

An Alternative Approach to the Short Term Prediction of Residential Property Prices in Hong Kong

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ABSTRACT

The behaviour of residential property prices in Hong Kong is so complex that the prediction of this strongly nonlinear time-series remains a difficult task for researchers. Traditional econometric models have been used frequently in modelling the time-series but the results obtained still leave room for improvement. In this study, moving away from traditional prediction methods, we use Radial Basis Function (RBF) to model and forecast short-term residential property price behaviour in Hong Kong. The performance of the RBF model was evaluated by a statistical approach. The result shows that the RBF is able to capture the nonlinearity embedded inside time-series. It successfully modelled the short-term price movement.

KEYWORDS

Artificial neural network
Radial basis function
Property price

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INTRODUCTION

Residential property prices in Hong Kong have exhibited strongly nonlinear behaviour in recent decades. The volatile and nonlinear price fluctuation in the market means that all participants in it struggle to predict future price movements accurately, with the difficulty increasing because the underlying functional relationship between input and output is unknown. Furthermore, the actual input variables are hardly detectable. Hence, it is an inherently complicated task to determine the underlying nonlinear structure of the property price time series.

Although it is a difficult job to model property price time-series, an appreciable number of attempts have been made to model the input-output mapping of the property price series and to analyze the market. (Hendry 1984, Drake 1993, Richard *et al.* 1996, Wilson *et al.* 2002, Edelstein *et al.* 2007, Garcia *et al.* 2008, Miles 2008) These studies have not only provided a methodology with which to forecast the residential property market, but have also offered policy makers essential clues for determining appropriate government policy. A successful prediction of future price movement and volatility can also provide a direction in which commercial banks can develop better risk management for mortgages, as volatility is a key determinant of mortgage default probability (Foster *et al.* 1984). This would also be socially useful because the residential property

market has long been one of the most vital markets in Hong Kong. Reliable modelling will be able to reduce the uncertainty borne by market participants so that the number of informed agents increases. Thus, a practical and reliable methodology for modelling the input-output mapping of property price time-series is necessary.

In recent years, apart from traditional models, many researchers have made use of artificial neural networks (ANNs) as an alternative in modelling the input-output mapping of time series. ANNs have the well-known ability to model the nonlinear behaviour of time series better than traditional econometric models. (Hill *et al.* 1996, Aminian *et al.* 2006, Moshiri *et al.* 2006) In this paper, we make use of ANNs to forecast the short term residential property price movement in Hong Kong. By using macroeconomic and other related variables as input, we extract the underlying nonlinear functional relationship between inputs and output for the price series.

The remainder of this paper is organised in four sections: Data Collection; Methodology; Results; and Conclusions.

DATA COLLECTION

The index we use for capturing the general residential property price movement in Hong Kong is from the Centa-City Index (CCI)¹, provided by Centaline Property Agency Ltd. The CCI is a property value index based on

¹ Data was obtained from http://www.centadata.com/ccinotes_c.htm

all the transaction records of the Land Registry. The estates included in the index are those with high transaction values and volumes that have been occupied for at least 12 months. The CCI is formulated as follows:

$$CCI_m = \frac{MV_m}{MV_{m-1}} \times CCI_{m-1} \quad (1)$$

where MV_m represents the total market value of the constituent estates for the month m . Hence, (1) can be written as:

$$CCI_m = \frac{MV_m}{MV_{m-1}} \times \frac{MV_{m-1}}{MV_{m-2}} \times CCI_{m-2} \quad (2)$$

We finally obtain equation (3) by repeating the above process where b is the base month (i.e. July 1997). The value of CCI at the base period is 100.

$$CCI_m = \frac{MV_m}{MV_b} \times CCI_b \quad (3)$$

METHODOLOGY

Hence, the CCI measures the change in aggregate value of real estate in Hong Kong compared to that at the base period, which is similar to how the Hang Seng Index works in the Hong Kong stock market. The data we use for training the model is taken from January 1998 to June 2008. During this period, the CCI exhibits two distinct trends. From 1998 to mid-2003, there is a clear downtrend, with an uptrend running from mid-2003 to early 2008. The trends and price movements of the CCI vary over the period in a highly nonlinear manner, which is why we use a nonlinear forecasting method in this study. The monthly movement of the CCI is shown on Figure 1.

