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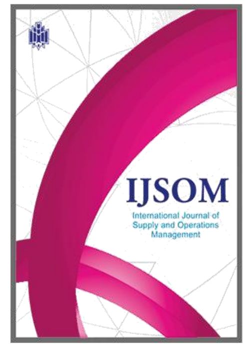

Hybrid Levenberg Marquardt and Back Propagation Neural Network for House Price Prediction in Taiwan

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Abstract

Price prediction is an influential tool in each market to enhance economic performance. In this regard, regression methods are often used. However, with the expansion of artificial intelligence, neural networks, machine learning, and deep learning, these methods can also be used for prediction. On the other hand, pricing in the housing market is always challenging, and forecasting the house price has been one of the concerns of economic activists in this field. Accordingly, in this research, a hybrid Levenberg Marquardt (LM) and Back Propagation (BP) neural network has been developed to forecast housing prices in Taiwan. This artificial intelligence method can provide a suitable forecast for housing price trends in the future by using the information in the form of Input and Output. This method uses inputs such as inflation rate, bank interest rate, minimum wage, and gross domestic product (GDP). Moreover, the housing price index is considered as the output of the model. In order to implement the proposed method, data from Taiwan from 1998 to 2022 was used. In this regard, a percentage of this data is used as training data, and the rest is used as test data in the artificial neural network. The results show that the RMSE of the proposed method is less than classic LM and BP methods. Finally, the proposed neural network will achieve the final housing price in Taiwan from 2023 through 2027. The results show that housing prices will trend upward in this country in the next five years.

Keywords: Prediction; Housing Price; Neural Network; Levenberg Marquardt; Backpropagation.

1. Introduction

In the macroeconomic dimension, housing is particularly important as house price fluctuations can significantly affect countries' economies. The researchers found that the total value of the residential assets is more than the commercial capital, and usually, the value of the investment made in the housing sector is more than the commercial sector (Ye et al., 2018). Moreover, the effect of housing wealth on consumption is significant, and a decrease in housing prices will lead to a decrease in consumption. Moreover, changes in the housing market play a significant role in business cycles Because investment in housing is a part of demand and impacts investment (Ye et al., 2018).

In Taiwan, housing and its market are among the topics that have been the subject of many urban issues, especially urban economics. Although housing is considered a commodity in economic studies, the reality is that housing is very diverse and has different types of markets. In other words, the housing market is not a single market but has sub-markets, each of which is separated from the other according to the variety of occupancy, unit type, residential unit life, quality, financing method, and size (Kuşan et al., 2010).

On the other hand, predicting economic influencing factors is one of the main issues for each business. Therefore, the problem of forecasting in the determination of monetary policies and investment analysis has more forms. Investing in the housing and land sector has always been the focus of capital market actors. In addition to investors, households

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consider their homes not only a place to live but also an asset in their portfolio (Ahmad et al., 2016; Azadeh et al., 2008).
In this regard, artificial neural networks (ANN) are introduced as an efficient tool in forecasting (Amber et al., 2015). ANN methods are based on a machine learning algorithm. The machine learning algorithm refers to computer programs that can improve their performance according to previous experiences (Ye & Kim, 2018). In other words, according to a large number of examples with the correct solution in machine learning methods, a program is produced that has generalizability and adaptively. Generalizability means that in the case of correct learning, the generated program will have the correct answer for new examples, and adaptability means that if the data changes, the program will have the ability to change (Kline, 2010).
ANNs are divided into different types from the aspects of structural topology and learning methods, and each of them shows appropriate performance in specific applications. An artificial neural network consists of a large number of nodes and directed line segments that connect the nodes. The nodes that are in the input layer are formed as sensory nodes, and the nodes in the output layer are called responding nodes. There are hidden neurons between the input and output neurons (Zhou et al., 2022).
One of the most important features of artificial neural networks is that they make their function closer to humans. The ANNs learning process is a challenging issue of updating the architecture of the network and its communication weights in such a way as to increase its efficiency (Amber et al., 2015; Ye & Kim, 2018). The act of changing and adjusting the weights between the nerves of a network to achieve a specific structure or desired output is called neural network learning. The conversion function is the mechanism for converting input signals into output signals. The driving function can be linear or non-linear. Two well-known and general types of transformation functions, Hyperbolic Sigmoid and Tangent, are used to predict time series models in neural networks (Ahmad et al., 2016; Zhou et al., 2022).
As neural networks are strongly dependent on the quality of input data (Ahmad et al., 2016; Zhou et al., 2022), new searches using recent computer technologies should be added to enhance prediction quality and reduce errors. In this way, some approaches have been developed in real estate by analyzing several criteria to determine house price prediction.
In this research endeavor, our aim is to construct a sophisticated framework employing artificial neural networks to forecast house prices by leveraging carefully chosen features as inputs and outputs. The application of artificial neural networks offers a promising avenue for enhancing the accuracy and granularity of predictive models in the realm of real estate valuation. By meticulously selecting pertinent features and structuring them within the neural network architecture, we endeavor to capture the intricate interdependencies and non-linear relationships inherent in housing market data. This endeavor is motivated by the imperative to address the inherent challenges and complexities associated with predicting property prices, which are influenced by a myriad of factors including economic indicators, geographical attributes, housing characteristics, and market dynamics. Through the fusion of advanced machine learning techniques with domain-specific knowledge, our framework aspires to transcend conventional methodologies, providing stakeholders with actionable insights to inform strategic decision-making processes in the realm of real estate investment, development, and management.
The rest of the paper is organized as follows. In Section 2, the background of research in housing pricing and artificial neural networks is discussed. In Section 3, the research methodology will be explained in detail, and in Section 4 and Section 5, the results and suggestions for future research will be presented, respectively.

2. Research background

The literature review is divided into two subsections for clarity. The first subsection covers general research topics pertaining to house price forecasting, while the second subsection delves into specific research areas concerning the application of artificial intelligence in house price prediction.

