \sum_{i=1}^{n_1} O_i^F W_{ij}^F + \theta_j^H \qquad (j = 1, 2, \ldots m) \tag{4}$$

θ_j is a bias term with a fixed value that enhances the convergence properties of the network (Dayhoff, 1990). The superscript H indicates the hidden layer. The summing of the weighted inputs in the hidden layer is carried out by a processor within the neuron. The sum obtained is called the activation of the neuron. This activation can be positive, zero, or negative, because the weightings and the inputs can be either positive or negative. The activation function of the hidden layer is

$$O_j^{\mathrm{H}} = f(I_j^{\mathrm{H}}) = f(\sum_{i=1}^{n_1} O_i^{\mathrm{F}} W_{ij}^{\mathrm{F}} + \theta_j^{\mathrm{H}}) \tag{5}$$

For the output layer *Y*, the *j*-th neuron in a hidden layer sends a signal to the output *k*-th neuron. That signal is multiplied by the weighting on the *j*, *k* synapse.

$$I_k^{Y} = \sum_{j=1}^{m_1} O_j^{\mathrm{H}} W_{jk}^{\mathrm{H}} + \theta_k^{Y} \quad (k = 1, 2, \dots g) \tag{6}$$

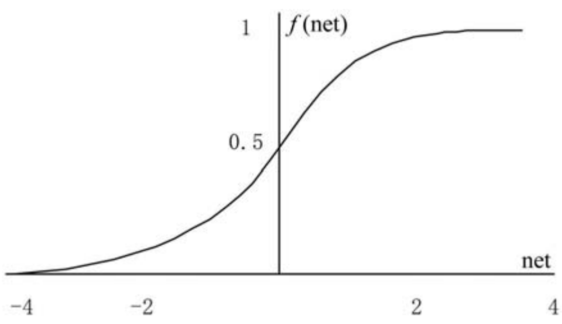
$$O_k^{Y} = f(I_k^{Y}) = f(\sum_{j=1}^{m_1} O_j^{\mathrm{H}} W_{jk}^{\mathrm{H}} + \theta_k^{Y}) \tag{7}$$

The sigmoid function (Eq. (8)) is a logistic function (Figure 3), which is a commonly used activation function. The function is advantageous within the context of many paradigms. This characteristic includes the fact that it is continuous and has a derivative at all points. The output from a sigmoid logistic function falls in a continuous range from 0 to 1:

$$O_k^{Y} = f(\mathrm{net}) = \frac{1}{1 + \exp^{(-\beta \mathrm{net})}} \qquad (\beta > 0) \tag{8}$$

β is the steepness of the sigmoid function (Boussabaine & Kaka, 1998).

Figure 3: The sigmoid function [Source: Callan, 1999]



The learning rule

Learning rules is one of the most attractive features of neural networks. Basic back propagation performs supervised learning (Shi, 1999), in which for every input pattern that is presented to the network during training there is a target output pattern. That is, its actual outputs (*Y'*) come close to some target outputs (*Y*) for a training set that contains *T* patterns (Smith, 2003). The goal is to adapt the parameters of the network so that it performs well for patterns from outside the training set.

A BP network typically starts out with random weights on its synapses. As the training proceeds, the network's weights are adjusted until it is responding more or less accurately. The discrepancy between what the network actually outputs and what it is required to output constitutes an error. This error can be used to adapt the weights (Rodriguez, 2003). Learning is achieved through the rule that adapts connection weights in response to input patterns (Adya & Collopy, 1998). For a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference (Russell, 1996). Figure 4 depicts where the output unit has an activation (i.e., output) of $Y'(t)$ and a target output $Y(t)$. The error (δ) is given by

$$\delta = Y(t) - Y'(t) \tag{9}$$

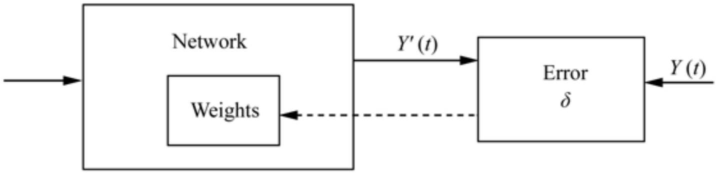
The signal coming into the output unit is s. The adjustment to be made (Δw) is

$$\Delta w = \eta \delta s \tag{10}$$

where η is a learning rate. The new weight is adjusted and added to the old weight:

$$w = w + \Delta w \tag{11}$$

Figure 4: Basic back propagation in pattern learning [Source: Callan, 1999]



