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An integrated framework for affordable housing demand projection and site selection

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Abstract. Highly priced properties cause affordability problems among low and middle-income buyers. To overcome this, the Malaysian government introduces affordable housing through National Urbanisation Policy, National Physical Plan, National Housing Policy, and Eleventh Malaysia Plan. Whilst having good market response, some areas experience either shortage or surplus of houses reflecting ineffective affordable housing policies. Inappropriate estimation technique and aggregate location estimations limit the accuracy and usability of demand estimations. Thus, this research aims to establish a framework to estimate local demands for affordable housing. This study selects and reviews the theoretical and modelling framework of Artificial Neural Network Model (ANN) due to its superior performance in forecasting demand. The ANN theoretical and modelling framework guides the modelling process, which includes data collection and preparation, model development, data analysis and model evaluation. Potential sites for affordable housing development identified from the model's coefficients are visualised spatially through Geographic Information System (GIS). Localised housing demand forecasts are highly beneficial for policy-makers and housing developers to allocate the number of supplies across locations. This allows maximum take-up rate for affordable housing, avoids supply and demand mismatch and thus achieving the national housing policy agenda.

1. Introduction

The process of urbanization creates a high demand for houses. This has caused a rapid increase in house prices including the low and middle cost houses [1]. Highly priced houses for the lower income market segment have caused oversupply in residential stocks. [2] reported that half of the total nation's unsold residential stocks are those below RM300,000 which represents the lower and middle cost housing. The oversupply of housing reflects the unaffordability of people from lower to middle income earners to purchase houses. An average Malaysian can only afford houses priced below RM165,060 [3]. Nonetheless, an economic report published by the Bank Negara Malaysia in 2015 highlighted that only 21% of new houses launched in Malaysia are priced below RM 250,000. There was increased severity of housing affordability observed especially in the three main states in Malaysia, Kuala Lumpur, Pulau Pinang, and Johor [4]. Moreover, the developers were less interested to develop low and medium cost houses [5] due to low profit margin [1]. Apart from high prices, poor take up rate in this property segment also include inconvenient location, lack of accessibility, unsuitable home design and the inability of buyers to secure end-financing [6][7].

In response to this severe housing situation, the Malaysian government and its agencies have launched various affordable housing policies. Nonetheless, they noted the challenge in matching the demand to supply based on spatial and affordability of people [8]. Imbalanced or mismatch of supply and demand would lead to either undersupply or oversupply of houses. Oversupply of houses caused by mismatch in demand would lead to waste in time, money, and resources. In most urban areas, houses are undersupplied implying ineffective low-cost houses policies by the government. Thus, it is irrelevant to allocate 30 percent low-cost houses in a housing development since it does not reflect the actual demand for low-cost houses [9].

Despite the crucial need to address the housing supply and demand mismatch, very few studies have focused on forecasting the housing demand, particularly the low-cost housing demand. The current literature was limited to the works of [9][10][11][12][13][14][15]. A forecast of housing demand using ANN model by these researchers suggest good predictive performance. Nonetheless, these studies were carried out based on a very general, aggregated data sampling area such as Johor Bahru [11][13] and Batu Pahat [12]. Inadequate information for a particular location would cause inaccurate house construction decisions by policy makers and developers [16]. Therefore, there is a need to predict the housing demand based on local areas to avoid oversupply or undersupply of houses.

A mismatch of supply and demand for affordable houses highlighted the need for forecasting the demand of affordable houses at specific locations. With demand estimations in place, the suppliers can react accurately to the actual market demand and thus avoiding a supply-demand mismatch.

2. Affordable Housing

2.1. Definition of affordable housing
There is a growing demand for affordable housing due to the rising costs of living in Malaysia especially within the urban areas [17][18]. Affordable housing is subsidised houses priced below the market price offered to the low and median income groups under the provision of a local or state legislation [19]. Different countries have different affordable housing policies targeting different groups. Thus to give a specific definition on the affordable housing is a difficult task [17]. In Malaysia, there is no specific definition for affordable housing. Each agency outlines different meanings for the term affordable housing.