2.1. Housing price forecast

Alonso (1694) performed the first study on influential factors of house prices. Next, Muth (1969) investigated housing prices in Chicago. Moreover, Wabe (1971) investigated the effects of residence and city characteristics on pricing. Kain and Quigley (1970) presented the most critical factor for house prices in the United States of America. Next, Lancaster (1966) presented housing quality as an important variable for house prices. Bown and Rossen (1982)

presented the housing price regression as a prediction tool for real estate management. In a study by Stevenson (2004), the house price in Boston houses was predicted using historical data and a weighted regression method.
Recently, novel methods have been used to predict house prices. Hagenauer and Helbich (2022) presented the geographically weighted artificial neural network, which is a useful tool to enhance prediction quality. Ye and Kim (2018) have conducted a study that defined the spatial pattern of housing price changes and their determinants using an optimized neural network. Brzinsky- Brzinsky-Fay et al. (2006) have used the decision tree method to evaluate the relationship between house price and house characteristics.
In recent years, artificial neural networks and fuzzy logic approaches have been used as alternative tools for modeling conventional value systems, Gao et al. (2022) proposed a multi-task neural network to predict house prices based on the house location. In this research, a comparison between neural network and regression methods was provided, and the efficiency of the neural network was observed.
Selim (2009) has compared hedonic regression (dual mental) and artificial neural network models to determine housing prices. 2004 Turkish household budget survey data is used as a document for the dataset. At the end of the study, due to the nonlinearity of the hedonic regression, it is explained that the artificial neural network can be a better alternative modeling method for determining housing prices in Turkey.
In another study, Mir et al. (2021) presented a fuzzy neural network to forecast based on the hedonic price. The experimental results of the study have shown that the fuzzy neural network forecasting model has a remarkable ability to approximate performance and is available for predicting real estate prices according to the quality of available data.
Lokshina (2003) has compared multiple regression, artificial neural networks and fuzzy logic. In evaluating real estate prices, the use of artificial neural networks and fuzzy logic has been proven, and it has been determined that the results are consistent with the use of artificial intelligence methods. In addition, it has been concluded that the performance of the multiple regression program for house prices is tolerable.

2.2. Forecasting using artificial neural networks

In price forecasting, the main issue is creating a mathematical forecasting model. Due to the significant growth of science and technology, various methods have been presented for price forecasting, forecasting methods such as statistical research methods, gray system methods, expert methods, fuzzy forecasting methods based on mathematics, combined methods and the wavelet analysis method, especially the neural network technique that is used for price prediction today (Mostafaeipour et al., 2018; Jafarian-Namin et al., 2019; Alhilali & Montazerolghaem, 2023; Lee et al., 2023; Khare et al., 2021; Lin et al., 2021; Goli et al., 2021; Goli et al., 2018; Goli et al., 2019).
A backpropagation (BP) neural network is usually based on a multi-layer pre-propagation neural network with a backpropagation error algorithm. A typical BP neural network has three layers. All input samples from the training set are fed into the network with initial random weights and thresholds (Lin et al., 2021). Thakkar and Chaudhari (2021) mentioned that this method was proposed for the first time in 1975. Currently, the BP algorithm is the most widely used neural network learning algorithm, and nearly 90% of neural network programs are based on the backpropagation algorithm.
Accordingly, BP neural networks can be suitable for predicting the price, which is non-linear, and different characteristics of the building show different behaviors. Therefore, a multi-layered BP neural network can be used to simulate prices at a macro level. BP neural networks have many advantages, but they have some inherent defects, such as low convergence speed and fluctuation during the training process, which can cause them to fall into the local minimum trap and make it difficult to recognize the structure of the network (ArunKumar et al., 2021).
The Levenberg Marquardt (LM) is a neural network that uses a combination of the gradient descent method and the Gaussian-Newton method to ensure fast local convergence speed and maintain better overall performance in a non-linear training algorithm. The main idea of this algorithm is that if the gradient value is reduced to a specified value, there is no need to continue repeating the algorithm. In addition, the network can optimize the weights for effective convergence by using a compatible combination of the slope descent method and Gaussian-Newton method and provide better speed and globality (escape from local optimality) of the network (Xu et al., 2015).
Recently, a novel approach to dynamic pricing was introduced by Özöğür Akyüz et al. (2023), wherein they developed a methodology for estimating house prices based on key property characteristics. This innovative technique combines elements of linear regression, clustering analysis, nearest neighbor classification, and Support Vector Regression. Meanwhile, Sharma et al. (2024) tackled the challenge of house price prediction through a regression framework, employing various machine learning methodologies to assess the significance of independent variables. Their study

utilized housing data from Ames City, Iowa, USA, and compared the efficacy of XGBoost, support vector machine, and multiple linear regression algorithms in predicting house prices.

There exists a critical need to address the limitations of the current methodology, particularly concerning susceptibility to local minima and training fluctuations, which hinder accurate housing price predictions. This underscores the necessity for an enhanced approach, one that can effectively navigate away from local minima and incorporate global optimization strategies.

In light of this research gap, the adoption of an improved BP neural network method emerges as imperative. To this end, the LM-BP algorithm is selected for neural network training due to its reputation as the swiftest algorithm proposed for training medium-sized neural networks. However, despite its speed advantages, there remains a notable gap in the literature regarding its efficacy in addressing the aforementioned shortcomings and achieving superior predictive accuracy in housing price estimation. Therefore, this study aims to bridge this gap by thoroughly investigating the performance of the LM-BP algorithm and its ability to mitigate the identified methodological deficiencies.

3. Research methodology

A BP neural network consists of an input, hidden, and output layer. Each layer contains several parallel computing neurons. These neurons are like the biological neurons of the human brain, and although they are functionally simple because they interact in high numbers, they create a network system with high performance. Neurons in different layers are completely connected, so neurons in the same layer are not connected (Ahmad et al., 2016; Zhou et al., 2022).

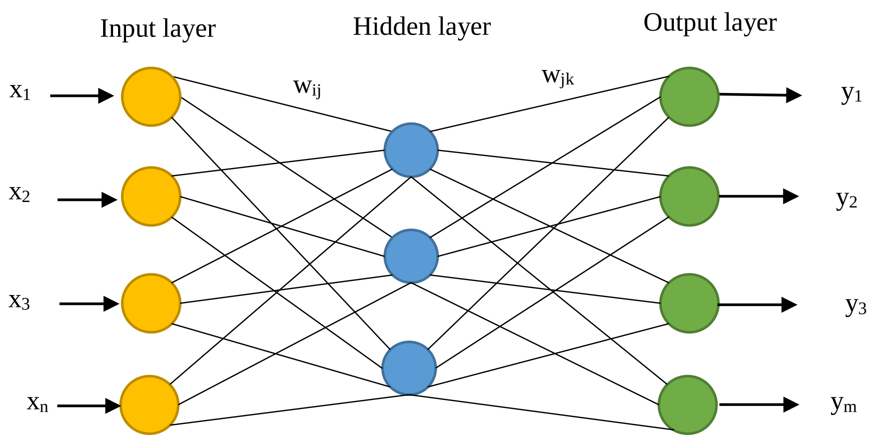

Figure 1. Structure of the proposed neural network

In Figure 1, if $x1, x2, \ldots, xn$ are the inputs of the BP neural network and factors affecting the price, $Y1, Y2, \ldots, Yn$ will be the output of the model as the final price. In addition, $F1, F2, \ldots, Fn$ is the real price (recorded by experts); W_{ij} are the weights of each node in the hidden layer and W_{jk} are the weights of each node in the output layer (Ahmad et al., 2016; Zhou et al., 2022). The number of input nodes in the neural network is n, the number of hidden layer nodes is l, and the number of output nodes is m. Finally, the threshold value for each node is demonstrated with d.

