The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0144-3585.htm

Rent index forecasting through neural networks

Xiaojie Xu and Yun Zhang
North Carolina State University, Raleigh, North Carolina, USA

Received 30 June 2021
Revised 10 October 2021
Accepted 14 October 2021

Abstract

Purpose – Chinese housing market has been growing fast during the past decade, and price-related forecasting has turned to be an important issue to various market participants, including the people, investors and policy makers. Here, the authors approach this issue by researching neural networks for rent index forecasting from 10 major cities for March 2012 to May 2020. The authors aim at building simple and accurate neural networks to contribute to pure technical forecasting of the Chinese rental housing market.

Design/methodology/approach – To facilitate the analysis, the authors examine different model settings over the algorithm, delay, hidden neuron and data spitting ratio.

Findings – The authors reach a rather simple neural network with six delays and two hidden neurons, which leads to stable performance of 1.4% average relative root mean square error across the ten cities for the training, validation and testing phases.

Originality/value – The results might be used on a standalone basis or combined with fundamental forecasting to form perspectives of rent price trends and conduct policy analysis.

Keywords Rental housing market, Rent price, Neural network, Forecasting

Paper type Research paper

1. Introduction

During the past decade, Chinese housing market has been fast growing. Without doubt, price-related issues have turned to be one of key concerns of different market participants, including the people, investors and policy makers. It is essential to have good understandings of price trends and fluctuations as they directly influence people's decisions on real estate investment and cities to work and reside, as well as regulatory agencies' policy analysis and design. Naturally, price-related forecasting in the housing market has attracted a great amount of attention from various forecasters and users from both the industry and academia.

In econometric studies, researchers have devoted much effort to produce robust and accurate forecasts of financial and economic time series. Some fundamental models, including the autoregressive, vector autoregressive and vector error correction approaches, as well as a diverse variety of their variations and extensions, have been widely investigated for generating forecasts for various purposes and uses (e.g. Shimizu *et al.*, 2006; Xu, 2014b, 2018e; Kim *et al.*, 2007; Xu, 2017c; Zohrabyan *et al.*, 2008; Xu, 2014a; Hyvärinen *et al.*, 2010; Xu, 2019c; Cabrera *et al.*, 2011; Xu, 2015a; Kawahara *et al.*, 2011; Xu and Thurman, 2015a; Xu, 2017a; Webb *et al.*, 2016; Xu, 2017b, 2018b; Yang *et al.*, 2018; Xu, 2019a, 2020; Xu and Zhang, 2021d). Recently, different machine learning approaches and algorithms, including the nearest neighbor, random forest, regression tree, support vector regression, deep learning, ensemble learning, boosting and bagging, have been found to be attractive and useful tools to many forecasting problems related to prices in the housing market (e.g. Chen *et al.*, 2017; Embaye *et al.*, 2021; Gu *et al.*, 2011; Ho *et al.*, 2021; Li *et al.*, 2020; Liu and Liu, 2019; Park and Bae, 2015; Plakandaras *et al.*, 2015; Rico-Juan and de La Paz, 2021; Xu and Li, 2021; Xu and Zhang, 2021c, f). In particular, previous work has shown that the neural network model is promising to forecast financial and economic time series, which generally tend to be highly chaotic and noised (e.g. Yang *et al.*, 2008; Wang and Yang, 2010; Xu and Zhang, 2021e; Yang *et al.*, 2010; Xu and Zhang, 2021b; Wegener *et al.*, 2016), including price series in the housing market

Journal of Economic Studies
Vol. 49 No. 8, 2022
pp. 1321-1339

0144-3585
DOI 10.1108/JES-06-2021-0316

(e.g. Abidoye and Chan, 2017, 2018; Azadeh *et al.*, 2014; Chiarazzo *et al.*, 2014; Igbinosa, 2011; Kang *et al.*, 2020; Kitapci *et al.*, 2017; Lam *et al.*, 2008; Li *et al.*, 2017; Morano *et al.*, 2015; Morano and Tajani, 2013; Nghiep and Al, 2001; Peterson and Flanagan, 2009; Selim, 2009; Terregrossa and Ibadi, 2021; Xin and Runeson, 2004; Xu and Zhang, 2021g; Yasnitsky *et al.*, 2021).

This study focuses on neural networks for rent index forecasting of 10 major cities in China for March 2012–May 2020, during which the house market grows rapidly. To authors' knowledge, this is the first study specifically on rent index in Chinese housing market. Analysis here should help expand knowledge of using machine learning models to forecast rental prices in the substantially growing Chinese market because previous research generally focuses on one certain city (Ho *et al.*, 2021; Lam *et al.*, 2008; Li *et al.*, 2020; Liu and Liu, 2019; Xin and Runeson, 2004). The analysis should also help shed light on more recent evidence of usefulness of machine learning to forecast house price related series in China because previous research examines earlier time periods of 1981Q1–2002Q4 (Xin and Runeson, 2004), December 2010–October 2017 (Liu and Liu, 2019), January 2005–November 2018 (Li *et al.*, 2020) and June 1996–August 2014 (Ho *et al.*, 2021). We aim at constructing simple and accurate neural networks to contribute to pure technical forecasts. To facilitate the analysis, we investigate various model settings across the algorithm, hidden neuron, delay and data spitting ratio and arrive at a rather simple neural network with six delays and two hidden neurons, which leads to stable performance of 1.4% average relative root mean square error across the 10 cities for the training, validation and testing phases. Results here can be utilized on a standalone basis or combined with fundamental forecasts in forming perspectives of rental price fluctuations and trends and conducting policy analysis.

2. Literature review

Geographically, machine learning modeling has been applied for price-related forecasts in housing markets across many different countries and/or regions, including the USA (Nghiep and Al, 2001; Peterson and Flanagan, 2009; Park and Bae, 2015; Plakandaras *et al.*, 2015), China (Gu *et al.*, 2011; Ho *et al.*, 2021; Lam *et al.*, 2008; Li *et al.*, 2020; Liu and Liu, 2019; Xin and Runeson, 2004; Xu and Li, 2021), Spain (Rico-Juan and de La Paz, 2021), Italy (Morano and Tajani, 2013; Chiarazzo *et al.*, 2014; Morano *et al.*, 2015), Iran (Azadeh *et al.*, 2014), Tanzania (Embaye *et al.*, 2021), Uganda (Embaye *et al.*, 2021), Malawi (Embaye *et al.*, 2021), Turkey (Selim, 2009; Kitapci *et al.*, 2017; Terregrossa and Ibadi, 2021), Nigeria (Igbinosa, 2011; Abidoye and Chan, 2017, 2018), Russia (Yasnitsky *et al.*, 2021) and South Korea (Kang *et al.*, 2020). The use of a wide range of machine learning models suggests their potential for price series forecasts in the housing market.

When building machine learning models, previous studies differ in model construction and forecasting purposes, which depend on their respective research focuses of the housing market. These could be building models from various house-related characteristics (e.g. the house type, age, lot size, number of units, number of baths, number of stories, exterior composition and location) for property valuations (Peterson and Flanagan, 2009; Selim, 2009; Igbinosa, 2011; Morano and Tajani, 2013; Chiarazzo *et al.*, 2014; Morano *et al.*, 2015; Abidoye and Chan, 2017, 2018; Kang *et al.*, 2020; Ho *et al.*, 2021; Xu and Li, 2021), from macroeconomic conditions (e.g. the gross national product, gross domestic product, stock market index, consumer price index, default rate, interest rate and unemployment) for valuations (Kang *et al.*, 2020), from prices themselves for technical forecasts (Gu *et al.*, 2011; Li *et al.*, 2020; Xin and Runeson, 2004), from house-related characteristics for technical forecasts (Chen *et al.*, 2017; Embaye *et al.*, 2021; Igbinosa, 2011; Kang *et al.*, 2020; Kitapci *et al.*, 2017; Lam *et al.*, 2008; Liu and Liu, 2019;

Morano and Tajani, 2013; Nghiep and Al, 2001; Park and Bae, 2015; Rico-Juan and de La Paz, 2021; Terregrossa and Ibadi, 2021; Yasnitsky *et al.*, 2021) and from macroeconomics for technical forecasts (Azadeh *et al.*, 2014; Kang *et al.*, 2020; Lam *et al.*, 2008; Liu and Liu, 2019; Plakandaras *et al.*, 2015; Rico-Juan and de La Paz, 2021; Xin and Runeson, 2004; Yasnitsky *et al.*, 2021).

