International Journal of Civil Engineering

Construction Management

Predicting the operation and maintenance costs of condominium properties in the project planning phase: An artificial neural network approach

K.J. Tu[1,]*, Y.W. Huang[2]

Received: September 2011, Revised: December 2012, Accepted: July 2013

Abstract

The decisions made in the planning phase of a building project greatly affect its future operation and maintenance (O&M) cost. Recognizing the O&M cost of condominiums' common facilities as a critical issue for home owners, this research aims to develop an artificial neural network (ANN) O&M cost prediction model to assist developers and architects in effectively assessing the impacts of their decisions made in the planning phase of condominium projects on future O&M costs. A regression cost prediction model was also developed as a benchmark model for testing the predictive accuracy of the ANN model. Six critical building design attributes (building age, number of apartment units, number of floors, average sale price, total floor area, and common facility floor area) which are usually available in the project planning phase, were identified as the input factors to both models; and average monthly O&M cost as the output factor. 55 of the 65 existing condominium properties randomly selected were treated as the training samples whose data were used to develop the ANN and regression models; the other ten as the test samples to compare and verify the predictive performance of both models. The study results revealed that the ANN model delivers more accurate and reliable cost prediction results, with lower average absolute error around 7.2% and maximum absolute error around 16.7%, as compared with the regression model. This study shows that ANN is an effective method in predicting building O&M costs in the project planning phase.

Keywords: *Project management, Facility management, Common facilities, Cost modeling.*

1. Introduction

1.1. Background

Existing studies have shown that the operation and maintenance cost (O&M cost) of a facility is greatly influenced by the planning and design decisions made in early design phases [1, 2]. Nonetheless, in practice, most of the decisions in the project planning phase are still made without assessing and knowing their financial impacts on building O&M costs, due to a lack of O&M cost prediction methods.

Consequently, unexpected problems have occurred in the subsequent building operation phase. For example, uninformed 'common facilities' decisions in the project

planning phase of condominium properties in Taiwan haveresulted in severe operational problems (the 'common facilities' in many properties became obsolete becausetheir O&M costs are too high for their residents to afford), as revealed in a domestic study [3].

To prevent such operational problems as 'unaffordable and obsolete common facilities' from occurring, it is important to develop cost prediction models capable of effectively assessing the implications of planning and design decisions made in the project planning phase on future building O&M costs. It's essential that management take a life-cycle perspective to 'optimize value for money in the ownership of physical assets by considering all the cost factors relating to the asset during its operational life' [4].

1.2. Literature review

'Cost modeling' has been an important research topic in the building construction field, and several cost models have been developed to achieve effective 'cost management' in different areas [5]. Some cost models were developed to predict the 'construction costs' of building certain type of structures or buildings in the 'early design phase' of building projects [6, 7, 8, 9]. Also, some cost models were developed to predict the 'O&M costs' of built facilities in the 'building operation phase' [10, 11]. Only a few cost models have been developed to provide historical O&M cost estimates as 'effective design

* *Corresponding author: kjtu@mail.ntust.edu.tw*
[1] *Assistant Professor Department of Architecture, National Taiwan University of Science and Technology*
[2] *Master of Science Department of Architecture, National Taiwan University of Science and Technology*

references' in the 'planning' phase of building projects [2, 12]. In theory, the actual O&M costs of a building are determined by factors such as the 'detailed building design decisions' (material and equipment specifications) made in the detailed design phase, as well as the 'managerial' factors (how a facility management crew is organized to operate and maintain a building) and the 'behavioral' factors (how building occupants use a building) in the O&M phase. To be effective in predicting buildings' O&M costs in the project 'planning phase', the cost prediction models should be able to account for the subtle and uncertain underlying relationships between the governing 'rough planning and design decisions' in the planning phase and the 'specifications and factors' emerging in the subsequent phases (detailed design and O&M). This study identified two plausible methods, i.e. artificial neural network and regression analysis, for developing two O&M cost prediction models.

Artificial neural network (ANN) is a mathematical informational processing model that is valuable and attractive for forecasting tasks due to its distinguishing features: it is a data-driven self-adaptive method with the ability to learn from past experience; it can generalize what's learned from the data and infer the unseen part of a population accurately; it can approximate a continuous function to any desired accuracy; and it is capable of performing nonlinear modeling without a priori knowledge about the relationships between input and output variables [13, 14]. ANN has been a general modeling tool for forecasting nonlinear time series, such as stock prices [15], foreign exchange rates [16], accident severity [17], and traffic volume [18] with high accuracy. ANN has also been applied to predict various aspects of building cost in different phases of a building's life cycle [7, 8, 11].

