Prediction of Real Estate Price Variation Based on Economic Parameters

Li Li and Kai-Hsuan Chu

Department of Financial Management, Business School, Nankai University
No.94, Weijin Road., Nankai District, Tianjin, China
Tel: 886-918218296; Fax:886-2-55592878; and E-mail: amanda.twku@gmail.com; artist.chu@best-rich.com

Abstract

It is well known that many economic parameters may more or less influence the real estate price variation. In addition, the banker and investor are also interesting to know the real estate price future change. There had not appropriate model for including these factors for price prediction. Here, the influences of most macroeconomic parameters on real estate price variation are investigated before establishing the price fluctuation prediction model. Here, back propagation neural network (BPN) and radial basis function neural network (RBF) two schemes are employed to establish the nonlinear model for real estates price variation prediction of Taipei, Taiwan based on leading and simultaneous economic indices. Those prediction results are compared with the public Cathay House Price Index or the Sinyi Home Price Index. The mean absolute error and root mean square error two indices of the price variation are selected as the performance index. The public related data of Taipei, Taiwan real estate variation during 2005 ~ 2015 are adopted for analysis and prediction comparison.

Key words: real estate price, macroeconomics, back propagation neural network, RBF neural network

Introduction

The real estates is not only the living requirement, it also represents the personal wealth and glory. In addition, the real estates price fluctuation may impact the households' investment and consumption situation [1]. It is also an important impact factor for investing company, real estates developer, banker and policy makers. Hence, it can be concerned as an important economic index. Global investors stampede on the real estates investment since 2000 year. Then, the United states real estates price crush in 2008 and cause a large global economic problems and crisis. Hence the real estates price variation trend is an important factor for financial manage person. However, there have too many influence variables and the effects are too complicated to understand or predict. Hence, how to establish the real estates price variation prediction model is still an interesting research topic.

Garch scheme was proposed to estimate the investment risk or product price [2]. Cointegration and error correction model were proposed to investigate the long/short term relationship between real estates prosperity and macro-economic indices [3]. Barras and Ferguson [4] found that many financial factors influence the real estates boom and their impact effects are too complex to model. The real estates market and price can be influenced by macro-economic indices, spatial and community and environmental differences [5]. All those variables are varying case by case depending the housing location and structure except macro-economic conditions [6]. Previously, the real estates current price was assessed by using hedonic regression model [7] or neural network model [7, 8]. However, those studies were focused on the current real estates evaluation. The price short term future variation prediction was not concerned much till now. How to catch the real estates changing tendency and predict the trend precisely is an important research topics for related foundation or government.

Lai [9] employed correction analysis, regression analysis, and cluster scheme to investigate the relation intensity between each macro economic variable and real estate price. He found that the customer price index, wholesale price index, interest rate, and GDP are more important variables related to the real estates price. But, previous researches had not harmonize conclusion. Collin and Evans [10] used the neural network for house price evaluation to distinguish the localize factor due to noise and house type. Different neural network models and fuzzy neural network model were proposed to predict the real estates variation [11]. Here, two nonlinear neural network modes are adopted in this study to predict the real estates fluctuation trend. There prediction accuracy will be compared based on Taipei city most recent 13 years real estates trading price. The important leading and simultaneous indices was chosen to establish neural network model for prediction the real estates price variation situation. The analysis results will be compared with that of all macro-economic parameters are considered.

Back Propagation Feedforward Neural Network Scheme

The dynamics of real estates price variation has complicate nonlinear behaviors and certain uncertainty. There have more than 15 macroeconomic variables influence real estates price variation. It is impossible to establish an accurate mathematical model for real estates price variation prediction with reasonable accuracy. Hence the mathematical model free feature of neural network algorithm is introduced to solve this kind of problems. The mathematical model of MP neuron was proposed by McCulloch and Pitts on 1943. Rumelhart and McClelland [12] proposed a multilayer feedforward neural network with back propagation learning scheme. The learning results are fed back to the neurons of the hidden and output layers to adjust their weighting matrix for the predictive learning objective. Here a feedforward neural network combined with back propagation algorithm is employed to establish a real estates price variation model correlated to

macro-economic parameters.
Multilayer feed forward neural network is consisted of many processing elements which are interconnected with data weighting. If the weighting between processing elements is larger, the influence of that connection is strong. The summation of those input signal multiplied with their corresponding weighting is used to determine the activation value.