Some previous studies focus on using a specific machine learning model for price-related forecasting in the housing market (Abidoye and Chan, 2017; Azadeh *et al.*, 2014; Chen *et al.*, 2017; Chiarazzo *et al.*, 2014; Gu *et al.*, 2011; Igbinosa, 2011; Kang *et al.*, 2020; Kitapci *et al.*, 2017; Lam *et al.*, 2008; Li *et al.*, 2020; Morano *et al.*, 2015; Xin and Runeson, 2004; Yasnitsky *et al.*, 2021), some on making comparisons among different machine learning models (Park and Bae, 2015; Li *et al.*, 2017; Liu and Liu, 2019; Ho *et al.*, 2021; Rico-Juan and de La Paz, 2021; Xu and Li, 2021; Embaye *et al.*, 2021), some on comparing machine learning models with traditional econometric approaches (Nghiep and Al, 2001; Selim, 2009; Peterson and Flanagan, 2009; Morano and Tajani, 2013; Plakandaras *et al.*, 2015; Li *et al.*, 2017; Abidoye and Chan, 2018) and some on putting forward model combinations (Terregrossa and Ibadi, 2021).

From the perspective of model performance, the literature has revealed promising accuracy via using machine learning approaches for price-related forecasting in the housing market. Empirical results show a mean absolute percentage error of less than 1% (Liu and Liu, 2019; Ho *et al.*, 2021), between 1 and 2% (Rico-Juan and de La Paz, 2021), between 2 and 3% (Plakandaras *et al.*, 2015; Liu and Liu, 2019), between 4 and 5% (Kang *et al.*, 2020), between 5 and 6% (Kang *et al.*, 2020; Li *et al.*, 2020; Plakandaras *et al.*, 2015), between 6 and 7% (Kang *et al.*, 2020), between 7 and 8% (Kang *et al.*, 2020) and between 8 and 9% (Kang *et al.*, 2020).

As compared to house price forecasting, research on rental price forecasting through machine learning (e.g. Clark and Lomax, 2018; Embaye *et al.*, 2021; Hu *et al.*, 2019; Li, 2018; Li and Li, 1996; Ma *et al.*, 2018; Ma and Liu, 2019; Ming *et al.*, 2020; Odubiyi *et al.*, 2019; Oshodi *et al.*, 2020, 2021; Oyedeji Joseph *et al.*, 2018; Oyedeji and Oyewale, 2018; Rafatirad, 2017; Tsai and Pan, 2014; Wang and Cao, 2019; Zhang *et al.*, 2019) seems relatively scare. Hu *et al.* (2019) explore the random forest, extra-trees, gradient-boosting, support vector, multi-layer perceptron neural network and k-nearest neighbor when building housing rent prediction models for Shenzhen in China in October 2017 and February 2018 and find that all of these algorithms, except for the support vector, generally present good performance with the random forest and extra-trees being the leaders. Li, 2018 proposes a light gradient boosting model for rent price forecasting based on housing information and achieves accuracy of 96%. Embaye *et al.* (2021) examine the Ridge, least absolute shrinkage and selection operator, tree, bagging, random forest and boosting approaches for forecasting house rental values in Tanzania, Uganda and Malawi and find that all of these machine learning models outperform the ordinary least square model except for the tree regression for several cases. Clark and Lomax (2018) investigate the generalized linear regression, machine learning and pseudo practitioner-based approaches for the mass appraisal purpose in English rental housing markets and determine that two tree-based models beat the regression-based model. Odubiyi *et al.* (2019) use the neural network model to assess the impact of the presence of a police station on rental prices of residential properties in Cape Town, South Africa, and achieve accuracy of 77.27%. Zhang *et al.* (2019) employ a least square-based linear weighting learner to combine price forecasts based on the XGBoost, light gradient boosting and CatBoost algorithms to improve model performance for the Chinese house rental market. Rafatirad (2017) studies different machine learning models for rental price forecasting of Virginia and Maryland and proposes a two-layer clustering approach to partition data based on the house type and zip code. Wang and Cao (2019) compare the linear regression, decision tree and random forest models for office rental price forecasting in Shanghai and find the random forest optimal. Ma and Liu (2019) utilize integrated learning constituted of the random forest, extra trees and light gradient boosting to improve performance from a single model for house rental price forecasting. Oshodi *et al.* (2021) apply the neural network to forecast rental values of residential properties in Cape Town, South Africa, and obtain accuracy of 66.67%. Ming *et al.* (2020) compare the random forest, light gradient boosting and XGBoost for forecasting rental prices in Chengdu and find the XGBoost optima with accuracy of 85%. Ma *et al.* (2018) explore the linear regression, regression tree, random forest and gradient boosting regression trees to estimate warehouse rental prices in Beijing and find the machine learning models perform better than the linear regression with the random forest being optimal. Oshodi *et al.* (2020) utilize the neural network to evaluate the impact of tourist sites on rental values of residential properties in Nigeria and arrive at accuracy of 93.75%. While machine learning models are promising tools for house rental price forecasting, some studies find them sub-optimal as compared to simpler models. For example, Li and Li (1996) find that an analytically built model from selected variables and parameters of rental values beats a neural network model when researching the rental market in Townsville, Australia.

3. Data

Data for analysis are obtained from the China Real Estate Index System (CREIS), which is an analytical platform designed to reflect market conditions and development trends of house markets in major Chinese cities. It was originated in 1994, which was initiated by the Development Research Center of the State Council, Real Estate Association, and National Real Estate Development Group Corporation. In 1995, 2005, CREIS was audited by experts from the Development Research Center of the State Council, Ministry of Construction, Ministry of Land and Resources, Banking Regulatory Commission, Real Estate Association and different universities. Currently, it periodically publishes different housing price indices that include the one hundred city index, city composite index, residential index, hedonic index, office building index, retail index, villa price index, second-hand housing sales index and rental price index and has become the system with the widest coverage in terms of house markets. Here, we use the rental price index.

The rental price index covers the following 10 major cities in China: Beijing, Shanghai, Tianjing, Chongqing, Shenzhen, Guangzhou, Hangzhou, Nanjing, Wuhan and Chengdu. Samples used to calculate the index include all residential properties in each city, including public housing, commercial housing and affordable housing. Each sample collected contains the following information: the property type, construction area, listed rental price, unit type, orientation, number of floors, floor of the rental property, furnishment, furniture, appliance, surrounding facility and rental payment option. More than 10,000 samples are collected each month for each city. The index value of Beijing in December 2005, which is 1,000, is used as the base period index across the 10 cities.

For a given city, its rental price index is calculated as: $I'_t = \frac{\sum P_i^t A_i^{t-1}}{\sum P_i^{t-1} A_i^{t-1}} \cdot I'_{t-1}$, where I'_t and I'_{t-1} are the indices at time t and $t-1$, A_i^{t-1} is the total construction area of project i at time $t-1$ and P_i^t and P_i^{t-1} are the average rental prices of project i at time t and $t-1$. The data range from March 2012 to May 2020. Rental price index series, together with their first differences, are plotted in Figure 1.

