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SALES RATE FORECASTING OF SINGLE-DETACHED HOUSES USING ARTIFICIAL NEURAL NETWORK TECHNIQUE

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Abstract: *Although the predicted number of sold units per month is one of the most necessary information to study the feasibility of detached-housing estate projects, traditional forecasting methods are limited. The research objective was to apply the Artificial Neural Network (ANN) technique to develop a sales rate forecasting model by compiling factors from an appropriate literature review. Then, 100 housing project data were collected from market research reports and the projects' websites and analyzed using the ANN technique. The results showed the ANN network with 16 input nodes from 10 factors: Selling price, Number of bathrooms, Number of bedrooms, Distance from the main road, Distance from the bus stop, Distance from the expressway, Distance from the metro station, Distance from the gas station, Distance from the shopping mall, and Project location zone. The acquired model had a Root Mean Square Error (RMSE) of ±6.296, and the slope and R2 values of the linear regression analysis between the forecasted rate and the actual rate were 0.620 and 0.571, respectively. The findings guide real estate developers and academia on the factors affecting the sales rate and provide a decision support model for investment and design of projects and confirm the potential of ANN in solving the problem with limited numbers of data.*

Keywords: *Prediction model; absorption rate; housing project; single-detached house; Artificial Neural Network*

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1. Introduction

Habitat is essential to human life and the human factor in life. Housing has been developed and continues to grow, with easy home loan rates affecting more housing developments to proliferate (Real Estate Information Center [REIC], 2018). During the Corona Virus Pandemic in the year 2020 – 2021, the type of housing project majorly developed by real estate developers was a single-detached housing project. It is because investors and foreign buyers, the main customers of condominium projects that used to be the most popular pre-crisis, were affected by the country's shutdown and the economic crisis (Real Estate Information Center [REIC], 2020). In the housing estate business, property developers have to accurately forecast the rate of sale (average number of units sold per month) for feasibility analysis, investment planning, and efficient management of sales and construction (Tochaiwat, 2020). Therefore, the expected sale rate of launching projects is one of the most critical information for the developers. However, while housing estate projects have high investments and highly competitive natures, an entrepreneur's sales forecast is mainly based on the expert's knowledge and experience. The number of specialists is limited because of the long experience-accumulation time (Nuntanach, 2021). Several researchers tried to create decision-support models for solving this problem. For example, Rico-Juan & De La Paz (2021) and Afonso et al. (2019) performed research works that presented the analysis of the housing market situation and forecasted the selling price of houses in housing projects using the Artificial Neural Network (ANN) and Random Forest. Temür et al. (2019) developed a model using the HYBRID Model that can predict home sales in Turkey. However, when the researcher reviewed relevant literature, no research used a model to predict the selling rate of an individual housing project. The researchers believe this is because the project's sales rate information is complicated to gather and treated as competitive-advantage information by regular real estate companies. This issue makes data collection complex and costly (Agency for Real Estate Affair, 2021).

For this reason, this research aimed to develop a high-potential model to determine the sales rates of the launching housing estate projects. The model's input data shall be the data the real estate developers have or can acquire from secondary sources such as a navigator website. There were two scopes of the content of this research. Firstly, Thailand's Land Subdivision Act B.E.2543 (A.D.2000) requires that housing projects with ten or more land plots be developed as housing estate projects (Kamolsuksatit, 2020). This research was scoped only to the housing estate projects in the developed model that can be fully utilized. Secondly, this research focused on the micro-scaled factors, e.g., project location, project facilities, and house features, because they affect each project (of a developer company and its competitors of the same market segment), so the developers must decide on the factors deliberately. For macro-scaled factors equally affect all projects (Ghumare et al., 2019).

The literature review revealed that the ANN is a potential tool for analyzing complex and multicriteria decision-making problems (Abiodun et al., 2018). For example, Temür et al. (2019) and Laszlo & Ghous (2020) stated that the ANN is a high-potential and highly accurate model. Nghiep & Al (2001) revealed that the ANN performed better than the Multiple Regression Analysis when using medium to large sample sizes. For these reasons, the researchers, therefore, chose this technique to develop a model for forecasting the sales rate of the housing estate project. Real estate developers can use input data and sales rates from the model to analyze project feasibility and formulate a prediction model of project sales rate that increases the competitiveness and success of the business more effectively.