A: Forward-propagation in the BP neural network

The output of the hidden layer is shown in Eq. (1).

$$O_j = f(\sum_{i=1}^{n} W_{ij} X_i - d_i), j = 1,2, \ldots l \tag{1}$$

The output of the output layer is shown in Eq. (2).

$$Y_k = f(\sum_{j=1}^{l} O_j W_{jk} - d_k), K = 1,2, \ldots m \tag{2}$$

According to the definition of mean square error in BP neural networks, the error caused by the actual output value and the obtained output value is calculated from Eq. (3).

$$E_k = \frac{1}{2}\sum_k (f_k - Y_k)^2 \tag{3}$$

B: Error in BP neural network

By replacing Eqs. (1) and (2) in Eq. (3), the error function will be achieved, which is shown in Eq. (4).

$$E_k = \frac{1}{2}\sum_k (f_{k-}f((\sum_{j=1}^{l} W_{ij}X_i - d_i) - d_k))^2 \tag{4}$$

The output point will be in Eqs. (5)-(6) by deriving the error function concerning the weights and the threshold value.

$$\frac{\partial E_k}{\partial W_{jk}} = -(F_k - Y_k)f'(\sum_{j=1}^{l} O_j W_{jk} - d_k)O_j' \tag{5}$$

$$\frac{\partial Ek}{\partial dk} = (F_k - Y_k)f'(\sum_{j=1}^{l} O_j W_{jk} - d_k) \tag{6}$$

Moreover, the error of the output node is obtained from Eq. (7).

$$\delta_k = (F_k - Y_k)f'(\sum_{j=1}^{l} O_j W_{jk} - d_k) \tag{7}$$

By inserting Eq. (7) in Eqs. (5) and (6), the following equations are achieved.

$$\frac{\partial Ek}{\partial Wjk} = -\delta_k O_j' \tag{8}$$

$$\frac{\partial Ek}{\partial dk} = -\delta_k \tag{9}$$

In the node of the output layer, according to the traditional BP neural network training algorithm, the formula for setting the weight and the threshold value is shown in Eqs. (11)-(12).

$$W_{jk}(e+1) = W_{jk}(e) + \Delta W_{jk} = W_{jk}(e) + \eta\delta_k O_j' \tag{10}$$

$$dk(e+1) = dk(e) + \eta\delta_k \tag{11}$$

Similarly, the weight and the threshold value in the hidden layer node are as Eqs. (12)-(13).

$$W_{ij}(e+1) = W_{ij}(e) + \Delta W_{ij} = W_{ij}(e) + \eta\delta_j x_i \tag{12}$$

$$\theta k(e+1) = \theta k(e) + \eta\delta_j \tag{13}$$

In Eqs. (10)- 13), the percentage of data that are selected for training in BP is equal to η. In order to improve the weight of nodes in the neural network, the LM algorithm is applied by using Eq. (14).

$$x(k+1) = x(k) - [J^T J + \mu I]^{-1} J^T e \tag{14}$$

where, J is the Jacobian matrix and the coefficient, μ is a constant value greater than zero. I is the identity matrix, and e is the error (Xu et al., 2015; Jia et al., 2015). Finally, by combining BP and LM in the process of prediction of the neural network, the proposed neural network is achieved, which is shown in Figure 2.

3.2. Model simulation

To validate the model and algorithm, the data obtained from Taiwan has been used from 1998 to 2022. Using the Levenberg-Marquard backpropagation algorithm in artificial neural networks, a price forecasting model for Taiwan has been presented. The relevant data is shown in Table 1.

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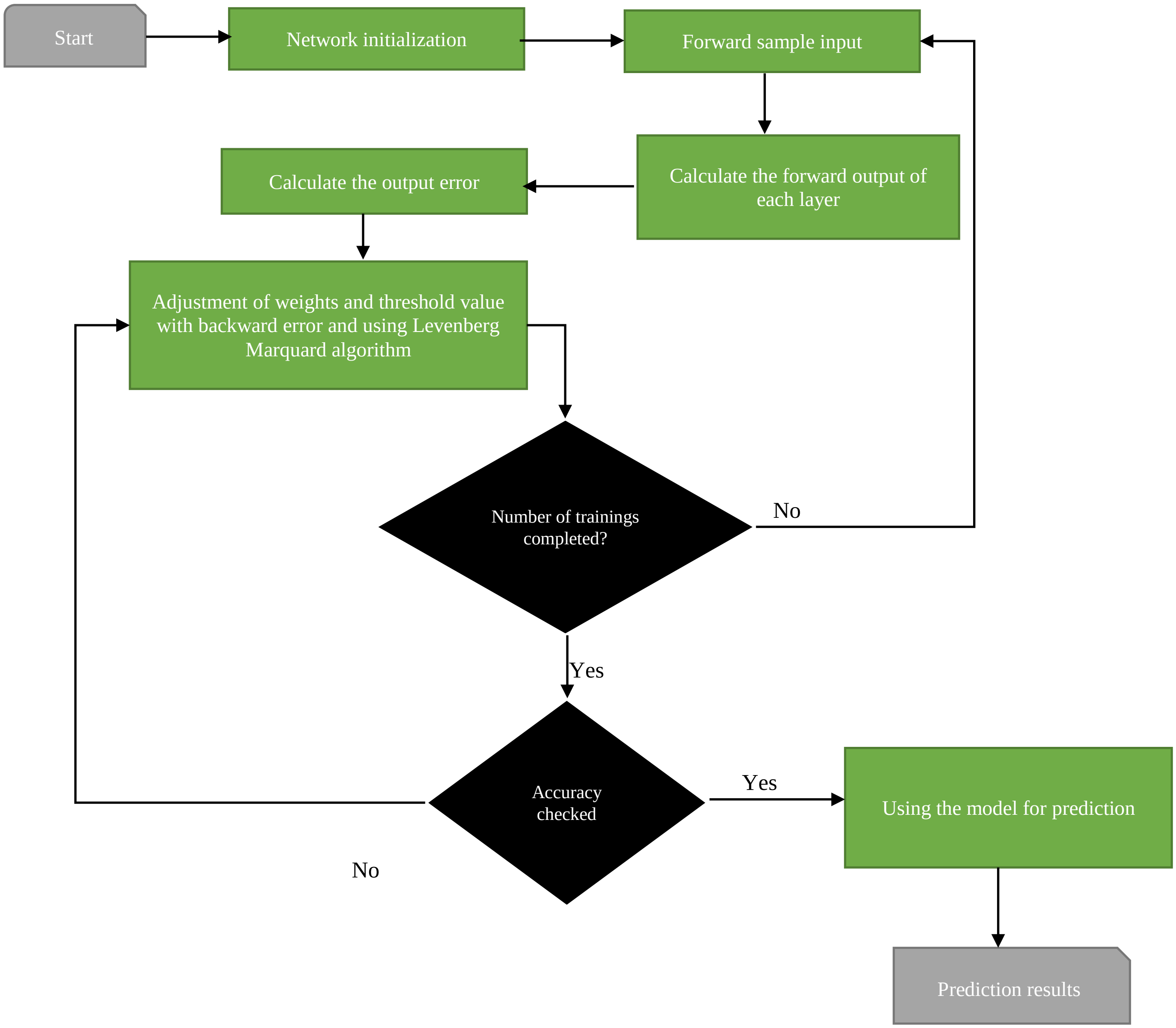