2.2. Affordable housing in Malaysia
In Malaysia, affordable housing are built for low, low-medium and medium income households because of their low housing affordability. The lower the income, the lower the housing affordability [20]. Households earning less than RM1,500.00 per month is thought to have a critical housing affordability [21]. Taking affordability into concern, these affordable houses should be within the capability of these income groups. Houses are considered affordable if it can be bought without serious financial risks where less than 30 percent of the household income is used to pay the monthly rent or mortgage [18]. Thus, most countries have set this as a basis or reference for assessing an individual's financial situation [17][22].

Apart from the household's affordability, the state government highlighted that affordable houses are houses that give comfort to the households (size and design) and community. Thus, based on these discussions, affordable housing can be defined as houses that are comfortable and financially accessible to low, low-medium and medium income households.

Affordable houses are categorized into three cohorts. These are determined based on the price ranges of each cohort. Low cost houses are houses priced below RM 42,000, low-medium cost houses are priced between RM 42,000 and RM 80,000, and medium cost houses are priced between RM 81,000 and RM 300,000.

2.3. Affordable housing demand
Based on the previous studies conducted by [9][11][12][13][14][23] the demand for housing can be assessed through a number of demographic and economic factors. These include birth rate, GDP rate,

housing stock, income rate, inflation rate, mortality baby rate, population growth, poverty rate, and unemployment rate.

The population growth indicates the temporal population trend in the form of percentage [24]. The population size is determined by child birth, child mortality and migration rates [15]. Thus, an increasing or decreasing child birth rate, child mortality rate, and migration rate will have either a positive or negative impact on the population growth. These statistics illustrate the socioeconomics of the population and best describes the demograhic. Therefore, [25] claim that they are the most appropriate indicator in determining the housing demand.

Inflation rate is used to compare the prices between goods or services in a different time period [24]. Income reflects an amount earned for self use or benefit [26]. Previous researchers such as [27][28][29] found strong links between household income and housing demand. Gross domestic product is the total value of goods and services for a period after removing goods and services costs and before removing fixed capital consumption allowance [24]. Housing stock shows the annual numbers of constructed or under construction housing units in a year [24]. Poverty rate refers to the numbers of people whose income is below the poverty line [24]. Finally, unemployment rate is the numbers of unemployed labor force [24].

The analysis of housing demand has recently become important for the decision makers and market actors due to the wide spread effects of housing sector on the economy. Thus, many researchers have attempted to examine the housing demand through various econometric models including OLS model [23][30][31][32][33] and the ANN model [9][11][12][13][14]. Although OLS is simple in application, it is marred with imprecision and inaccuracy [34]. Compared to the OLS, ANN produces a more accurate estimation and prediction. This is illustrated in OLS and ANN comparative works by [34] and [35].

3. Artificial Neural Network Model (ANN)

3.1. Definition of Artificial Neural Network Model (ANN)

As its name would suggest, this model replicates the human brain's neural architecture by simulating the human brain's functions [36]. In a human's brain, their brain neurons will respond to the inputs from other brain neurons and transport the outputs through other neurons [37]. In ANN, nodes are used to represent the brain's neurons and these nodes are connected to each other in layers of processing. ANN comprises of interconnected input, hidden, and output node layers. The input layer, which consists independent variables are processed in the hidden layer(s) before finally transferred to the output layer, represented in the form of dependent variable(s).

The ANN equation is formulated as follows:

$$X_j = \sum W_{ij} Y_i \tag{1}$$

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 artificial neuron *i* to artificial neuron *j*, and *n* is the number of input signals to artificial neuron *i*.

The output from artificial neuron *j* is a function of the transfer function as follows:

$$O_j = f(X_j) \tag{2}$$

where O_j is the output signal from artificial neuron *j* and $f(X_j)$ is the transfer function of artificial neuron *j*.

3.2. Key Strengths of Artificial Neural Network Model (ANN)

There are a number of strengths relating to the use of ANN model. The most notable strength of ANN model is the ability to consider linear and non-linear relationships of dependent and independent variables. The self-learning ability of ANN permits incomprehensible data analysis, discovering relationships among data, and forecasting of future trends [38].

Due to these advantages, ANN was used for various purposes including estimation, forecasting, and classification across diverse fields including computer science, economics, engineering, genetics, linguistics, and psychology.