2. Review of Relevant Literature

2.1 Factors Affecting the Sales Rate of Housing Estate Projects

The housing development process consists of a variety of specific factors which vary according to local conditions (Henilane, 2016). These factors attract customers to buy houses in a project, leading to the sales rate of the project. Therefore, the factors affecting the sales rate of housing estate projects are the project features that affect customers' buying decisions (Gibler & Nelson, 2003). The literature review reveals several studies that show different factors affecting the customer's home-buying decision (Opoku & Abdul-Muhmin, 2010; Tochaiwat, K. et al., 2018) in categorizing the factors affecting the sales rate of a housing estate project. It found that the factors collected from several studies can be categorized into four groups, i.e., project feature, house feature, project location, and location zone, as shown in Table 1.

Table 1. Factors that affect the sales rate of housing estate projects from works of literature

Literature	Project Feature	House Feature	Project Location	Location Zone
Tochaiwat (2020)	✓	✓	✓	✓
Opoku & Abdul-Muhmin (2010)	✓	✓		
Koklic & Vida, (2006)	✓	✓	✓	✓
Elsinga & Hoekstra (2005)		✓		
Hsu et al., (2012)	✓	✓	✓	✓
Wang, (2013)	✓	✓	✓	✓
Zeng, (2013)	✓	✓	✓	
Maoludvo & Apriamingsih, (2015)	✓		✓	✓
Chia et al., (2016)		✓	✓	✓
Aryani & Tu (2017)	✓	✓		
Khan et al., (2017)		✓	✓	✓
Kumar & Khandelwal, (2018)	✓		✓	
Mang et al., (2018)			✓	✓
Sbakhi et al., (2018)	✓	✓	✓	✓
Suttiwongpan et al., (2019)	✓		✓	✓
Ismail & Shaari, (2020)		✓	✓	✓

2.1.1 Project Features

These are the features describing the project information. The common area is one of the project's highlights and is often used as a critical selling point (Ariyawansa, 2010). Literature shows that a good common area's properties should be responsive to residents' use (Rinchumphu et al., 2013). The quality of the common areas affects the house price (Wen et al., 2019). These areas usually consist of swimming pools, fitness, car parks, sidewalks, and garden areas within the project (A.L.M. Media Properties, 2014; Wattanachai et al., 2021). In addition, Suttiwongpan et al. (2019) surveyed the effects of the decision to buy houses of the elements of common areas such as sidewalks, roads, universal design elements, and waste management systems. These factors mainly influence the satisfaction of buying a house and the sales rate of the project (Salisu et al., 2019). The common areas can also include utilities within the project that support the quality of life and facilitate and promote the well-being of residents (Land & Houses, 2016). In addition, Wang (2013) and Aryani & Tu (2017) found that project facilities are an excellent contributing factor in purchasing a house in a housing estate project. Pultawee & Tochaiwat (2022) categorized subdivision project facilities into five categories by the customer's willingness to pay aspects: (1) facilities with utility value, (2) facilities supporting quality of life, (3) facilities showing identification, (4) facilities supporting relationship and (5) facilities supporting work.

2.1.2 House Features

The house features reflect the needs of the consumers. It is the fundamental factor that stimulates purchasing decisions and affects the selling rate of housing estate projects (Tochaiwat, 2020; Sbakhi et al., 2018). Therefore, project developers must address and respond to the fundamental needs of their customers (Quester et al., 2007). A house has several features, including its type, size, design, and functionality. The literature review found that the design, interior decoration, and the outside view influence home buyers' purchasing decisions (Kumar & Khandelwal, 2018). The well-designed house features, especially the function of the house, can enhance higher purchasing demand and stimulate decision-making, leading to a higher sales rate for the project (Elsinga & Hoekstra, 2005; Nahmens & Ikuma, 2009). Therefore, entrepreneurs need to study suitable houses' features and styles to increase their projects' sales rate (Nasar & Elmer, 2016). According to Chia et al. (2016), the design of a house is the essential factor affecting residents' purchasing decisions. However, buyers always pay attention to the house's good environment within the project when buying one. In addition to the design, entrepreneurs should consider the house features compatible with the surrounding environment (Hsu et al., 2012).