Regression analysis is a statistical approach typically used to model the relationship between a 'response variable' and several explanatory variables, and has been widely adopted to develop various kinds of cost models in the building construction field [5, 19]. Despite its limitations in accounting for the 'uncertainty and variability' inherent in the real world in cost models [20], it's still considered a standard approach and often used to develop benchmark cost models to be compared against the cost models adopting other prediction techniques, such as neural network or case-based reasoning [9, 11].

1.3. Research objectives

The objective of this research is to develop an artificial neural network O&M cost prediction model to assist developers and architects in predicting the impacts of their common facility design decisions made in the planning phase of condominium projects on future O&M costs. Another O&M cost prediction model based on regression technique is further developed and used as a benchmark for testing and verifying the predictive accuracy of the ANN model.

This paper is organized as follows: Section 2 discusses theoretical framework of the O&M cost prediction models. Section 3 describes the research methods employed to develop both cost models. Section 4 and 5 present both the ANN and regression models developed. Section 6 reports the comparative results of predictive accuracies between both models. Section 7 concludes the paper.

2. Theoretical Framework of O&M Cost Prediction Models

2.1. Design decisions in the project planning phase

The design process of a typical condominium project in Taiwan can be roughly divided into four stages: programming, schematic design, design development, and construction documentation. In this study, the term 'planning phase' refers to the programming and schematic design stages of a building project; and the 'design decisions' made in this phase' refer broadly to the programming decisions made as well as the schematic design decisions or schemes proposed.

In the programming stage, programming decisions such as the economic goals (profit and sale prices) and the scope of the project, the types and sizes of dwelling units and common facilities, amenities and landscaping, preliminary cost structure and schedule are made. In the schematic design stage, various concepts and design schemes, including site planning, adjacencies and spatial relationships among dwelling units and common facilities, configuration of dwelling units and common facilities, building form, and cost estimate and construction schedule, are proposed and explored.

In the project planning phase, the developer and architect (key decision makers) may have to go through several 'programming-schematic design-evaluation' cycles in order to identify an optimal design scheme to be further developed in the subsequent 'design development' stage. During these cycles, an effective decision support tool or O&M cost prediction model is needed to assist them in conducting the 'evaluation' tasks, i.e. to assess the feasibility of various proposed design schemes and the financial consequences of these design decisions on future O&M costs.

2.2. Required features of O&M cost prediction models

The O&M cost prediction model to be developed should possess two features in order to be functional and effective. First of all, since the proposed concepts and design schemes are emerging or developing in project planning and the design decisions made are often 'rough' and lack detailed design information, the O&M cost prediction model should be capable of making 'accurate' O&M cost estimates based on the 'limited design information' available.

Secondly, since numerous rounds of design scheme proposals and evaluations are expected to be performed and explored within a limited timeframe in the project planning phase, the O&M cost prediction model should be capable of delivering 'responsive' and 'informative' O&M cost estimates to facilitate the design evaluation and decision-making processes involving developers and architects.

2.3. Output factor: operation and maintenance cost

In Taiwan, the cost to operate and maintain the common facilities in a condominium property usually consists of three parts: service cost (administration, security, cleaning, landscaping), energy consumption cost (water, electricity), and maintenance cost (repair and maintenance of building equipment, refurbishment of building structure). These O&M expenses are typically paid by the 'management fund' of the condominium property (management fees are collected from each household monthly in proportion to the size of its apartment unit).

In this research, the predicted 'average monthly O&M cost' of the common facilities in a condominium project is regarded as a useful indicator for the decision makers. It can be compared against its future 'monthly management funds' collected from all households, and thus allows the property developers and architects to assess the operational cost performance and the affordability of the proposed common facility design schemes from a 'management perspective'. It is identified as the output factor of the proposed cost models and is defined as follows:

Average monthly O&M cost [NTD[1]/month]: annual total building O&M cost of the common facilities in a condominium property divided by twelve.

2.4 Input factors: common facility design attributes

Literature review and expert interviews were conducted to identify appropriate input factors to the developed O&M cost prediction model. These input factors should be meaningful and relevant to the key design decisions made by the property developers and architects as well as being known or retrievable in the proposed design schemes in the project planning phase.

Chen and Chen found that older apartment buildings in Taiwan incurred higher refurbishment costs, and larger and taller buildings incurred higher O&M costs [3]. These findings suggest that building age, the number of apartment unit or total floor area, and the number of floors in a condominium property may affect its O&M cost.

Six experts experienced in planning, designing and managing condominium properties were interviewed and an open ended question 'what design decisions in the planning phase of a condominium project may affect its future O&M cost?' was asked. Content analysis on experts' responses was then conducted. Additional factors that may affect a building's O&M costs, such as the grade or class of condominiums, and the size or diversity of common facilities, were identified.

The resulting six building design attributes were identified as the potential input factors to the developed O&M cost prediction model and defined as follows:

Building age [years]: the age of the condominium building (since the year it acquired its building use permit). It is believed that the older the building, the worse its condition, the more facility problems it has, and the higher its O&M cost. In the project planning phase, a series of building ages can be input to predict the future 'life cycle O&M cost' of the common facilities in a condominium property.