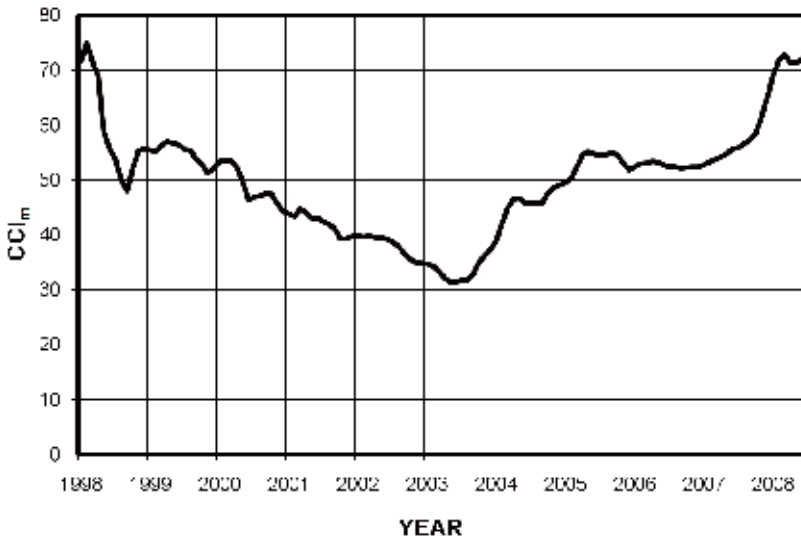


Figure 1 Time series of the CCI from January 1998 to June 1998 (adopted from http://www.centadata.com/cci/notes_c.htm)

In analysing the dynamics of property prices, econometric models are typically used. Hendry (1984) introduced an econometric model for existing UK residential property prices that used excess demand as a function of a range of parameters such as real income and lending rate in modelling the changes in house prices. Richard *et al.* (1996) extended Hendry's excess demand function by giving it stochastic and dynamic properties. Drake (1993) employed the Johansen cointegration technique to derive a long-term equilibrium of UK house prices. Miles (2008) found that in forecasting housing prices, a generalized autoregressive model is superior to autoregressive moving average and generalized autoregressive conditional heteroscedastic models. Furthermore, Edelstein *et al.* (2007) introduced a two-equation system to model the residential property price cycle. The two equations are developed econometrically to set up the demand and supply sides of the residential property market.

Although most residential property price modelling has used econometric models, Hill *et al.* (1996) found that ANNs are superior to traditional time series forecasting methods. Artificial neural networks have been successfully used in various areas, such as economic data (Aminian *et al.* 2006), financial price series (Moshiri *et al.* 2006, Pai *et al.* 2006, Blynski 2006), earth science and astronomy (Valdes, 2006), residential sub-markets (Garcia *et al.* 2008) and fire dynamical system (Lee *et al.* 2004). Hence, they can be viewed as powerful tools for use in

modelling the input-output mapping of time series. With the presence of input and output data, ANNs are able to model the underlying function and structure from input to output by changing the weight between each neuron to minimise the error that arises. Another benefit of using ANNs is that they do not have to make any assumptions to form the model, which is not true of conventional econometric models. In this study, we adopt ANNs in forecasting the short-term residential property price. To model a property price time-series, time-lagged observations are usually used as inputs to ascertain the underlying function or structure of the input-output mapping. Wilson *et al.* (2002) proposed the use of a time-lagged property price as a single input to forecast the future residential property price. In our model we add other time-lagged observations as inputs to obtain a better result.

Development of network architecture

The network form we use here is the radial-basis function (RBF) model. Park *et al.* (1993) provided evidence that RBF is a universal function approximator. Hornik (1991) also found that feed-forward neural networks with activation functions that are arbitrarily bounded and non-constant are universal function approximators. The activation function we adopted in the hidden neurons is a Gaussian function as shown in equation (4) where \mathbf{x} is the input vector, $\boldsymbol{\mu}_i$ and $\boldsymbol{\Sigma}_i$ are centre and spread of the i^{th} hidden neuron of the RBF. Linear functions as shown in equation (5) is adopted in the output layer of the RBF where \mathbf{w} is the set of weights of the links connecting the

outputs of the hidden neurons to the output neuron.

$$\phi_i(\mathbf{x}) = -(\mathbf{x} - \boldsymbol{\mu}_i)^T \boldsymbol{\Sigma}_i^{-1}(\mathbf{x} - \boldsymbol{\mu}_i) \quad (4)$$

$$f(\mathbf{x}) = \mathbf{w} \cdot \mathbf{x} \quad (5)$$

These satisfy the condition proposed by Hornik (1991) to ensure that our RBF model can be further verified as a universal function approximator.