$$net_j^k = \sum W_{ji}^k O_i^{k-1} - \theta_j^k \tag{1}$$

$$O_j^k = f(net_j^k) \tag{2}$$

In general, it is interconnected with a sequential method as Fig. 1. The neurons of each layer are connected with the neurons of other layer. Each layer has one or more neurons without interconnection. The back propagation learning method employs the error between the real output of a neural network and the desired value to adjust the weighting values in network. The object function is defined as

$$E = \frac{1}{2}\sum_j (Y_{dj} - O_j)^2 \tag{3}$$

The objective function, the correction value of the weighting can be obtained

$$W_{ji}^k = \eta \delta_j^k O_i^{k-1} \tag{4}$$

and

$$\theta_j^k = -\eta \delta_j^k \tag{5}$$

where η is the learning rate parameter and δ_j^k is defined as

$$\delta_j^k = -\frac{\partial E}{\partial net_j^k} \tag{6}$$

If the processing element j is on the output layer, then

$$\delta_j^k = (y_{dj} - O_j) f'(net_j^k) \tag{7}$$

Otherwise

$$\delta_j^k = f'(net_j^k) \sum_l \delta_l^{k+1} W_{lj}^{k+1} \tag{8}$$

The activation function used in this research is a linear function, $f(net_j^k) = m \cdot net_j^k$, for output layer and a sigmoid function for the hidden layer.

$$f(net_j^k) = \frac{1 - \exp(-\lambda \cdot net_j^k)}{1 + \exp(-\lambda \cdot net_j^k)} \tag{9}$$

By using the steepest descent method to modify the weighting values in order to minimize n this study, the neural network toolbox of MATLAB commercial software was employed to establish the real estates price variation prediction model between macro-economic parameters and the Cathay House Price Index or the Sinyi Home Price Index. In this data analysis, we need to choose the input macro-economic parameters number, Hiddern layer nodes number, output index, learning cycles, error function and weighting learning rate, respectively. In this study, they are 11(6), 20, Cathay and Sinyi price indices, 500 cycles, ….. and 0.1, respectively.

Radial Basis Function (RBF) Neural Network Scheme

Other neural network have been proposed for the two-layer NN with linear weights between them (e.g. using RBF) [13]. The reason to use a RBFNN instead of another neural network (e.g., multilayer neural network) is that the RBFNN connection weights for the nonlinear maps is linear achieve.

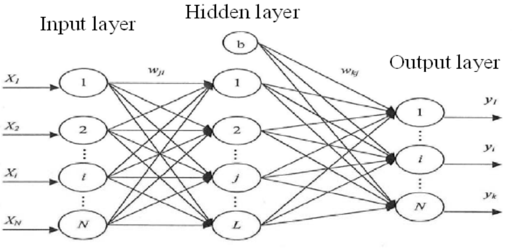

Fig. 1 The multilayer back propagation feedforward neural network diagram.

Hence, the stability analysis of the overall system is not difficult to achieve, the updating law for adjusting is substantially simplified, and the converging speed of the connection weights is rapid [14] (Sanner and Slotine 1992). Here a RBFNN is employed to model the relationship between macro-economic parameters and variation of the Cathay House Price Index or the Sinyi Home Price Index. Only one hidden layer is used in the RBFNN and the semi-affine nonlinear functions are employed as the activation function in hidden layer instead of sigmoid functions. Gaussian functions are used as the activation functions of each neuron in the Hidden layer of this novel controller. The excitation value of these Gaussian functions is the distance between the input value of sliding variable $s(t)$ and the central position of a Gaussian function.

$$\theta_j = (s - c_j)^2 = \|s - c_j\| \tag{10}$$

Where c_j is the central position of neuron j. The weightings, w_j, between input layer neurons and hidden layer neurons are specified as constant 1.0. The weightings, w_k , between hidden layer neurons and output layer neurons are adjusted based on an adaptive rule. The output of a RBFNN is

$$g(s) = \sum_{j=1}^{n} w_j \phi_j (\|s - c_j\|) \tag{11}$$

The structure of a RBFNN is shown in Fig. 2. In addition, the Gaussian functions parameters σ_j and c_j can be specified as constants for general-purpose applications. Here, the spread factor σ_j is chosen as 0.6 and the center of functions c_j is specified as integral constants from –5 to +5.