2.1.3 Project Location and Area

The literature review found that project location is one of the most critical factors affecting the project's sales rate (Li et al., 2020). On the other hand, poor location will negatively affect project performance (Mang et al., 2018). Koklic & Vida (2006) and Maoludvo & Apriamingsih (2015) discussed the Distance between the project, the landmark, and the selling price. Moreover, Maoludvo & Apriamingsih (2015) revealed that location affects the type of project. In addition, Khan et al. (2017) and Ismail & Shaari (2020) reported that the younger generations value location and neighborhood as the most influential factors in choosing their future houses. It is consistent with the research by Rahman et al. (2019), which found that project location is the essential factor for the residents' home-buying decision, directly affecting the sales rate. Property developers, therefore, also need to pay attention to the demographic characteristics of the residents of each location in the project design process (Zeng, 2013).

Mostly, it was found that the impact of location on a residence depends on the Distance to the workplaces or essential places, such as shopping malls, public transport stations, and public utilities (Suttiwongpan et al., 2019). In this research, the researchers determined the characteristics of the location by using two groups of factors as follows: (1) the project location group, which consists of distances from essential places to the project, and (2) the location zone where the project is located, consisting of 10 zones in Bangkok and its vicinity, namely (1) Northern Bangkok, (2) Inner Bangkok, (3) Eastern Bangkok, (4) Thon Buri, (5) Bangkok Central Business District (CBD), (6) Nakhon Pathom, (7) Nonthaburi, (8) Pathum Thani, (9) Samut Prakan and (10) Samut Sakhon (Real Estate Information Center, 2022).

In summary, the results of the literature review revealed that there are four groups of factors that have effects on the sales rate of housing projects found in literature reviews: (1) house features, (2) project features, (3) project location, and (4) location zones. The researchers will bring these groups of factors for further study.

2.2 Artificial Neural Network Model

Artificial Neural Network (ANN) is one of the most well-known artificial intelligence models for its high accuracy. The analytical mechanism was obtained by simulating the processes of the human brain. The ANN learns from the essential information and uses these experiences to predict the future (Matel et al., 2022). The ANN model consists of three layers: the input layer, the hidden layer, and the output layer, through the connecting process. The relationship between the input and output layers is used to find the relationship between the two nodes and determine the binding weight. The hidden layer will pass the data on to another hidden layer. Then another hidden layer calculates the result based on the weighted value, and those computed results are delivered to the output layer by showing the model results (Panyafong et al., 2020; Geetha & Nasira, 2014).

From the literature review, the ANN technique is used in many areas of the real estate business, particularly for sales price forecasts (Afonso et al., 2019; Laszlo & Ghous, 2020; Rahman et al., 2019; Lim et al., 2016). Additionally, Rahman et al. (2019) discussed the problems of nonlinearity, consistency, and inequality of the Hedonic and the ANN models. The result suggests that the ANN model is to be used. Afonso et al. (2019) compared the ANN and Random Forest models' performances in predicting New Zealand house prices and revealed that the ANN model had a higher prediction performance. Similarly, Lim et al. (2016) found that the ANN model had higher predictive performance than the Autoregressive Integrated Moving Average (ARIMA) model in predicting condominium prices in Singapore. Laszlo & Ghous (2020) also developed an ANN price forecast model for Hong Kong real estate and revealed its ability to effectively learn, summarize and combine the time series.

For other uses of the ANN model in the housing business, Nghiep & Al (2001) and Morano et al. (2015) used the ANN model in home valuations. In contrast, Zainun et al. (2010) and Rico-Juan & De La Paz (2021) used the ANN model to predict the market demand for a housing estate. Nghiep & Al (2001) compared an ANN model and a Multiple Regression Analysis (M.R.A.) models and found that the ANN model was better at predicting the housing values for medium to large numbers of data. At the same time, Morano et al. (2015) concluded that the ANN is also suitable for predicting property values in Italy even with limited data. This issue aligns with Zainun et al. (2010), who forecast the demand for affordable homes in Malaysia using the ANN model. In addition, Rico-Juan & De La Paz (2021) also presented the development of the financial ANN model to support real estate investors and home developers in making decisions.

