



ADVANCING MALAYSIAN HOUSE PRICE INDEX PREDICTIONS: THE POTENTIAL OF ARTIFICIAL NEURAL NETWORK

Aida Julia Aminuddin¹, Nurul Hana Adi Maimun², Hishamuddin Mohd Ali³, Tan Shang Yin⁴, Abdul Jalil Omar⁵

^{1,2,3,4} *Centre for Real Estate Studies (UTMCRES),
Institute for Smart Infrastructure and Innovative Construction (ISIIC),
UNIVERSITI TEKNOLOGI MALAYSIA*

⁵ *Malaysian Real Estate Institute,
Faculty of Technology Management and Business,
UNIVERSITI TUN HUSSEIN ONN MALAYSIA*

Abstract

This study develops a localized house price index by employing an Artificial Neural Network (ANN) forecasting model to enhance the organization and efficiency of the Malaysian property market. Traditional Malaysian House Price Index (MHPI), based on a hedonic model, exhibits multicollinearity among house attributes, limiting its ability to accurately capture house price trends. While MHPI provides aggregate indices, the construction of disaggregate indices remains underexplored, potentially reducing the effectiveness of local housing market analysis and long-term planning. This research aims to identify key house attributes influencing prices and to evaluate the capability of ANN in forecasting the Johor Bahru house price index. The study applies ANN to disaggregate transaction data of double-story terrace houses in Taman Mutiara Rini and Taman Bukit Indah, comparing actual and forecasted prices using R-squared (R^2), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Deviation (MAD). Findings reveal significant differences between forecasted and actual indices, demonstrating ANN's superior ability to capture local price variations. The study highlights ANN as a robust tool for constructing disaggregate house price indices, offering improved insight and efficiency for monitoring and planning within local housing markets in Malaysia.

Keywords: Localized house price index, Artificial Neural Network, Johor Bahru, Disaggregate housing data, Forecasting

¹ Corresponding author. Email: ajulia3@graduate.utm.my

INTRODUCTION

The housing market plays a critical role in national economic performance and local development, as housing price movements influence wealth distribution, investment decisions, and consumer confidence (Gobalkrishnan & Md Yusof, 2023; Yalpir, 2014). Accurate forecasting of housing prices is therefore essential for homebuyers, investors, financial institutions, and policymakers in designing effective housing and economic policies (Gobalkrishnan & Md Yusof, 2023; Munusamy et. Al, 2015).

Historically, the Hedonic Price Model (HPM) has been widely used for modelling house prices in real estate economics. However, HPM's reliance on linear functional forms and its sensitivity to multicollinearity, heteroskedasticity, and nonlinearity limit its ability to capture complex relationships present in real estate data (Abd. Rahman et al., 2019; Sa'at et al., 2021). These limitations often lead to reduced predictive accuracy in real-world forecasting scenarios.

To address these limitations, machine learning approaches, particularly Artificial Neural Networks (ANN) have gained attention for housing price prediction due to their flexibility in modelling nonlinear and high-dimensional data without strong parametric assumptions (Aminuddin & Adi Maimun, 2022; Gobalkrishnan & Md Yusof, 2023; Sa'at et al., 2021). ANN models have shown superior forecasting performance compared to traditional econometric techniques by effectively capturing complex patterns in housing market data (Gobalkrishnan & Md Yusof, 2023; Sridhar & Sathyanathan, 2022).

Despite these advances, studies focusing specifically on the Malaysian context remain limited, especially in terms of integrating modern ANN approaches and comparing their forecasting performance directly with HPM. Existing Malaysian research demonstrates ANN's potential with Penang housing price index forecasting (Gobalkrishnan & Md Yusof, 2023) and Johor Bahru case studies (Abd. Rahman et al., 2019), but these studies are geographically narrow and not sufficiently comprehensive across Malaysian housing markets as a whole. This gap suggests a need for more extensive, updated investigations into ANN performance in Malaysian house price modelling (Aminuddin & Adi Maimun, 2022).