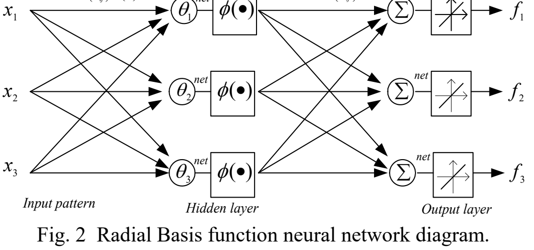

Fig. 2 Radial Basis function neural network diagram.

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Data Analysis and Performance Comparison of Neural Network Prediction Schemes

Here, the Cathay House Price Index and the Sinyi Home Price Index season variation rate are selected as the matched target. Gross domestic product, money supply M2, gross net income (GNI), economic grow rate, prosperity signal, house price tendency index, house price/GNI ratio, building permit of residence, consumer price index, benchmarking lending rate, new house-purchasing loans are selected as the effective influence parameters. In the beginning, all the seasons data of these macro-economic variables are searched from all official public publication source or real estate companies between 2005 2nd quarter and 2015 2nd quarter. Since, each variable has different scale value, the season change rate are calculated for further analysis. Since, the Cathay House Price Index is the pre-sale house market price statistic data and the Sinyi Home Price Index is for the current available house market price statistic data, they have significant difference. They are investigated separately with different neural network models.

(A) Cathay house price index variation prediction

The BPF and RBF neural network models with 11 macro-economic parameters input are established based on 40 seasons public data to learn the appropriate weighting gain of neural network. Then, they are employed to predict the further 13 seasons house price index variation tendency. The computation results are plotted in Fig. 3 for comparison. In order to distinct their difference, their indices difference are shown with the variation percentage in figure. It can be observed that the prediction results of RBFNN is better than that of BPFNN. The computed normalized real estates prices overall variation based on RBFNN and BPFNN are plotted in Fig. 4 for comparing with that of Cathay house price. It can be observed that the estimation results are matched with that of Cathy house price very well. The prediction errors of RBF and BPF are less than 5% and 4 %, respectively. It can be observed that the prediction results of BPFNN is better than that of RBFNN.

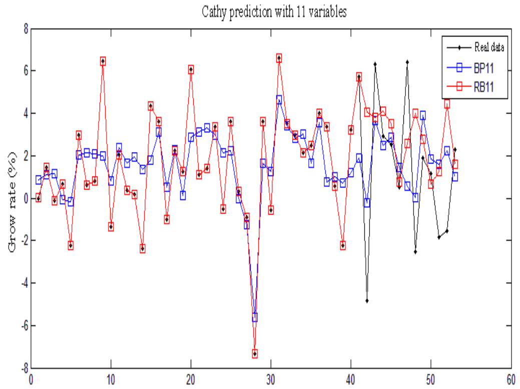

Fig. 3 The comparison of BP and RBF NN prediction results for Cathay index.

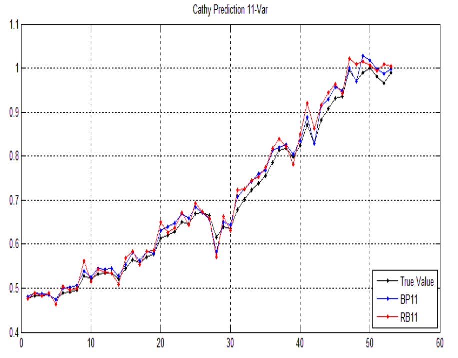

Fig. 4 Comparison of RBF and BPF normalized house price estimation with that of Cathy house price.