However, the literature review revealed that no work had used the ANN to predict the sales rate of housing estate projects. This model will be helpful for developers of housing projects to decide on a new project launch and determine the project style to achieve the desired sales rate.

3. Research Methodology

The ANN model development process needs to consider critical factors to be used as inputs to the forecast model. The list of input variables was recruited from the proper literature review process, then the resulting list of factors was further used as the model's inputs in the following step. It should be noted that the list of the location zones used in this study was from Thailand's Real Estate Information Center (2022)

Then, the 100 sets of data are collected on the factors affecting the sales rate of single-detached houses in the housing project according to the list. The data on these factors were collected from real estate market survey reports published by the Agency for Real Estate Affair (2021), Pornchokchai (2019), Nastasi & Schensul (2005), Agency for Real Estate Affair (2011), Agency for Real Estate Affair (2014), Agency for Real Estate Affair (2017). The data were reviewed, and some missing information was gathered from the real estate project's website. The data obtained was inputted into RapidMiner, recommended by Laszlo & Ghous (2020) for high accuracy and processing time. It was used in several studies, such as Geetha & Nasira (2014), Çelik & Basarir (2017) and Dechkamfoo et al. (2022), to develop an artificial neural network for forecasting landslide risk. The data were divided into two groups: 90 data for model development, and ten were randomized to validate the models obtained by systematically sampling for model testing. The network is initiated according to the simple rules Ranjan et al. (2019) recommended and then modified to find the least RMSE. Furthermore, the obtained models were tested with separate data for model testing.

4. Research Results and Discussion

4.1 Results Factors Affecting the Sales Rate of a Single-detached House in Housing Projects

The list of 27 factors consists of eight project feature factors, nine house feature factors, and ten project location factors. Because the zone of the project location also affects the project performance (Rahman et al., 2019; Real Estate Information Center , 2022) the factor of the location zone acquired from the literature review was then added to the list, as shown in Table 2.

4.2 Artificial Neural Network model

After the trial-and-error processing of 120 cycles using the RapidMiner program, the researchers obtained the model, as shown in Figure 1.

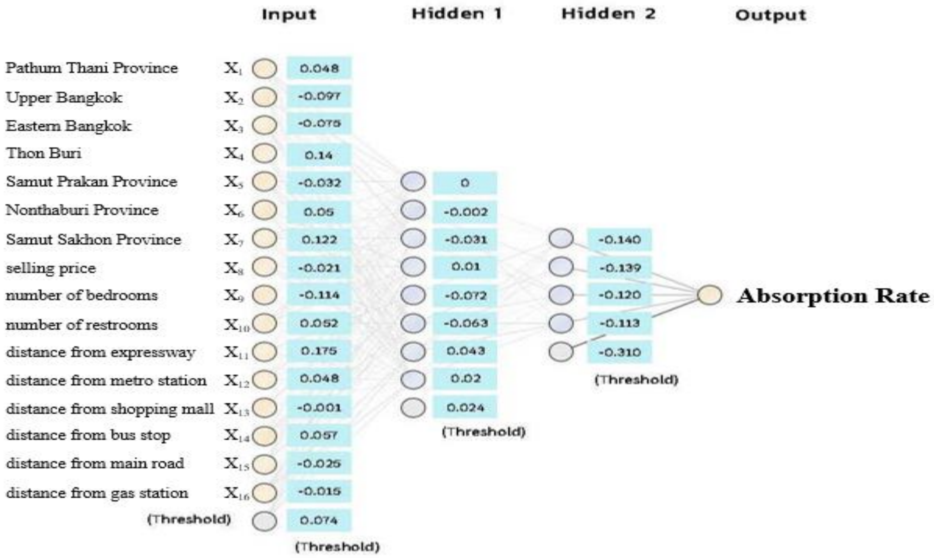

Figure 1. The ANN model for the prediction of the sales rate of a single-detached house project