This study aims to address this gap by examining the effectiveness of Artificial Neural Networks (ANN) in forecasting Malaysian house price indices. By demonstrating ANN's capability to manage nonlinear relationships and complex market data structures, this research contributes to a more robust understanding and application of advanced forecasting techniques for stakeholders such as investors, policymakers, and real estate professionals. Furthermore, this study aligns with national strategies such as Rancangan Malaysia Ketiga Belas, 2026-2030 (RMK-13) and National Artificial Intelligence

(AI) Action Plan 2030 by encouraging the adoption of advanced computational methods to improve housing market forecasting and informed policy design.

LITERATURE REVIEW

Importance of Accurate Housing Price Forecasting

Accurate forecasting of housing prices is a critical objective in real estate research because housing markets are fundamental to economic stability, household wealth, and financial decision-making. House price indices are used by policymakers, financial institutions, and investors to monitor market trends, assess affordability, and inform policy responses (Munusamy et al., 2015). Demand and supply dynamics, macroeconomic conditions like GDP and interest rates, and property heterogeneity make forecasting complex (Norazmawati Md. Sani @ Abd. Rahim, 2025). This complexity motivates the use of advanced forecasting techniques beyond traditional econometric models.

Hedonic Price Model (HPM): Traditional Approach and Limitations

The Hedonic Price Model (HPM) is one of the most established econometric methods for house price forecasting. It decomposes house prices into attributes such as location, size, age and estimates their implicit values (McCluskey et al., 2012; Selim, 2009). HPM's interpretability and grounding in economic theory explain its popularity in real estate literature. However, HPM assumes linear relationships among variables (Abd. Rahman et al., 2019; Sa'at, et al., 2021). This assumption often reduces forecasting accuracy when dealing with real-world housing market data, which tend to be nonlinear and high-dimensional.

In the Malaysian context, conventional forecasting has often relied on aggregated indices constructed from macroeconomic variables, which can mask local market nuances and result in limited usefulness for accurate pricing (Adi Maimun, 2011; Adi Maimun et al., 2012). Complementary work has proposed alternative econometric models to improve index construction (Nik Nor Amalina Nik Mohd Sukrri et al., 2025; Zamri et al., 2024), but these still face challenges capturing nonlinear effects.

Rise of Machine Learning and ANN in House Forecasting

The shortcomings of HPM have spurred increased interest in Machine Learning (ML) techniques, particularly Artificial Neural Networks (ANN), which are flexible in modelling complex, nonlinear relationships without strict parametric assumptions (Ja'afar et al., 2021). ANN comprises layers of interconnected nodes that simulate neural processing, enabling pattern recognition, adaptation, and generalization from training data (Agatonovic-Kustrin & Beresford, 2000; Maind & Wankar, 2014). ANN has been shown to outperform traditional models in

various forecasting contexts, especially where relationships among variables are nonlinear and interactive (Li, 2025).

Comparative Studies: ANN vs HPM

A growing body of research has compared Artificial Neural Networks (ANN) with Hedonic Pricing Models (HPM) and other traditional forecasting approaches in the housing market. For instance, Sa'at et al. (2021) evaluated forecasting performance using Malaysian housing transaction data and found that ANN consistently outperformed HPM across multiple statistical and predictive metrics, demonstrating higher accuracy, lower error rates, and greater robustness in capturing market dynamics. The study highlighted that while HPMs rely on linear assumptions and are sensitive to the specification of independent variables, ANNs are capable of modeling non-linear relationships and complex interactions among multiple housing attributes, including land size, building size, tenure type, and age of the property.

International studies similarly underscore ANN's strengths in housing market forecasting. Sa'at and Adi Maimun (2019) reported that ANNs are particularly effective in learning complex patterns from historical data, yielding lower forecasting errors and stronger predictive generalization than traditional regression-based models. These findings indicate that ANNs are more adaptable to diverse datasets and can account for multifactor influences—such as economic indicators, demographic changes, and spatial heterogeneity—that often challenge traditional models.

The collective evidence from both local and international studies suggests that ANNs not only improve forecasting accuracy but also offer practical advantages for stakeholders. Real estate developers, policymakers, and investors can leverage ANN models to anticipate market trends, optimize pricing strategies, and inform investment decisions. Moreover, the flexibility of ANN frameworks allows researchers to incorporate a wide range of variables and tailor model structures, such as the number of hidden layers and nodes, to specific housing contexts, thereby enhancing their applicability across different regions and housing markets.

