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리모델링 오피스 빌딩의 가격 예측 모델

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Monetary Value Prediction (MVP) model of the renovated office building

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ABSTRACT

Monetary value prediction (MVP) model of the renovated office building

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오피스 빌딩의 노후화와 환경문제로 인해, 최근 건설 산업은 빌딩의 물리적, 경제적 및 환경적 측면을 개선시키기 위해서 리노베이션 공사가 활발해지고 있다. 리노베이션 공사와 관심이 증가하는 과정에서, 리노베션을 계획하고 있는 발주자에게 가장 중요한 의사결정 요소 중 하나는 완성된 리노베이션 공사로 인해 오피스 빌딩의 금전적 가치 변화를 평가하는 것이다. 또한, 자산관리측면에서 볼 때, 리노베이션 공사로 인해 에너지 효율성, 유지관리, 보수 공사 등의 측면에서 건물의 성능이 개선되기 때문에 빌딩의 임대료 및 임대율 등과 가치가 개선될 것으로 기대된다. 이러한 장점에도 불구하고, 이러한 가치를 예측하는 관련 연구나 방법은 아직까지 거의 이루어지지 않았다. 그러므로, 본 연구는 실제로 리노베이션이 완료된 오피스 빌딩의 90개의 사례를 기반으로 인공지능 기술과 다변량 데이터 분석 기술을 사용하여 리노베이션 후의 오피스 빌딩의 금전적 가치 예측 (MVP) 모델들을 개발하였다.

한편, 빌딩의 금전적 가치는 일반적으로 부동산감정평가방법의 3방법 (원가법, 수익환원법, 거래사례비교법)에 의해 평가지만, 원가법은 주로 신축 빌딩의 가치 평가에 적용된다. 반면에, 오피스 빌딩에는 주로 수익환원법과 거래사례비교법을 적용하여 가치가 평가된다. 하지만, 기존의 감정평가방법을 적용하여 리노베이션에 따른 오피스 빌딩의 금전적 가치 변화를 평가할 수 있는 방법이나 연구가 미흡하다. 이에 본 연구에서는 오피스 빌딩의 가치 평가가 가능한 수익환원법과 거래사례비교법의 원리를 적용하여 MVP 모델을 개발되었다.

수익환원법의 원리를 적용하여 개발된 MVP 모델 I은 오피스 빌딩의 가치에 영향을 미치는 요인과 가치를 활용하여 다중회귀분석을 적용하였다. 또한, 거래사례비교법의 원리를 적용하여 개발된 MVP 모델 II는 과거 거래된 사례와 유사한 이력과 특징을 지닌 사례를 활용하여 가치를 평가할 수 있는 사례기반추론기법을 적용하였다.
본 연구에서 개발된 2개의 MVP 모델을 검증하기 위해 실제 거래가격의 데이터를 가진 16개의 사례에 적용하였고, 기존의 감정평가방법과 비교를 하였다. 그 결과 감정평가방법이 정확도 측면에서 개발된 2개의 MVP 모델보다 약간 높았다. 하지만, 요구된 정보의 양, 데이터 획득의 용이성, 시장의 반영 등 다양한 측면에서 비교하였을 때, MVP 모델 II가 프로젝트 계획단계에서 리노베이션 후의 오피스 빌딩의 가격을 쉽고 정확하게 예측하는데 가장 적합하다고 평가되었다. 또한, 개발된 모델 및 방법은 다음과 같은 기여가 기대된다. (1) 리노베이션 공사를 계획하고 있는 발주자에게 의사결정 지원한다, (2) 오피스 빌딩 리노베이션 시장을 증진에 기여할 것으로 기대된다, (3) 경제성 측면에서 리노베이션 작업에 따른 효과에 초점을 둔 미래 연구에 초석이 될 것으로 기대된다.

1. Introduction

1.1. Research background and objectives

Since the 1960's, industrialization of Korea has been rapidly developed, and many office buildings have been quickly constructed. However, owing to the gradual deterioration of office buildings and related environmental concerns, these buildings are often tried to improve their physical, economic, and environmental aspects. Generally, a building's performance can be upgraded by any of the following four methods: maintenance, rehabilitation, renovation, and reconstruction. Among the four methods, renovation is similar to rehabilitation, which focuses on extending the lifespan of a building without making changes to its original features; however, it involves making changes to the original characteristics of the building and replacing parts or entire systems to improve the building's performance (Rosenfeld and Shohet 1999). Recently, renovation work for buildings has been emphasized, as opposed to the construction of new buildings, because it can generate a profit by reducing construction time, costs, and emission of greenhouse gases (Jensen and Masleas 2015).

From the perspective of asset management, an important factor influencing the decision making of clients considering office building renovation is the economic effect incurred by the renovation (Kim et al. 2017). In other words, once the renovation-engendered economic benefit is determined in a comparison with the renovation input cost, the client tends to decide whether to proceed with the renovation work for the existing project. In addition, as building renovation can result in improving building performance in terms of energy efficiency, maintenance, and repair work, building renovation is expected to increase the lease rate of buildings significantly (Cho and Yoon 2016). Consequently, it seems natural that renovation of office buildings can improve monetary valuation. Despite the importance of the economic impact of such renovations, research and methods on the monetary value prediction (MVP) of planned office-building renovations remain insufficient.

In general, evaluation of the monetary value of a building is accomplished using three appraisal methods: the respective cost, income, and sales comparison (SC) approaches. The cost approach among these evaluates the value of property that can be determined by subtracting depreciation from the initial construction costs, and it is mainly used for economic estimation of new buildings because it has objective data and high explanatory power (Kontrimas and Verikas, 2011). On the other hand, the income approach and the SC approach are mainly used to estimate the monetary value of office buildings rather than residential buildings. The income approach is based on the premise that the value of property can be reflected by the present worth of future income, and thus, the value can be determined by discounting future cash flows generated by the property. Recently published Kim et al. (2016) revealed that the income approach enables a more accurate valuation of renovation office building (ROB) compared to other appraisal methods (i.e., the cost approach and sales comparison approach). However, despite the accuracy, owners find it infeasible to apply ICA (Income Capitalization Approach) to particular office buildings because of the difficulty in collecting data that is necessary for the implementation of the model. The SC approach evaluates the value of a building by considering cases with similar attributes and transaction histories among the traded cases in the past, and by making a correction according to the current situation. In this context, the SC approach can have strong persuasive power because the greater is the cumulative number of past trading cases, the higher is the prediction accuracy. Moreover, it is basically implemented based on historical transaction cases that were already objectively evaluated by the market. Despite these advantages, minimal research exists on the SC approach for evaluating the value of renovated office buildings. In other words, as there are few transaction cases of renovated office building (ROB), and it is not easy to acquire information, such as transaction prices owing to the private nature of the transactions in the private sector, few studies have been conducted on the application of the SC approach for monetary value evaluation of ROBs.

By collecting transaction cases of ROBs and applying the principle of appraisal methods (i.e., the income approach and SC approach) which can estimate the monetary value of office buildings, this study strives to develop models for predicting the economic effects of renovation (i.e., monetary value after renovation) based on the analysis of information from the collected cases. Accordingly, this study is expected to enable prediction of the monetary value of the post-renovation office building before the work is realized. It can thereby be used as a tool for the client considering renovation of the given office building to decide whether to proceed with the renovation.

1.2. Research framework

As described in the background study, the post-renovation office-building monetary value to clients considering renovation is one of the most important factors in the business decision-making process. Nevertheless, research on monetary value estimation of the ROBs remains insufficient. Based on this background, it is necessary to develop a method for estimating the monetary value of ROBs by applying the principle of the income and SC approach, which is expected to be the most effective in terms of value estimation of the ROBs. This study is largely composed of five steps.

- Step 1: A literature review on existing appraisal methods for estimating the price of buildings was conducted. It was then assessed whether the existing methods were applicable to develop the monetary value prediction (MVP) model of ROBs (as described in Section 2).

- Step 2: For developing the MVP model, the actual cases of office buildings that were renovated were surveyed, with a total of 90 cases collected. The MVP model was constructed using the collected cases, and three types of information were considered for renovation: the physical and locational attributes for each case, renovation scope, and transaction price (as described in Section 3).

- Step 3: Based on the data, the MVP model I, in accordance with the income approach, was developed using the multivariate data analysis (MDA) technique, which statistically analyzed the relationship between the independent variables (i.e., the variables influencing the monetary value of office buildings) and dependent variables (i.e. the transaction price of each case) (as described in Section 4).