Number of apartment units [unit]: the total number of apartment units in the buildings within a condominium property. It is speculated that the larger the number of apartment units and residents, the more heavily the common facilities are used and consumed, and the higher its O&M cost.

Number of floors [floor]: total number of floors (including basement floors) of the buildings within a condominium property. It is supposed that a condominium property with taller buildings is equipped with more complicated and sophisticated mechanical systems, and thus incurs higher O&M cost.

Average sale price [NTD/ping[2]]: the average of the sale prices of apartment units in a condominium property at the time of investigation. It's suggested that a condominium property with higher sale price is often furnished with a higher grade of common facilities, its residents demand a higher level of common facility service quality, and therefore it costs more to operate and maintain.

Common facility area [ping]: total floor area designated as common facilities in the buildings within a condominium property. It is assumed that a larger common facility area incurs more O&M work, and thus results in higher building O&M cost.

Total floor area [ping]: total floor area (including basement floors) of the buildings within a condominium property. It is conjectured that a condominium property with larger total floor area is more likely to accommodate more households and residents, to have larger or special common facilities (such as larger courtyard, swimming pool, or spa), and thus is more likely to incur higher building O&M cost.

3. Research Methods

3.1. Sampling and data collection

Firstly, 200 condominium properties were randomly selected from a population of 6,682 condominium properties whose condominium commissions have officially been registered by Taipei City Government and Taipei County Government. Then the administrative boards of these 200 condominium properties were contacted and 65 of them agreed to participate in this research and became the samples of this study. All 65 condominium properties are private residential properties consisting of individually owned apartment dwelling units, mostly occupied by owners with a small portion rented out to tenants.

Members of the boards of the 65 condominium properties were interviewed between August and November, 2009. Data regarding the average monthly O&M cost and the six design attributes, and the operation and management systems (how the board is organized, how the buildings and common facilities are operated and

[1] NTD = New Taiwan Dollar, 1 EUR≈ 40 NTD.

[2] 'Ping' is a conventional measure of 'area' often used in Taiwan, 1 ping ≈ 1.8m * 1.8m ≈ 3.3 m^2.

maintained, how the O&M cost is shared by residents) of individual condominium properties were collected during the interview.

3.2. Development and verification of cost models

The division of the collected data into training and test sets of appropriate sizes is a critical issue for ANN model development [14]. This research decided to allocate ten of the total samples as 'test samples' (15%), and the remaining 55 as 'training samples' (85%). Ten 'test samples' were first randomly selected from a total of 65 samples. The data set collected from the remaining 55 'training samples' were then used to develop the ANN and regression O&M cost prediction models. Finally, the data set of the ten 'test samples' were used to compare and verify the predictive accuracy of both models.

The data distributions of the output factor or dependent variable (average monthly O&M cost) and the input factors or independent variables (six design attributes) of the 55 'training samples' were inspected (Table 1). Since the variations of the data in 'Common facility area', 'Total floor area', and 'Average monthly O&M cost' were considered large, these three variables were natural log transformed before being used with the other four variables to develop the regression model.

Table 1 The data distributions of the dependent and independent variables of the 55 training samples.

	Independent Variables						Dependent variable
	Building age (year)	**Apt. unit number (unit)**	**Floor number (floor)**	**Average sale price (NTD/ping)**	**Common facility area (ping)**	**Total floor area (ping)**	**Avg. monthly O&M cost (NTD/month)**
Minimum	1	20	6	82,000	184	1,357	100,000
Maximum	18	800	33	550,000	7,155	34,431	1,969,000
Average	7.0	187.2	16.8	210,763.6	2,112.5	8,023.5	450,967.4
S.D.	4.7	173.0	6.2	108,662.1	1,976.8	6,955.1	413,465.3

4. The Artificial Neural Network (ANN) Model

The development of the ANN model involves two phases of tasks: modeling and training phases. In the modeling phase, the popular multilayer perceptrons (MLP) network architecture was adopted, and the ANN model was structured to include an input layer of six processing neurons (building design attributes) and an output layer of one processing neuron (average monthly O&M cost) as the target. The number of hidden layers between the input and output layers and the number of hidden neurons were to be determined during the subsequent training phase.

In the training phase, data on six input factors from 55 training samples were first normalized by employing the 'along channel normalization' method, and loaded into the Neuralyst v1.4 software along with the O&M cost data (output factor). The following steps were then taken to identify the parameter setting of the ANN model that resulted in minimal mean square error:

Parameter setting: A set of parameter values, such as the number of hidden layers (0, 1, or 2) and the number of neurons in hidden layers (4, or 5), the learning rate (0~1) determining the magnitude of weight changes among neurons during each training iteration, as well as the momentum (0~1) affecting convergence speed without oscillations, were assigned in the software. Transfer functions able to properly specify the relationship between the inputs and outputs of a node and a network were reviewed and selected.