ANN Applications in Malaysian House Price Index Modelling

Despite the growing global momentum in applying Artificial Neural Networks (ANN) to housing market forecasting, evidence from Malaysia remains limited. Gobalkrishnan and Md Yusof (2023) applied ANN to the Penang House Price Index using quarterly data and reported high forecasting accuracy, demonstrating the model's ability to capture complex, localized patterns in housing market dynamics. Their study highlighted how ANN can effectively incorporate

temporal trends and non-linear interactions among multiple market variables, outperforming conventional models in predictive performance.

Similarly, Abd. Rahman et al. (2019) applied ANN to forecast housing prices in Johor Bahru and observed superior predictive results compared to traditional regression-based methods. Their findings suggest that ANN models are capable of accommodating diverse housing attributes and local market characteristics, providing more accurate and reliable forecasts for property developers, investors, and policymakers.

Collectively, these studies underscore the potential of ANN for housing market forecasting in Malaysian contexts, while also revealing gaps in current research. Most existing studies focus on specific regions, such as Penang or Johor Bahru, and often rely on a limited set of variables or aggregate data. This highlights the need for broader application of ANN models across other regions and property types in Malaysia, as well as the exploration of micro-level datasets that capture property-specific characteristics, market demand, and socio-economic influences. Expanding ANN applications in this manner can enhance understanding of regional housing market dynamics, improve forecast accuracy, and provide a more robust foundation for data-driven policy and investment decisions.

Malaysian House Price Index Challenges

The Malaysian House Price Index (MHPI), published quarterly by the Valuation and Property Services Department (JPPH), provides an aggregated measure of housing market trends by compiling transaction data derived from stamp duty records. While the MHPI serves as an important benchmark for tracking national housing price movements, it faces several limitations that can constrain its accuracy and practical utility. One key limitation is its insufficient hyperlocal granularity; by aggregating transactions at state or district levels, the index often masks variations in micro-markets, such as specific neighbourhoods or property subtypes, where price dynamics may differ substantially.

Additionally, generally the HPI relies heavily on macroeconomic variables and aggregated transaction data, which may not fully capture property-specific factors such as land size, building age, tenure type, or ownership structure. Discrepancies between listed and actual transaction prices, regional market heterogeneity, and aggregation bias further reduce the precision of the index, potentially leading to under- or overestimation of housing market trends in particular areas (Lim, 2019; Saudin et al., 2020; Tan & Razali, 2016). These limitations are particularly consequential for stakeholders such as policymakers, developers, and investors, who require accurate, high-resolution data to make informed decisions about pricing, investment, and planning. Consequently, there is a growing need for alternative forecasting methods, such as Artificial Neural

Networks (ANN), which can integrate micro-level housing attributes and capture non-linear relationships across multiple variables. By addressing the MHPI's aggregation and granularity limitations, ANN models provide a more nuanced and precise tool for analyzing local housing markets and supporting data-driven decision-making.

Comparative Analysis: ANN vs HPM

Table 1 synthesizes key differences between ANN and HPM across forecasting criteria, illustrating ANN's advantages in predictive accuracy, adaptability, and handling of complex datasets, while acknowledging HPM's simplicity and interpretability.

Table 1: Comparison of ANN and HPM in Housing Price Forecasting

Criteria	Artificial Neural Network (ANN)	Hedonic Price Model (HPM)	References
Prediction Accuracy	High – captures nonlinear patterns and interactions	Moderate – assumes linearity, less accurate with complex datasets	Gobalkrishnan et al. (2023), Li (2025), Sa'at et al. (2021)
Data Requirements	Large datasets preferred for training	Can work with smaller datasets, but limited by data structure	Abd. Rahman et al., (2019), Munusamy et al. (2025)
Handling of Nonlinearity	Excellent – inherently models nonlinear relationships	Poor – linear assumptions restrict flexibility	Aminuddin et al. (2022), Sa'at et al. (2021)
Model Complexity	High – multiple layers, parameters, training required	Low – straightforward regression-based estimation	Agatonovic-Kustrin & Beresford (2000), Maind & Wankar (2014)
Interpretability	Moderate – results harder to explain	High – coefficients clearly indicate attribute effects	Li (2025), Munusamy et al. (2025)
Scalability	High – can handle larger datasets and features	Moderate – scalability limited by linear regression assumptions	Sa'at et al. (2021)
Computational Power	High – requires significant computation for training	Low – analytical solution, less computational demand	Abd. Rahman et al., (2019), Li (2025)
Flexibility in Modelling	High – can integrate macro and micro variables, time-series, or hybrid inputs	Limited – relies on predefined variables and linear forms	Gobalkrishnan & Md Yusof (2023)