BP through time is a very powerful tool, which has applications to pattern recognition, signature analysis, dynamic modelling, and the control of systems over time (Smith, 2003), forecasting, and optimisation (Chao & Skibniewski, 1994) among others. Tay and Ho (1992) used the BP model in estimating sale prices of apartments, comparing the results to a traditional MRA model. They used a large data set of 1055 properties and obtained a mean percentage error of 3.9%, whereas the MRA result was 7.5%. The results indicate that BP provided better estimates than the linear MRA. In contrast, the work of Evans et al. (1992) used a much smaller data set of 34 properties. They compared three different structures and found that 7-5-1 (seven inputs, five hidden neurons, and one output) obtained the smallest mean percentage error. They also highlighted the potential of neural networks in being able to estimate statistically significant models with a high degree of accuracy even with small samples. More recent studies undertaken by McCluskey et al. (1996) and Rossini (1997) produced inconclusive results. McCluskey et al. (1996) used 416 data from Northern Ireland. Three different neural network configurations were used to investigate the effect of different network topologies for predictive accuracy. The results were compared to an MRA model, and it was found that the regression model outperformed two out of three neural networks. Rossini (1997) designed three procedures for residential property valuation, comparing them with an MRA model. His assessment supports the use of MRA ahead of ANN but is not completely conclusive.

Empirical Study

The empirical study begins with reduced-form model. In accordance with literature review, the quantity demand for houses can be denoted as

$$Q_{\mathrm{d}} = f(G, H, D, t) \qquad (t=1, 2, 3, \ldots n) \qquad (12)$$

where Q_{d} = aggregated quantity demand for new houses during period t, G = macroeconomic variables, H = housing related variables, and D = demographic variables.

The supply of housing is a function of house prices, construction costs including interest rates, material costs and labour costs, and land supply.

$$Q_{\mathrm{s}} = f(S, t) \qquad (t=1, 2, 3, \ldots n) \qquad (13)$$

where Q_{s} = aggregated quantity of new supply during period t, S = supply variables.

Under an assumption of supply-demand equilibrium within the given period, i.e., $Q_d=Q_s$, Eq. (12) and (13) give a reduced-form price function:

$$P = f(Q_{\mathrm{d}}, Q_{\mathrm{s}}, t) \qquad (t=1,2,3, \ldots n) \tag{14}$$

where P = house prices of new units sold during period t as dependent variable.

According to the reduced-form price model, the ANN method can be used for forecasting housing prices. The selection of valid training input variables is the first step. The second step is to design the neural network for learning, to perform pattern recognition, and to generalise. After the neural model is tested, the predicted outcome may be validated.

Data selection and transformation

Before adapting the parameters for the neural network, one must obtain a training database, because the generalisation performance of the neural network depends on the training set supplied (Hu, 1997). Quarterly time-series data from the first quarter of 1981 to the fourth quarter of 2002 obtained from the *Hong Kong Monthly Digest of Statistics* (various issues) are used in this study. Table 1 is the variables collected for the empirical study.

Before applying the BP model, manipulation of the collected data for training and testing is necessary. This is done by normalizing input data to a value between (0, 1). The purpose is to speed up the training process and improve the generalisation performance of the neural network. In theory this is unnecessary, since any scaling can be compensated within the network by adjusting the inputs to the hidden layer weights. In practice, initial network weights are chosen randomly. Hence if one input variable has a large range and another has a small range but both exhibit a similar amount of variance, the network may ignore the small input, because of the large contribution from the other input (Ge *et al*., 2003). To treat all inputs equally, it is advisable to standardise the input by using the following equation:

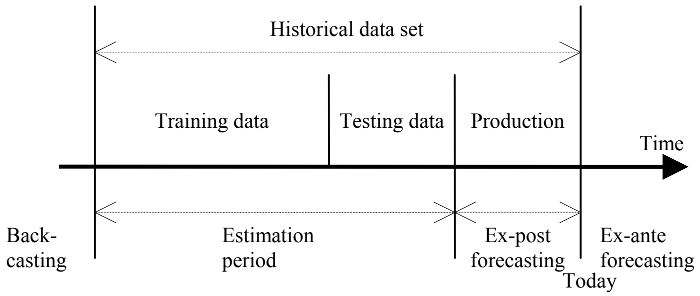
$$f(X) = 1/(1 + \exp(-(X - \overline{X})/\mathrm{sd})) \tag{15}$$

where *f(X)* is the normalised variable, X is the original variable, $\overline{X}$ is the average of all values of that variable in the pattern file, and sd is the standard deviation of those values. This may also help the interpretation of network weights. After applying the neural network, the output can be reversed by the original weights. The data are ready for extraction and training. The training data extraction is chosen by the percentage of the random selection method. Figure 5 illustrates the forecasting method.

Table 1: Definition of variables [Source: Census and Statistics Department, HK Government]

Variable	Name	Definition
Dependent	HP	The private housing price index (1989=100)
Independent	HHI	The median of household incomes, Hong Kong dollars per household
	HSI	Hang Seng index (1964=100)
	PC	Private consumption expenditure at constant 2001=100, Hong Kong dollars
	GDP	Gross domestic product at constant 2001=100, Hong Kong dollars
	GDPC	Gross domestic product – Construction at constant 2001=100. Hong Kong dollars
	r	The real rates of interest, percentage per annum from Hang Seng Bank
	PO	Policy or political events (1=event; 0= no event)
	RI	The private rental index (1989=100)
	ASP	Agreements for the sale and purchase of building units (Number)
	P	Total population number
	HN	Household number
	PA	Population number aged 20–59
	MN	Number of marriages
	BN	Number of births
	EM	Unemployment rate, percentage
	LS	Land supply available for private residential development. Residential units/flats with consent to commence work by floor area (square meter) as a proxy
	NS	New residential units completed privately developers (number of units)
	CI	Construction cost index (1968=100)

Figure 5: Periods of forecasting [Source: Higgins, 2000]



Training and testing

The process of training the network involves the establishment of weights so that the average square error over the training set is minimised. In the training phase, sets of data with known results are inserted into the network and processed as they pass forward through the layers to the output neurons. For each data set presented to the network, the output neurons give a set of values that at first differ greatly from the correct results. Consequently, the differences between the correct results and the network outputs are back propagated as an error function through the network from the output to the input, changing the connection weights and neuron bias values to reduce the output errors. The training process is repeated many thousands of times on the same data sets until the network has learned the underlying pattern in the data (Chester, 1993).

A three-layer neural network structure is used with one input layer and one hidden layer. The numbers of neurons are selected on an *ad hoc* basis. One output layer of housing prices is required. The determination of the number of hidden layers and nodes is crucial. If there are too many hidden layers, the neural network will not learn the underlying pattern. Too few means that the neural network will not pick up the full details of the underlying pattern in the data (McCluskey et al. 1996). Therefore, the most appropriate topology is determined by experimentation. NeuroShell2 gives the number of hidden neurons for a three-layer network computed with the following equation:

Number of hidden neurons = ½ (Inputs + Outputs) + square root of
the number of patterns in the training file (16)

As the training proceeds, the network's weights are continually adjusted until the error in the calculated outputs converges to an acceptable level. The trained network can then be tested by applying it to test patterns. The trained network can be examined by test data sets; as each data set is put into the network, the outputs are a function of the values of the inputs, the function being the pattern that the network had learned during the training phase. The test patterns must not participate in training.

Network performance indicators

One aspect of performance justification of a neural network model is the effectiveness of the approach. To evaluate the accuracy of the network's performance, the mean absolute error (MAE) or the mean square error (MSE) test is applied as a measurement of deviation between actual and predicted values (Shi, 1999). The smaller the value of the mean average error and mean square error are, the smaller the difference between the predicted time series and the actual one, the higher the accuracy. The coefficient of multiple determinations (R^2) and the correlation coefficient (r) can also be indicators of the network performance. Thus, the R^2 efficiency, the MSE, the MAE, and the correlation coefficient are used as network performance indicators.

Results

The key to success is in choosing the correct predictive variables (Hu, 1997). Four models have been found with a comparative good result. Input variables of the four models are shown in Table 2. Table 3 shows the empirical results of the four models by criteria and structure.