Network training: For each set of parameter values assigned, the back propagation algorithm was used for neural network training, in which weights of a network are iteratively modified to minimize the overall mean or total squared error between the desired and actual output values for all output nodes over all input patterns. As a result, a 'root mean squared error (RMSE)', indicating the forecasting error of the set of parameter values was generated.

Trial and error: By repeatedly assigning different sets of parameter values, as well as performing neural network training, a best combination of learning rates, momentum, number of hidden layers, number of neurons in hidden layers, the learning rules and the momentum, as well as the transfer function that resulted in a minimal root mean squared error (RMSE) was identified.

As a result, the ANN model with a network architecture consisting of an input layer of six input neurons, a hidden layer of five neurons, and an output layer of one neuron was established (Fig. 1).

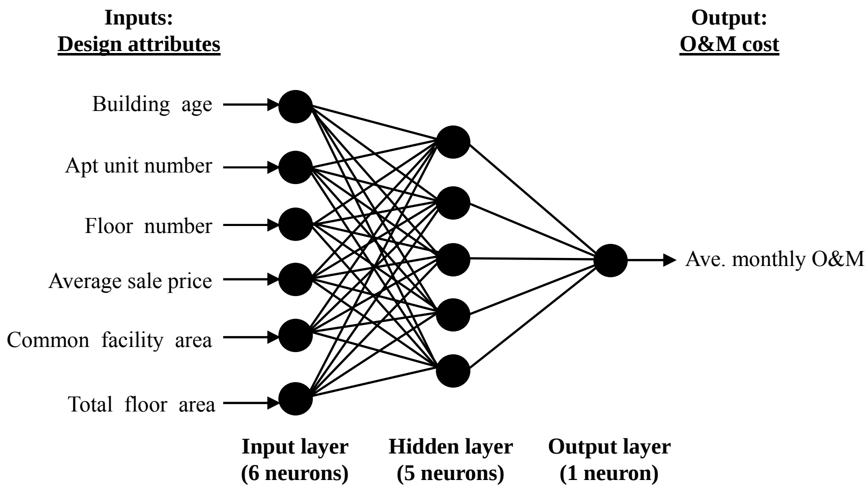


Fig. 1 The neural network architecture for predicting O&M costs of condominium properties.

The generalized delta rules and a sigmoid transfer function were adopted. When the learning rate was 1.0 and the momentum was 0.85, the root mean squared error (RMSE) was reduced to 0.031 after 2981 training epochs. The training was found adequate and stopped.

5. The Regression Model

A general regression model for predicting the O&M costs of condominium properties is first given as in equation (1):

$$Y = \beta_0 + \beta_1 \times X_1 + \beta_2 \times X_2 + \beta_3 \times X_3 + \beta_4 \times X_4 + \beta_5 \times X_5 + \beta_6 \times X_6 + \varepsilon \qquad (1)$$

where Y is the natural logarithm of the average monthly O&M cost of a certain condominium property (NTD/month); X_1 is its building age (year); X_2 is the total number of apartment units (unit); X_3 is the total number of floors (floor); X_4 is the average sale price (NTD/ping); X_5 is the natural logarithm of its common facility area (ping); X_6 is the natural logarithm of its total floor area (ping); and β_i (i = 1, 2, ..., 6) are the corresponding coefficients of the six independent variables, each indicating the degree of effect each independent variable has on the dependent variable.

To establish the Regression O&M cost prediction model, the statistical software SAS JMP IN V.3 was employed to perform statistical analyses on the data set of the 55 training samples. First of all, correlations across the six independent variables were examined to detect whether 'multi-collinearity' exists among these variables (Table 2). It was found that X_5 (common facility area) and X_6 (total floor area) are highly correlated (coefficient r = 0.87). Since 'common facilities' are the major components in condominiums that incur O&M costs, and the design information of 'common facility area' is usually available in the planning phase of a condominium project, this research decided to keep X_5, while eliminating X_6 from the regression model.

Table 2 The correlation coefficients among the six independent variables (six design attributes) of the 55 training samples.