- Step 4: As in step 3, based on the data, the MVP model II (in accordance with the SC approach) was developed by revising and applying the implementation frame of the case-based reasoning (CBR) technique, which is a known artificial intelligence technique and is theoretically similar to the SC approach (as described in Section 5).

- Step 5: Two models were developed in this study and the existing appraisal (i.e., the income approach) was verified by applying the 16 cases, and discussed in terms of seven aspects: view of accuracy, required data, accessibility of the required data, evaluation method, reflection of the market, renovation scope, and possibilities for future development (as described in Section 6).

2. Real estate appraisal of renovated office building

2.1. Existing appraisal methods

Appraisal is defined in Korea as "Deciding the economic value of land, etc., and indicating the value (price denominated in monetary units) of the result" in article 2, paragraph 7 of the law on Property Price Notification and Appraisal Estimation (hereinafter referred to as the "Property Price Disclosure Law").

The economic value of money is usually determined by considering three aspects: (i) How much of it is produced by the input cost. (Costability); (ii) How much of it is traded in the market? (Marketability); and (iii) How much profit can you receive from it? (Profitability) (Ham, 2007). Based on these three aspects, appraisal methods are largely divided into three methods, each of which is then divided into price and rent: the cost method (costability), the income method (profitability), and the sale comparison (SC) method (marketability). Because each method has different advantages and disadvantages, appropriate methods should be applied according to the nature of the object and the estimation purpose.

2.1.1. The cost approach

The cost approach, which is one of thea cost methods that follows the principles of costability, is defined to as '"A method of calculating the present value of a target object by modifying the replacement cost of a target object at the price point' point" in Article 4, paragraph 3 of the law on real estate appraisal . The basic equation is expressed as in Eq. 2.1.

$$Estimated\ price = Replacement\ cost - Depreciated\ cost \tag{2.1}$$

The cost approach estimates the value of a building with consideration of the estimated land value, depreciated building cost, and other improvements. This approach is mainly applied to the objective estimation, because the subject of the appraisers is less involved . And, itIt is a relatively logical approach due to the rational based on the ‘principle of substitution (that is, the price of a real estate is formed in relation to the price of another property or commodity that can be substituted’)’.

The cost approach is usually used for conducting appraisals of new buildings, because of their lower degree of depreciation of such buildings and the relative ease of obtaining the recent cost data. This approach can be used to estimate all types of properties, and it is the most reliable means of estimating unique properties (Kontrimas and Verikas, 2011). The approach is also appropriate for estimation of unique- purpose real estate such as public buildings, docks, airports, industrial complexes, churches, and hospitals. Since Because the transaction cases of these properties are not infrequent and are do not generate the profits, there are many cases where it is difficult to use the income approach and the SC approach. Therefore, for the unique-purpose properties, cost data is the most reliable as evidence of market value.

2.1.2. The income approach

The income approach, which is one of the income methods that follows the principles of profitability, is defined to as '“A method of calculating the estimation price at the price point by returning the net income expected to be generated in the future to capitalization rate’ rate” in Article 4, paragraph 6 of the law on real estate appraisal . In With the income approach, the property value can be defined asis defined in Eq. 2.2, and the net operating income (NOI) in Eq. 2.1 can be estimated as inis estimated as in Eq. 2.3 (Oregon 2012).

$$Value\ of\ property = \frac{Net\ operating\ income\ (NOI)}{Capitalization\ rate} \tag{2.2}$$

$$NOI = Potential\ gross\ income - Loss\ for\ vacancy - Operating\ expenses \tag{2.3}$$

The income approach estimates the value by converting it to the present point, based on the net income expected to occur in the future. Because the price is determined by the profit of the substitute real estate, it is theoretically based on the principle of prediction and principle of substitution. According to the income approach, the more real estate that generates income, the higher the value; the less real estate that doesn't generate income, the smaller the value (Lim, 2016).

The advantage of the income method is that it is more rational than other methods. Assuming that the value of real estate is the value of the expected future benefit when converted to the present value, it is the most appropriate method to define the value of real estate. Investors are more interested in generating future benefits rather than the input cost of past real estate or market prices. Therefore, the income method is the most convincing method. In addition, the income method can be applied in various fields, including feasibility analysis of development projects, cost benefit analysis, investment consultation, enterprise management, asset status diagnosis, and site selection (An, 1988).

The income approach is suitable for predominantly profitable real estate properties, because the profit and value of the building are proportionally evaluated (Kontrimas and Verikas, 2011). For these reasons, the income approach has been mainly applied to the value estimation of rental properties such as office buildings moreso than schools, parks, properties provided for the public interest, and multi-family housing.

2.1.3. The sales comparison approach

The SC approach follows the principles of marketability, and is defined as "A method of calculating the price by applying the ejaculation correction and the modification of the view point according to the current status of the object compared to the transaction case having the identity or similarity with the target object" in Article 4, paragraph 2 of the law on real estate appraisal. If there is a recent transaction case similar to the target real estate, the general seller or buyer will not sell or buy less than the price of the transaction case. The basic equation is expressed in Eq. 2.4.

$$\textit{Comparative price} = \textit{Case price} \times \textit{Ejaculation correction rate} \times \textit{Local} \qquad (2.4)$$

factor comparison value × *Area comparison value* × *Individual factor comparison value* × *Other corrections*

The advantage of the SC method is that if transactions are frequent and cases are sufficient, it can be applied to all real estate. When used in conjunction with other methods, it is also the basis for supporting estimation by the cost or income approach. The logic of the comparative method for similar real estate is applied to the cost approach (such as estimation of depreciation) and income approach (such as the data on income and expense and the capitalization rate). In addition, whereas the income approach is subject to inaccuracy or subjectivity for predicting future operating income, the SC approach avoids subjectivity. The cost approach excludes the reproduction cost that may be generated and subjectivity of depreciation estimation. This SC approach has stronger persuasiveness than other methods, and the person recognizes the price being formed in the market as the value of the target property (Park, 2002).

The SC approach uses direct evidence of the market's opinion of the value of a property. This approach estimates the market value of a property by comparing it to similar properties that have recently been sold on the market. The sale comparison approach is based on the premise that the fair market value of a property is closely and directly related to the sales prices of comparable, competitive properties (Sen et al., 2002).

2.2. Appraisal method of the renovated office buildings

The methods for conducting real estate appraisals of ROBs have rarely been developed. Consequently, while renovation usually improves the profitability of office buildings by improving the vacancy rate of the rooms, it is difficult for existing appraisal methods, including the cost and sale comparison approaches, to incorporate profitability improvement into the appraisal process; this leads to uncertainties in decision-making among owners regarding building renovations (Kim et al. 2016).

The cost approach is typically used for conducting appraisals of new buildings, because of the lower degree of depreciation of such buildings and relative ease of obtaining recent cost data. However, while buildings that have been used for a long time may be renovated, there are limitations to applying the cost approach to such buildings, because: (i) long-used buildings have a large degree of depreciation, because of several years since construction and (ii) there is difficulty calculating the replacement cost and depreciation amount. It is thus difficult to estimate the value of the ROB by applying the cost approach (Park, 2002). Owing to these disadvantages, few studies have estimated the value of a ROB using this approach.

According to a recently conducted research by Kim et al. (2016), the income approach represents the valuation of ROBs in a relatively accurate manner. In this research, to verify the accuracy of the income approach for appraisals of ROBs: (i) 25 ROB cases were collected, for which data is secured for the application of the income approach, including transaction prices after renovation work, and (ii) a comparison between the actual transaction price and appraised price using the income approach was conducted. The results show that the average difference rate between the two prices was 9.46%. Because the acceptable prediction accuracy in terms of project cost and schedule, among others, in the early project phase (during which information availability is limited) is usually 90%, an error rate of 9.46% can be interpreted to show that the income approach can appropriately evaluate the price of a ROB (Kim et al. 2016).

While it has been revealed that the income approach accurately appraises the monetary value of a building after renovations, there are still problems in using the approach. Kim et al. (2016) revealed that the income approach requires various data. In addition, it is difficult for building owners to conduct a value appraisal, despite the tangibility of the aforementioned information. Because of difficulties in acquiring information and the complexity of the price evaluation process in the income approach, owners who do not have enough expertise in using the income approach may find its application tedious. Thus, although the income approach can appraise the monetary value of a ROB in a relatively accurate manner, the approach lacks usability and applicability for project owners.