The model_1 performs better among the four models (Figure 6). This result is similar to, and in many cases better than, those reported in previous studies (Tay & Ho, 1992; Evans et al., 1992; McCluskey et al., 1996; Rossini, 1997; Lake et al., 1998). The model is suitable for forecasting.

Table 2: Input variables

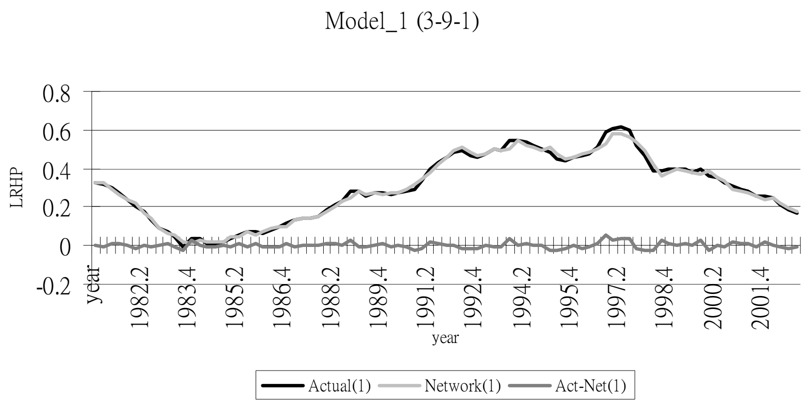
Model	Input variables	Network structure
Model_1	one period lagged housing price, agreement for sale and purchase of units, and rental index	3-9-1
Model_2	total population, real household income, unemployment rate, and interest rates	4-8-1
Model_3	population, household income, land supply, number of transactions for units, construction cost, GDP, and mortgage rate	7-8-1
Model_4	population, household income, land supply, number of transactions for units, construction cost index, GDP, interest rate, unemployment rate, number of marriages, number of births, rental index, GDP-construction, Hang Seng Index, number of private completion for units, private consumption expenditures, household numbers, policy/political events, and population aged 20–59	18-30-1

Table 3: Model descriptions

	Model_1	Model_2	Model_3	Model_4
R^2	0.9918	0.9475	0.9744	0.9844
r^2	0.9918	0.9494	0.9753	0.9847
Mean squared error (MSE)	0.000	0.001	0.001	0.000
Mean absolute error (MAE)	0.011	0.031	0.017	0.014
Min. absolute error	0.000	0.000	0.000	0.000
Max. absolute error	0.055	0.095	0.122	0.071
Correlation coefficient *r*	0.996	0.9744	0.9876	0.9923
Percent within 5%	62.921	26.136	59.091	61.905
Percent within 5% to 10%	23.596	28.409	17.045	14.286
Percent within 10% to 20%	8.989	18.182	11.364	14.286
Percent within 20% to 30%	0	9.091	9.091	5.952
Percent over 30%	4.494	18.182	3.409	3.571
Data set	88	88	88	88
Net structure	3-9-1	4-8-1	7-9-1	18-21-1
Design	54:17:17	54:17:17	54:17:17	54:17:17

R^2: the coefficient of multiple determinations; r^2: the correlation coefficient

Figure 6: Forecasting results for Model_1



Discussion

The empirical studies tested whether the housing price determinants as input variables are important for building accurate forecasting models using the ANN method. The findings were:

a. Relevant variables produce better forecasting result in ANN model. Irrelevant variables produced less accurate forecasting models.
b. The well-designed network structure of ANN helps to establish effective housing price forecasting models.

The findings reveal that the most accurate forecasting model is Model_1 with three variables. The least accurate model is model_2, based on the four input variables. Model_1 shows better forecasting results, which demonstrate that the housing price determinants in Hong Kong are the lagged housing price, the rent, and the unit transaction volume. The present findings of housing price determinants demonstrate some crucial replications of findings from the literature. These replications provide a foundation to build on the theory of the housing market and its relationship with housing price. The lagged housing price supports the models developed in the literature in which the quantities supplied and demanded adjust slowly towards the equilibrium, concomitant with a significant positive impact of lagged price changes (Hendershott, 2000).

