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ENHANCING THE ACCURACY OF MALAYSIAN HOUSE PRICE FORECASTING: A COMPARATIVE ANALYSIS ON THE FORECASTING PERFORMANCE BETWEEN THE HEDONIC PRICE MODEL AND ARTIFICIAL NEURAL NETWORK MODEL

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Abstract

The Hedonic Price Model (HPM), a prominent model used in real estate appraisal and economics, has been argued to be marred with nonlinearity, multicollinearity and heteroscedasticity problems that affect the accuracy of price predictions. An alternative method called Artificial Neural Network Model (ANN) was identified as capable of addressing the shortcomings of HPM and produces superior predictive performance. Hence, this study aims to evaluate the forecasting performance between HPM and ANN using Malaysian housing transaction data from the period between 2009 to 2018, sourced from the Valuation and Property Service Department, Johor Bahru. The models' performance was evaluated and compared based on their statistical and predictive performance. Results showed that ANN outperformed HPM in both statistical and predictive performance. This study benefits the expansion of academic and practical knowledge in enhancing the accuracy of house price forecasting.

Keywords: Property forecasting, property valuation, predictive accuracy, hedonic price model, artificial neural network

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INTRODUCTION

The era of the fourth industrial revolution (IR 4.0) saw the explosion of new technologies such as Artificial Intelligence (AI), biotechnology, collaborative robots, internet of things, nanotechnology, quantum computing and 5G telecoms. All industries, including the real estate industry, are increasingly investing in advanced analytical tools to remain competitive and responsive to fast growing market demands. For instance, the application of AI in property valuation is crucial to cope with the fast changing and high demand for property valuation services (Yalpir, 2014; Sa'at and Adi Maimun, 2019b). Although AI has been explored since the 1990s, the adoption rate was slow. At present, the Hedonic Pricing Model (HPM) still dominates both literature and applications due to its flexibility and straightforwardness in estimation. Nonetheless, the nonlinearity, multicollinearity and heteroscedasticity problems (Kilpatrick, 2011; Antipov & Pokryshevskaya, 2012; Rahman et al., 2018) that plagued HPM may cause biased estimates and specification errors that may reduce prediction accuracy (Adi Maimun, 2011). Inaccurate predictions will negatively affect the decisions of policy-makers, valuers and developers. Thus, an improved property forecasting model is vital to enhance the efficiency and accuracy of forecasting.

An AI model, known as Artificial Neural Network Model (ANN), was able to address the shortcomings of HPM (Tabales et al., 2013). Like humans, the ANN has self-learning ability, permits analysis on a large dataset, identifies relationships between variables, and predicts a future trend (Mohd Radzi et al., 2012). Despite the advantages and good forecasting performance, ANN received less attention than HPM (Mooya, 2015; Abidoye & Chan, 2016; 2017), including its use in Malaysia. In response to the Malaysia Government's vision towards IR 4.0 through "Industry 4WRD: NATIONAL POLICY ON INDUSTRY 4.0" and to improve the accuracy of house price forecasting, this paper aims to evaluate the forecasting performance between HPM and ANN in the Malaysian context. This paper offers two benefits. Firstly, it expands academic knowledge on AI-based property forecasting. Secondly, it guides researchers, valuers and investors on AI for property valuation, index and investment.

This paper is structured as follows. An overview of the literature on house price forecasting models is provided, followed by an elaboration on the theoretical framework of HPM and ANN. Based on previous studies findings, it is hypothesised that ANN will outperform HPM in both statistical and predictive performance. The following section explains and justifies the methodology used in this study, followed by a discussion of findings.

THE HPM THEORETICAL BACKGROUND

Theoretically, HPM is executed through regression analysis (Selim, 2009). It is assumed that consumers are willing to purchase a commodity that consists of a bundle of property attributes to fulfil their needs and satisfaction (Limsonbunchai et al., 2004). Property attributes can be classified into locational, structural, and neighbourhood attributes and may impact property prices, either positively or negatively depending on the situation (Suhaimi et al. 2021; Zihannudin et al. 2021). Location attributes represent the geographic location of the property and access to the city centre and facilities, structural attributes represent the physical characteristics and conditions of the property while neighbourhood attributes represent the socioeconomic, local authority services, externalities and facilities of the neighbourhood where the property is located.

The following equation illustrates the house price function.

$$P = f\,(L, S, N) \qquad \text{(Eq. 1)}$$

Where P represents house prices, L represents locational attributes, S represents structural attributes, and N represents neighbourhood attributes.