The ANN model in Figure 1 has 16 input nodes (X_1 to X_{16}), derived from 10 factors: namely, Pathum Thani Province (X_1), Upper Bangkok (X_2), Eastern Bangkok (X_3), Thon Buri (X_4), Samut Prakan Province (X_5), Nonthaburi Province (X_6), Samut Sakhon Province (X_7), selling price (X_8), number of bedrooms (X_9), number of restrooms (X_{10}), Distance from the expressway (X_{11}), Distance from metro station (X_{12}), Distance from a shopping mall (X_{13}), Distance from the bus stop (X_{14}), Distance from the main road (X_{15}) and Distance from the gas station (X_{16}). The model's output node is the project's sales rate. It shows all the factors that become the model's input nodes, as shown in Table 2.

Table 2. List of factor groups, factors, and input node factors of the model

Factor	Group of Factors	Input Node of ANN	Remark
1. Price	House feature	-	Nominal
2. Entrepreneur	House feature	Selling price (X_8)	Scale
3. Number of bedrooms	House feature	-	Ordinal
4. Number of bathrooms	House feature	Number of bedrooms (X_9)	Ordinal
5. Number of parking	House feature	Number of bathrooms (X_{10})	Ordinal
6. House area	House feature	-	Ordinal
7. Land plot area	House feature	-	Scale
8. Land price	House feature	-	Scale
9. Number of houses	Project feature	-	Scale
10. Swimming pool	Project feature	-	Scale
11. Fitness	Project feature	-	Dummy
12. Clubhouse	Project feature	-	Dummy

Factor	Group of Factors	Input Node of ANN	Remark
13. Security	Project feature	-	Dummy
14. Meeting room	Project feature	-	Dummy
15. Working area	Project feature	-	Dummy
16. Yoga area	Project feature	-	Dummy
17. Location zone	Location zone	Located in Pathum Thani Province (X_1), Located in North Bangkok (X_2), Located in Eastern Bangkok (X_3), Located in Thonburi (X_4), Located in Samut Prakarn (X_5), Located in Nonthaburi (X_6), Located in Samut Sakorn (X_7)	Nominal
18. Distance from the expressway	Project location	Distance from the expressway (X_{11})	Scale
19. Distance from the train station	Project location	Distance from the expressway (X_{12})	Scale
20. Distance from shopping mall	Project location	Distance from a shopping mall (X_{13})	Scale
21. Distance from park	Project location	-	Scale
22. Distance from the bus stop	Project location	Distance from the bus stop (X_{14})	Scale
23. Distance from market	Project location	-	Scale
24. Distance from a hospital	Project location	-	Scale
25. Distance from the main road	Project location	Distance from the main road (X_{15})	Scale
26. Distance from the temple	Project location	-	Scale
27. Distance from the gas station	Project location	Distance from the gas station (X_{16})	Scale

4.2 Artificial Neural Network Model

The ANN model was obtained with an RMSE of ±6.296, which was lower than the RMSE of the Multiple Regression Analysis model (RMSE of 6.875). It was concluded that the result of the ANN model was more accurate than that of the M.R.A. model. The ratio of error and the mean was 6.296 / 13.687 = 46.00%, which was considered sufficient for the analysis in the project feasibility stage (Project Management Institute, 2017). In addition, when the researchers used the test data to determine the relationship between the sales rate values obtained from the ANN forecasting model and the actual sales rate, it was found that the two values were linearly correlated. The Beta (β) and R^2 values are 0.620 and 0.571, respectively, showing the model's acceptable forecasting capability (Roldán & Sánchez-Franco, 2012; Figueiredo Filho et al., 2011;).