Selection of parameters

Input parameters

One of the criteria for selecting suitable input parameters is their potential relationship to output. As stated above, the use of lagged prices in modelling residential property prices has been proven successful (Wilson *et al.* 2002). In addition, Hort (1998) found evidence that movement in income has a vital effect on the movement of real house prices in Sweden. This provides our rationale for using lagged nominal GDP as one of our input parameters. Edelstein *et al.* (2007) stated that macroeconomic variables, including the interest rate, crucially affect the residential property price cycle. Furthermore, at the sub-market level, Case *et al.* (1997) suggested that an increase in transaction volume tends to be tied to increases in property prices. With reference to the above pioneer works, we adopt four inputs to forecast the CCI: time-lagged CCI, nominal GDP, best lending rate² and transaction volume, expressed as CCI_{m-1} , GDP_{m-1} , BLR_{m-1} and $Volume_{m-1}$, respectively.

Output parameters

The horizon we forecast is one month ahead of the present month. Moshiri (2000) suggested that artificial neural networks are superior to other econometric models because they can forecast an inflation time series over a one-month horizon. Hence, we also try to forecast the residential property price one-month ahead. As a result, the output we use for our network is the CCI in the month m .

The number of nodes in different layers

In the input layer, we employ four nodes. Each node represents each input variable mentioned above at a period of $m-1$. For the hidden layer, the amount of hidden neurons required is suggested by the following formula (Ward Systems, 1996) where N represents the number of hidden neurons, N_{in} and N_{out} are, respectively, the numbers of inputs and outputs of the problem and N_{sample} is the total number of training samples.

$$N = \frac{N_{in} + N_{out}}{2} + \sqrt{N_{sample}} \quad (6)$$

In line with equation (6), we recruit 10 hidden neurons into our network as an initial trial. We then examine the effect of varying the number of hidden neurons by ± 5 : that is, from 5 to 15. The results of this variation are presented in Section 4. Finally, we have only one single desired output which is the CCI in month m . The architecture of the fully interconnected RBF network is shown in Figure 2.

² The best lending rate is the rate quoted and updated by the Hongkong and Shanghai Banking Corporation Limited

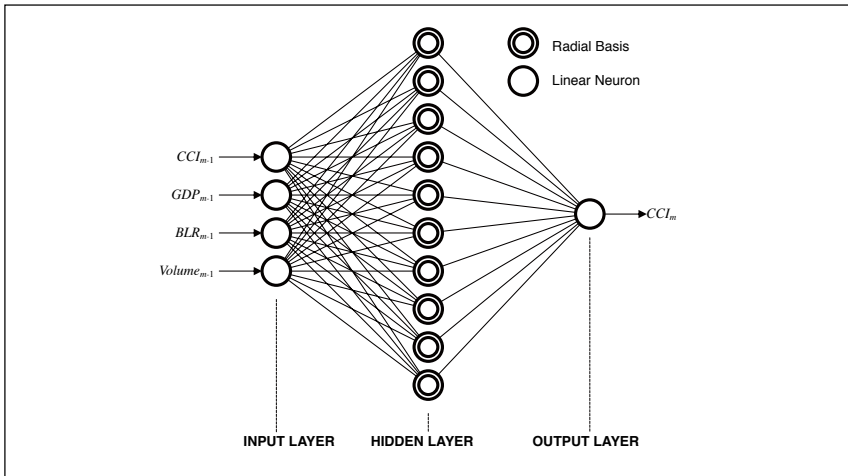


Figure 2 Architecture of the Radial Basis Function adopted in this study

Network training and performance evaluation

Throughout our data, from January 1998 to June 2008, we have 125 samples. These samples are divided into 3 groups of samples namely training samples, validation samples and test samples. The training errors, which are obtained from applying the RBF model to the training samples, are used to adjust the weights of the RBF models by Turboprop algorithm (Ward, 1996). It utilizes an independent weight update size for each different weight, rather than the usual method of having a single learning rate and momentum that apply to all weights. Furthermore, the step sizes are adaptively adjusted as learning progresses. Turboprop is simpler to use than the other methods because it does not require setting of the learning rate and momentum. The validation error which is obtained by applying the adjusted model to the validation samples is used to

maintain the generality of the model to avoid over-fitting. For every epoch of network training, the intermediate network trained by the training samples is applied to the validation samples to evaluate the prediction error (i.e. validation error). For early-stop validation approach, the network training is stopped when the validation error reaches its minimum and starts to increase. The typical progresses of training and validation errors during the network training are illustrated in Figure 3. The test samples do not involve in network training. Upon the completion of network training, the trained network is applied to the test samples. The prediction errors reveal the performance of the trained RBF model.