Meanwhile, equation 2 below defines the general equation for HPM:

$$Y_{it} = \beta_0 + \beta_1(X_1m_1) + \beta_2(X_2m_2) + \beta 3(X_3m_3) + \beta 4(X_{nmn}) + \varepsilon_i \qquad \text{(Eq. 2)}$$

Where; Y_{it} = Forecasted House Price; m = Price of house i at time period t; X = Property attributes; β = Regression coefficient; ε_i = Error term

Despite the flexibility and simplicity of HPM, Selim (2009) argued that the HPM performance gradually decreases due to its instability in producing price coefficients. HPM is ineffective at capturing nonlinearity and is exposed to multicollinearity and heteroscedasticity problems that lead to inaccurate estimations (Limsonbunchai et al., 2004; Kilpatrick, 2011; Antipov & Pokryshevskaya, 2012). The drawbacks of HPM also led to the application of ANN to enhance forecasting accuracy.

THE HPM THEORETICAL BACKGROUND

The ANN, which originated from McCulloch and Pitts (1943), is a computing system inspired by biological neurons that mimicked the human brain's learning process (Pagourtzi et al., 2007). In ANN, nodes represent the brain's neurons and are connected through input, hidden, and output node layers. There are four stages involved in ANN modelling, namely Input criteria (Phase 1), Data processing (Phase 2), ANN modelling (Phase 3) and Model evaluation (Phase 4) (Sa'at & Adi Maimun, 2019a;b). The general equation for ANN is:

$$X_{jj} = \text{Total } W_{ij}Y_i;\ O_j = f(X_j) \qquad \text{(Eq. 3)}$$

Where: X_j is the net input to artificial neuron (j), Y_i is the value of input signal from artificial neuron (i), W_{ij} is the weight from an artificial neuron, (i) to artificial neuron (j). n is the number of input signals to artificial neuron (i), O_j is the output signal from artificial neuron (j), $f(X_j)$ is the transfer function of artificial neuron (j). Figure 1 below visualizes the neural net topology.

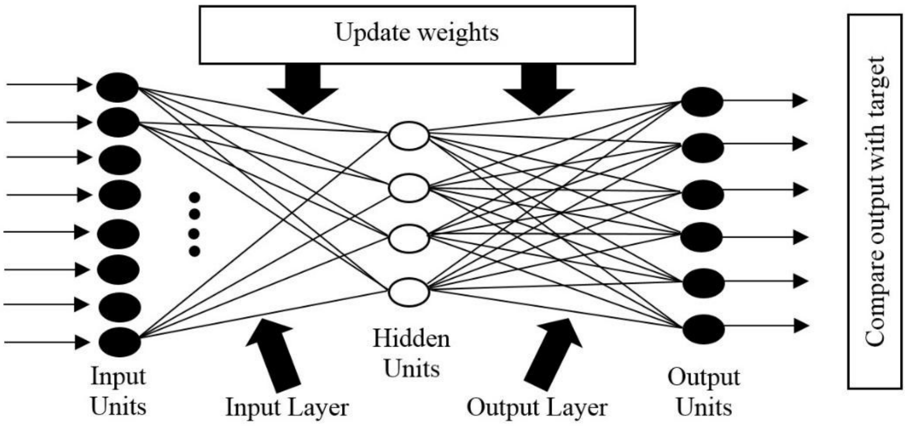

Figure 1: Neural Net Topology

The input layer, consisting of independent variables, is processed in the hidden layer(s) before being transferred to the output layer, represented as the dependent variable(s). At least one input layer, several hidden layers (s), and one output layer are required to operate ANN. The network topology is specified through a series of trials and errors to ensure no over-parameterisation and an excessive number of neurons. The back-propagation method is the most commonly used in the ANN learning algorithm. It minimises the discrepancies between actual value and forecasted value by adjusting the network's weights and biases.

PREVIOUS STUDIES ON HOUSE PRICE FORECASTING

An overview of the literature reveals that only two studies are based in Malaysia (Table 1). Most studies included locational, structural and neighbourhood attributes as independent variables due to the significant impact on house prices (De and Vupru, 2017). These variables may include main floor area, distance to facilities/amenities/city, elevator, building exteriors, garden, number of bedrooms/floors/households, population size, and type of garage/house. ANN was highlighted to be the best forecasting model based on the high R^2 value compared to HPM model. Different software or tools are used to develop ANN, including NeuroShell2, Matlab and Visual Gene Developer.