In addition, the SC approach may produce a good appraisal result for a ROB, because the approach is implemented with data from historical transaction cases that are similar to the targeted buildings. If the transaction cases of similar office buildings (i.e., ROBs) were analyzed and the transaction prices of the transaction cases were utilized, it is expected that the value of the ROBs can be objectively estimated. However, it is difficult to collect cases of the ROBs and information from the cases. Moreover, it is insufficient to deem the collected cases as similar to those of the ROBs based on the objective criteria.

Therefore, this study aims to develop models for predicting the monetary value of post-renovation office buildings, by applying the principle of two methods (i.e., the income and SC approach) that can be used to evaluate the price of ROBs among the appraisal methods.

3. Data collection and construction of database[1)]

3.1. Data collection of renovated office building

As described in Section 1.2, for developing the model to prediction the monetary value of the post-renovation office building, the process of collecting cases of office buildings that have actually been renovated is essential. Accordingly, this study collected cases of ROBs in Seoul, where there is actively conducted the renovation work and transaction of office buildings in Korea. Many of Seoul's office buildings are located in the central business district (CBD), gangnam business district (GBD), and yeouido business district (YBD), and there are more office buildings, which have already completed renovations or are planning renovation, than other areas. Futhermore, since there are more cases, which completed the renovation and traded, than other areas, the cases of ROB in this study are collected based on three areas.

A total of 360 cases were collected as a result of collecting cases of ROBs based on three regions. Through the first and second screening phases, we eventually collected 90 cases of the ROBs. Only 16 cases among these were complete cases that can obtain data on transaction price and information on office building. On the other hand, since it is very difficult to obtain data related to the transaction price of the office building, 74 cases were incomplete cases that can only obtain the information on office building. The collected cases and the detailed information of each case collected by using (i) rei-korea, (ii) officefind, (iii) onnara real estate properties information, and (iv) real estate properties planet.

1) This section was developed based on the contents of a research (ID: NRF-2014R1A1A1004766) and a paper (Kim et al., 2016) which was one of the outputs from the research.

3.2. Appraisal assessment

In this study, the cases with both transaction price data and information on the office building are needed to develop the model for predicting the monetary value of RBOs. As previously mentioned, 16 cases with complete data sets were insufficient to construct the data set needed to develop the model. The price of 74 cases with partial data sets was estimated to supplement the number of cases. In doing so, the income capitalization approach (ICA) of the appraisal method was applied to the 74 cases.

As shown in Eqs. 2.2 and 2.3, the price evaluation of a particular ROB through ICA requires NOI and the capitalization rate of the relevant building. First, NOI, as shown in Table 3.1, uses the calculation method from four institutions: Ministry of Land, Infrastructure, and Transport (MLIT); National Pension (NP); Genstar; and Korea Association of Real Estate Investment Trusts (KAREIT).

Table 3.1 Net Operating Income (NOI) estimation methods (Jin, 2014)

Institution	NOI Estimation Method
MLIT	NOI = Deposit Operating Income + Monthly Lease Income + Maintenance Fee Income + Miscellaneous Income - Operation Cost
NP	NOI = Monthly Lease Income + Deposit Operating Income + Maintenance Fee Income + Miscellaneous Income - Operation Cost
Genstar	NOI = Operation Profit - Operation Cost - Loss for Vacancy = {Deposit * Treasury Bond Interest Ratio + Monthly Lease Income * Lease Area * 12 + Maintenance Fee * Loss for Vacancy * 12} - {Monthly Maintenance Fee * Lease Area * 12 * 80(%)} - {Deposit * Treasury Bond Interest Ratio + Monthly Lease Income * Lease Area * 12 + Maintenance Fee * Loss for Vacancy * 12} * Vacancy Ratio
KAREIT	NOI = Operation Profit - Operation Cost + Non-Operation Profit

As shown in Table 3.1, the NOI calculation method of the MLIT excludes the Operating Cost (OC) from the Deposit Operating Income (DOI), Monthly Lease Income (MLI), Maintenance Fee Income (MFI), and Miscellaneous Income (MI). However, as the information on DOI and MI is often determined by the intention of the owner, there are limits to obtaining objective and quantified data. Similarly, the calculation method proposed by NP (National Pension excludes OC from DOI, MLI, MFI, and MI. However, the information on DOI is limited, because it is difficult to obtain information from individuals for the same reasons as MLIT. Meanwhile, the calculation method proposed by KAREIT (Korea Association of Real Estate Investment Trusts) excludes OC from Operating Profit (OP) and Non-OP. However, the calculation of OC requires information on consignment management costs, utility expenses, facility management costs, benefits, hospitalization fees, premiums and various fees. The calculation of Non-OP requires information on interest profit, miscellaneous profit, and other operating profit. This information is more difficult to calculate than the information used by the previous two institutions (MLIT and NP). Therefore, this study is limited to applying the calculation method of the NOI proposed by MLIT, NP, and KAREIT.

The calculation method proposed by Genstar excludes the OC and Loss for Vacancy (LC) from OP. It requires detailed information on deposits, MLI, maintenance fee (MF), treasury bond interest ratio (TBIR), and vacancy ratio (VR). Because this information is easier to acquire than those of the previous three institutions, the calculation method of NOI proposed Genstar is widely used.

In conclusion, it is essential to calculate the NOI in the process of calculating ICA. The widely used NOI calculation method of Genstar was applied, according to the availability of data acquisition.

Genstar requires information on deposits, MLI, monthly maintenance fee (MFF), TBIR, and VR. TBIR is obtained through the Bank of Korea. While the transaction time for the renovation of office buildings is quarterly, it is difficult to apply the TBIR of the Bank of Korea, because it is denoted by daily quotes. Therefore, as shown in Figure 3.1, it is used by applying the TBIR, which is the average of the daily quotes for each quarter. As a result, it is possible to enter a value for the TBIR in each case. For instance, if the transaction time of a ROB is in the third quarter of 2015, the TBIR is applied at 1.72%.

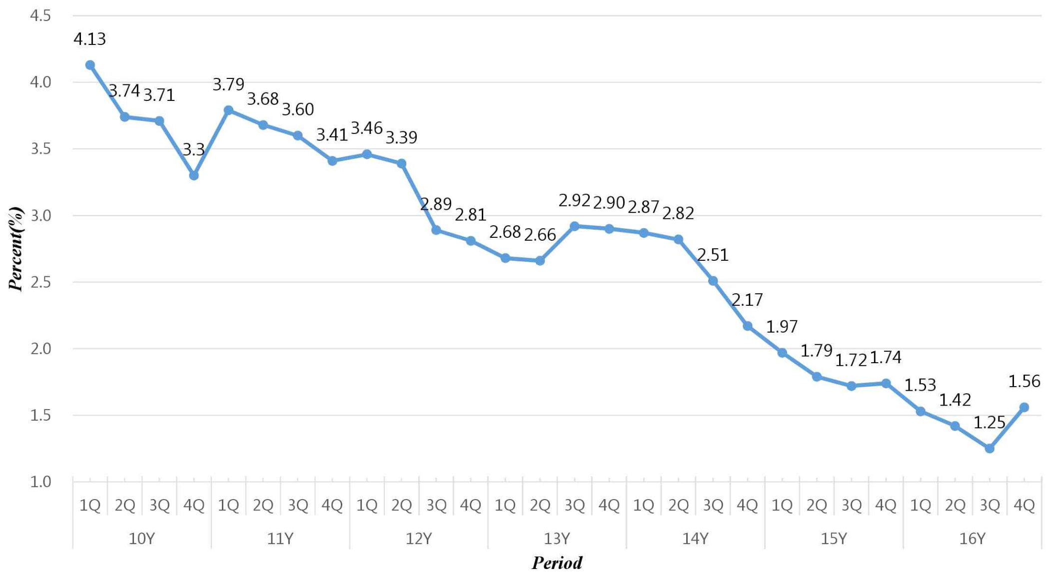

Figure 3.1 Quarterly variation of TBIR

As shown in Figure 3.2, the VR is based on data published by MLIT. Because the data for each region is published since 2013, the VR of the ROBs that were traded before 2012 is based on the VR of the entire Seoul area. For instance, if the ROB is located in YBD and the transaction time is the first quarter of 2012, the VR is applied by 5.10%. If the ROB is located in YBD and the transaction time is the fourth quarter of 2015, the VR is applied by 9.40%