Figure 2. The flowchart of the proposed LM-BP neural network

Table 1. Input data of neural network obtained from the Central Bank of the Republic of China (Taiwan)

Year	Population	Value of National currency in USD over time	Gold price (NTD)	Inflation Rate (%)	Bank interest rate (%)	Liquidity	GNP - NTD	GDP -NTD	Price index of construction
1998	21928591	33.4447	293.97	1.68	-	1635617	19332090	9366337	65.66
1999	22092387	32.2661	278.46	0.18	-	1444021	20074574	9804503	65.28
2000	22276672	31.2252	279.01	1.26	-	1381843	21745407	10328549	64.97
2001	22405568	33.8003	271.08	-0.01	2.5	1373363	20698572	10119429	64.31
2002	22520776	34.575	309.88	-0.2	1.875	1452575	21954637	10630911	65.67
2003	22604550	34.418	359.8	-0.28	1.4	1273526	23286278	10924029	68.73
2004	22689122	33.422	409.72	1.61	1.525	1264937	26267032	11596241	78.44
2005	22770383	32.167	444.74	2.31	1.99	1442018	27543546	12036675	78.99
2006	22876527	32.531	603.46	0.6	2.2	1414340	29750175	12572587	84.72
2007	22958360	32.842	695.39	1.8	2.635	1173040	32132831	13363917	92.34
2008	23037031	31.517	871.57	3.52	1.42	1196407	32576101	13115096	105.26
2009	23119772	33.049	972.35	-0.87	0.9	1198561	29669541	12919445	95.93
2010	23162123	31.642	1224.53	0.97	1.135	1213899	35350998	14060345	98.99
2011	23224912	29.464	1571.52	1.42	1.355	1128449	36954978	14262201	102.29
2012	23315822	29.614	1668.57	1.93	1.355	1118006	37055931	14677765	103.14
2013	23373517	29.77	1411.23	0.79	1.355	1079702	37605629	15270728	102.79
2014	23433753	30.368	1266.4	1.2	1.355	1073783	39417787	16258047	104.67
2015	23492074	31.898	1160.06	-0.3	1.205	1004108	38074608	17055080	101.71
2016	23539816	32.318	1,250.80	1.39	1.035	964536	37789843	17555268	100
2017	23571227	30.439	1,257.12	0.62	1.035	948049	39209655	17983347	102.4
2018	23588932	30.156	1,268.49	1.35	1.035	984815	40632005	18375022	105.84
2019	23603121	30.925	1,392.60	0.56	1.035	972043	40418403	18908632	108.19
2020	23561236	29.578	1769.64	-0.23	0.755	946251	40690915	19798597	109.73
2021	23375314	28.022	1,798.61	1.96	0.755	920703	-	21710598	121.72
2022	23198133	31.242	1,816.24	2.75	1.325	801784	-	23015636	-

3.2.1. Selecting the activation function

Depending on the purpose of the network application, the BP neural network has different activation functions. The sigmoid function will be a good choice if the network is used for classification and recognition. If the grid is used to approximate a simple function, a linear function is used. However, according to this research, which is intended to predict housing price consumption and is closer to a complex non-linear function, the sigmoid activation function (Xu et al., 2015) has been used.

3.2.2. Selecting input and output nodes

According to the structure of input data, from 8 factors including Population, Value of National currency in USD, Gold price (NTD), Inflation Rate, Bank interest rate, Liquidity, GNP - NTD, GDP - NTD, the Price index of construction, the input title and the final price of housing are considered as output in the proposed neural network, which can be seen in Figure 3.