Table 1: Summary of House Price Forecasting Literature

No	Author (Year)	Study Area	Variables	Model	Software	R^2
1	Lin & Mohan (2011)	USA	Sale price, living/land area, age of building, no. of bedrooms/bath rooms/fireplace, external building styles, location	HPM, ANN	NIL	NIL
2	Mohd Radzi et al. (2012)	Malaysia	House price index, employment/interest rate, population, household income	ANN	NeuroShel l2	0.9932
3	McCluskey et al. (2013)	Ireland	Sale price, property size, garage/property/class/glazing type, no. of storey's/bedrooms, age of building, property type, travel to work time, location	HPM, ANN, SAR, GWR	NIL	HPM: 0.788 **ANN: 0.823** SAR: 0.887 GWR: 0.879
4	Morano & Tajani (2013)	Italy	Sale price, floor level, panoramic view, life expectancy, heating type	HPM, ANN	NIL	HPM: 0.972 **ANN: 0.999**
5	Chiarazzo et al. (2014)	Italy	Asking price, property size, no. of bedrooms/bathrooms, improvement, lift, property/construction type, location, garden, beach, garage, travel time, public transport, neighbourhood, pollution, zone, population	ANN	NIL	0.83
6	Ghorbani & Afgheh (2017)	Iran	Sale price, floor/land area, age of building, no. of rooms, building façade, lift, indoor decoration, cooling system, balcony, location, street width	HPM, ANN	Eviews 6, Neurosolut ion5	HPM: 0.88 **ANN: 0.98**
7	Kitapci et al. (2017)	Turkey	Sale price, floor size, no. of rooms/bathrooms, no. of floor, parking, age of building, lift, heating/property/floor type location, insulation, kitchen cabinet	ANN	Matlab	NIL
8	Abidoye & Chan (2019)	Nigeria	Price index, population, real gross domestic product, domestic export/import, household size/income/stock, interest/inflation/unemployment rate	SVM, ANN, ARIMA	Eviews 9.5 R	SVM: 0.94 **ANN: 0.92** ARIMA: 0.73
9	Rahman et al. (2018)	Malaysia	Sale price, land area, main floor area, location, transaction year	ANN	Visual Gene Developer	NIL

RESEARCH METHODOLOGY

Over 4,000 sale observations between 2009 and 2018 in Johor Bahru were sourced from the Valuation and Property Services Department Johor Bahru. The dataset included a wealth of attributes influential to house prices such as location, land area, main floor area, type of lot and type of tenure. To ensure no outliers, several observations were removed from the dataset based on the following rule of thumb: (1) invalid number of land lots, (2) redundant data, (3) no land area, (4) sales transaction below RM80,000.00, (5) sales transaction above RM800,000.00 and (6) incomplete or confusing information. The finalised set of data for analysis contained 3,732 observations.

A total of 21 variables, including ten years of sales transaction data, four different mukims, two types of tenure, three types of lot, land area, and main floor area were used as inputs. A feed-forward structure with only one and two hidden layer(s) was tested based on its Root Mean Square Error (RMSE) value. Contrary to previous studies, this study used RMSE rather than R2 to evaluate the model's predictive performance because it better reflects its performance in generalising the dataset. Higher estimation accuracy relates to lower RMSE value. Meanwhile, the Back Propagation Algorithm is used to train the Neural Network. IBM SPSS is applied to execute both HPM and ANN. Figure 2 illustrates the ANN designed model for this study.

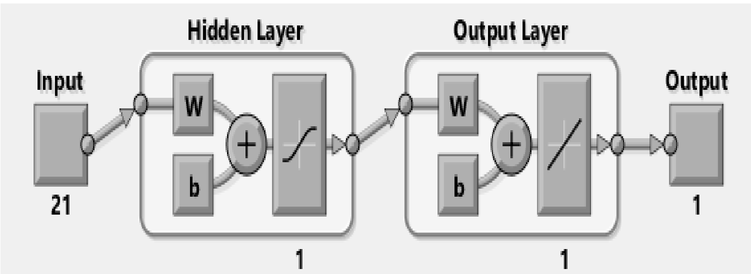

Figure 2: ANN Designed Model

Datasets were divided into three sets, namely the training set (60%), testing set (30%) and validation set (10%). The number of hidden neurons were identified randomly by performing a series of trial and error process. Hidden neurons were gradually increased for each training and testing process to minimise the error between actual and forecasted prices. The number of cycles for processing datasets depended on the epochs (stopped once it reached the local minimum). ANN is designed to undergo two phases. The first phase is training an ANN where the model would learn by itself to find the unknown implicit function in forecasting house prices.

Housing data from years 2009 to 2017 were used to find the unknown function.

$$Y = mx + c \qquad \text{(Eq. 4)}$$

Where: Y = forecasted house prices, m = gradient, x = property attributes (inputs), and c = biases.