(B) Sinyi house price index variation prediction

The BPF and RBF neural network models with 11 macro-economic parameters input are established based on 40 seasons public data to learn the appropriate weighting gains of neural network. Then, they are employed to predict the further 13 seasons house price index variation tendency. The computation results are plotted in Fig. 5 for comparison. In order to distinct their difference, their indices difference are shown with the variation percentage in figure. It can be observed that the prediction results of RBFNN is better than that of BPFNN. The computed normalized real estates prices overall variation based on RBFNN and BPFNN are plotted in Fig.6 for comparing with that of Sinyi house price. It can be observed that the estimation results are matched with that of Cathy house price very well. The prediction errors of RBF and BPF are less than 4% and 3.6 %, respectively. It can be observed that the prediction results of BPFNN is better than that of RBFNN.

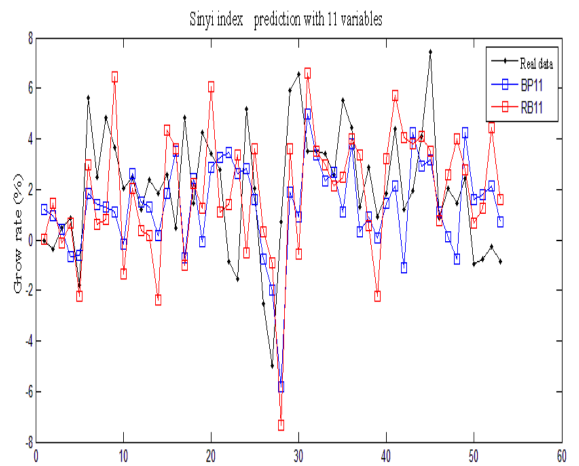

Fig. 5 The comparison of BP and RBF NN prediction results for Sinyi index.

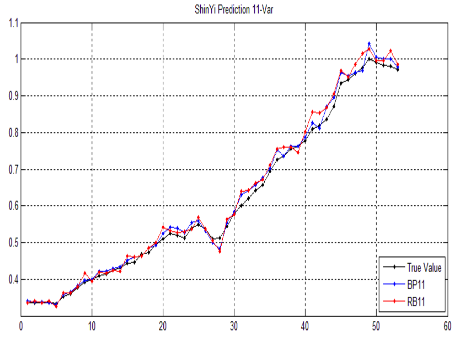

Fig. 6 Comparison of RBF and BPF normalized house price estimation with that of Sinyi house price.

Discussion

Based on last section data analysis, the prediction performance of BPFNN and RBFNN models can be compared with the mean absolute percentage error (MAE) and the percentage root mean square error (RMSE) two indices. The overall computation results are summarized in Table 1. It can be observed that the RBF neural network has better prediction performance than that of BPF neural network for the Cathay house price index variation. Conversely, the BPF neural network has better prediction performance than that of RBF neural network for Sinyi house price index variation. But, there difference is not obvious.

Actually, there have other variables can not be systematized in this analysis. For example government policy change, global economic crisis and local social events…etc. They may cause a quick conversion and the impact level is difficult to evaluate. It is still a problem need to study and model. The grey model can appropriate predict the real estates price fluctuation based on target index only without macro-economic indices variation introducing.

Table 1 The prediction results performance comparison

House price index	Economic variables	index	BPFNN	RBFNN
Cathay house price index	11 parameters	MAE	1.71 %	0.67 %
		RMSE	2.05 %	1.90 %
Sinyi house price index	11 parameters	MAE	2.06 %	2.34 %
		RMSE	2.58 %	2.95 %

Conclusion

The RBF and BPF neural networks are introduced to model the complicated correlation function between macro-economic parameters variation and house price index variation. 40 seasons leading data sets are employed to training the neural network. Then, the less 13 seasons data sets are used to evaluate the prediction accuracy between NN model output and the Cathay or Sinyi house price index. The data analysis results show that the house price variation prediction results is not accurate enough. However, the house price variation trend is still can be established for investor, developer and government reference.

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