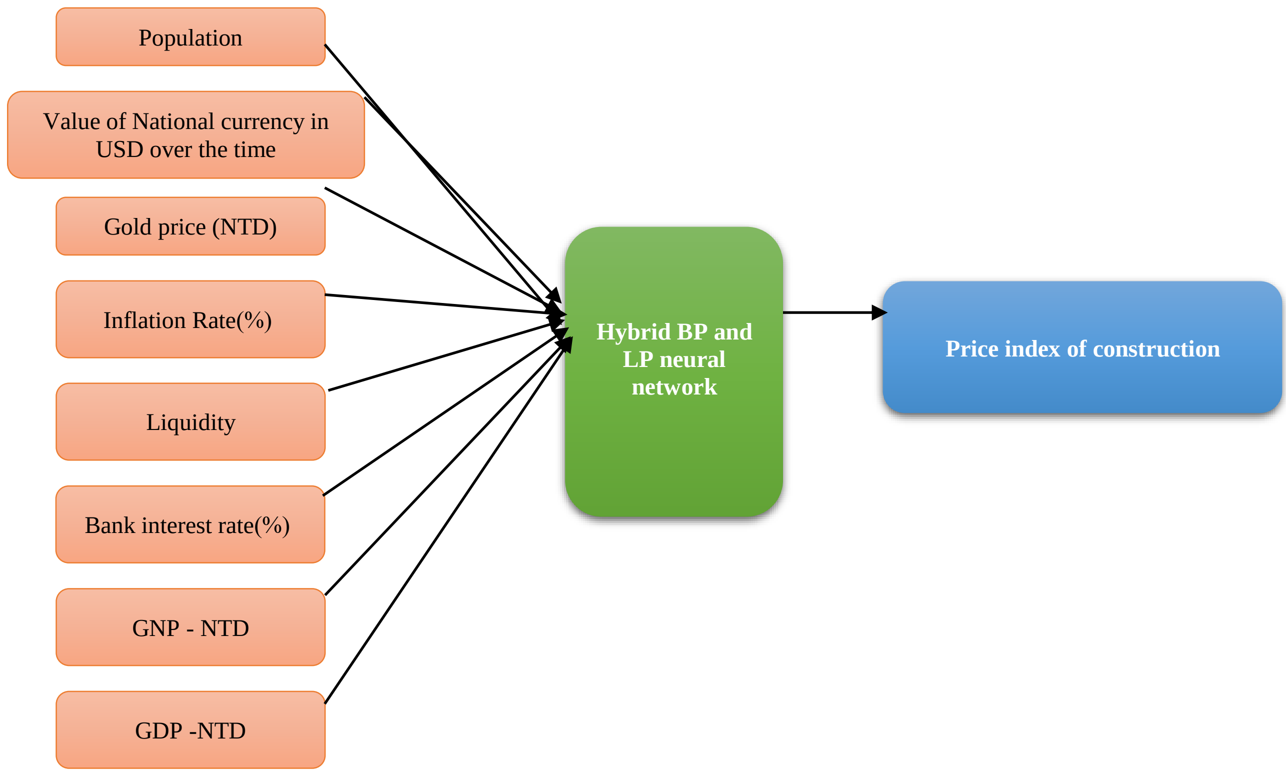

Figure 3. Housing price prediction model in Taiwan

3.2.3. Specifying the number of hidden layers and nodes

According to the core concept of neural networks (Ahmad et al., 2016; Zhou et al., 2022; Xu et al., 2015; You & Cao, 2015), the BP neural network can be suitable with one hidden layer for any non-linear function, but due to the complexity of this problem, three hidden layers have been used. In general, the formula for determining the hidden layer nodes is as Eq. (15).

$$P < \sqrt{n + m} + a \tag{15}$$

where, n is the number of input nodes, m is the number of output nodes and a natural number smaller than 10. Therefore, the number of hidden layer nodes (P) is obtained. If P is too small, the accuracy of the research will be very low, and it will not be able to reflect the main laws well; subsequently, it will also have a significant error. On the other hand, if P is too large, it increases the complexity of the problem and, subsequently, the training time of the network (You & Cao, 2015). According to the presented rules, the number of hidden layer nodes is 21 in this model.

3.2.4. Determining the learning rate (η)

There is a direct formulation to determine the learning rate (You & Xu, 2014). Past studies show that the learning rate is usually between 0.01 and 0.7 (Ahmad et al., 2016), according to Eqs. (10) - (13), convergence speed slows down if η is too small. On the other hand, if η is too large, it may not converge or even diverge (You & Xu, 2014). After several trials and errors, considering this problem's complexity, $\eta = 0.7$ is used.

3.2.5. Determining the Target error and number of training repetitions

In this research, the target error is zero, and the neural network tries to reduce the error to zero. The number of training repetitions was also considered 1000 repetitions, and these values were obtained from the trial and error method. Next, 70% of data are used for training, 10% for validation, and 20% for testing. In order to calculate the performance of the neural network, the root means square error (RMSE), which is calculated based on Eq. (16), is used (Amber et al., 2015; Ye & Kim, 2018; Zhou et al., 2022).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(xactual, i - xpredicted)^2}{n}} \tag{16}$$

4. Numerical results

In this study, using the LM-BP neural network, data related to housing prices in 1998 to 2022 were used, and the house price index was predicted for 2023 to 2027. In this regard, the number of layers and hidden layer neurons was determined by paying attention to the input and output layers in the proposed neural network. In Figure 4 and Figure 5, the trend of the most critical input variables of the proposed method is analyzed.