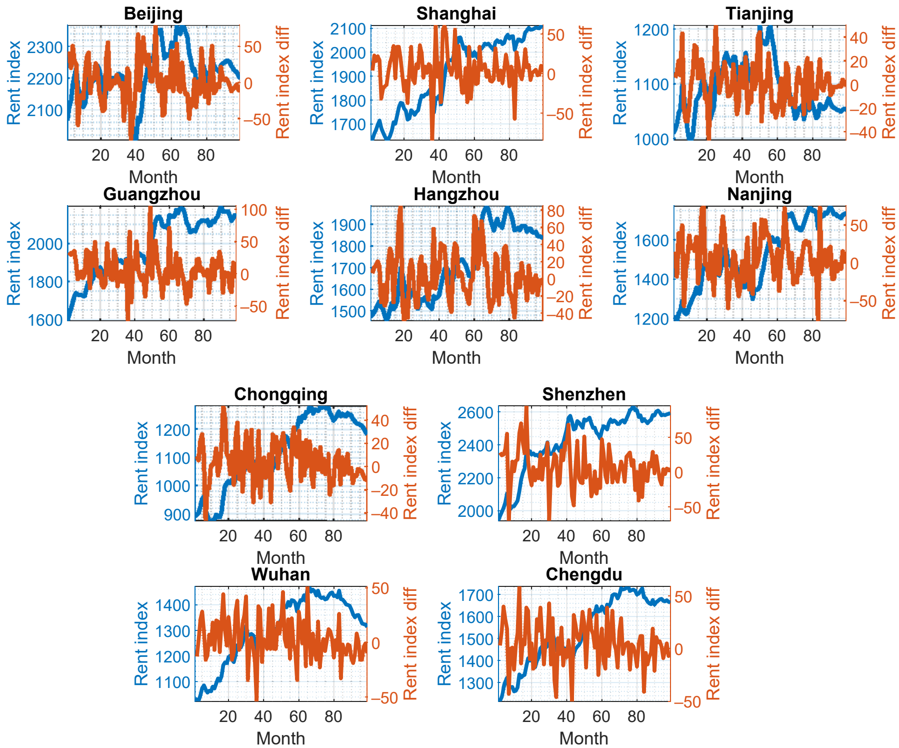

Figure 1.
Rental price indices of 10 major Chinese cities. Months are from March 2012 to May 2020

4. Method

We adopt the nonlinear autoregressive (NAR) model for forecasting, which can be expressed as $x(t) = f(x(t-1), \ldots, x(t-d))$, where x is the rent index of a certain city under consideration, t denotes time, d represents the number of delays and f is the function. We focus on the short-term forecast of one month ahead.

We apply the NAR based on a two-layer feedforward network, which has a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. We note that the output $x(t)$ is fed back through delays to the input of the network and model training would be in the form of open loops for efficiency, in which the true output is used rather than feeding back the one estimated. Specifically, employing the open loop would ensure that the input to the feedforward network is more accurate and the resulting network would have an architecture that is pure feedforward.

Our final forecasting models are based on two hidden neurons and six delays. We adopt the Levenberg–Marquardt (LM) algorithm (Levenberg, 1944; Marquardt, 1963) to estimate the models and split the data randomly for training, validation and testing based on the ratio of 80% vs 10% vs 10%.

The LM algorithm approximates the second-order training speed to avoid the expensive Hessian matrix (H) computation (Paluszek and Thomas, 2020). The approximation utilized is $H = J^T J$, where $J = \left[\frac{\partial f}{\partial x_1} \quad \frac{\partial f}{\partial x_2}\right]$ for a non-linear function

$f(x_1, x_2)$ whose $H = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{bmatrix}$. $g = J^T e$ represents the gradient, where e denotes an error vector. The rule of $x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e$ is employed to update weights and biases, where I is the identity matrix. The algorithm would be similar to Newton's method when $\mu = 0$ and it would become gradient descent with small step sizes when μ is large. μ would be decreased because of less need for faster gradient descent after successful steps. The LM algorithm not only has good attributes of steepest-descent algorithms and Gauss-Newton techniques but also avoids many of their limitations. In particular, it can deal with the slow convergence issue efficiently (Hagan and Menhaj, 1994).

There are many algorithms that could be used for model training. Here, we also take into consideration the scaled conjugate gradient (SCG) (Møller, 1993) and Bayesian regularization (BR) (MacKay, 1992; Foresee and Hagan, 1997) algorithms. The SCG and BR algorithms, as well as the LM algorithm, have been applied in many different varieties of areas (e.g. Doan and Liong, 2004; Kayri, 2016; Khan *et al.*, 2019; Selvamuthu *et al.*, 2019; Xu and Zhang, 2021a). Comparative studies of the three algorithms can be found from, e.g. Baghirli (2015) and Al Bataineh and Kaur (2018).

Backpropagation algorithms perform weight adjustments in the steepest descent as the performance function would decrease rapidly in the direction, which, however, does not always represent the fastest convergence. Conjugate gradient algorithms conduct searches along the conjugate direction, which in general, lead to faster convergence as compared to the steepest descent. Most algorithms adopt the learning rate to determine the length of the updated weight step size. For conjugate gradient algorithms, the step size is modified in iterations. Thus, the search is performed along the conjugate gradient direction to decide the step size to reduce the performance function. Besides, to avoid the line search in conjugate gradient algorithms that is time consuming, the SCG algorithm can be taken into consideration, which is fully automated and supervised and is faster as compared to the LM backpropagation.

The Bayesian regularized NN does not require a lengthy cross validation process. Bayesian regularization would convert a nonlinear regression to a statistical problem in the fashion of a ridge regression and the algorithm would consider the probabilistic nature of weights in a NN related to data. If more hidden layers of neurons are built in a NN, chances of overfitting would increase dramatically. For the BR algorithm, all models that are unreasonable complicated would be penalized through pushing extra linkage weights toward zeros and the NN would concentrate on training and calculating weights that are nontrivial. Certain parameters would converge to constants with the NN growing. The BR NNs tend to be more parsimonious as compared to basic backpropagation NNs and reduce chances of overfitting because of volatilities and noises in data.

Finally, in arriving at our final model aforementioned, we also consider different model settings over the delay, hidden neuron and data spitting ratio in addition to the algorithm. To be more specific, we explore delays of two, three, four, five and six, hidden neurons of two, three, five and eight, and data spitting ratios of 60% vs 20% vs 20%, 70% vs 15% vs 15%, and 80% vs 10% vs 10% for training, validation and testing. Table 1 lists all model settings investigated, where the setting #133 is used to build our final forecasting models.

Table 1. Explored model settings

Setting	Algorithm	Delay	Hidden neuron	Training ratio	Validation ratio	Testing ratio	Setting	Algorithm	Delay	Hidden neuron	Training ratio	Validation ratio	Testing ratio
#1	LM	2	2	70%	15%	15%	#91	LM	2	5	60%	20%	20%
#2	SCG	2	2	70%	15%	15%	#92	SCG	2	5	60%	20%	20%
#3	BR	2	2	70%	15%	15%	#93	BR	2	5	60%	20%	20%
#4	LM	3	2	70%	15%	15%	#94	LM	3	5	60%	20%	20%
#5	SCG	3	2	70%	15%	15%	#95	SCG	3	5	60%	20%	20%
#6	BR	3	2	70%	15%	15%	#96	BR	3	5	60%	20%	20%
#7	LM	4	2	70%	15%	15%	#97	LM	4	5	60%	20%	20%
#8	SCG	4	2	70%	15%	15%	#98	SCG	4	5	60%	20%	20%
#9	BR	4	2	70%	15%	15%	#99	BR	4	5	60%	20%	20%
#10	LM	5	2	70%	15%	15%	#100	LM	5	5	60%	20%	20%
#11	SCG	5	2	70%	15%	15%	#101	SCG	5	5	60%	20%	20%
#12	BR	5	2	70%	15%	15%	#102	BR	5	5	60%	20%	20%
#13	LM	6	2	70%	15%	15%	#103	LM	6	5	60%	20%	20%
#14	SCG	6	2	70%	15%	15%	#104	SCG	6	5	60%	20%	20%
#15	BR	6	2	70%	15%	15%	#105	BR	6	5	60%	20%	20%
#16	LM	2	3	70%	15%	15%	#106	LM	2	8	60%	20%	20%
#17	SCG	2	3	70%	15%	15%	#107	SCG	2	8	60%	20%	20%
#18	BR	2	3	70%	15%	15%	#108	BR	2	8	60%	20%	20%
#19	LM	3	3	70%	15%	15%	#109	LM	3	8	60%	20%	20%
#20	SCG	3	3	70%	15%	15%	#110	SCG	3	8	60%	20%	20%
#21	BR	3	3	70%	15%	15%	#111	BR	3	8	60%	20%	20%
#22	LM	4	3	70%	15%	15%	#112	LM	4	8	60%	20%	20%
#23	SCG	4	3	70%	15%	15%	#113	SCG	4	8	60%	20%	20%
#24	BR	4	3	70%	15%	15%	#114	BR	4	8	60%	20%	20%
#25	LM	5	3	70%	15%	15%	#115	LM	5	8	60%	20%	20%
#26	SCG	5	3	70%	15%	15%	#116	SCG	5	8	60%	20%	20%
#27	BR	5	3	70%	15%	15%	#117	BR	5	8	60%	20%	20%
#28	LM	6	3	70%	15%	15%	#118	LM	6	8	60%	20%	20%
#29	SCG	6	3	70%	15%	15%	#119	SCG	6	8	60%	20%	20%
#30	BR	6	3	70%	15%	15%	#120	BR	6	8	60%	20%	20%
#31	LM	2	5	70%	15%	15%	#121	LM	2	2	80%	10%	10%