The 18 input variables yield better forecasting results than the four and seven input variables. The result demonstrates that the model based on the 18 input variables generates more information and better learning than the others do.

The improved results of models from the four-input, seven-input, and 18-input variables demonstrate that relevant variables are critical for neural network modelling. The four variables are: population, household income, unemployment, and mortgage rates that indicate an R^2 of 0.94. The R^2 is improved to 0.97 by adding the variables of land supply, unit transaction volume, construction cost, and GDP, and by dropping the unemployment variable for the seven-input model. This result explains that the added new variables contribute to housing price variations. By adding variables to cover 18 variables, including unemployment rate, rent, export, Hang Seng Index, birth, marriage, private completion, private consumption expenditures, household numbers, and different age groups of the population, the R^2 reaches 0.98. The evolution of modelling results illustrates that unit transaction volume, land supply, rent, and economic indicators, apart from the original four variables, perform important roles in housing price changes. Construction cost, policy and export contribute less to the price. The results further demonstrate that neural networks can indicate contributory variables to the price. Irrelevant variables may not produce a better forecasting model.

Learning from historical data through training is one of the important characteristics of the neural network modelling. One may argue about the process of training the network to learn from previous data, in that the results may be the same after training although there may be different input variables. The findings suggest that different housing price determinants affect the forecasting. This implies that housing price determinants are also important for building effective models using the neural network method. An effective housing price forecasting model can be developed when the true determinants are identified. The true determinants for housing prices need to be based on economic theory. Irrelevant input variables may develop an unsatisfactory model.

A forecast using samples was simulated for the best-developed model, i.e., Model_1. The housing prices for the period 2003:1 to 2005:4 were forecasted based on the trained structure of the model. The finding suggests that the housing price in Hong Kong may remain stable and show a smooth upward trend in the period from 2003 to 2005. The forecasted result is consistent with the literature (Bank of China Group, 2004) that Hong Kong's general price level may stop falling in the fourth quarter of 2004, thus putting an end to deflation.

The findings also suggest that the neural network model allows a wide range of variables to be calculated for property price forecasting. It was capable of handling a large volume of time-series data in this study through computer software in a very short period. It also demonstrates a great ability to solve non-linear problems. From the forecasting and accuracy point of view, its range and sophistication exceed that of other methods (Lake et al., 1998).

Neural networks offer an important alternative to traditional methods of data analysis and modelling. Compared to multiple regression models, a neural network is much more flexible, as the neural network is trained to best represent the relationships and processes that are implicit, albeit invisible, within the data (Abrahart & See, 1998). The empirical results can be used to examine how well property prices have been modelled.

An ANN model was generated after thousands of times of learning and error corrections. Particularly when there are large sample sizes with many input variables, the multi-dimensional non-linearity relationships create difficulty for the development of models of causal relationship equations. It was found that suitable applications of the neural network model might solve situations that have large input variables and non-linear problems.

In summary, the neural network provides an effective method for property price forecasting in Hong Kong. Its accuracy in forecasting is capable of producing great results when well-identified relevant variables are used as inputs. The structural design for modelling is also important.

Conclusions

This study employs BP neural networks to produce housing price models for Hong Kong using empirical data. It is found that more participative variables, the better the results. If there are inadequate input variables in the participating model, the model will reflect the lower coefficient of determination and the higher mean square error. The results also lead us to conclude that the neural network methodology has the ability for learning, generalisation, and convergent time series. The model of 3 input variables and 18 input variables has demonstrated this capability. It was found that the lagged housing price with one period, rental index and the numbers of agreement for sales and purchases units are the major determinants for the housing price performance in Hong Kong. The designed testing structure is also relevant to the model development. Too few or too many hidden neurons will not produce satisfactory models.

The BP model is a good alternative to the traditional *MRA* for modelling house price forecasting. In general, the method offers several advantages over traditional methods for the modelling of housing prices in Hong Kong. It has the ability to map complicated non-linear relationship between the housing prices vector and independent variables. It can predict trend movements without the need to quantify some data, and also has the advantage of being relatively inexpensive and easy to apply. However, it has limitations. For example, because the model is built through learning and adjusted weights during training, there is no actually expressed formula for the model. It also requires a great deal of data for learning to achieve optimum results. Thus, further comparisons are necessary.

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