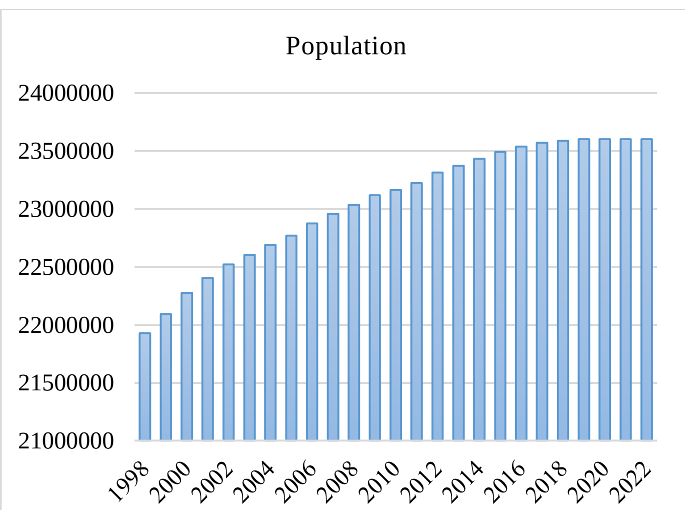

Figure 4.a. The trend of the population in Taiwan

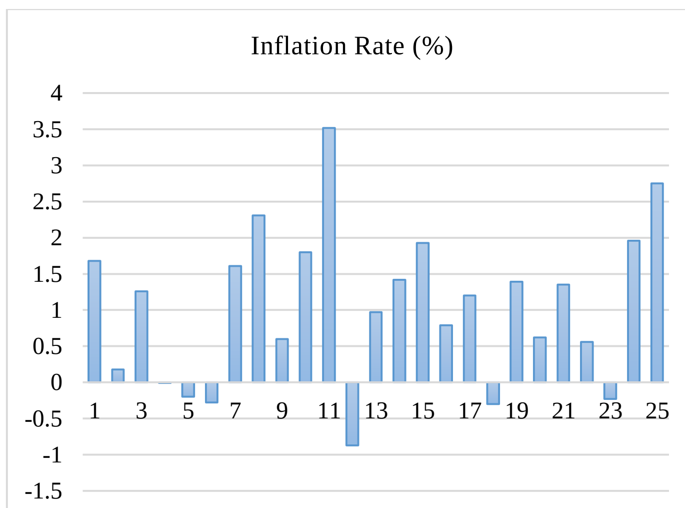

Figure 4.b. The trend of the inflation rate in Taiwan

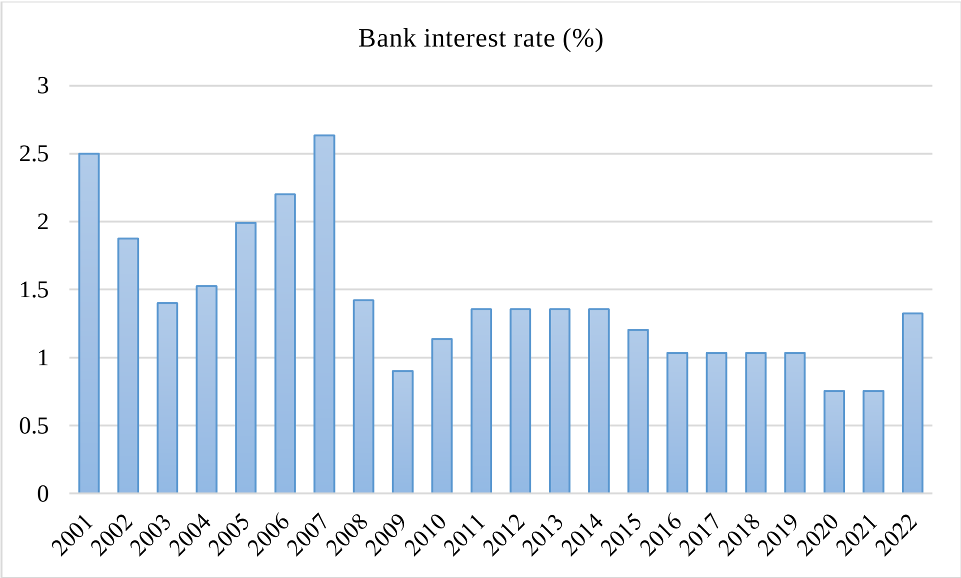

Figure 4.c. The trend of the bank interest rate in Taiwan

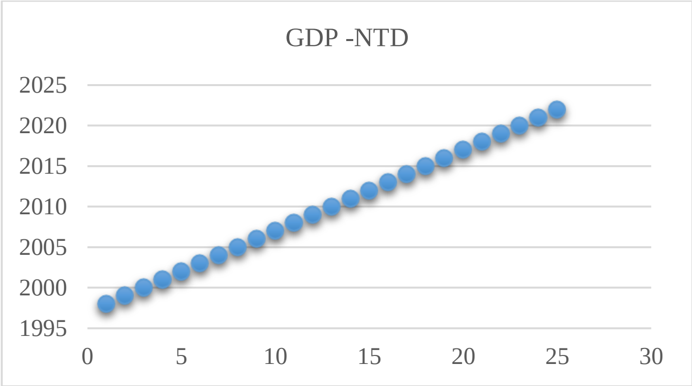

Figure 5.a. The trend of GDP in Taiwan

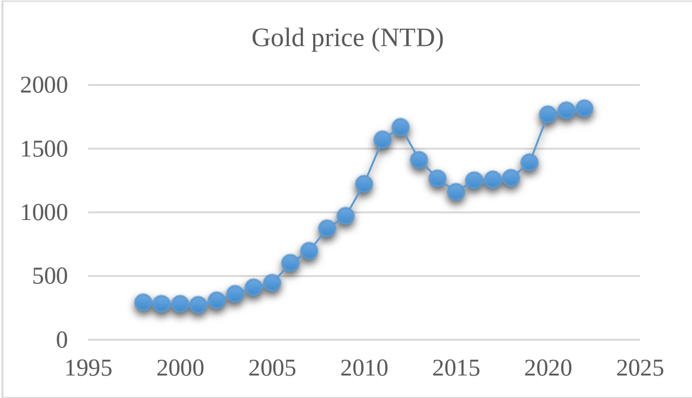

Figure 5.b. The trend of gold price

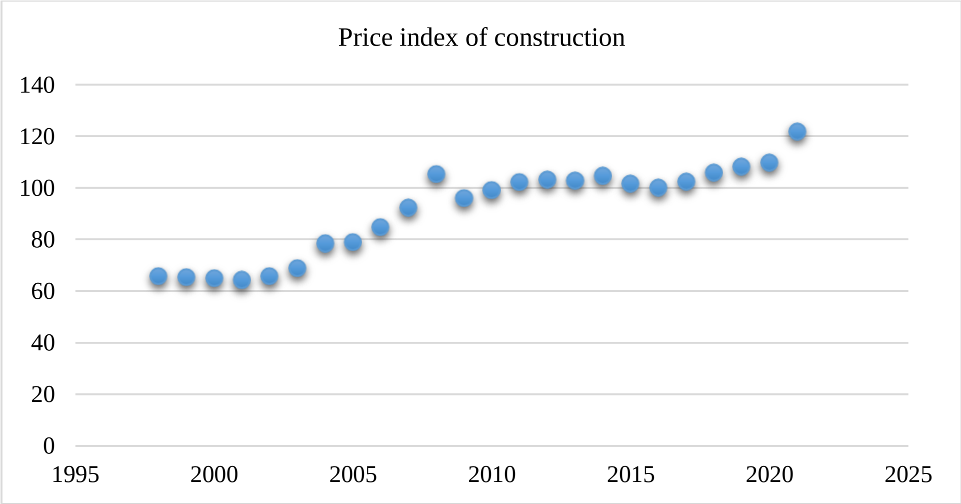

Figure 5.c. The trend of the price index of construction in Taiwan

The trends in Figure 4 show that the population of Taiwan has been increasing from 1998 to 2022. This increase in population shows that the demand for housing in Taiwan has an upward trend. Also, according to Figure 4.b, the inflation rate is above 1% in most years, which is a driver in increasing housing demand. On the other hand, the financial indicators presented in Figure 5 show that the price index of construction in Taiwan has constantly been increasing. In other words, the cost of construction of each house in Taiwan has been increasing, which is consistent with the Taiwanese inflation chart. Accordingly, it can be concluded that based on the available information, it is expected that the number of applicants to purchase housing in this country will increase, and as a result, housing prices in this country will increase.
The output of fitting and prediction is obtained after importing the input and output variables into the proposed neural network. The graphical illustration of the error function, which has emerged as a normal distribution function, can be seen in Figure 7.