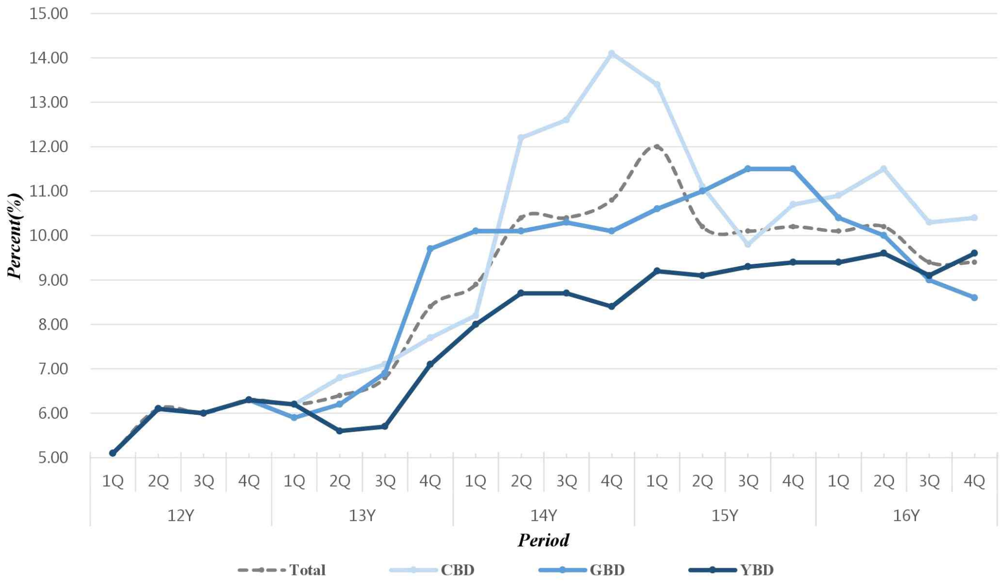

Figure 3.2 Quarterly VR per each region in Seoul

Based on this information, the NOI required in Equation 3.1 was calculated, and the capitalization ratio (CR) was selected as follows. Two types of CR currently represent the office building market in Korea. The first CR is based on the estimation price, which is the data on the income rate of the office building of MLIT (Lee and Lee, 2012). This type calculates the CR by estimating the value of predetermined sample office buildings every quarter. The other is the CR based on the actual transaction price, which calculates the CR based on the transaction price of the office building actually traded, as well as quarterly or semi-annual reports published by real estate asset management companies and real estate information companies (Lee and Lee, 2012).

Because this study will collect cases on ROBs , the CR used is the one based on the actual transaction price. Figure 3.3 shows the quarterly CR per region. If the ROB is located at GBD and the transaction time is the fourth quarter of 2012, the CR of the office building is applied by 5.80%.

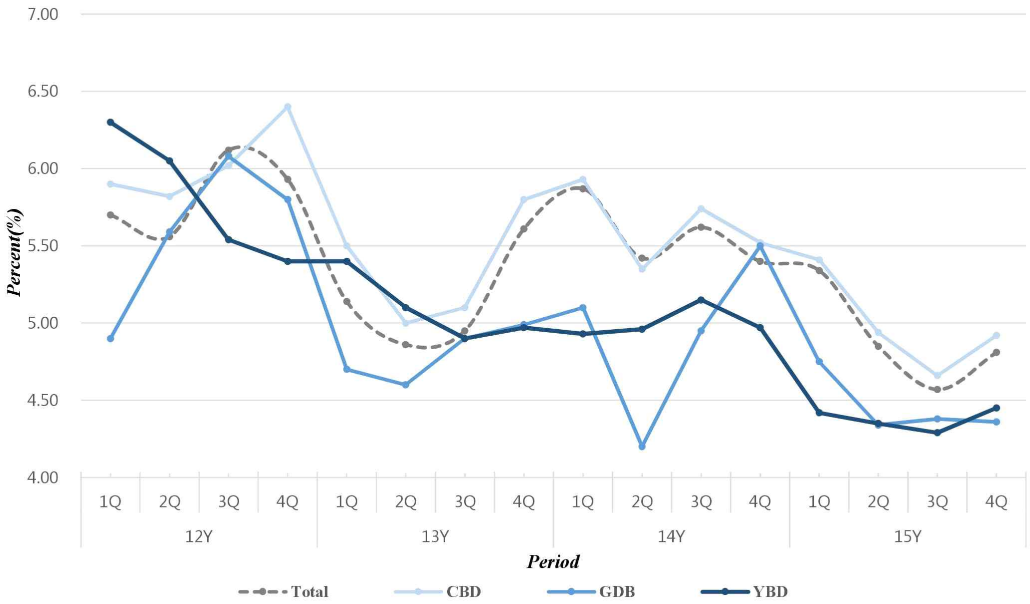

Figure 3.3 Quarterly CR per each region in Seoul

By utilizing the determined NOI and CR for applying the ICA, the suitability of the ICA was examined by applying it to 16 cases with complete data sets. As shown in Table 3.2, the result of applying the ICA to 16 cases shows that the difference between the actual transaction price and the estimated price has an average error rate of 9.33%. It is expected that the ICA can predict the value of ROBs relatively accurately. It is expected that the price prediction results (i.e., the last column of Table 3.3) by the ICA in the 74 cases is quite reliable.

Hence, 74 cases supplemented by the ICA were used to construct the database for developing the model, and 16 cases with complete data sets were used to verify the accuracy of the developed model.

Table 3.2 Introduction of 16 complete cases and results from application of ICA for the cases

No.	Region	Renovation Time	Transaction Time	Actual transaction price (a) (US $ million)	Data for applying ICA and equivalent estimated appraisal value						
					Deposit (US$/m2)	Monthly lease income (US$/m2)	Monthly operating cost (US$/m2)	Lease area (m2)	Vacancy ratio (%)	Capitalization ratio (%)	
1	GBD	2012Y	2015Y 3Q	159.50	790.0	79.0	35.0	2,4529.0	5.1	4.38	
2	GBD	2003Y	2015Y 2Q	160.00	650.0	65.0	32.0	3,7708.5	11	4.34	
3	GBD	2003Y	2015Y 2Q	132.10	670.0	67.0	32.0	2,4515.1	11	5.34	
4	GBD	2010Y	2012Y 1Q	193.00	810.0	81.0	35.0	3,2685.7	5.1	4.9	
5	GBD	2010Y	2013Y 4Q	83.00	550.0	55.0	26.5	2,7497.0	9.7	4.99	
6	GBD	2015Y	2015Y 1Q	55.70	780.0	78.0	28.0	9615.3	10.6	4.75	
7	GBD	2016Y	2015Y 2Q	87.50	690.0	69.0	32.0	1,6695.8	11	4.34	
8	YBD	2011Y	2015Y 4Q	400.00	777.5	77.5	36.0	6,9826.5	9.4	4.45	
9	YBD	2015Y	2015Y 1Q	64.50	500.0	50.0	15.0	1,6632.6	9.2	4.42	
10	CBD	2009Y	2015Y 4Q	650.00	1130.0	113.0	51.0	8,7683.1	10.7	4.92	
11	CBD	2014Y	2015Y 1Q	202.50	890.0	89.0	35.0	3,7266.5	13.4	5.41	
12	CBD	2014Y	2014Y 1Q	109.00	630.0	63.0	32.0	2,5983.6	8.2	5.93	
13	CBD	2010Y	2012Y 4Q	197.90	800.0	80.0	32.0	3,7182.4	6.3	6.4	
14	CBD	2014Y	2016Y 4Q	250.00	1006.1	100.6	37.6	3,2488.1	10.4	5.89	
15	CBD	2014Y	2016Y 3Q	170.80	930.0	93.0	33.0	3,3022.9	10.3	5.59	
16	CBD	2015Y	2014Y 4Q	231.00	850.0	85.0	36.0	4,2321.6	14.1	5.52	
											Average

※ $c = \{|a-b| \div a\} \times 100\%$

※ GBD = Gangnam Business District; YBD = Yeouido Business District; CBD = Central Business District

Table 3.3 Introduction of 74 cases with partial data sets and the estimated appraisal value by ICA