Criteria	Artificial Neural Network (ANN)	Hedonic Price Model (HPM)	References
Ability to Handle Missing Data	Moderate – can impute or learn patterns from incomplete data	Low – missing data may require preprocessing or exclusion	Li (2025), Sa’at et al. (2021)
Real-Time Forecasting	Yes – capable of dynamic updates and retraining	No – static estimation based on historical data	Gobalkrishnan et al. (2023), Li (2025)
Robustness	High – less sensitive to model misspecification	Moderate – errors can propagate due to model assumptions	Peterson & Flanagan (2009), Sa’at et al. (2021)

Source: Author’s Review

Studies by Abidoye (2017) have reported that by adopting the ANN approach, their datasets for testing purposes can be processed at a greater speed and the results produced are more reliable and accurate. According to McCluskey et. al (2013), the greater improvement in the learning efficiency of ANN is due to the effort of many researchers. Previous comparative property modelling studies by Ng and Skitmoreb (2008), Nguyen and Cripps (2001), Julio and Esperanza (2004), Khalili and Nowbahar (2010; 2011), Khashei and Bijari (2011), Amanpour et al. (2015), Ghorbani and Afgheh (2017), Sa’at et al. (2019), and Stubnova et al. (2020) demonstrate the superiority of ANN model in forecasting performance compared to the other model.

Specifically, the ANN model illustrates a lower forecasting error between five per cent and ten per cent only. Several studies in real estate have used the ANN approach as the subject because of its ability to examine relationships in complex non-linear data sets due to the absence of the restrictive assumption of linearity about the nature of data relationships and functional form (Lin & Mohan, 2011; Nguyen & Cripps, 2001; Zurada et. al, 2006). Their findings demonstrated that ANN could perform tasks in the same way as traditional, parametric statistical techniques such as regression and other classification techniques, but with better prediction performance.

RESEARCH METHODOLOGY

This study adopts a quantitative analytical approach, grounded in empirical datasets obtained from the Valuation and Property Services Department (JPPH) Johor and the National Property Information Centre (NAPIC), covering the period from 2000 to 2016. A total of 2,325 residential sale transactions were sourced from the Valuation and Property Services Department Johor Bahru (VPSDJB). The dataset exhibits variation in transaction volume across years, reflecting fluctuations in market activity over the 17-year period. Within Mukim Pulau, two residential areas consistently recorded double-storey terrace house

transactions, making them suitable for longitudinal analysis. These areas were selected as the core samples to assess the capability of the ANN model in forecasting localised house price trends. Emphasising well-defined, smaller samples is crucial for constructing a robust and representative local House Price Index (HPI), as it enables the model to capture micro-market dynamics that may be diluted when analysing broader geographic datasets.

In the context of neural network modelling, three principal domains are required to hypothesise and demonstrate the locality of house prices: input variables, hidden layers, and the output variable. These components collectively define the structure and learning capability of the Artificial Neural Network (ANN). A detailed description of the specific neural network architecture employed in this study is presented in Table 2.

Table 2: Prime selection of variables

Type of Variables	The Variables
Output	House Transaction Value
Input	• Land Area • Main Floor Area • Ancillary Floor Area • Age of Building • Type of Lot • Type of Ownership • Type of Tenure • Scheme

Prior to applying the backpropagation algorithm, it is essential to preprocess and organise the dataset. This includes identifying the property attributes that significantly influence the output variable, house transaction value. The selection of appropriate and relevant input variables ensures that the ANN undergoes an effective learning, testing, and validation process.