(continued)

Setting	Algorithm	Delay	Hidden neuron	Training ratio	Validation ratio	Testing ratio	Setting	Algorithm	Delay	Hidden neuron	Training ratio	Validation ratio	Testing ratio
#32	SCG	2	5	70%	15%	15%	#122	SCG	2	2	80%	10%	10%
#33	BR	2	5	70%	15%	15%	#123	BR	2	2	80%	10%	10%
#34	LM	3	5	70%	15%	15%	#124	LM	3	2	80%	10%	10%
#35	SCG	3	5	70%	15%	15%	#125	SCG	3	2	80%	10%	10%
#36	BR	3	5	70%	15%	15%	#126	BR	3	2	80%	10%	10%
#37	LM	4	5	70%	15%	15%	#127	LM	4	2	80%	10%	10%
#38	SCG	4	5	70%	15%	15%	#128	SCG	4	2	80%	10%	10%
#39	BR	4	5	70%	15%	15%	#129	BR	4	2	80%	10%	10%
#40	LM	5	5	70%	15%	15%	#130	LM	5	2	80%	10%	10%
#41	SCG	5	5	70%	15%	15%	#131	SCG	5	2	80%	10%	10%
#42	BR	5	5	70%	15%	15%	#132	BR	5	2	80%	10%	10%
#43	LM	6	5	70%	15%	15%	#133	LM	6	2	80%	10%	10%
#44	SCG	6	5	70%	15%	15%	#134	SCG	6	2	80%	10%	10%
#45	BR	6	5	70%	15%	15%	#135	BR	6	2	80%	10%	10%
#46	LM	2	8	70%	15%	15%	#136	LM	2	3	80%	10%	10%
#47	SCG	2	8	70%	15%	15%	#137	SCG	2	3	80%	10%	10%
#48	BR	2	8	70%	15%	15%	#138	BR	2	3	80%	10%	10%
#49	LM	3	8	70%	15%	15%	#139	LM	3	3	80%	10%	10%
#50	SCG	3	8	70%	15%	15%	#140	SCG	3	3	80%	10%	10%
#51	BR	3	8	70%	15%	15%	#141	BR	3	3	80%	10%	10%
#52	LM	4	8	70%	15%	15%	#142	LM	4	3	80%	10%	10%
#53	SCG	4	8	70%	15%	15%	#143	SCG	4	3	80%	10%	10%
#54	BR	4	8	70%	15%	15%	#144	BR	4	3	80%	10%	10%
#55	LM	5	8	70%	15%	15%	#145	LM	5	3	80%	10%	10%
#56	SCG	5	8	70%	15%	15%	#146	SCG	5	3	80%	10%	10%
#57	BR	5	8	70%	15%	15%	#147	BR	5	3	80%	10%	10%
#58	LM	6	8	70%	15%	15%	#148	LM	6	3	80%	10%	10%
#59	SCG	6	8	70%	15%	15%	#149	SCG	6	3	80%	10%	10%
#60	BR	6	8	70%	15%	15%	#150	BR	6	3	80%	10%	10%
#61	LM	2	2	60%	20%	20%	#151	LM	2	5	80%	10%	10%

(*continued*)

Table 1.

Setting	Algorithm	Delay	Hidden neuron	Training ratio	Validation ratio	Testing ratio	Setting	Algorithm	Delay	Hidden neuron	Training ratio	Validation ratio	Testing ratio
#62	SCG	2	2	60%	20%	20%	#152	SCG	2	5	80%	10%	10%
#63	BR	2	2	60%	20%	20%	#153	BR	2	5	80%	10%	10%
#64	LM	3	2	60%	20%	20%	#154	LM	3	5	80%	10%	10%
#65	SCG	3	2	60%	20%	20%	#155	SCG	3	5	80%	10%	10%
#66	BR	3	2	60%	20%	20%	#156	BR	3	5	80%	10%	10%
#67	LM	4	2	60%	20%	20%	#157	LM	4	5	80%	10%	10%
#68	SCG	4	2	60%	20%	20%	#158	SCG	4	5	80%	10%	10%
#69	BR	4	2	60%	20%	20%	#159	BR	4	5	80%	10%	10%
#70	LM	5	2	60%	20%	20%	#160	LM	5	5	80%	10%	10%
#71	SCG	5	2	60%	20%	20%	#161	SCG	5	5	80%	10%	10%
#72	BR	5	2	60%	20%	20%	#162	BR	5	5	80%	10%	10%
#73	LM	6	2	60%	20%	20%	#163	LM	6	5	80%	10%	10%
#74	SCG	6	2	60%	20%	20%	#164	SCG	6	5	80%	10%	10%
#75	BR	6	2	60%	20%	20%	#165	BR	6	5	80%	10%	10%
#76	LM	2	3	60%	20%	20%	#166	LM	2	8	80%	10%	10%
#77	SCG	2	3	60%	20%	20%	#167	SCG	2	8	80%	10%	10%
#78	BR	2	3	60%	20%	20%	#168	BR	2	8	80%	10%	10%
#79	LM	3	3	60%	20%	20%	#169	LM	3	8	80%	10%	10%
#80	SCG	3	3	60%	20%	20%	#170	SCG	3	8	80%	10%	10%
#81	BR	3	3	60%	20%	20%	#171	BR	3	8	80%	10%	10%
#82	LM	4	3	60%	20%	20%	#172	LM	4	8	80%	10%	10%
#83	SCG	4	3	60%	20%	20%	#173	SCG	4	8	80%	10%	10%
#84	BR	4	3	60%	20%	20%	#174	BR	4	8	80%	10%	10%
#85	LM	5	3	60%	20%	20%	#175	LM	5	8	80%	10%	10%
#86	SCG	5	3	60%	20%	20%	#176	SCG	5	8	80%	10%	10%
#87	BR	5	3	60%	20%	20%	#177	BR	5	8	80%	10%	10%
#88	LM	6	3	60%	20%	20%	#178	LM	6	8	80%	10%	10%
#89	SCG	6	3	60%	20%	20%	#179	SCG	6	8	80%	10%	10%
#90	BR	6	3	60%	20%	20%	#180	BR	6	8	80%	10%	10%

Table 1.

5. Result

We run each model setting in Table 1 across rent indices of the 10 cities and calculate distribution statistics, i.e. the minimum, mean, median, maximum and standard deviation, of the relative root mean square error (RRMSE) for training, validation and testing based on each setting over the ten series. The results are shown in Figure 2. Balancing model performance and its stability, we arrive at the setting #133 as the final specification.

Having the setting #133 as our final choice, we analyze sensitivities of performance to different settings by changing one setting each time. The results are shown in Figure 3, where distribution statistics, i.e. the minimum, mean, median, maximum and standard deviation, of the RRMSE for training, validation and testing based on each setting over the 10 series are displayed. The comparison between the setting #133 and settings #134 and #135 tests the sensitivity to the algorithm, between the setting #133 and settings #121, #124, #127 and #130 the sensitivity to the delay, between the setting #133 and settings #148, #163 and #178 the sensitivity to the hidden neuron and between the setting #133 and settings #13 and #73 the sensitivity to the data splitting ratio. These results support the setting #133 as the final choice as it optimally balances performance and stability.