5. Discussion of Research Results

The input layer of the derived ANN model shows ten factors significantly affect the sales rate, ranked by their weights in descending order: (1) Project location zone (X_1-X_7), (2) Selling price (X_8), (3) Number of bedrooms (X_9), (4) Number of restrooms (X_{10}), (5) Distance from the expressway (X_{11}), (6) Distance from metro station (X_{12}), (7) Distance from a shopping mall (X_{13}), (8) Distance from the bus stop (X_{14}), (9) Distance from the main road (X_{15}), and (10) Distance from the gas station (X_{16}), respectively. These factors are from the literature about the house features, the project features, the project location, and the project location zone that affect the sales rate of the project. From the analysis, the factors affecting the sales rate of housing estate projects depend mainly on the house features and the location of the projects, which are also considered by buyers when they look for houses. Considering the RMSE values and the model validation results with the data testing set, the ANN model effectively forecasted sales rates during the project feasibility analysis. This point is consistent with Rico-Juan & De La Paz (2021), Afonso et al. (2019), Nghiep & Al (2001), and Zainun et al. (2010), who asserted that the ANN could be an effective analysis technique. However, the number of data is limited. These findings are consistent with Morano et al. (2015) but different from Nghiep & Al (2001), which confirms that the ANN remains an attractive option even with limited data. However, the model's accuracy is not yet very high due to the limited data available. It is challenging to collect the selling rate of a housing project, as this information can help compete for projects in formulating marketing strategies.

6. Conclusion and Suggestions

From the model construction using the ANN, it was found that there were ten variables affecting the sales rate from this research, with details sorted by weight of factors as follows: (1) Location zone, (2) Selling price, (3) Number of bedrooms, (4) Number of restrooms, (5) Distance from the expressway, (6) Distance from the metro mall, (7) Distance from the shopping mall, (8) Distance from the bus stop, (9) Distance from the main road and (10) Distance from the gas station. The findings were consistent with the literature review, stating that the house features, the project location, and the location zone affect the potential sales rate. The analysis also found that most of the factors affecting the sales rate of housing estate projects are due to the project location and the house features. In making the decision, the buyers will take various factors into account and consider them together. The model obtained from the research is accurate enough to be used in the project feasibility study and to determine the project's style and model to achieve the sales rate required by the real estate developers.

The results demonstrated the potential of the ANN model to forecast average monthly sales rates for single-detached housing projects, although the amount of data collected is small. The researchers also have specific recommendations for those involved in applying the results as follows:

1) For real estate developers and people involved in project development and management:

The acquired model helps predict the sales rate of a housing estate project. It is an effective tool in performing project design and feasibility study of a housing estate project using the data available to the project developers, such as the project information, the house feature, and project location (zone of location and distances to the essential places). For an ongoing project, developers can also use the model to simulate the sales rate if one or more features change, such as launching a new type of house, adding or changing project facilities, or changes in surrounding projects. It can solve the existing problem where the sales rate is difficult to be predicted because it depends on the experience of the experts, which is rare and sometimes questionable because of the unique nature of real estate projects. For the mentioned reasons, large-scale real estate companies with many projects should develop their own ANN models, like the advice of 5. Rico-Juan & De La Paz (2021) uses this research methodology as an example.

The factors and categories derived from this research should be considered as guidelines in the project design and the development process, especially the land acquisition, the project design, the budgeting, the marketing, and sales, to encourage homebuyers to buy a house in the project.

2) For academics and researchers:

This research confirmed the potential of applying ANN to decision-making with limited data, like Morano et al. (2015) and Zainun et al. (2010). It also showed a list of factors that affect the sales rate of a housing estate project, which the interested academia can use for further study.

As to the research limitation, this research has limited data. It is because data on housing project sales rates are challenging to collect. Therefore, research requiring such information should have a well-planned data collection process. Interested researchers may develop similar models with more significant sample numbers, which will be more accurate, as proposed by Nghiep & Al (2001). In addition, interested parties may apply the methodology of this research to other types of real estate projects, such as condominiums, industrial estates, or hotels (predicted occupancy rate). This technique presents the factors influencing the success of the project and obtains models that enable more efficient decision-making. Finally, interested researchers can perform further studies by adding macro-scale factors such as inflation, interest rate, government policy, and international policy or using other approaches such as qualification or quantification (e.g., factor analysis). It can compare the results with the results of this study to better understand the factors affecting housing estate project sales rates.

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