	Building age	Apt. unit number	Floor number	Average sale price	ln (Common facility area)	ln (Total floor area)
Building age	1					
Apt. unit number	-0.04	1				
Floor number	-0.45	0.49	1			
Average sale price	-0.11	-0.38	0.04	1		
ln (Common floor area)	-0.21	0.78	0.60	-0.13	1	
ln (Total floor area)	-0.07	0.69	0.50	-0.27	**0.87**	1

Multiple regression analysis was then performed on the remaining five independent variables (X_1 ~X_5) and one dependent variable (Y). The results of the multiple regression analysis indicate that approximately 83% (R^2) of the variation in the dependent variable Y (O&M cost) can be explained by three statistically significant independent variables: X_2 (apartment unit number, β_2 = 0.0012, $p<0.01$), X_4 (average market unit price, β_4 = 0.0015, $p<0.01$) and X_5 (common facility area, β_5 = 0.5233, $p<0.001$); and the independent variables X_1 (building age) and X_3 (floor number) are not statistically significant factors (Table 3). The final regression model was formulated as equation (2):

Table 3 Results of multiple regression analysis of the O&M cost prediction model.

	Regression Model

	Y: ln (Average monthly O&M cost) [NTD / month]			
	β	SE	T-value	Prob > |t|
X_1: Building age [year]	0.0121	0.0108	1.12	0.2680
X_2: Apt. unit number [unit]	0.0012**	0.0004	2.95	0.0049
X_3: Floor number [floor]	0.0102	0.0102	0.99	0.3249
X_4: Average sale price [thousand NTD]	0.0015**	0.0005	3.21	0.0023
X_5: ln (Common facility area) [ping]	0.5233***	0.0707	7.40	<0.0001
Intercept [β_0]	8.1690***	0.4534	18.02	<0.0001
R-square [R^2]	0.83			
Notes	F-Ratio = 46.5564***; N = 55; *p<0.05; **p<0.01; ***p<0.001			

$$Y = 0.0121\times X_1 + 0.0012\times X_2 + 0.0102\times X_3 + 0.0015\times X_4 + 0.5233\times X_5 + 8.1690 \quad (2)$$

6. Model Testing Results and Applications

6.1. Predictive accuracy

The predictive accuracy of the ANN model was examined against the benchmark regression model by comparing the actual O&M costs of the ten test samples with the costs predicted by both models. Data of the six design attributes and actual O&M costs of the ten test samples are shown in Table 4.

Table 4 Data on the six building design attributes and the actual O&M costs of the ten test samples.

Test subjects	Independent variables						Dependent Variable
	Building age (year)	**Apt. unit number (unit)**	**Floor number (floors)**	**Average sale price (NTD/ping)**	**Common facility area (ping)**	**Total floor area (ping)**	**Avg. monthly O&M cost (NTD/month)**
TS-1	1	23	16	295,000	339	1,357	110,000
TS-2	3	93	14	150,000	1,492	3,746	239,500
TS-3	4	191	18	82,000	419	5,945	285,954
TS-4	2	182	15	145,000	2,548	4,675	362,782
TS-5	8	99	19	300,000	1,135	7,095	457,774
TS-6	2	210	17	110,000	2,048	7,060	502,093
TS-7	10	250	17	145,000	2,035	15,845	666,939
TS-8	7	576	14	120,000	7,155	22,358	880,000
TS-9	5	506	28	190,000	5,715	19,049	950,000
TS-10	15	410	20	120,000	6,724	24,013	1,588,171

To predict the O&M costs of the ten test samples with the 'ANN model', the data of the six design attributes were provided as the inputs to the ANN mode in Neuralyst v1.4l, and their O&M costs were generated as the outputs. To predict the O&M costs of the ten test samples with the 'regression model', the data of the five independent variables (X_1~X_5) were fed into equation (2), and their O&M costs calculated. The O&M costs predicted by both models and their deviations from the actual O&M costs (expressed in percentage of error) are tabulated in Table 5 and illustrated in Fig. 2.

Table 5 The actual O&M costs and those predicted by the ANN and the regression models.

Test samples	Actual O&M cost (NTD/month)	ANN model		Regression model	
		Predicted O&M cost (NTD/month)	**Error** %	**Predicted O&M cost** (NTD/month)	**Error** %
TS-1	110,000	102,732	-6.6%	140,884	28.1%
TS-2	239,500	226,018	-5.6%	269,265	12.4%
TS-3	285,954	238,190	-16.7%	148,410	-48.1%
TS-4	362,782	383,749	5.8%	392,378	8.2%
TS-5	457,774	511,867	11.8%	327,910	-28.4%
TS-6	502,093	438,836	-12.6%	350,624	-30.2%
TS-7	666,939	678,523	1.7%	425,185	-36.2%
TS-8	880,000	899,042	2.2%	1,089,964	23.9%
TS-9	950,000	1,027,912	8.2%	1,106,027	16.4%
TS-10	1,588,171	1,568,176	-1.3%	1,014,385	-36.1%
Avg. abs. error			7.2%		26.8%
Max. abs. error			16.7%		48.1%