We show model performance (the RRMSE) across rent indices of the 10 cities based on the setting #133 in Figure 4. In addition, we present detailed visualization of forecasting results for each of the ten series for the training, validation and testing phases based on the setting #133 in Figure 5. Each subfigure in Figure 5 also contains a linear fit line and an auxiliary line for perfect forecasting. In general, coefficients of linear fit lines in Figure 5 are close to one and the linear fit lines are close to auxiliary lines for perfect forecasting, except for Beijing and Tianjing. For Beijing, the RRMSEs are 1.38 and 1.77% for the training and testing phases. For Tianjing, the RRMSEs are 1.69, 1.65 and 1.17% for the training, validation and testing phases. Therefore, the models still generate decent forecasts for these two cities. Overall, the final models lead to stable performance of 1.41% average RRMSE across the 10 cities for the training, validation and testing phases, suggesting usefulness of the neural network for

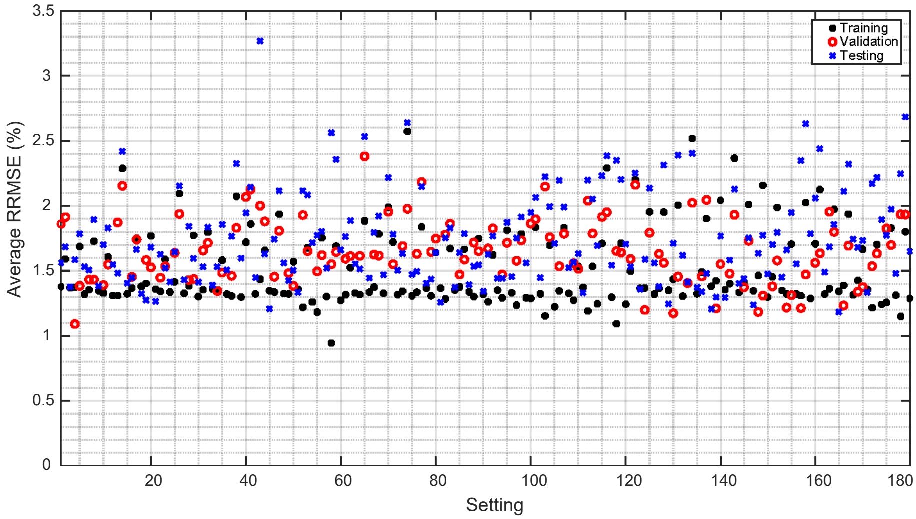

Figure 2.
Distribution statistics of the RRMSE across all model settings

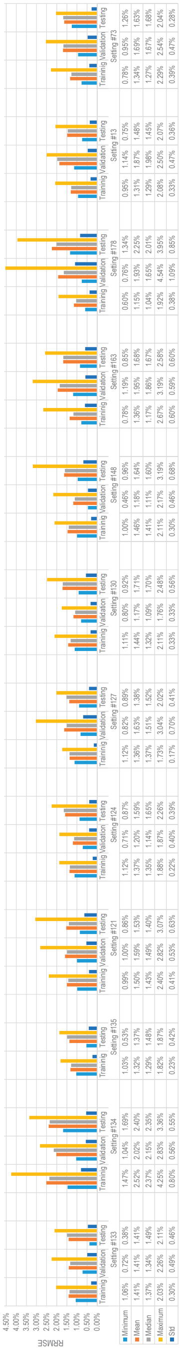

Figure 3.
Sensitivities of model performance (the RRMSE) to different settings

forecasting rent indices of different cities that are associated with different market conditions and regulatory environment.

6. Conclusion

House price related forecasting is a key concern for the people and policy makers. In this study, we focus on this issue in a data set of monthly rent indices from 10 major cities in China for the period of March 2012–May 2020 during which the housing market is rapidly growing. In particular, we examine the univariate neural network model with great potential for forecasting noised and chaotic economic and financial data. By exploring different model settings over the algorithm, delay, hidden neuron and data spitting ratio, we reach a rather simple neural network with six delays and two hidden neurons that leads to stable performance of 1.4% average relative root mean square error across the 10 cities. The models can serve as a standalone tool or be combined with fundamental forecasting methods (Xu, 2018a, c) in forming perspectives of rental price fluctuations and trends and conducting policy analysis. Our empirical framework also is easy to implement, which is important to many decision makers (Brandt and Bessler, 1983), and has potential to be generalized for house price related forecasting of other cities in China or other countries or regions.

Future research of interest might be investigating the potential of combining time series models that incorporate fundamental economic factors and pure technical machine learning approaches for rental price forecasting. It should also be a worthwhile avenue for future research to explore economic significance of forecasting using the neural network (e.g. Yang *et al.*, 2008; Wang and Yang, 2010; Yang *et al.*, 2010). Wegener *et al.* (2016) point out that cointegration degrees and system linearities (Xu, 2018d) could be important to forecasting accuracy under the neural network framework. As including error correction terms could help deal with the information loss issue caused by data differencing in a cointegrated system (Xu, 2015b, 2019b), hybrid forecasting approaches that combine cointegration analysis and neural networks (e.g. Wegener *et al.*, 2016) can be of interest to pursue as well for future studies, maybe for long-term forecasting in particular. This would also need the extension of current univariate modeling here to multivariate through appropriate ways to select relevant price information (Xu, 2014c; Xu and Thurman, 2015b) from other cities for forecasting of a city's rental price.

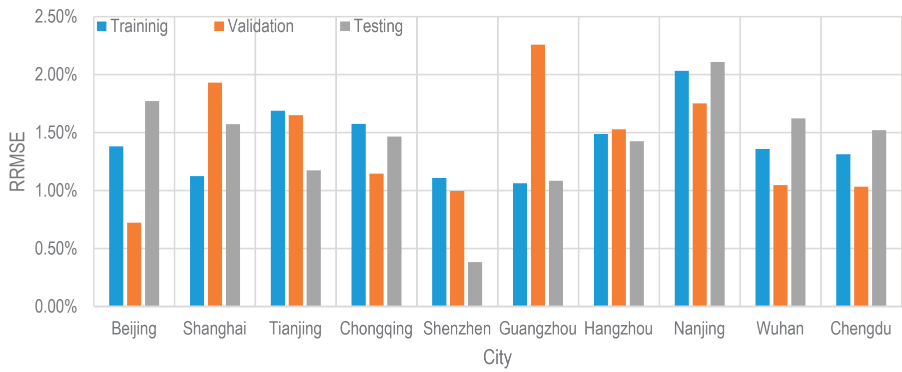

Figure 4.
Model performance (the RRMSE) across rent indices of the 10 cities based on the setting #133