After the unknown implicit function is determined, the simulation phase occurs. This is the phase where the implicit function is used to forecast house prices using the finalised dataset. In the simulation phase, only the 2018 year dataset is used. The forecasted values produced by ANN and HPM are compared.

RESULTS AND DISCUSSION

The ANN learning and momentum rates were performed through simultaneous trial and error processes. This training process involved 32 sets of data that varied in partition and activation function (hidden and output layers). The training algorithm used for the trial and error processes is Levenberg-Marquardt (trainmlm). The predictive performance of each set is evaluated through RMSE. The dataset with the lowest RMSE value indicates the highest prediction accuracy. Table 2 illustrates dataset number 4 with a data partitioning ratio 60:30:10, and sigmoid for activation function in hidden and output layers produced the lowest RMSE value. This indicated that the configuration for set number 4 produced the best predictive performance. Hence, set number 4 was selected to compare with RMSE value produced by HPM.

Table 2: Ranking for Testing 32 Datasets with Varying Activation Function and Different Number of Hidden Layer

Set	No of Hidden Layer	Data Partitioning	Activation Function in Hidden Layer	Activation Function in Output Layer	MSE	RMSE	Rank
1	1	70:15:15	Sigmoid	Sigmoid	0.0013	0.0361	5
2	1	70:20:10	Sigmoid	Sigmoid	0.0013	0.0361	6
3	1	60:20:20	Sigmoid	Sigmoid	0.0013	0.0361	7
4	**1**	**60:30:10**	**Sigmoid**	**Sigmoid**	**0.0020**	**0.0047**	**1**
5	1	70:15:15	Hyperbolic-Tangent	Hyperbolic-Tangent	0.0042	0.0648	19
6	1	70:20:10	Hyperbolic-Tangent	Hyperbolic-Tangent	0.0053	0.0728	23
7	1	60:20:20	Hyperbolic-Tangent	Hyperbolic-Tangent	0.0054	0.0735	24
8	1	60:30:10	Hyperbolic-Tangent	Hyperbolic-Tangent	0.0083	0.0911	31
9	2	70:15:15	Sigmoid	Sigmoid	0.0010	0.0316	2
10	2	70:20:10	Sigmoid	Sigmoid	0.0015	0.0387	13
11	2	60:20:20	Sigmoid	Sigmoid	0.0013	0.0361	8
12	2	60:30:10	Sigmoid	Sigmoid	0.0022	0.0469	16
13	2	70:15:15	Hyperbolic-Tangent	Hyperbolic-Tangent	0.0036	0.0600	17
14	2	70:20:10	Hyperbolic-Tangent	Hyperbolic-Tangent	0.0056	0.0748	25
15	2	60:20:20	Hyperbolic-Tangent	Hyperbolic-Tangent	0.0058	0.0762	28
16	2	60:30:10	Hyperbolic-Tangent	Hyperbolic-Tangent	0.0085	0.0922	32
17	1	70:15:15	Hyperbolic-Tangent	Sigmoid	0.0010	0.0316	3
18	1	70:20:10	Hyperbolic-Tangent	Sigmoid	0.0014	0.0374	12
19	1	60:20:20	Hyperbolic-Tangent	Sigmoid	0.0013	0.0361	9

20	1	60:30:10	Hyperbolic-Tangent	Sigmoid	0.0021	0.0458	15
21	1	70:15:15	Sigmoid	Hyperbolic-Tangent	0.0043	0.0656	20
22	1	70:20:10	Sigmoid	Hyperbolic-Tangent	0.0058	0.0762	27
23	1	60:20:20	Sigmoid	Hyperbolic-Tangent	0.0053	0.0728	23
24	1	60:30:10	Sigmoid	Hyperbolic-Tangent	0.0078	0.0883	29
25	2	70:15:15	Hyperbolic-Tangent	Sigmoid	0.0012	0.0346	4
26	2	70:20:10	Hyperbolic-Tangent	Sigmoid	0.0013	0.0361	10
27	2	60:20:20	Hyperbolic-Tangent	Sigmoid	0.0013	0.0361	11
28	2	60:30:10	Hyperbolic-Tangent	Sigmoid	0.0020	0.0447	14
29	2	70:15:15	Sigmoid	Hyperbolic-Tangent	0.0038	0.0616	18
30	2	70:20:10	Sigmoid	Hyperbolic-Tangent	0.0046	0.0678	21
31	2	60:20:20	Sigmoid	Hyperbolic-Tangent	0.0060	0.0775	28
32	2	60:30:10	Sigmoid	Hyperbolic-Tangent	0.0081	0.0900	30

Table 3 tabulates the statistical performance for HPM and ANN based on their MSE and RMSE values. ANN produced lower MSE (0.0020) and RMSE (0.0047) compared to HPM. This means ANN produced a more accurate prediction closer to the actual house prices than HPM.