For these collected total 125 samples, the ratio of the number of training samples, validation samples and test samples is chosen to be 2:1:1.

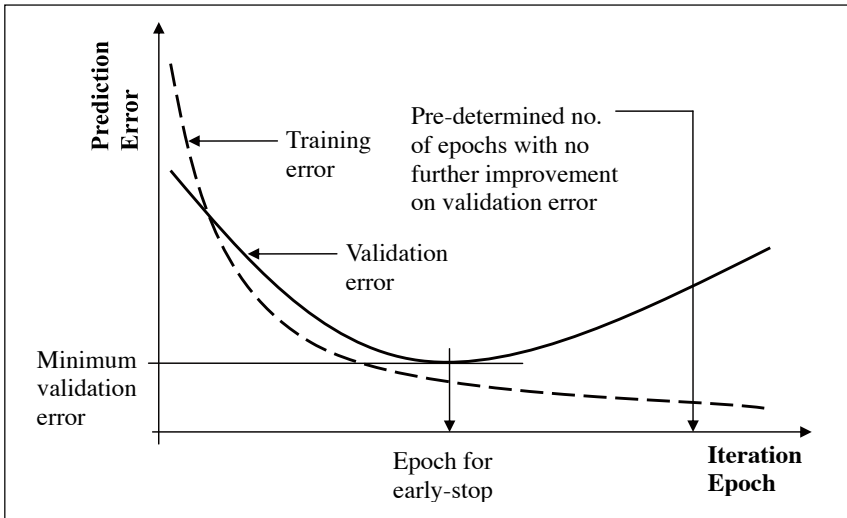


Figure 3 Early-stop validation for network training

Therefore, we randomly extract 62 as training samples, 32 as validation samples and 31 as test samples. Of these three kinds of patterns, the training patterns are used to train the networks, and the validation patterns are employed as a stop-training medium if their average error does not decrease for 20,000 consecutive epochs. This procedure ensures that there is no over-fitting of the problem because when training is stopped with reference to errors of a suitably smaller set it tends to reduce the possibility of over-fitting when compared to a large set. Finally, the test patterns are used for measuring the accuracy of the model. We use the correlation coefficient (r^2) to evaluate the relationship between desired outputs and the actual outputs of the test set.

The approach to model learning, based on back-propagation learning, is called Turboprop. (Ward Systems, 1996) This

approach changes the size of weight updates independently towards different links between neurons, instead of using a uniform learning rate for the entire set of weights. Hence, a training process that is faster than traditional approaches can be achieved.

As the time series involves a random process, random extraction is carried out 30 times to ensure all patterns have equal probability of being selected as test patterns so that a more objective picture of the model's performance can be obtained. (Lee *et al.* 2004a, 2004b, Aminian *et al.* 2006) After the randomly extracted data points are trained once according to our rule and the results are recorded, we start another random extraction process, and continue in this manner until all 30 extractions have been completed. Figure 4 is a flow chart of the neural network training.