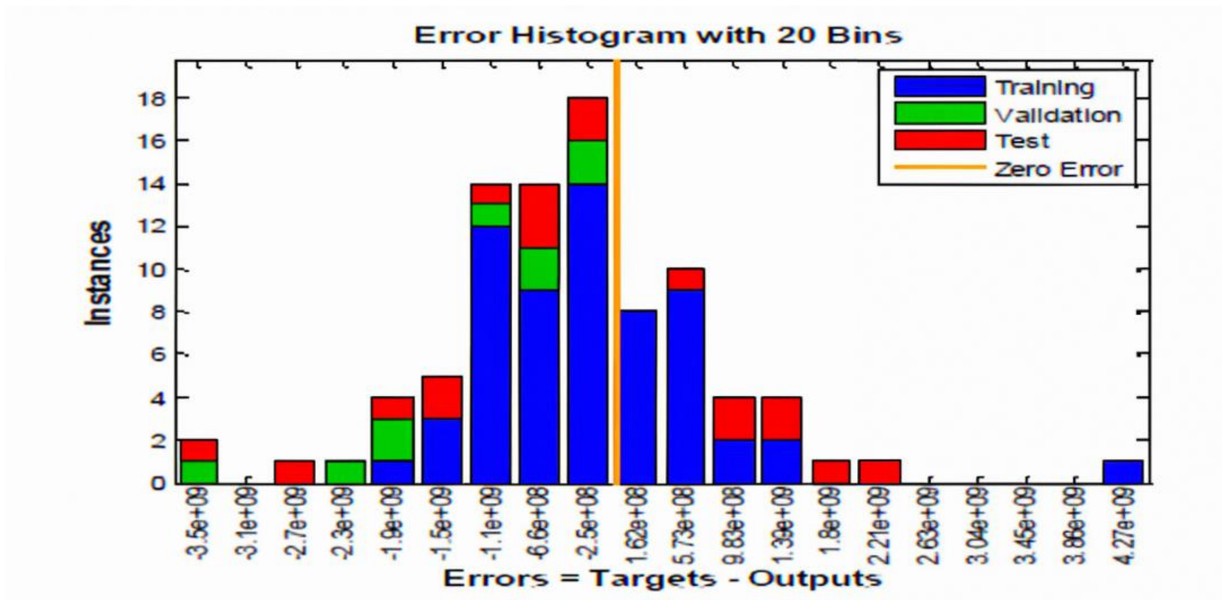

Figure 6. LMBP neural network error histogram

Moreover, the data of training (70%), validation (10%), and test (20%) reached the desired error rate with 12 repetitions, and the validation was stopped with 6 exits times (Validation Check = 6). The regression of training, validation, and test data is shown in Figure 7.

As seen in Figure 7, the LM-BP neural network has provided R2=100% in the training data, R2=99% in the test data, and R^2=99% in the total data, indicating its efficiency and minimum error in fitting data and prediction. In order to provide a better evaluation of this neural network, its RMSE index was compared with that of MLP and BP neural networks. In this regard, the effect of the percentage of total data for training (%Train) on the quality of the different ANNs has been analyzed. The relevant results are presented in Table 2 and Figure 8.

Table 2. RMSE for the different types of ANN and train percentage

	%Train	70%	80%	90%	95%
	MLP	0.324	0.303	0.293	0.290
Method	BP	0.373	0.319	0.307	0.295
	LM-BP	0.316	0.293	0.274	0.260