3.3. Real Estate Applications of Artificial Neural Network Model (ANN)

The real estate applications of ANN began in the 1990s. These house pricing studies have shown superior forecasting performance for ANN compared to the traditional method (Ordinary Least Squares or OLS). Besides house price forecasting, there is a recent growing interest for forecasting housing demand using ANN.

Previous studies including [9][10][11][12][13][14] have applied the ANN model to forecast the demand for housing in various location. These studies demonstrated excellent forecasting performance by ANN model. [10] employed the ANN method alongside Autoregressive Integrated Moving Average (ARIMA) method to forecast the low cost housing demand in Malaysian urban areas. The study observed superior forecasting performance for ANN model. [11] and [13] analysed the Johor Bahru low cost housing demand over four years period through ANN model. The results indicate good predictive performance with a MAPE of only 16.44%. In the same year, [12] observed excellent forecasting performance for another urban location based in Johor, which is Batu Pahat. The model produces no excess in MAPE value (0%) implying a hundred percent forecasting accuracy of the ANN model. In another study in Pahang and using the same method, [14] discovered a good predictive performance for ANN model with 2.63% of MAPE value between actual data and forecasted data. In contrast to previous studies, [9] attempted to enhance the ANN model by establishing a new algorithm and tested the model's predictive accuracy in forecasting the demand for Johor low cost housing. The new method shows good prediction performance with a 6.62% of MAPE value.

3.4. Integration of Artificial Neural Network Model (ANN) and Geographic Information System (GIS)

Advances in technology particularly GIS facilitates decision-making, improves understanding and enhances strategic planning through integrated information and visualisation. In real estate, GIS is used for various reasons including site selection and land suitability analysis. Locational data such as demographics and aerial photographs analysed through GIS facilitates ideal locations for real estate development. As a result, the success of a location can be optimised and the opening of suboptimal locations can be avoided [39]. Any type of analysis models can be enhanced with the integration of geographic information system [40]. [41] emphasised that locational issues are best addressed with the integration of GIS and formal locational analysis. [42] supports this notion arguing that a GIS analysis without considering formal locational analysis would create a "black box" and is detrimental rather than beneficial.

In the past years, many researchers have adopted GIS and ANN in their studies. For instance, [40] integrates ANN with GIS to produce an automated property valuation system. A total of 591 house transactions in Albacete, Spain was used to estimate prices through ANN. A study based in Indonesia conducted by [43] demonstrated the effectiveness of ANN and GIS to assess the suitability of land for wetland rice. Meanwhile [44] improved methods for geospatial site selection to identify new and suitable landfill sites in Perak by using ANN as decision rules. The study demonstrated excellent results through high modeling accuracy and reduced cost. Thus, this paper proposes the utilisation of GIS alongwith ANN to ensure high accuracy in selecting potential sites for affordable housing.

4. The Proposed Framework for Affordable Housing Demand Estimation and Site Selection

4.1. Phase 1: Input criteria

The proposed framework for site selection consists of four stages; namely the input criteria, data processing and establishing ANN dataset, ANN modelling and evaluation and spatial visualisation (Figure 1). Stage 1 ascertains the demand factors or criterias for affordable housing. Significant macro demand factors identified based on the literature is taken as a basis in data collection for each local area. These data include a ten-year monthly data series on the local birth rate, GDP rate, housing stock, income rate, inflation rate, mortality baby rate, population growth, poverty rate, and unemployment rate and applications for affordable housing. Statistical data (census publications) are collected from the Department of Statistics Malaysia and local authorities while number of applications for affordable housing is collected from the Ministry of Urban Wellbeing, Housing, and Local Government.

4.2. Phase 2: Data processing and establishing ANN dataset
Upon completion of data collection, the data is prepared by going through processes of data cleansing, data quantification and data format conversion in stage 2. This study applies the feed forward structure with one hidden layer and back propagation algorithm to minimize forecasting errors in the training set by adjusting the weight and thresholds of the network.

4.3. Phase 3: ANN modelling
The dataset is divided into three sets for training, testing, and validation purposes. The dependent variable or the output layer (numbers of qualified affordable housing applications) is regressed against the input layer or independent variables (birth rate, GDP rate, housing stock, income rate, inflation rate, mortality baby rate, population growth, poverty rate, and unemployment rate).