The validation of the ANN model is essential to determine whether the network is capable of accurately forecasting local house prices. After generating the predicted values from the trained network, these outputs are transferred into a validation dataset to assess the model's generalisation performance. The forecasted observations are evaluated by examining the coefficient of determination (R^2), which indicates how well the model explains the variance in actual house prices. This step ensures that the neural network has successfully learned the underlying patterns in the data.

Additionally, the overall performance and predictive accuracy of the model are assessed using established error metrics, including the Mean Absolute Deviation (MAD) (*Equation 1*), Mean Absolute Percentage Error (MAPE) (*Equation 2*), and Root Mean Square Error (RMSE) (*Equation 3*). These

measures collectively provide a comprehensive evaluation of the ANN's forecasting capability and reliability.

The test accuracy metrics MAD, MAPE, and RMSE are employed to evaluate whether the ANN model provides reliable and robust forecasts of local house prices. A higher R^2 value combined with a lower RMSE indicates that the model fits the data well and successfully captures the underlying price patterns. Additionally, MAD serves as an alternative to MAPE, particularly suitable for datasets with low transaction volumes.

$$MAD = \frac{\sum_{t=1}^n |A_t - F_t|}{n} \quad (\text{Equation 1})$$

$$MAPE = \frac{\sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|}{n} \times 100 \quad (\text{Equation 2})$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (A_t - F_t)^2}{n}} \quad (\text{Equation 3})$$

where A_t represents actual house price, F_t represents forecasted house price, n represents number of samples.

In this study, the Root Mean Square Error (RMSE) is used to assess the mean squared difference between actual and forecasted local house price values. While RMSE is conceptually similar to the Mean Squared Error (MSE), it is preferred because RMSE provides the error in the same units as the original data, facilitating more intuitive interpretation of model accuracy. Consequently, RMSE is selected over MSE as the primary metric for testing the predictive performance of the ANN model.

ANALYSIS AND DISCUSSION

In house price forecasting, assessing the regression coefficient (R^2) is a crucial step to evaluate the predictive capability of an ANN model. As highlighted, the

input variables, specifically Land Area (LA) and Main Floor Area (MFA), exhibited multicollinearity in preliminary analyses. However, this study addresses potential multicollinearity issues by leveraging the nonlinear mapping capabilities of the ANN, allowing the network to capture complex relationships that linear regression alone may not fully represent. Table 3 summarises the regression analysis outcomes across the training, testing, and validation datasets. The proportion of data allocated follows the specifications outlined.

Table 3: Regression Coefficient (R^2) Observations of Local House Price Forecasting

Neural Network Scheme	Dataset	Taman Mutiara Rini (R^2)	Taman Bukit Indah (R^2)
Set 1	Training	0.178	0.352
	Testing	1.000	0.922
	Validation	0.999	0.927
Set 2	Training	0.063	0.387
	Testing	0.643	0.923
	Validation	0.960	0.887

The results indicate that linear regression produced by the ANN is formed progressively during the validation process. For Taman Mutiara Rini, the initial training phase shows low responsiveness of neurons, with R^2 values of 0.178 (Set 1) and 0.063 (Set 2), suggesting a weak linear relationship between input and output variables at early stages. Conversely, Taman Bukit Indah exhibits relatively stronger linearity, with R^2 values of 0.352 (Set 1) and 0.387 (Set 2) during training.

These findings demonstrate that, despite initial multicollinearity concerns, the ANN effectively captures the underlying patterns between inputs and the house price output. By the testing and validation stages, R^2 values markedly improve, indicating successful learning and strong predictive performance. Empirical observations thus support the claim that the ANN model is capable of overcoming multicollinearity effects while providing robust local house price forecasts.

The best-fitting ANN model for forecasting local house prices is summarised in Table 4. The network architecture is simplified into three layers, consistent with the pattern 2-1-1, to facilitate clear interpretation and efficient learning.