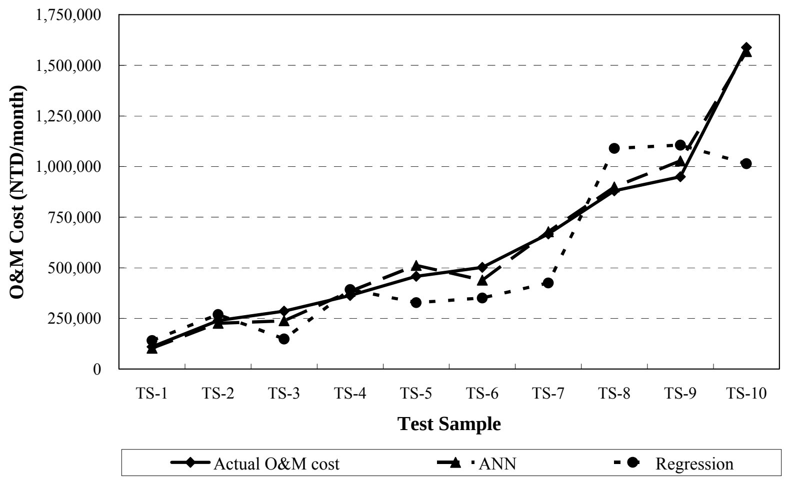


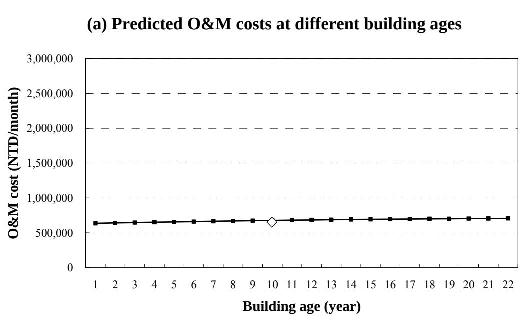
Fig. 2 The actual O&M costs and those predicted by the ANN and the regression models of the test samples.

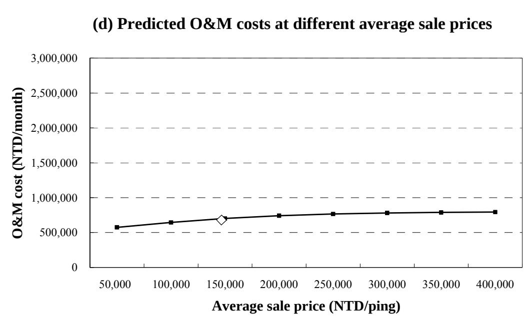
Table 5 reveals that the ANN model outperforms the regression model in predicting the O&M costs of condominium properties. The absolute errors of the O&M costs predicted by the ANN model range from 1.7 to 16.7%, with an average absolute error of 7.2%; whereas, the absolute errors of the O&M costs predicted by the regression model range from 8.2 to 48.1%, with an average absolute error of 26.8%. The O&M costs predicted by the ANN model have a lower average absolute error as well as smaller deviations from the actual costs, indicating the ANN model generates more 'accurate' cost prediction results. Besides, the ANN model also generates cost results with a smaller maximum absolute error than the regression model (16.7% vs. 48.1%). This means the degree of possible errors of the ANN model is smaller than that of the regression model, indicating the ANN model generates more 'reliable' cost prediction results. In conclusion, the ANN model is a more accurate and reliable cost prediction model as compared with the regression model.

6.2. Applications of the ANN model

TS-7 was randomly selected from the ten test samples and used as an example to illustrate how the ANN model can be applied in the project planning phase to assist the property developer and architect in assessing the O&M cost implications of their developing common facility design decisions.

Let's assume that the six building design attributes of TS-7 (six independent variables in Table 4) represent one proposed design scheme regarding its common facilities in the project planning phase. To assess the effects of one building design attribute, say 'building age', on TS-7's future O&M costs (to examine its life cycle O&M costs), a set of possible values of 'building age' were specified first. Then, each of these 'building age' values and the values of the remaining five building design attributes (kept unchanged) were fed into the ANN model. Finally, a set of corresponding O&M costs were predicted and a trend line indicating the life cycle O&M costs of TS-7 (given the five remaining design attributes) was plotted (Fig. 3-a). Likewise, the aforementioned steps were taken to examine and exhibit the effects of the other five building design attributes on O&M cost (Fig. 3-b~3-f).