Table 3: Statistical Performance of HPM and ANN

Forecasting Model	MSE	RMSE
HPM	0.0024	0.0490
ANN	**0.0020**	**0.0047**

At the simulation phase, an analysis was performed on ten latest transactions in 2018 to identify the best model that predicts the closest to the real market (Table 4). Overall, ANN outperformed HPM as it produced values closer to the actual price, reflected in lower error values. Nonetheless, specific prediction values deviated more than 10% from the actual value.

Table 4: Predictive Performance of HPM and ANN for 2018 House Prices

Actual Price (RM)	HPM			ANN		
	Forecasted Price (RM)	Error (RM)	Error (%)	Forecasted Price (RM)	Error (RM)	Error (%)
655000	480448	-174552	26.65	498549	-156451	23.89
550000	619236	69236	-12.59	638182	88182	-16.03
708000	551493	-156507	22.11	587877	-120123	16.97
518000	512399	-5601	**1.08**	514311	-3689	0.71
500000	639971	139971	-27.99	645406	145406	-29.08
600000	534735	-65265	10.88	572759	-27241	4.54
480000	499150	19150	-3.99	528329	48329	-10.07

642000	615268	-26732	4.16	636276	-5724	0.89
550000	516811	-33189	6.03	549103	-897	**0.16**
560000	508934	-51066	9.12	511145	-48855	8.72

A total of 364 sales transactions in 2018 were utilised to visualise the discrepancies between the actual value and predicted value (HPM and ANN) (Figure 3). The closer the forecasted house price trend line with the actual sale price, the more accurate the forecasting model predicts house prices. Figure 3 depicts that the ANN line trend (indicated by grey line) is closer to the actual sale price trend than the HPM model's price trend. This proved that ANN produced a more accurate estimation compared to the traditional forecasting model, which is HPM.

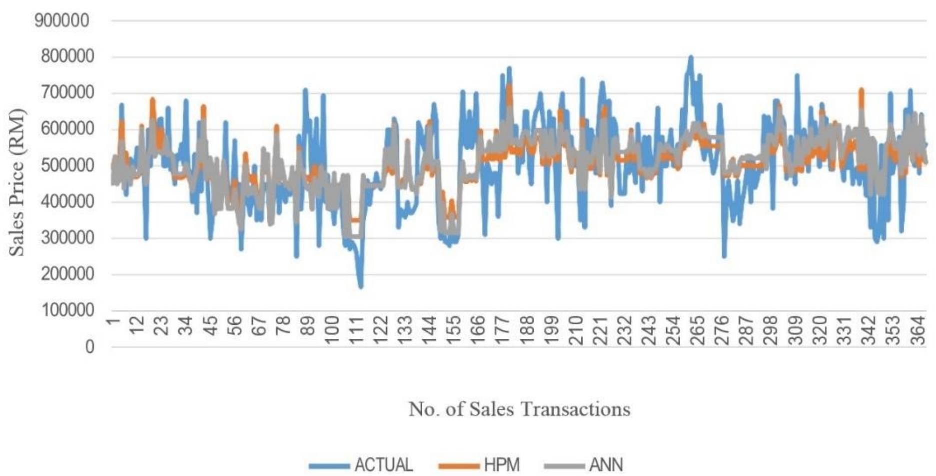

Figure 3: House Price Trend for Sales Transaction in 2018

CONCLUSION

This paper evaluated the forecasting performance of HPM and ANN using house sales data. Overall, neural network algorithm set 4 with only one hidden layer - using Sigmoid as the activation function for hidden and output layers is the most appropriate algorithm for forecasting Malaysian house prices. As hypothesised, ANN outperformed HPM in forecasting performance as measured through lower RMSE. This supported the findings of McCluskey et al. (2013), Ghorbani and Afgheh (2017) and Abidoye and Chan (2018). Nonetheless, several ANN error values are more than 10%, which might be caused by the omission of other price-influential variables in the model. This study expanded existing knowledge by shedding light on the forecasting performance between HPM and ANN. Academics and practitioners can use the study findings to choose the best model and technique to forecast house prices. Although good forecasting performance was observed for ANN, it is suggested that future studies consider additional variables to improve forecasting accuracy. Future research may also explore other AI models such as autoregression, autoregressive integrated moving average, fuzzy logic, support vector machine and spatial-temporal models to uncover the potential of AI in forecasting house prices in specific and real estate as a whole.

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