No.	Region	Renovation Time	Transaction Time	Data for applying ICA and equivalent estimated appraisal value						
				Deposit (US$/m2)	Monthly lease income (US$/m2)	Monthly operating cost (US$/m2)	Lease area (m2)	Vacancy ratio (%)	Capitalization ratio (%)	Estimated appraisal value (US $ million)
1	GBD	2012Y	2015Y 1Q	535.6	53.6	21.0	29,784.8	13.4	5.41	115.27
2	GBD	2011Y	2015Y 1Q	700.0	70.0	31.0	16,130.6	13.4	5.41	82.00
3	GBD	2002Y	2015Y 1Q	700.0	70.0	31.0	16,436.4	13.4	5.41	83.56
4	GBD	2004Y	2015Y 1Q	650.0	87.0	26.0	8,172.7	13.4	5.41	50.70
5	GBD	2001Y	2015Y 1Q	750.0	75.0	32.0	13,808.6	13.4	5.41	75.09
6	GBD	2012Y	2015Y 1Q	108.0	108.0	43.0	212,379.6	13.4	5.41	1658.39
7	GBD	2011Y	2015Y 1Q	750.0	75.0	36.0	22,856.8	13.4	5.41	124.95
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
70	YBD	2007Y	2015Y 1Q	455.0	45.5	26.5	5,252.3	9.20	4.42	59.60
71	YBD	2010Y	2015Y 1Q	500.0	52.0	29.0	6,537.8	9.20	4.42	84.59
72	YBD	2016Y	2015Y 1Q	450.0	45.0	27.0	10,215.6	9.20	4.42	114.80
73	YBD	2015Y	2015Y 1Q	610.0	61.0	30.0	4,495.6	9.20	4.42	67.95
74	YBD	2010Y	2015Y 1Q	400.0	43.0	22.5	7,920.7	9.20	4.42	84.49

※ GBD = Gangnam Business District; YBD = Yeouido Business District; CBD = Central Business District

4. Monetary Value Prediction (MVP) model I in accordance with the income approach[2)]

4.1. Development strategy

This study developed a model, as shown in Figure 4.1, for predicting the price of an office building after renovations. The multivariate data analysis (MDA) method was adopted to develop a model capable of predicting the monetary value of a ROB. The factors influencing the price of a ROB were used to apply the MDA method. The MDA method requires two types of variables: independent and dependent. The aforementioned factors were defined as dependent variables, while the price information of a ROB resulting from the variation in these factors was defined as an independent variable.

Regarding data collection on ROB cases using these variables, this study (i) gathered all tangible cases required to develop a population of ROBs; (ii) screened the cases for presenting the factors influencing the property price (i.e., independent variables) during the first screening phase; and (iii) during the second screening phase, extracted cases with historical transaction data (i.e., dependent variable) from the cases screened in the first phase (Figure 4.1 "ⓐ"). Through these data collection phases, 16 ROB cases with complete data sets (where completeness implies that all required data of independent and dependent variables was set perfectly) were collected, while 74 ROB cases with partial data sets (implying missing dependent variables) were prepared (Figure 4.1 "ⓑ"). As noted by Kim et al. (2016), the ICA, which is one of the representative methods for building appraisal approaches, estimated the price of a ROB more accurately compared to other approaches. As such, the prices of 74 cases with partial data sets were estimated using the ICA (Figure 4.1 "ⓒ").

Based on these two types of data sets, a price prediction model was deduced by applying a multiple regression analysis (MRA) to 74 cases that were supplemented by ICA (Figure 4.1 "ⓓ"). Subsequently, by using 16 cases with complete data sets of independent

2) This section was developed based on the contents of a research (ID: NRF-2014R1A1A1004766) and a paper (Kim et al., 2017) which was one of the outputs from the research.

and dependent variables, the developed model was verified (Figure 4.1 "ⓔ"). In the course of applying the MRA, two rounds of it (i.e., the first and second regression analyses) were conducted to deduce the prediction model that is better-suited to reflect the characteristics of a ROB. Subsequently, it was revealed that the model resulting from the second MRA was superior in terms of applicability and accuracy, compared to the model resulting from the first MRA.

Finally, the model developed in the course of this study were analyzed in terms of usability and accuracy, among others, to present the advantages and disadvantages of the proposed model (Figure 4.1 "ⓕ").

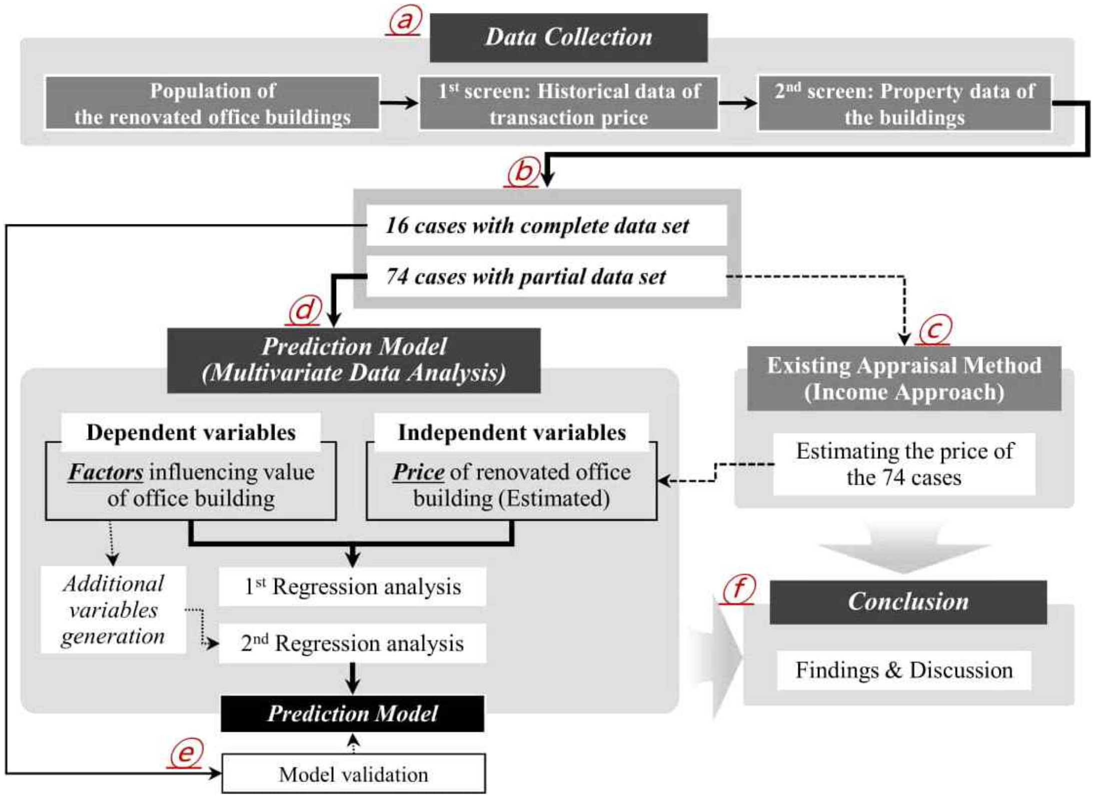

Figure 4.1 Development strategy of MVP model

4.2. Methodology

4.2.1. Multiple regression analysis (MRA)

Regression analysis is an analytical method that sets one variable as dependent variable and sets other variable(s) as independent variable(s), and finds determines the relationship between them as a mathematical model. In general, independent variables and dependent variables are set by cause and result, and it estimates the model or conducts a test. At this time, if there is only one variable, it is defined as 'Simple simple regression'., and ifIf there are two or more independent variables, it is called 'mMultiple regression'.

In the relationship between two variables, the setting of the independent variable and the dependent variable must be determined based on the logical validity. Although the result of regression analysis shows that independent variables are statistically significant by setting one of two arbitrary variables as an independent variable and the other as a dependent variable without any logical basis, it can not be assumed that there is an independent-dependency relationship between the two variables (Lee and Lim, 2005).

Multiple regression analysis is an extension of simple regression analysis, and is a technique for analyzing relationships between two or more independent variables and one dependent variable. The basic equation is expressed as Eq. 4.2.

$$Y = B_0 + B_1X_1 + B_2X_2 + \cdots + B_nX_n \tag{4.2}$$

where, Y = Dependent variable,

B_0 = Constant,

B_n = Regression coefficient,

X_n = Independent variable.

Multiple regression analysis should be applied to the regression model, by selecting the variables with high influence on the dependent variable as input and removing the variables with insufficient explanatory power. It is classified into enter selection, forward selection, backward selection, and stepwise selection according to the input variable selection method. Enter selection considers all the independent variables included by the researcher simultaneously. With this method, the influence of a specific independent variable when other independent variables are controlled is known, and all independent variables considered by the researcher can simultaneously know the degree explaining the dependent variable (Lee and Lee, 2005). Forward selection fits the model using only the selected final explanatory variables, if there are no significant explanatory variables to add. If there are no significant influential factors to add, this method can optimize the model by using only the final explanatory variables. However, as the once-selected variables must remain in the regression model, there is a disadvantage that cannot guarantee that the optimal model was selected. Backward selection begins with the assumption that the initial model is a perfect model, then removes the unnecessary variables. The first step is to find the variables with the least contribution after fitting the regression model that includes all candidate factors. If the F-test for the variable is significant, it results in a complete model. Otherwise, it is removed and the next step is completed (Lim, 2010). Stepwise selection addresses the disadvantages of forward selection and backward selection. When other variables exist in the regression equation, only the variables that have an influence on the dependent variable are included in the regression equation, in the order of the variables with high explanatory power. However, the independent variables included in the regression equation at the previous stage are removed if the explanatory power becomes very low towing to later incoming variables. This method is useful for finding the regression equations consisting of only variables whose explanatory power has reached a certain level when explaining the dependent variable.