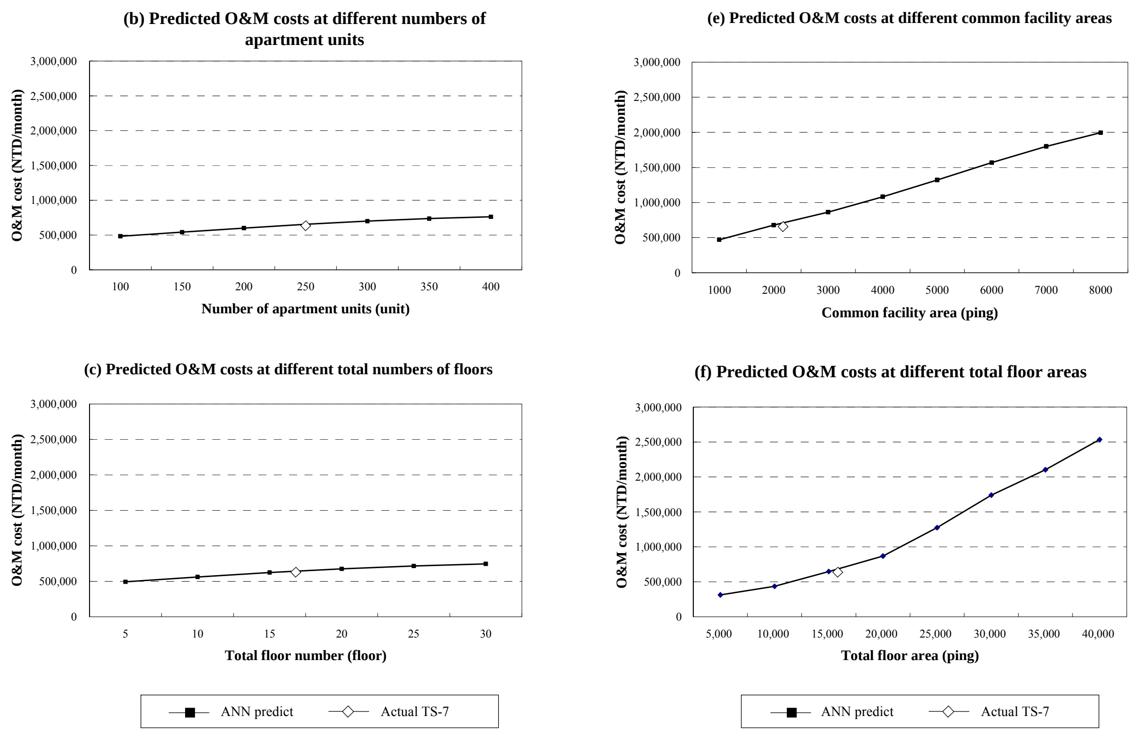


Fig. 3 The effects of each design attribute on the future O&M costs of the TS-7 project and the resulting trend line predicted by the ANN model.

The magnitude of the effects of one design attribute on its future O&M cost is revealed by the slope of its trend line. As shown in Fig. 3, TS-7's O&M cost is mainly affected by its 'common facility area' and 'total floor area' (steeper slopes), less affected by its 'apartment unit number', 'total floor number' and 'average sale price', and almost not affected by 'building age' (O&M costs remain stable throughout its building life). One can further explore different design schemes of the common facilities by changing the values of a certain design attribute (such as common facility area) to estimate the corresponding O&M costs. For example, if the 'common facility area' is enlarged from 2035 to 3000 ping (47% increase), the average monthly O&M cost is estimated to go up from 678,523 to 864,087 NTD (27% increase), as shown in Fig. 3-e. The O&M cost implication and affordability of this new proposed design attribute can then be evaluated by the property developer and architect. If necessary, other 'common facility area' values can be further proposed and researched until an optimal 'common facility area' decision is identified. Similarly, the operational feasibilities of other alternative design attributes and schemes can be assessed, and optimal common facility design decisions reached.

In addition, one can test the ANN model's ability to generalize and predict the trend of O&M costs correctly for a given design attribute by examining the relationship between the actual O&M cost of TS-7 (666,939 NTD) and its predicted trend lines shown in the corresponding plots in Fig. 3. Generally speaking, the actual O&M cost of TS-7 is relatively close to the predicted trend line in each plot, suggesting that the ANN model developed is effective in generalizing and predicting the trends of the O&M costs of condominium properties.

7. Conclusions

This research has contributed to the 'cost modeling' research field, from the project management and facility management perspectives, by developing an effective ANN cost prediction model in predicting buildings' future O&M costs in the project planning phase. With this decision support tool, it is expected that the operational feasibility or affordability of proposed design schemes can be ensured in the project planning phase, and unexpected operational problems, such as common facilities obsolescence, can be minimized.

Six design attributes (building age, number of apartment units, number of floors, average sale price, common facility area, total floor area) of a condominium project, on which information is usually available in the project planning phase, were identified as the input factors to the cost prediction models to predict future O&M costs (average monthly O&M cost). 65 existing condominium properties were first randomly selected. 55 of them were identified as the 'training samples', whose data on the six design attributes and the O&M cost were collected and used to develop the ANN and the regression models. The remaining ten were treated as the 'test samples', whose data were used to compare and verify the predictive accuracy of both models.