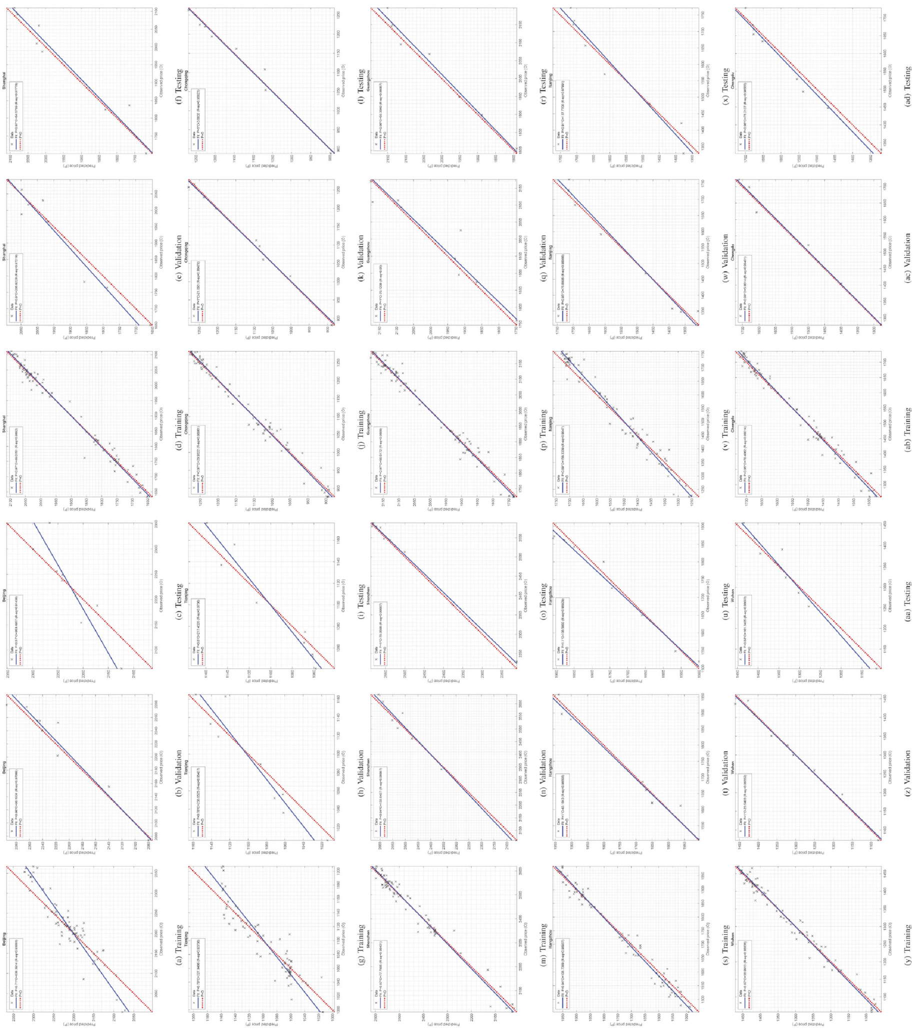

Figure 5.
Visualization of
forecasting across rent
indices of the 10 cities
based on the
setting #133

References

Abidoye, R.B. and Chan, A.P. (2017), "Modelling property values in Nigeria using artificial neural network", *Journal of Property Research*, Vol. 34, pp. 36-53, doi: 10.1080/09599916.2017.1286366.

Abidoye, R.B. and Chan, A.P. (2018), "Improving property valuation accuracy: a comparison of hedonic pricing model and artificial neural network", *Pacific Rim Property Research Journal*, Vol. 24, pp. 71-83, doi: 10.1080/14445921.2018.1436306.

Al Bataineh, A. and Kaur, D. (2018), "A comparative study of different curve fitting algorithms in artificial neural network using housing dataset", *NAECON 2018-IEEE National Aerospace and Electronics Conference*, IEEE, pp. 174-178, doi: 10.1109/NAECON.2018.8556738.

Azadeh, A., Sheikhalishahi, M. and Boostani, A. (2014), "A flexible neuro-fuzzy approach for improvement of seasonal housing price estimation in uncertain and non-linear environments", *South African Journal of Economics*, Vol. 82, pp. 567-582, doi: 10.1111/saje.12047.

Baghirli, O. (2015), *Comparison of Lavenberg-Marquardt, Scaled Conjugate Gradient and Bayesian Regularization Backpropagation Algorithms for Multistep Ahead Wind Speed Forecasting Using Multilayer Perceptron Feedforward Neural Network*, Uppsala University.

Brandt, J.A. and Bessler, D.A. (1983), "Price forecasting and evaluation: an application in agriculture", *Journal of Forecasting*, Vol. 2, pp. 237-248, doi: 10.1002/for.3980020306.

Cabrera, J., Wang, T. and Yang, J. (2011), "Linear and nonlinear predictablity of international securitized real estate returns: a reality check", *Journal of Real Estate Research*, Vol. 33, pp. 565-594, doi: 10.1080/10835547.2011.12091317.

Chen, J.H., Ong, C.F., Zheng, L. and Hsu, S.C. (2017), "Forecasting spatial dynamics of the housing market using support vector machine", *International Journal of Strategic Property Management*, Vol. 21, pp. 273-283, doi: 10.3846/1648715X.2016.1259190.

Chiarazzo, V., Caggiani, L., Marinelli, M. and Ottomanelli, M. (2014), "A neural network based model for real estate price estimation considering environmental quality of property location", *Transportation Research Procedia*, Vol. 3, pp. 810-817, doi: 10.1016/j.trpro.2014.10.067.

Clark, S.D. and Lomax, N. (2018), "A mass-market appraisal of the English housing rental market using a diverse range of modelling techniques", *Journal of Big Data*, Vol. 5, pp. 1-21, doi: 10.1186/s40537-018-0154-3.

Doan, C.D. and Liong, S.y. (2004), "Generalization for multilayer neural network bayesian regularization or early stopping", *Proceedings of Asia Pacific Association of Hydrology and Water Resources 2nd Conference*, pp. 5-8.

Embaye, W.T., Zereyesus, Y.A. and Chen, B. (2021), "Predicting the rental value of houses in household surveys in Tanzania, Uganda and Malawi: evaluations of hedonic pricing and machine learning approaches", *Plos One*, Vol. 16, e0244953, doi: 10.1371/journal.pone.0244953.

Foresee, F.D. and Hagan, M.T. (1997), "Gauss-Newton approximation to bayesian learning", *Proceedings of International Conference on Neural Networks (ICNN'97)*, IEEE, pp. 1930-1935, doi: 10.1109/ICNN.1997.614194.

Gu, J., Zhu, M. and Jiang, L. (2011), "Housing price forecasting based on genetic algorithm and support vector machine", *Expert Systems with Applications*, Vol. 38, pp. 3383-3386, doi: 10.1016/j.eswa.2010.08.123.

Hagan, M.T. and Menhaj, M.B. (1994), "Training feedforward networks with the marquardt algorithm", *IEEE Transactions on Neural Networks*, Vol. 5, pp. 989-993, doi: 10.1109/72.329697.

Ho, W.K., Tang, B.S. and Wong, S.W. (2021), "Predicting property prices with machine learning algorithms", *Journal of Property Research*, Vol. 38, pp. 48-70, doi: 10.1080/09599916.2020.1832558.

Hu, L., He, S., Han, Z., Xiao, H., Su, S., Weng, M. and Cai, Z. (2019), "Monitoring housing rental prices based on social media: an integrated approach of machine-learning algorithms and hedonic modeling to inform equitable housing policies", *Land Use Policy*, Vol. 82, pp. 657-673, doi: 10.1016/j.landusepol.2018.12.030.

Hyvärinen, A., Zhang, K., Shimizu, S. and Hoyer, P.O. (2010), "Estimation of a structural vector autoregression model using non-gaussianity", *Journal of Machine Learning Research*, Vol. 11, pp. 1709-1731.

Igbinosa, S.O. (2011), "Determinants of residential property value in Nigeria–a neural network approach", *African Research Review*, Vol. 5, pp. 152-168, doi: 10.4314/afrrev.v5i5.13.

Kang, J., Lee, H.J., Jeong, S.H., Lee, H.S. and Oh, K.J. (2020), "Developing a forecasting model for real estate auction prices using artificial intelligence", *Sustainability*, Vol. 12, p. 2899, doi: 10.3390/su12072899.

Kawahara, Y., Shimizu, S. and Washio, T. (2011), "Analyzing relationships among arma processes based on non-gaussianity of external influences", *Neurocomputing*, Vol. 74, pp. 2212-2221, doi: 10.1016/j.neucom.2011.02.008.

Kayri, M. (2016), "Predictive abilities of bayesian regularization and levenberg–marquardt algorithms in artificial neural networks: a comparative empirical study on social data", *Mathematical and Computational Applications*, Vol. 21, p. 20, doi: 10.3390/mca21020020.

Khan, T.A., Alam, M., Shahid, Z. and Mazliham, M. (2019), "Comparative performance analysis of levenberg-marquardt, bayesian regularization and scaled conjugate gradient for the prediction of flash floods", *Journal of Information Communication Technologies and Robotic Applications*, Vol. 20, pp. 52-58.

Kim, J., Leatham, D.J. and Bessler, D. (2007), "Reits' dynamics under structural change with unknown break points", *Journal of Housing Economics*, Vol. 16, pp. 37-58, doi: 10.1016/j.jhe.2007.04.001.

Kitapci, O., Tosun, Ö., Tuna, M.F. and Turk, T. (2017), "The use of artificial neural networks (ann) in forecasting housing prices in ankara, Turkey", *Journal of Marketing and Consumer Behaviour in Emerging Markets*, Vol. 5, pp. 4-14.