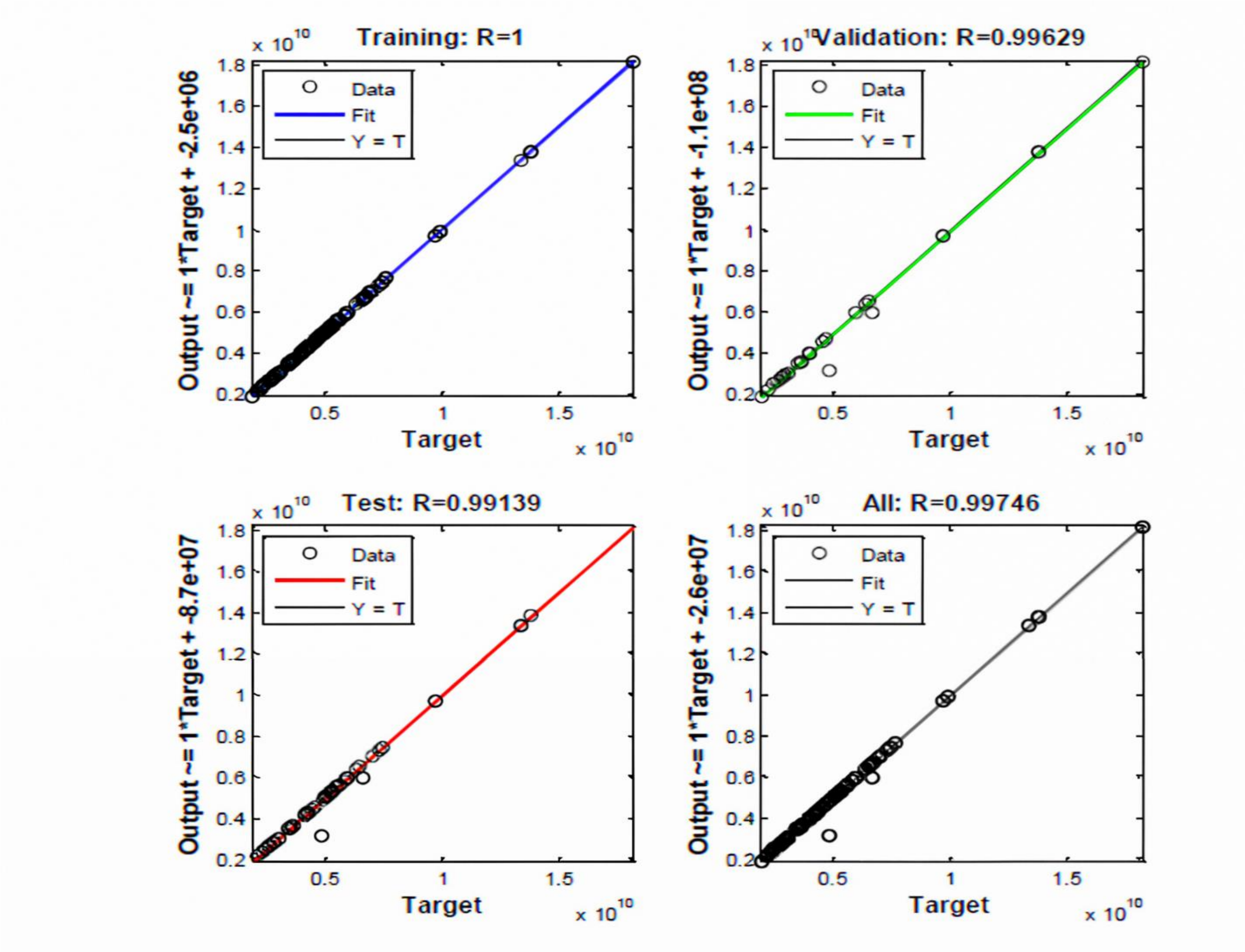

Figure 7. Regression of training, validation, and test data

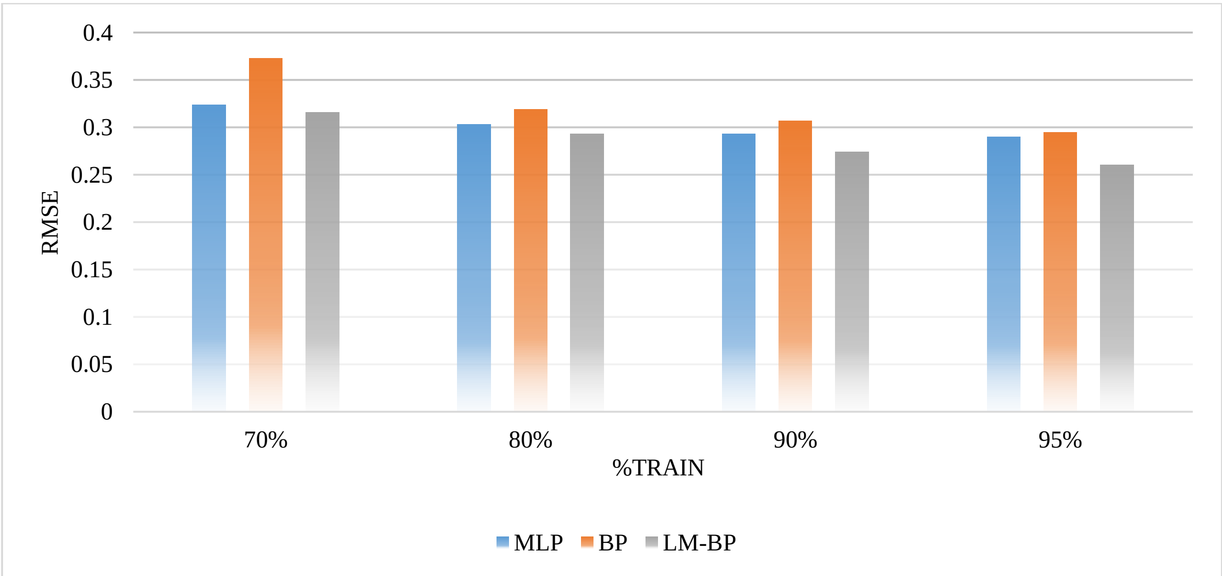

Figure 8. Comparison of different ANNs

As shown in Figure 8, the increase in %Train in all neural networks causes a decrease in RMSE. In other words, the more percentage of data is considered for training, the error of the neural network decreases. The comparison between ANNs shows that in all investigated modes, the BP neural network has the highest RMSE value, which indicates the weakness of this type of ANN. Meanwhile, the LM-BP had the lowest RMSE value in all cases. Therefore, it can be concluded that the combination of LM and BP has created significant growth in the quality of the proposed neural network. Finally, the housing price prediction chart in Taiwan from 2023 to 2027 is shown in Figure 9.

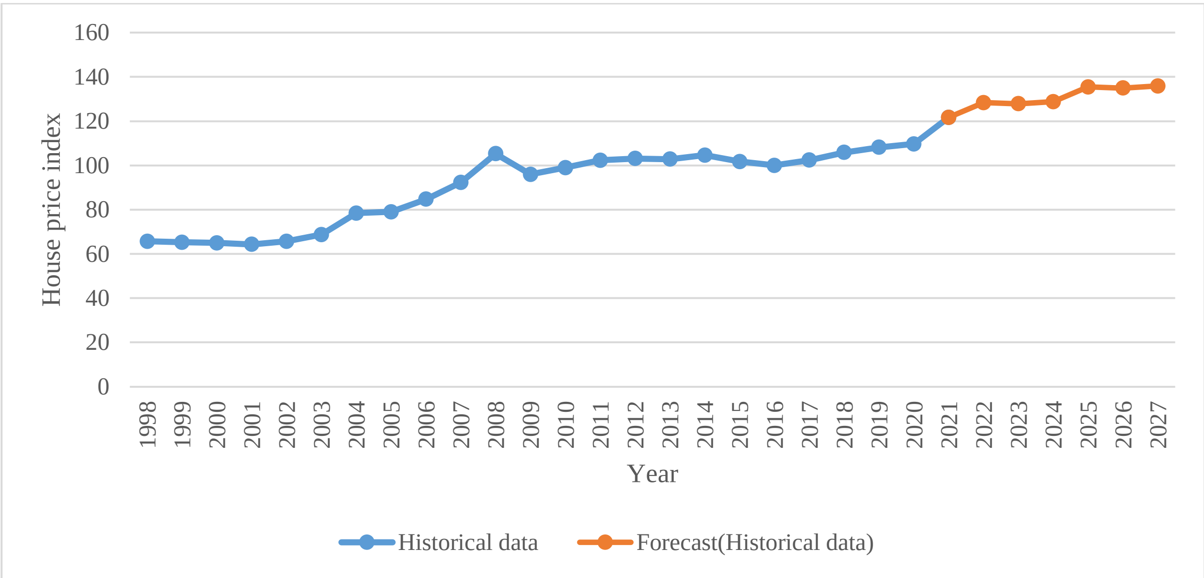

Figure 9. Prediction of the housing price index in Taiwan for the years 2023 to 2027

As can be seen from Figure 9, housing prices in Taiwan are expected to rise in the next 5 years. It should be noted that in the input parameter analysis, it was mentioned that the demand for the house is increasing in Taiwan. Therefore, the prediction results coincide with the analysis of its input variables. Moreover, during these 5 years, the highest price growth is predicted for 2023 and the lowest price growth for 2027. Based on the simulation of the training data from the case study data in Taiwan, the results show that the LM-BP artificial neural network has shown an acceptable performance in predicting the housing market prices in Taiwan.

5. Conclusion

In this research, using one of the LM-BP neural network forecasting strategies, a forecast of the housing price index in Taiwan for the next 5 years has been presented. The results show that the LMBP neural network has an outstanding performance with high accuracy and stability for housing price prediction. The ability and possibility to predict housing prices are of great importance for the beneficiaries of this field because it allows builders, sellers, and buyers to predict the final price of housing with a series of input and selection data.

An integral managerial implication derived from this study pertains to the formulation of a forward-looking perspective on the trajectory of house prices within the Taiwanese market. Through rigorous analysis, the findings indicate a discernible upward trajectory in housing prices across Taiwan. Furthermore, it is conceivable that the methodology elucidated in this research holds broader applicability beyond the confines of Taiwan and may be extrapolated to various other national contexts. However, it is essential to acknowledge a primary limitation inherent in this study, namely, the reliance on data sourced from diverse variables and the examination of price trends solely within the metropolitan regions of Taiwan. This limitation underscores the necessity for future research endeavors to encompass a more comprehensive dataset, incorporating a broader geographic scope to render the findings more robust and generalizable.

As a suggestion for future research, fuzzy logic can also be combined with this model because the expression of opinion in human societies is always presented with uncertainty and doubt in mind, so it becomes more flexible feedback based on different inputs.

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