Table 4: Optimal ANN Model Parameters

No	Parameter	Value
1	Input layer	2 (Main Floor Area and Land Area)
2	Hidden Layer	1 (node of first hidden layer = 10)
3	Output layer	1 (house price)

Training, testing, and validation of each sample set were conducted using a learning rate of 0.01 and a momentum coefficient of 0.1. These parameters were carefully selected to ensure that the ANN could effectively learn the underlying relationships between input features and house prices, while maintaining stability and convergence during the learning process. The resulting network demonstrates strong predictive performance, validating the model's suitability for constructing a reliable local House Price Index (HPI). Moreover, the performance of MAPE, RMSE, and R^2 was evaluated for both sets of Taman Mutiara Rini and Taman Bukit Indah, as summarized in Table 5.

Table 5: Final Observations of ANN Model Accuracy

Accuracy Performance	Taman Mutiara Rini		Taman Bukit Indah	
	Set 1	Set 2	Set 1	Set 2
R^2	0.999	0.960	0.927	0.887
MAD	0.104	0.118	0.034	0.035
RMSE	0.112	0.125	0.039	0.039
MAPE (%)	14.321	16.308	4.407	4.549

The results indicate that Set 1 and 2 of Taman Bukit Indah achieved the lowest MAPE, demonstrating superior predictive accuracy compared to Taman Mutiara Rini. These observations suggest that a larger sample size improves the ANN model's ability to capture accurate forecasted trends, as more data enables the network to generalize effectively. For Taman Mutiara Rini, Set 1 also demonstrated higher predictive accuracy, with R^2 indicating strong agreement between forecasted and actual house prices. The observed price trends for both sets closely align, confirming that the ANN model can accurately capture local market fluctuations.

Overall, these results validate the study's hypotheses. Increasing the number of samples in the training and testing processes enhances the ANN model's robustness by reducing bias and balancing the influence of actual house prices. Consequently, Set 1 for both residential areas is identified as providing the strongest performance in terms of MAPE, MAD, and RMSE, highlighting its suitability for forecasting local house price trends with high accuracy.

CONCLUSION

In the overall analysis of forecasting local house prices, the neural network was structured with a single hidden layer comprising ten nodes, forming a 2-1-1 topology. The parameter settings for the variables remained constant throughout the formation of the neural network pattern, ensuring stability and consistency in the training process. A small learning rate was predominantly applied, which contributed to a substantial reduction in the sum of errors between actual and forecasted house prices, indicating effective model convergence.

Model accuracy was evaluated using statistical measures, including Mean Absolute Deviation (MAD), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Additionally, the regression coefficient (R^2) was considered to assess the goodness-of-fit of the ANN model relative to these error metrics. The results demonstrated that the ANN model is well-fitted, as evidenced by higher R^2 values compared to the RMSE, confirming the model's predictive reliability. Furthermore, the development of the local House Price Index using the ANN forecasts allowed for the identification of undervalued and overvalued properties, providing insightful implications for local market assessment and decision-making.

This study also addresses a notable gap in Malaysian housing research. Unlike previous studies that primarily relied on macro-level variables, the use of microdata in the ANN framework enables a more nuanced and precise understanding of housing market dynamics. The study's findings underscore the potential of ANN models as a reliable tool for policymakers, real estate developers, and investors to anticipate market trends, assess risks, and make informed decisions in the Malaysian context.

In terms of research implications, this study highlights the importance of careful model design and parameter selection such as the number of hidden layers and nodes to optimize ANN performance. The results suggest that ANN frameworks can be adapted and applied to other geographic regions in Malaysia, potentially improving forecasting accuracy in diverse housing markets. Future research could focus on further optimizing ANN models for Malaysian housing data, exploring alternative machine learning architectures, or integrating additional socio-economic and spatial variables. Comparative studies across different Malaysian states could also provide insights into regional housing market variations, enhancing the applicability and generalizability of ANN-based forecasting models.

In conclusion, this study demonstrates that ANN models provide highly accurate and reliable forecasts of housing market trends in Johor, effectively capturing complex, non-linear relationships among diverse housing attributes. By outperforming traditional HPM approaches, ANNs offer a powerful tool for policymakers, developers, and investors to anticipate market movements and make informed decisions. The findings also highlight the potential for applying and optimizing ANN models across different regions in Malaysia, paving the way for more precise, data-driven housing market analyses in future research.

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