4.3. Model development

4.3.1. Regression modeling

Since studies have rarely been conducted to measure the change in monetary value arising from the renovation work on an office property, it is very difficult to directly derive the factors that influence the monetary value of a ROB for this study. Therefore, candidate factors that have a possibility of influencing the monetary value of a ROB were preferentially selected for analyzing the existing studies that analyzed the monetary value of office property. As a result of analyzing the existing studies, factors influencing the price of office buildings can be classified into three characteristics (i.e., locational characteristics, physical characteristics, and transactional characteristics) (Cho et al. 2009; Colwell et al. 1998; Dermisi and McDonald 2010; Lee 2005; Lee and Lee 2013; Mun et al. 2015; Munneke and Barrett 2000; Park et al. 2011; Yang 2014). After repetitive deliberations on the emphasized factors, 13 independent variables (i.e., X_1 to X_{13}) were set, as shown in Table 4.1. Among the 13 variables, the physical characteristics of the office building were represented by several independent variables because most previous research treated the physical characteristics of an office building as the key elements for determining the value of the building. The variables representing the physical characteristics of a building included gross area of floors (X_1), ground area of the property (X_2), building footprint (X_3), number of floors (X_4), number of underground floors (X_5), exclusive rate of the lease area (X_6), building coverage ratio (X_7), floor area ratio (X_8), number of parking spaces (X_9), number of elevators (X_{10}), and years elapsed since construction (X_{11}). Here, X_1 denotes the sum of building floors, and X_7 and X_8 represent means of a value of X_3 and X_1 divided by X_2, respectively. In addition, this research adopts X_4 and X_5 separately because the underground floor is mainly used as a public space, including parking and apparatus rooms, which might be not leasable, but can significantly influence the monetary value of the office building. Meanwhile, walking time to the subway (X_{12}) and officially assessed land price (X_{13}) were included because the former represented locational characteristics while the latter represented transactional characteristics. In addition, the dependent variable was set to the monetary value of a ROB (i.e., Y), which is also the purpose of this study.

Table 4.1 Variables for MRA application

Type of Variable		Explanation	Analysis inclusion	
			1st MRA	2nd MRA
Dependent variable		Y: Monetary value of ROB	○	○
Independent variables	Basic variables	X_1: Gross area of floors	○	○
		X_2: Ground area of the property	○	
		X_3: Building footprint	○	
		X_4: Number of floors	○	
		X_5: Number of underground floors	○	○
		X_6: Exclusive rate of the lease area	○	
		X_7: Building coverage ratio (i.e., X_3/X_2)	○	
		X_8: Floor area ratio (i.e., X_1/X_2)	○	
		X_9: Number of parking spaces	○	
		X_{10}: Number of elevators	○	
		X_{11}: Years elapsed since construction	○	
		X_{12}: Walking time to the subway	○	
		X_{13}: The officially assessed land price	○	○
	Additional variables	$AV_1=X_1 \times X_{11}$		○
		$AV_2=X_5 \times X_{11}$		○
		$AV_3=X_{13} \times X_{11}$		○

The first MRA with 13 independent variables in Table 4.1 was conducted using IBM SPSS statistics 23.0. Since the analysis considered only three variables (i.e., X_1, X_5, and X_{13}) in the first regression model, the model was interpreted as being insufficient to reflect the characteristic of ROB properly (please refer to the details in the "Multiple regression analysis" section). Consequently, the second regression analysis was designed by considering both the three extracted variables from the first regression analysis and the additional variables that were generated by using the variable interaction method. The methods that can be used to generate additional variables are variable transformations, dummy variables, and variable interaction. The variable interaction, among the three methods, can be used when a specific independent variable has a significant effect on the other independent variables, and it is shown to derive the regression model, including the target variable

(Hair et al. 2006; Hong et al. 2011). Therefore, a variable interaction was used to conduct additional MRAs; additionally, as shown in Table 4.1, three additional variables (AV_1 to AV_3) were generated by using the three variables (X_1, X_5, and X_{13}), which had a significant influence on the dependent variable after the first regression analysis, and X_{11} (elapsed year) explained the characteristic of a ROB. The second regression analysis was conducted using the above three additional variables and the three basic variables that were included in the first regression model.

4.3.2. Multiple regression analysis

As shown in Tables 4.2 and 4.3, the regression model, as in Eq. 4.3, is derived from the first regression analysis result.

$$\begin{aligned} Y = & -3{,}610{,}371.635 + 708.723 \times X_1 \\ & + 1{,}521.130 \times X_{13} - 1{,}306{,}371.771 \times X_5 \end{aligned} \quad (4.3)$$

Where, Y = Monetary value of ROB,

X_1 = Gross area,

X_5 = Number of underground floors,

X_{13} = The officially assessed land price.

The adjusted R^2 value of the model resulting from the first regression analysis was 0.974 (Table 4.2), and the gross area (X_1) had a significant effect on the monetary value of an ROB, as demonstrated by the beta value of 99.5% in the standardized coefficients in Table 4.2. As shown in Eq. 4.3, the first regression model also includes the number of underground floors (X_5) and the officially assessed land price (X_{13}). However, the results of the first regression analysis that comprised only three variables were insufficient to show the characteristics of the ROB. Therefore, a second regression analysis was performed with the additional variables.

As shown in Table 4.3, the regression model given in Eq. 4.4 is derived from the second result of the regression analysis. However, since the independent variable in the order of magnitude is larger than the dependent variables, the square root of the independent variable was used in the second regression analysis:

$$\sqrt{Y} = 615.848 + 0.039 \times X_1 + 0.001 \times AV_1 + 7.041 \times AV_2 + 0.189 \times X_{13} \tag{4.4}$$

Where, Y = Monetary value of ROB,

X_1 = Gross area,

X_{13} = The officially assessed land price,

AV_1 = $X_1 \times X_{11}$ (Gross area×Years elapsed since construction),

AV_2 = $X_5 \times X_{11}$ (Number of underground floors×Years elapsed since construction)

As shown in Table 4.3, the results of the second regression analysis revealed that the adjusted R^2 value decreased slightly from 0.974 to 0.948, while the standard error of the estimate significantly decreased from 4,118,327.429 to 521.120. As shown in Table 4.3 and Eq. 4.4, the model developed during the course of this study comprised four variables for the second regression (X_1, AV_1, AV_2, and X_{13}); additionally, since each additional variable includes the same independent variables (i.e., X_1 and X_{11} in AV_1 and AV_2) in its regression equation, it is essential to check for multicollinearity. In general, tolerance, variance inflation factor (VIF), or condition index is used to check for multicollinearity. If the tolerance value, VIF value, and condition index value are less than 1, 10, and 15, respectively, then it can be confirmed that there is no multicollinearity between the independent variables (Hair et al. 2006; Liou and Huang 2008). The tolerance values were less than one for all variables, from 0.190 to 0.903. The VIF values were less than 10, from 1.107 to 5.252, and the condition indices were less than 15, from 1.000 to 8.8804. Since the result of the second regression analysis revealed that there is no multicollinearity among the independent variables, it can be adopted as a final model.