Lam, K.C., Yu, C. and Lam, K. (2008), "An artificial neural network and entropy model for residential property price forecasting in Hong Kong", *Journal of Property Research*, Vol. 25, pp. 321-342, doi: 10.1080/09599910902837051.

Levenberg, K. (1944), "A method for the solution of certain non-linear problems in least squares", *Quarterly of Applied Mathematics*, Vol. 2, pp. 164-168, doi: 10.1090/qam/10666.

Li, H. and Li, V. (1996), "Forecasting house rental levels: analytical rent model versus neural network", *Journal of Urban Planning and Development*, Vol. 122, pp. 1184-2127, doi: 10.1061/(ASCE)0733-9488(1996)122:4(118).

Li, J. (2018), "Monthly housing rent forecast based on lightgbm (light gradient boosting) model", *International Journal of Intelligent Information and Management Science*, Vol. 7, pp. 58-65.

Li, R.Y.M., Fong, S. and Chong, K.W.S. (2017), "Forecasting the reits and stock indices: group method of data handling neural network approach", *Pacific Rim Property Research Journal*, Vol. 23, pp. 123-160, doi: 10.1080/14445921.2016.1225149.

Li, Y., Xiang, Z. and Xiong, T. (2020), "The behavioral mechanism and forecasting of Beijing housing prices from a multiscale perspective", *Discrete Dynamics in Nature and Society*, Vol. 2020, pp. 1-13, doi: 10.1155/2020/5375206.

Liu, R. and Liu, L. (2019), "Predicting housing price in China based on long short-term memory incorporating modified genetic algorithm", *Soft Computing*, Vol. 23, pp. 11829-11838, doi: 10.1007/s00500-018-03739-w.

Ma, T. and Liu, N. (2019), "Research of prediction on house rent based on intergration learning", *Finance*, Vol. 9, pp. 586-594, doi: 10.12677/fin.2019.96065.

Ma, Y., Zhang, Z., Ihler, A. and Pan, B. (2018), "Estimating warehouse rental price using machine learning techniques", *International Journal of Computers Communications and Control*, Vol. 13, pp. 235-250, doi: 10.15837/ijccc.2018.2.3034.

MacKay, D.J. (1992), "Bayesian interpolation", *Neural Computation*, Vol. 4, pp. 415-447, doi: 10.1162/neco.1992.4.3.415.

Marquardt, D.W. (1963), "An algorithm for least-squares estimation of nonlinear parameters", *Journal of the Society for Industrial and Applied Mathematics*, Vol. 11, pp. 431-441, doi: 10.1137/0111030.

Ming, Y., Zhang, J., Qi, J., Liao, T., Wang, M. and Zhang, L. (2020), "Prediction and analysis of chengdu housing rent based on xgboost algorithm", *Proceedings of the 2020 3rd International Conference on Big Data Technologies*, pp. 1-5, doi: 10.1145/3422713.3422720.

Møller, M.F. (1993), "A scaled conjugate gradient algorithm for fast supervised learning", *Neural Networks*, Vol. 6, pp. 525-533, doi: 10.1016/S0893-6080(05)80056-5.

Morano, P. and Tajani, F. (2013), "Bare ownership evaluation. Hedonic price model vs artificial neural network", *International Journal of Business Intelligence and Data Mining*, Vol. 8, pp. 340-362, doi: 10.1504/IJBIDM.2013.059263.

Morano, P., Tajani, F. and Torre, C.M. (2015), "Artificial intelligence in property valuations: an application of artificial neural networks to housing appraisal", *Advances in Environmental Science and Energy, Planning*, pp. 23-29.

Nghiep, N. and Al, C. (2001), "Predicting housing value: a comparison of multiple regression analysis and artificial neural networks", *Journal of Real Estate Research*, Vol. 22, pp. 313-336, doi: 10.1080/10835547.2001.12091068.

Odubiyi, T., Oguntona, O., Oshodi, O., Aigbavboa, C. and Thwala, W. (2019), "Impact of security on rental price of residential properties: evidence from South Africa", *IOP Conference Series: Materials Science and Engineering*, IOP Publishing, 012001, doi: 10.1088/1757-899X/640/1/012001.

Oshodi, O., Oyedeji, O. and Aigbovboa, C. (2020), "Does proximity to tourist site affect the rental value of residential properties? empirical evidence from Nigeria", *MATEC Web of Conferences*, EDP Sciences, p. 04003, doi: 10.1051/matecconf/202031204003.

Oshodi, O., Ohiomah, I., Odubiyi, T., Aigbavboa, C. and Thwala, W. (2021), "Forecasting rental values of residential properties: a neural network model approach", *Collaboration and Integration in Construction, Engineering, Management and Technology*, Springer, pp. 309-313, doi: 10.1007/978-3-030-48465-1_52.

Oyedeji Joseph, O., Oshodi Olalekan, S. and Oloke Olayinka, C. (2018), "Property rental value classification model: a case of osogbo, osun state, Nigeria", *Covenant Journal of Research in the Built Environment*, Vol. 6, pp. 52-64.

Oyedeji, O. and Oyewale, J. (2018), "Classification modelling for the impact of historical site on residential property rental value in osogbo, Nigeria", *International Journal of Property Sciences*, E-ISSN: 2229-8568, Vol. 8, pp. 13-26.

Paluszek, M. and Thomas, S. (2020), *Practical MATLAB Deep Learning: A Project-Based Approach*, Apress, New York.

Park, B. and Bae, J.K. (2015), "Using machine learning algorithms for housing price prediction: the case of fairfax county, Virginia housing data", *Expert Systems with Applications*, Vol. 42, pp. 2928-2934, doi: 10.1016/j.eswa.2014.11.040.

Peterson, S. and Flanagan, A. (2009), "Neural network hedonic pricing models in mass real estate appraisal", *Journal of Real Estate Research*, Vol. 31, pp. 147-164, doi: 10.1080/10835547.2009.12091245.

Plakandaras, V., Gupta, R., Gogas, P. and Papadimitriou, T. (2015), "Forecasting the us real house price index", *Economic Modelling*, Vol. 45, pp. 259-267, doi: 10.1016/j.econmod.2014.10.050.

Rafatirad, S. (2017), "A technical report on real-estate rent prediction", Technical Report, George Mason University.

Rico-Juan, J.R. and de La Paz, P.T. (2021), "Machine learning with explainability or spatial hedonics tools? an analysis of the asking prices in the housing market in alicante, Spain", *Expert Systems with Applications*, Vol. 171, 114590, doi: 10.1016/j.eswa.2021.114590.

Selim, H. (2009), "Determinants of house prices in Turkey: hedonic regression versus artificial neural network", *Expert Systems with Applications*, Vol. 36, pp. 2843-2852, doi: 10.1016/j.eswa.2008.01.044.

Selvamuthu, D., Kumar, V. and Mishra, A. (2019), "Indian stock market prediction using artificial neural networks on tick data", *Financial Innovation*, Vol. 5, p. 16, doi: 10.1186/s40854-019-0131-7.

Shimizu, S., Hoyer, P.O., Hyvärinen, A., Kerminen, A. and Jordan, M. (2006), "A linear non-Gaussian acyclic model for causal discovery", *Journal of Machine Learning Research*, Vol. 7, pp. 2003-2030.

Terregrossa, S.J. and Ibadi, M.H. (2021), "Combining housing price forecasts generated separately by hedonic and artificial neural network models", *Asian Journal of Economics, Business and Accounting*, Vol. 21, pp. 130-148, doi: 10.9734/ajeba/2021/v21i130345.

Tsai, W.P. and Pan, N.H. (2014), "The application of the artificial neural network in student dormitory rent–with taiwan sugar corporation hsianghe dormitory as an example", *Journal of Statistics and Management Systems*, Vol. 17, pp. 23-46, doi: 10.1080/09720510.2013.857915.

Wang, Z. and Cao, B. (2019), "Prediction of office building rental upon spatiotemporal data", *Proceedings of the 2019 2nd International Conference on Data Science and Information Technology*, pp. 168-174, doi: 10.1145/3352411.3352438.