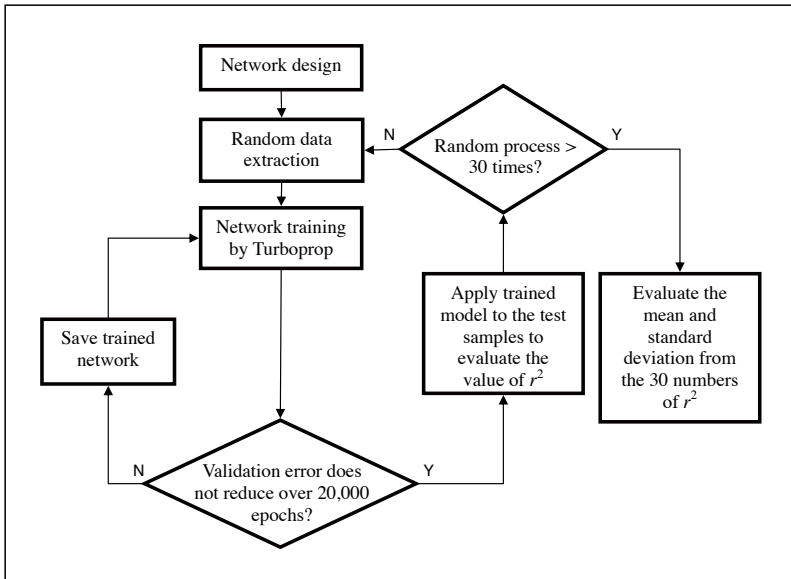


Figure 4 Methodology in network training and performance evaluation

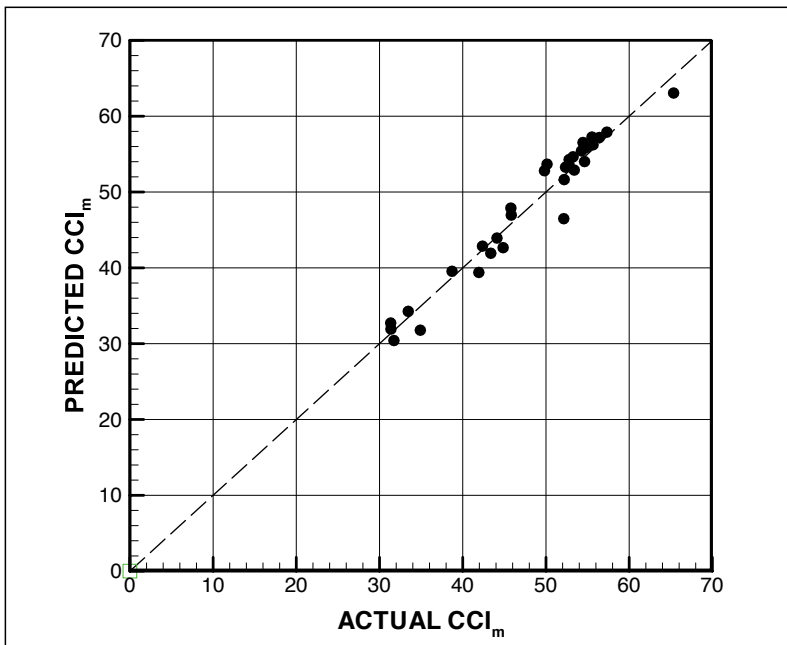


Figure 5 Typical results of the predicted CCI_m by RBF and the CCI_m of the actual data. The predicted results reasonably agree with the actual data.

RESULTS

The model’s performance is measured by the correlation coefficient (r^2) between the prediction and the data of the test set. It is defined in equation (5).

$$r^2 = \frac{[\sum (x - \bar{x})(y - \bar{y})]^2}{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2} \quad (5)$$

Figure 5 shows the typical simulation result of the total 30 runs. It shows that the predicted results reasonably agree

with the actual results with value of $r^2 = 0.957$.

Table 1 summarises the results of the model with 30 runs with randomly extractions of data for training, validation and test samples. The standard deviation of these 30 results is only 0.016, which reveals that the model is able to extract the underlying nonlinear functional relationship between input and output parameters to a very high extent.

Table 1 Descriptive statistics of Correlation Coefficient (r^2) on the results of 30 runs

Statistical results	Values
Mean of r^2	0.959
Standard deviation of r^2	0.016
Minimum value of r^2	0.932
Maximum value of r^2	0.986

Figure 6 illustrates the probability distribution of the r^2 value from the 30 simulations. It is presented by beta distribution since the r^2 value is bounded within the domain of [0, 1]. The figure indicates that the probability of r^2 value being less than 0.9 is practically zero. The distribution exhibits a vigorously upward sloping curve when $r^2 > 0.93$, which indicates that the probability density of r^2 is clustering for $r^2 > 0.93$. This result confirms that the RBF provides a well-performed and reliable modelling method in the prediction of residential property prices over a one-month horizon.

Apart from measuring and evaluating the capacity ANNs to predict price series, we have also investigated the effect of the number of hidden neurons on ANN performance. The results of employing ANN structures with 5 to 15 hidden neurons in our 30 randomly timed extractions are given in Figure 7. As variation in the number of hidden neurons has an insignificant effect on the model’s performance, we finally adopt 10 hidden neurons as a rule of thumb and with reference to equation (6). A possible explanation for this minute difference is that the capacity to approximate a functional relationship may start in a particular dimensionality of hidden space.