Table 4.2 Model summary

Model	Independent variables	R	R^2	Adjusted R^2	Standard error of the estimate
1st regression	13[a]	0.988	0.975	0.974	4,118,327.429
2nd regression	6[b]	0.975	0.951	0.948	521.120

[a] 13 Basic variables in Table 4.1

[b] X_1, X_5, X_{13}, AX_1, AX_2, and AX_3

Table 4.3 Coefficients and collinearity statistics

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	Collinearity statistics	
		B	Standard error	Beta			Tolerance	VIF
1st regression	Constant	-3,610,371.635	11,877,556.685	-	-3.040	0.003	-	-
	X_1	708.723	14.585	0.995	48.592	0.000	0.793	1.261
	X_{13}	1,521.130	445.475	0.065	3.415	0.001	0.913	1.096
	X_5	-1,036,371.771	31,0089.592	-0.068	-3.342	0.001	0.808	1.238
2nd regression	Constant	615.848	187.849	-	3.278	0.002	-	-
	X_1	0.039	0.004	0.613	10.276	0.000	0.190	5.252
	AV_1	0.001	0.000	0.314	5.377	0.000	0.199	5.031
	AV_2	7.041	1.949	0.102	3.612	0.001	0.847	1.180
	X_{13}	0.189	0.057	0.092	3.342	0.001	0.903	1.107

4.4. Model validation

Validation was conducted to confirm the accuracy with which the model developed through this study can predict the price of a ROB. As described in Figure 4.1, using 16 cases with complete data sets, a comparison between the actual transaction price and the predicted price through the developed models was conducted to verify the developed models. However, since the predicted price of the second regression model is applied to the square root value, the square root value was applied to 16 cases for verifying the second regression model (i.e., (d) in Table 4.4).

Table 4.4 shows the application results of the deduced models via first and second regression models with 16 cases, and each model shows 13.63% and 8.81% average error rates respectively. As per the result of the first model application, the error rate of Case 12 was 1.38%, which almost matched the actual price, but that of Case 5 was 42.60%, which was three times the average error rate. In addition, in the application results of the first regression model, the range of error rates indicated an irregular appearance. Contrarily, the average error rate of the second regression model was 4.82% lower than that of the first regression model. The error rate of Case 15 was 1.02%, which is the lowest error rate in all application cases, while Case 16 showed the highest error rate of 23.52%, and many cases were predicted in a relatively accurate manner. In addition, the range of error rate of the model indicated a regular appearance.

By comparing the results derived from the application of the two models to the actual cases, it can be concluded that the second regression analysis model is more appropriate. First, the results of the regression analysis are statistically significant and there is no multicollinearity. Second, the developed model includes a variable (i.e., X_{11}, years elapsed since construction), which reflects a representative characteristic of the ROBs. Third, in the validation, whereas the average error rate is 4.82 percentage points higher than that of the first regression model, and the developed model can predict the price of ROBs relatively accurately. Therefore, the second regression model was finally selected in this study; furthermore, if additional variables are converted to the multiplication of the basic values, then the model can be formulated as given in Eq. 4.5:

$$\sqrt{Y} = 615.848 + 0.039 \times X_1 + 0.001 \times X_1 \times X_{11} + 7.041 \times X_5 \times X_{11} + 0.189 \times X_{13} \tag{4.5}$$

Where, Y = Monetary value of ROB,

X_1 = Gross area,

X_5 = Number of underground floors,

X_{11} = Years elapsed since construction,

X_{13} = The officially assessed land price.

Table 4.4 Application results of the developed MRA models

Actual cases		Prediction results by the developed models				
		1st regression model		2nd regression model		
No.	Transaction Price (a)	Estimated value (b)	Error Rate (c) (%)	Converted transaction price (d)	Estimated value (e)	Error Rate (f) (%)
1	159.50	120.75	24.30%	3,993.75	3,536.27	11.45%
2	160.00	198.19	23.87%	4,000.00	4,405.35	10.13%
3	132.10	139.74	5.78%	3,634.56	3,693.42	1.62%
4	193.00	175.33	9.16%	4,393.18	4,098.23	6.71%
5	83.00	118.36	42.60%	2,880.97	3,214.06	11.56%
6	55.70	49.15	11.76%	2,360.08	2,549.64	8.03%
7	400.00	422.17	5.54%	6,324.56	5,733.74	9.34%
8	64.50	65.58	1.67%	2,539.69	2,733.24	7.62%
9	650.00	574.93	11.55%	8,062.26	8,359.67	10.56%
10	202.50	229.19	13.18%	4,500.00	4,703.43	4.52%
11	109.00	123.14	12.98%	3,301.51	2,917.79	11.62%
12	197.90	200.63	1.38%	4,448.60	4,190.92	5.79%
13	250.00	199.51	20.20%	5,000.00	4,349.25	13.02%
14	87.50	74.63	14.70%	2,958.04	2,829.43	4.35%
15	170.80	200.79	17.56%	4,132.80	4,175.10	1.02%
16	231.00	226.60	1.90%	4,806.25	3,675.73	23.52%
Average		-	13.63%			8.81%

※ $c = \{|a-b| \div a\} \times 100\%$
※ $f = \{|d-e| \div d\} \times 100\%$

5. Monetary Value Prediction (MVP) model II in accordance with the Sc approach[3)]

5.1. Development strategy

The proposed transaction-case-based MVP model was developed with consideration of the concept of case-based reasoning (CBR), a well-known artificial intelligence technique. The CBR technique solves a new problem by focusing on past cases through reusing their obtained information and knowledge. Therefore, a significant theoretical similarity exists between the CBR and SC approaches in terms of the implementation principle. Considering this similarity, in the process of developing the MVP model based on the SC approach, we adopted and revised an implementation framework of the CBR technique that applies to extracting cases with similar characteristics.

The MVP model consists of two major parts: i) a database for containing the information related to physical and locational attributes of the ROB cases, and ii) algorithms for implementing the MVP of the office building considered to be renovated. As shown in Figure 5.1, the DB stores the collected ROB cases and three types of information for each case: the physical and locational attributes of each case, renovation scope, and transaction price. The MVP algorithm is composed of four main steps.

- Step 1: Calculate the “attribute similarity” between attributes of past cases in the DB and attributes of the office building case (i.e., Case A′ in Figure 5.1) which is being considered for renovation work.

- Step 2: Calculate the “case similarity” between the targeted office building and the historical cases in the DB based on the calculated attribute similarity, which is the result of Step 1.

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3) This section was developed based on the contents of a research (ID: NRF-2014R1A1A1004766 & 2017R1D1A3B03029277) and a paper (Cho et al., 2017) which was one of the outputs from those research.

- Step 3: Extract the “case” with the highest case similarity value based on the results of the case similarity for each case.

- Step 4: “Correcting the price” with consideration of the value change over time based on the transaction price of the extracted case.

According to the above steps, the proposed model developed is implemented as follows. If a renovation is being planned for an office building (Case A in Figure 5.1), the changed building appearance according to the renovation plan can be defined as the attribute values (i.e., Attributes of Case A′ in Figure 5.1). Based on these attribute values, by means of Steps 1 to 3, the MVP model finds the historical ROB case in the DB (i.e., RC_j in Figure 5.1) with the highest similarity to Case A′. Finally, by means of Step 4, which is necessary for adjusting the past transaction price of the extracted case into the current value of the price, a monetary value of Case A′ can be estimated by adjusting the past transaction price of the extracted case in the previous steps with consideration of the value change over time of money.

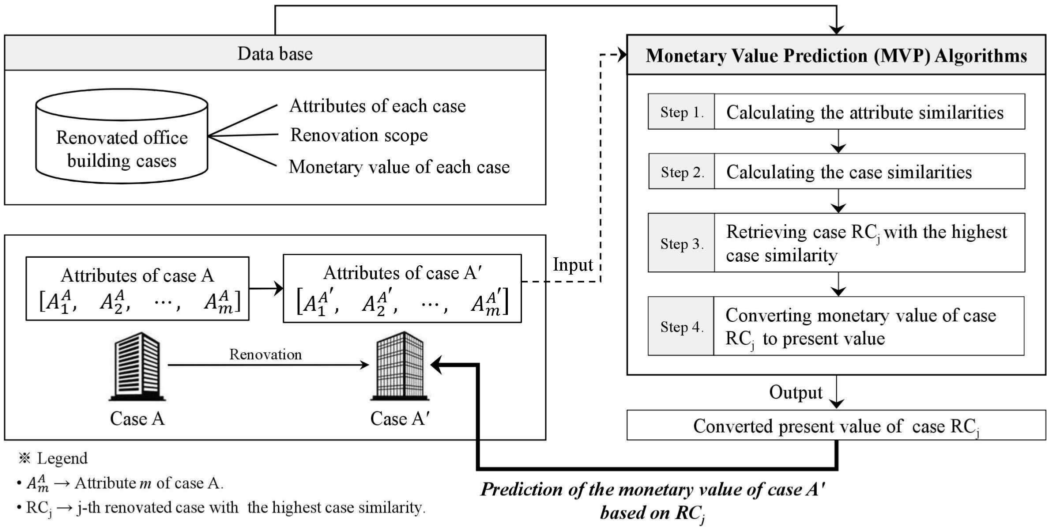

Figure 5.1 Development strategy of MVP model Ⅱ

5.2. Methodology

5.2.1. Case-based reasoning (CBR)

As described in Figure 5.1 and section 5.1, the MVP model was developed based on the sales comparison approach. The sales comparison approach is similar to the CBR technique, and estimates the monetary value of the current evaluation object by referring to past similar transaction cases.