A series of trials and errors are performed to ascertain the learning and momentum rates. The number of hidden neurons are identified randomly by increasing the numbers of hidden neurons after each training and testing process. The variance between given and predicted outputs are observed through minimum average error. The error is minimised when the value decreases. This simulation is performed for up to 30,000 cycles of test sets. The result of this process will suggest the best neural network to forecast demand.

4.4. Phase 4: Model evaluation and spatial visualisation
At the fourth stage, the ANN model results are evaluated through statistical tests such as Root Mean Squared Error (RMSE), Mean Absolute Deviation Error (MAD), and Mean Absolute Percentage Error (MAPE). Low values of RMSE, MAD, and MAPE signifies good forecasting performance. In addition, coefficients of each independent variable derived from the model will also be examined if they reflect the current market situation. Affordable housing demand are estimated based on local urban locations within a district using coefficients derived from the model. Finally, housing demands for a district and local urban locations are visualised through GIS to illustrate the existing and future demand for affordable houses.

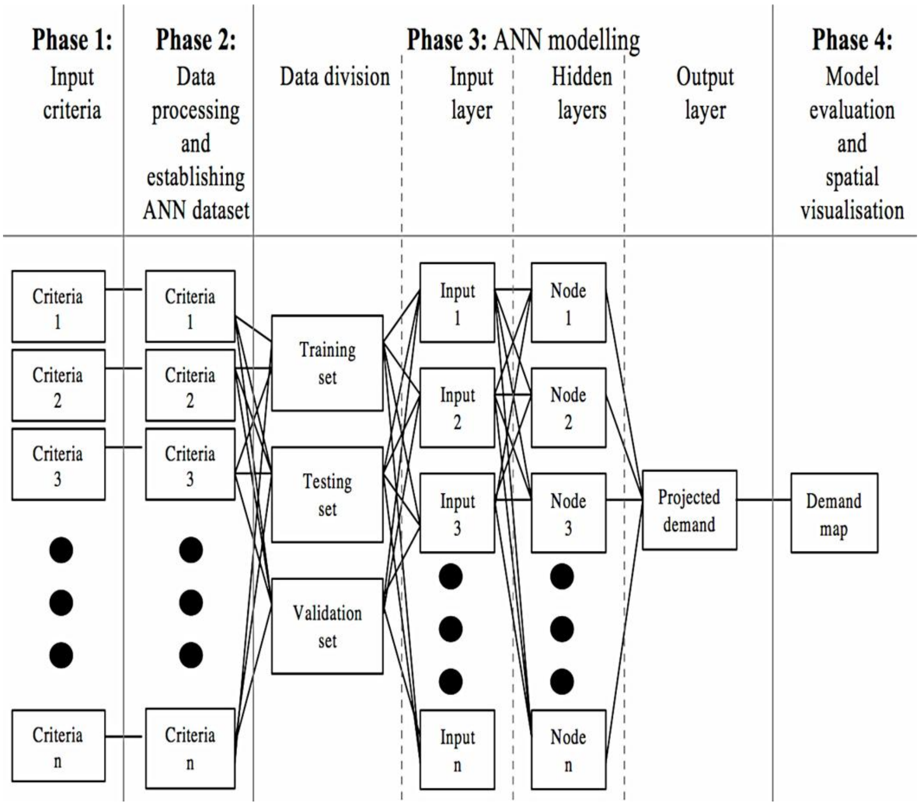

Figure 1. An integrated framework of ANN and GIS for affordable housing demand projection and site selection

5. Conclusion

Under the [45], the government of Malaysia is dedicated to provide Malaysians, particularly the low income group sufficient and good quality affordable housing. An estimated total of 653,000 affordable housing units are targeted to be built within the year 2016-2020 time frame [45]. These houses will be allocated under *Program Bantuan Rumah (PBR), Perumahan Penjawat Awam 1Malaysia (PPA1M), Program Perumahan Rakyat (PPR), Perumahan Rakyat 1Malaysia (PRIMA), Rumah Mesra Rakyat 1Malaysia (RMR1M),* and *Rumah Wilayah Persekutuan (RUMAWIP)* programs. This shows the Malaysian government commitments with the [46], which calls for adequate, shelter for all. Therefore, the proposed framework will provide support to the government in attaining the national agenda, which is to provide sufficient, affordable homes especially to the low-income groups.

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