Wang, T. and Yang, J. (2010), "Nonlinearity and intraday efficiency tests on energy futures markets", *Energy Economics*, Vol. 32, pp. 496-503, doi: 10.1016/j.eneco.2009.08.001.

Webb, R.I., Yang, J. and Zhang, J. (2016), "Price jump risk in the us housing market", *The Journal of Real Estate Finance and Economics*, Vol. 53, pp. 29-49, doi: 10.1007/s11146-015-9518-z.

Wegener, C., von Spreckelsen, C., Basse, T. and von Mettenheim, H.J. (2016), "Forecasting government bond yields with neural networks considering cointegration", *Journal of Forecasting*, Vol. 35, pp. 86-92, doi: 10.1002/for.2385.

Xin, J.G. and Runeson, G. (2004), "Modeling property prices using neural network model for Hong Kong", *International Real Estate Review*, Vol. 7, pp. 121-138.

Xu, X. (2014a), "Causality and price discovery in US corn markets: an application of error correction modeling and directed acyclic graphs", *Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting*. Minneapolis, MN, doi: 10.22004/ag.econ.169806.

Xu, X. (2014b), "Cointegration and price discovery in us corn markets", *Agricultural and Resource Economics Seminar Series*, North Carolina State University, Raleigh, NC, doi: 10.13140/RG.2.2.30153.49768.

Xu, X. (2014c), "Price discovery in us corn cash and futures markets: the role of cash market selection", *Selected Paper Prepared for Presentation at the Agricultural and Applied Economics Association's 2014 AAEA Annual Meeting*, Minneapolis, MN. doi: 10.22004/ag.econ.169809.

Xu, X. (2015a), *Causality, Price Discovery, and Price Forecasts: Evidence from Us Corn Cash and Futures Markets*, North Carolina State University.

Xu, X. (2015b), "Cointegration among regional corn cash prices", *Economics Bulletin*, Vol. 35, pp. 2581-2594.

Xu, X. (2017a), "Contemporaneous causal orderings of us corn cash prices through directed acyclic graphs", *Empirical Economics*, Vol. 52, pp. 731-758, doi: 10.1007/s00181-016-1094-4.

Xu, X. (2017b), "The rolling causal structure between the Chinese stock index and futures", *Financial Markets and Portfolio Management*, Vol. 31, pp. 491-509, doi: 10.1007/s11408-017-0299-7.

Xu, X. (2017c), "Short-run price forecast performance of individual and composite models for 496 corn cash markets", *Journal of Applied Statistics*, Vol. 44, pp. 2593-2620, doi: 10.1080/02664763.2016.1259399.

Xu, X. (2018a), "Causal structure among us corn futures and regional cash prices in the time and frequency domain", *Journal of Applied Statistics*, Vol. 45, pp. 2455-2480, doi: 10.1080/02664763.2017.1423044.

Xu, X. (2018b), "Cointegration and price discovery in us corn cash and futures markets", *Empirical Economics*, Vol. 55, pp. 1889-1923, doi: 10.1007/s00181-017-1322-6.

Xu, X. (2018c), "Intraday price information flows between the csi300 and futures market: an application of wavelet analysis", *Empirical Economics*, Vol. 54, pp. 1267-1295, doi: 10.1007/s00181-017-1245-2.

Xu, X. (2018d), "Linear and nonlinear causality between corn cash and futures prices", *Journal of Agricultural and Food Industrial Organization*, Vol. 16, 20160006, doi: 10.1515/jafio-2016-0006.

Xu, X. (2018e), "Using local information to improve short-run corn price forecasts", *Journal of Agricultural and Food Industrial Organization*, Vol. 16, doi: 10.1515/jafio-2017-0018.

Xu, X. (2019a), "Contemporaneous and granger causality among us corn cash and futures prices", *European Review of Agricultural Economics*, Vol. 46, pp. 663-695, doi: 10.1093/erae/jby036.

Xu, X. (2019b), "Contemporaneous causal orderings of csi300 and futures prices through directed acyclic graphs", *Economics Bulletin*, Vol. 39, pp. 2052-2077.

Xu, X. (2019c), "Price dynamics in corn cash and futures markets: cointegration, causality, and forecasting through a rolling window approach", *Financial Markets and Portfolio Management*, Vol. 33, pp. 155-181, doi: 10.1007/s11408-019-00330-7.

Xu, X. (2020), "Corn cash price forecasting", *American Journal of Agricultural Economics*, Vol. 102, pp. 1297-1320, doi: 10.1002/ajae.12041.

Xu, L. and Li, Z. (2021), "A new appraisal model of second-hand housing prices in China's first-tier cities based on machine learning algorithms", *Computational Economics*, Vol. 57, pp. 617-637, doi: 10.1007/s10614-020-09973-5.

Xu, X. and Thurman, W. (2015a), "Forecasting local grain prices: an evaluation of composite models in 500 corn cash markets", *Selected Poster prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Joint Annual Meeting*, San Francisco, CA. doi: 10.22004/ag.econ.205332.

Xu, X. and Thurman, W.N. (2015b), "Using local information to improve short-run corn cash price forecasts", *Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management,*, St. Louis, MO, doi: 10.22004/ag.econ.285845.

Xu, X. and Zhang, Y. (2021a), "Corn cash price forecasting with neural networks", *Computers and Electronics in Agriculture*, Vol. 184, 106120, doi: 10.1016/j.compag.2021.106120.

Xu, X. and Zhang, Y. (2021b), *High-frequency Csi300 Futures Trading Volume Predicting through the Neural Network*.

Xu, X. and Zhang, Y. (2021c), "House price forecasting with neural networks", *Intelligent Systems with Applications*, Vol. 12, 200052, doi: 10.1016/j.iswa.2021.200052.

Xu, X. and Zhang, Y. (2021d), "Individual time series and composite forecasting of the Chinese stock index", *Machine Learning with Applications*, Vol. 5, 100035, doi: 10.1016/j.mlwa.2021.100035.

Xu, X. and Zhang, Y. (2021e), "Network analysis of corn cash price comovements", *Machine Learning with Applications*, Vol. 6, 100140, doi: 10.1016/j.mlwa.2021.100140.

Xu, X. and Zhang, Y. (2021f), "Network analysis of housing price comovements of a hundred Chinese cities", *National Institute Economic Review*, doi: 10.1017/nie.2021.34.

Xu, X. and Zhang, Y. (2021g), "Second-hand house price index forecasting with neural networks", *Journal of Property Research*, doi: 10.1080/09599916.2021.1996446.

Yang, J., Su, X. and Kolari, J.W. (2008), "Do euro exchange rates follow a martingale? Some out-of-sample evidence", *Journal of Banking and Finance*, Vol. 32, pp. 729-740, doi: 10.1016/j.jbankfin.2007.05.009.

Yang, J., Cabrera, J. and Wang, T. (2010), "Nonlinearity, data-snooping, and stock index etf return predictability", *European Journal of Operational Research*, Vol. 200, pp. 498-507, doi: 10.1016/j.ejor.2009.01.009.

Yang, J., Yu, Z. and Deng, Y. (2018), "Housing price spillovers in China: a high-dimensional generalized var approach", *Regional Science and Urban Economics*, Vol. 68, pp. 98-114, doi: 10.1016/j.regsciurbeco.2017.10.016.

Yasnitsky, L.N., Yasnitsky, V.L. and Alekseev, A.O. (2021), "The complex neural network model for mass appraisal and scenario forecasting of the urban real estate market value that adapts itself to space and time", *Complexity*, Vol. 2021, pp. 1-17, doi: 10.1155/2021/5392170.

Zhang, K., Shen, L. and Liu, N. (2019), “House rent prediction based on joint model”, *Proceedings of the 2019 8th International Conference on Computing and Pattern Recognition*, pp. 507-511, doi: 10.1145/3373509.3373578.

Zohrabyan, T., Leatham, D.J. and Bessler, D.A. (2008), “Cointegration analysis of regional house prices in US”, *Proceedings of Regional Research Committee NC-1014*, St. Louis, Missouri, doi: 10.22004/ag.econ.48138.

Corresponding author
Xiaojie Xu can be contacted at: xxu6@ncsu.edu