It's shown that the ANN model is capable of delivering more accurate and reliable cost prediction results as compared against the benchmark regression model. In particular, the ANN model generates O&M cost prediction results with a lower average absolute error (7.2%) and a lower maximum absolute error (16.7%) than the regression model. Although the testing results from this ANN model are encouraging, it's important to recognize the limitations of the ANN approach, and to further validate and improve this ANN model. A number of future research tasks are identified. First of all, it is suggested that more condominium samples, especially those with greater diversities in various design attributes, be included and data collected to train and update this ANN model, as well as to validate its cost performance from the 'cross-sect ional' perspective. Secondly, it is proposed that a group of samples be identified and their O&M cost data be recorded annually for many years to further validate the predictive accuracy of this ANN model from the 'longitudinal' perspective. Finally, it is expected that the ANN model will be developed into a functional design decision support tool with friendly user interface to facilitate the process of identifying optimal building design decisions (minimizing O&M costs and operational problems) in the project planning phase.

Acknowledgement: The author would like to thank the National Science Council, the Executive Yuan of Taiwan for sponsoring this research (Project No. NSC 91- 2211-E-011-051).

References

[1] Dell'Isola A.J, Kirk S.J. Life Cycle Costing for Facilities, Kingston, MA: Reed Construction Data, 2003.
[2] Bogenstätter U. Prediction and optimization of life-cycle costs in early design**,** Building Research and Information**,** 2000, Vol. 28, No. 5/6, pp. 376-386.
[3] Chen J.H, Chen G.L. The investigation of the appropriateness and management of common facilities in condominiums, Research Project Report, The Architectural and Building Research Institute, The Ministry of Interior, Taiwan, 1999.
[4] Woodward D.G. Life cycle costing–theory, information acquisition and application, International Journal of Project Management, 1997, Vol. 15, No. 6, pp. 335-344.
[5] Newton S. An agenda for cost modelling research, Construction Management and Economics, 1991, Vol. 9, No. 2, pp. 97-112.
[6] Chou J.S, O'Connor J.T. Internet-based preliminary highway construction cost estimating database, Automation in Construction, 2007, Vol. 17, No. 1, pp. 65-74.
[7] Günayd1n H.M, Doğan S.Z. A neural network approach for early cost estimation of structural systems of buildings, International Journal of Project Management, 2004, Vol. 22, No. 7, pp. 595-602.
[8] Hegazy T, Ayed A. Neural network model for parametric cost estimation of highway projects, Journal of Construction Engineering and Management, 1998, Vol. 124, No. 3, pp. 210-218.
[9] Kim G.H, An, S.H, Kang K.I. Comparison of construction cost estimating models based on regression analysis neural networks, and case-based reasoning, Building and Environment, 2004, Vol. 39, No. 10, pp. 1235-1242.
[10] Boussabaine A.H, Kirkham R.J. Simulation of maintenance costs in UK local authority sport centres, Construction Management and Construction, 2004, Vol, 22, No. 10, pp. 1011-1020.
[11] Christian J, Pandeya A. Cost predictions of facilities, Journal of Management in Engineering, 1997, Vol. 13, No. 1, pp. 52-61.
[12] Kirkham R.J, Boussabaine A.H, Awwad B.H. Probability distributions of facilities management costs for whole life cycle costing in acute care NHS hospital buildings, Construction Management and Economics, 2002, Vol. 20, No. 3, pp. 251-261.
[13] Taylor J.G. Neural networks and their applications, New York, John Wiley and Sons, 1996.
[14] Zhang G, Patuwo B.E, Hu M.Y. Forecasting with artificial neural networks: The state of the art, International Journal of Forecasting, 1998, Vol. 14, No. 1, pp. 35-62.
[15] Kohzadi N, Boyd M.S, Kermanshahi B, Kaastra I. A comparison of artificial neural network and time series models for forecasting commodity prices, Neurocomputing, 1996, Vol. 10, No.2, pp. 169-181.
[16] Hann T.H, Steurer H. Much ado about nothing? Exchange rate forecasting: Neural networks vs. linear models using monthly and weekly data, Neurocomputing, 1996, Vol. 10, No. 4, pp. 323-339.
[17] Rezaie Moghaddam F, Afandizadeh Sh, Ziyadi M. Prediction of accident severity using artificial neural network, International Journal of Civil Engineering, 2011, Vol. 9, No. 1, pp. 41-49.
[18] Afandizadeh Sh, Kianfar J. A hybrid neuro-genetic approach to short-term traffic volume prediction, International Journal of Civil Engineering, 2009, Vol. 7, No. 1, pp. 41-48.
[19] Lowe D.J, Emsley M.W, Harding A. Predicting construction cost using multiple regression techniques, Journal of Construction Engineering and Management, 2006, Vol, 132, No. 7, pp. 750-758.
[20] Garza J, Rouhana K. Neural network versus parametric-based application, Cost Engineering, 1995, Vol. 37, No. 2, pp. 14-18.