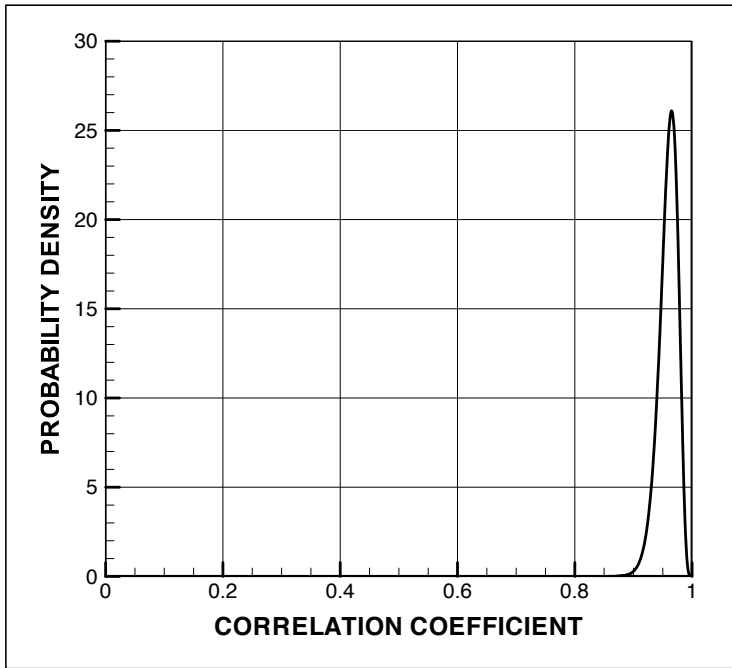


Figure 6 Probability distribution of the Correlation Coefficient. Beta distribution was adopted since the value of Correlation Coefficient is bounded between 0 and 1.

CONCLUSIONS

The modelling and forecasting of residential property prices has long been a complicated process for researchers. Most previous studies used econometric models that attempted to generate the underlying function of the time series. However, few of those models can be used extensively and successfully.

In this study we used ANN, which are well known for their capacity to model nonlinear time-series but rarely used in modelling and forecasting residential property price time-series. By using ANN, we modelled the short-

term price behaviour of residential property from January 1998 to June 2008. For the model, we recruited radial-basis function networks as our network architecture and used time-lagged observations as input to forecast short-term price movement. Moreover, to obtain an objective picture of the model's performance, we randomly extracted data points for training and testing 30 times so that each data point had an equal probability of being put into a test set.

Our results reveal that the performance of the model, measured by the correlation coefficient, is so promising

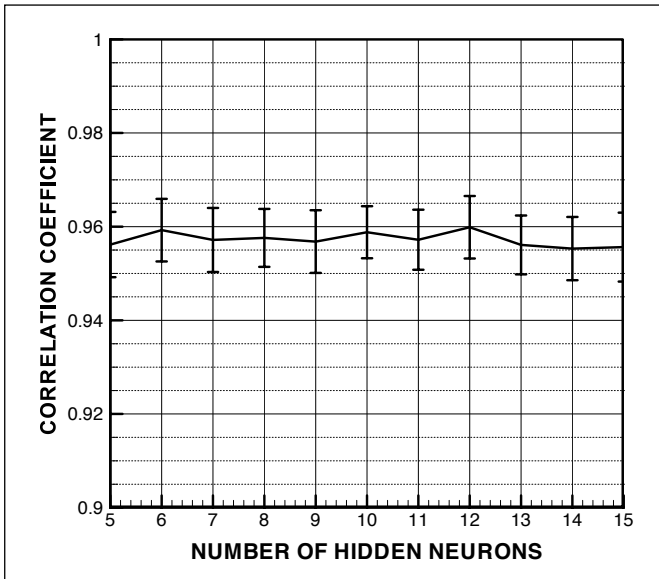


Figure 7 Correlation Coefficient under different amounts of hidden neurons. The error bars states the 95% confidence intervals

that short-term residential property price behaviour in Hong Kong can be modelled very successfully. The standard deviation of the 30 values of the correlation coefficient is so minute that the reliability of the model is guaranteed. Furthermore, even if we vary the number of hidden neurons in the network architecture, there is no significant change in the model's performance.

Our study provides an effective methodology for modelling residential property price movement. Due to their very promising accuracy, ANNs could be used to model the underlying nonlinear function of property price behaviour in any region.

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