Case-based reasoning is a data mining technique that remembers similar situations that have been applied to solve problems in the past, and solves new problems by reusing the information and knowledge of those situations (Aamodt & Plaza, 1994). This technique does not require a model for problem solving, and collecting cases is a task of acquiring knowledge. It is easy to maintain vast amounts of information, because the collection of cases is used in the simultaneous acquisition and learning of new knowledge (Kim & Kang, 2004). The CBR consists of four phases, as shown in Figure 5.2:

i) Retrieve: This phase retrieves the previous case that is most similar to the new problem from the established DB.

ii) Reuse: This step reuses one or more similar case data and knowledge retrieved to solve the problem.

iii) Revise: If the retrieved case is not suitable for solving the new problem, this phase analyzes and compensates for differences between the retrieved case and the new problem, and it revises the retrieved case accordingly.

iv) Retain: This phase stores the proposed solution in a DB so that it can be used in future problems.

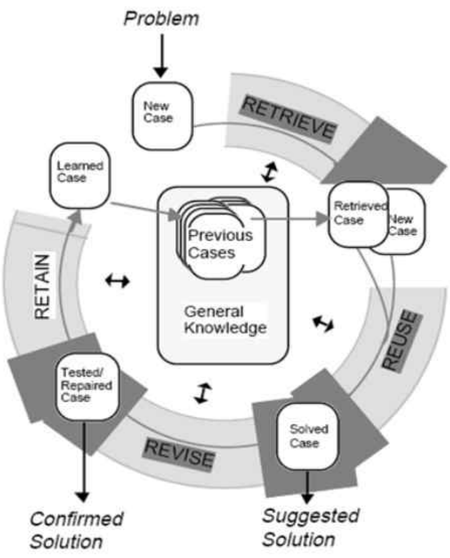

Figure 5.2 Cycle of CBR (Aamodt and Plaza, 1994).

There are three methods for retrieving similar cases with CBR: inductive retrieval method, knowledge-based retrieval method, and nearest-neighbor retrieval method. These methods may be used in combination (Lee, 1988).

i) Inductive Retrieval Method

The inductive retrieval method is the best model if the proposed extraction is well defined. The case is indexed by the significant influence factors on the results made and induced from the data itself. Because it is extracted by a decision tree, it has the advantage that the speed of case retrieval is faster than the nearest-neighbor method. However, it has the disadvantage that if the case data is missing, case retrieval becomes impossible. When increasing the cases, each one should be added to the decision-making map.

ii) Knowledge-Based Retrieval Method

The knowledge-based retrieval method applies to the existing sectoral knowledge to extract the associated cases, and is similar to the rule-based system.

iii) Nearest-Neighbor Retrieval Method

The nearest-neighbor retrieval method is applies the weighted case after extracting cases similar to new cases by the certain similarity measure among those stored in the database. This method is appropriate if there is no need to focus only on solving a specific problem. This method is generally useful when the size of the case set is small, because the time required for extraction increases as the number of cases increases. Figure 5.3 shows the process of the nearest-neighbor retrieval method.

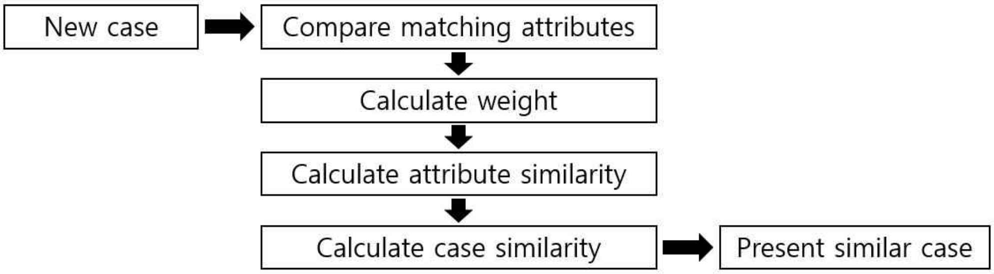

Figure 5.3 Process of nearest-neighbor retrieval method

5.2.2. Literature Review

The previous studies using the CBR technique in cost engineering were conducted on the basis of two major approaches: i) development of a technique to predict the construction cost and ii) study on improving the prediction accuracy of the construction cost.For the first approach, Yau and Yang (1998) investigated the suitability of CBR for price predicting. They demonstrated that evaluations lacking detailed information are particularly useful in the preliminary design phase when using cost models based on previous similar projects. Ji et al. (2011) developed a CBR cost estimate model for building projects using a Euclidean distance concept and genetic algorithms. This model was shown to enhance the cost estimation accuracy and act as a basis for further research on the fundamentals of the case-based reasoning method. Jin et al. (2012) strived to improve the prediction performance of the CBR-based cost prediction model. They focused on the CBR technique that has become widely used in predicting costs of construction projects. An improved CBR model using multiple regression analysis (MRA) in the revision phase of the CBR technique was developed. Kim et al. (2004; 2005) developed a cost prediction model based on CBR combined with an artificial neural network and MRA. They compared each model. CBR was shown to be more useful than other models in terms of clarity of the explanation on the construction cost prediction, updating ease, consistency of variables, and long-term use.

For the second prediction accuracy approach, Doğan et al. (2006; 2008), An et al. (2007), Ahn et al. (2014), Park et al. (2004; 2010), Ji et al. (2011), Biswas et al., (2014), and Relich and Pawlewski (2017) studied techniques for applying the optimal attribute weights in the retrieval phase of CBR to retrieve the most similar cases. They strived to improve the CBR performance by applying various methods, such as the analytic hierarchy process, genetic algorithm, feature counting, multiple regression analysis, gradient descent method, artificial neural network, and decision tree.

As described above, the CBR technique in the field of construction engineering and management has been widely used to identify cases similar to the target problem for predicting the construction cost in the early stage of a project. The performance of the technique was determined to be comparatively excellent. Therefore, in the process of developing the transaction case-based methodology for estimating the monetary value of an office building, the CBR technique is a reliably appropriate methodology for retrieving similar transaction cases from the past.

5.3. Model development

5.3.1. Model implement attributes

In previous section 4.2.1, previous studies on factors influencing the value of office buildings were analyzed, and factors influencing the value of the ROBs were extracted. In other words, as a result of analyzing the existing studies, 13 numerical attributes that were repeatedly mentioned were defined as the candidate factors influencing the ROB monetary value. These attributes were the gross floor area, site area, building area, number of floors, number of underground floors, exclusive rate of the lease area, building coverage ratio, floor area ratio, number of parking spaces, number of elevators, years elapsed since construction, walking time to the subway, and officially assessed land price.

In addition, the renovation scope was added as the candidate factor influencing the ROB monetary value because it was expected that the renovation scope would have a significant effect on the construction cost, construction period, and, consequently, the monetary value change of the office building after renovation. According to the analysis results on the collected office renovation cases, the renovation scope in this study can be largely classified into four groups: Scope 1, interior renovation work (namely Scope 1), such as work on the lobby, common use space, parking lot, and elevator; Scope 1 and equipment renovation work (Scope 2), including changes in mechanical and electrical equipment, cooling and heating systems, and air conditioning equipment; Scope 2 and exterior renovation work (Scope 3), including exterior finish and windows; and Scope 3 and vertical and horizontal building extension (Scope 4). Therefore, as shown in Table 5.1, this study selected a total of 14 variables as the candidates of attributes that influence ROB monetary value.

Table 5.1 Candidates of attributes influencing ROB monetary value

Type of variable	ID.	Attributes	Range
Numerical variable	X_1	Gross area	2,562.25 – 212,379.55 m^2
	X_2	Site area	389.93 – 21,390.11 m^2
	X_3	Building area	232.73 – 10,592.40 m^2
	X_4	Number of floors	2 – 60 floors
	X_5	Number of underground floors	1 – 8 floors
	X_6	Exclusive rate of the lease area	40.60 – 87.50 %
	X_7	Building coverage ratio	22.37 – 88.42 %
	X_8	Floor area ratio	180.45 – 1,484.90 %
	X_9	Number of parking spaces	0 – 1,310
	X_{10}	Number of elevatros	0 – 35
	X_{11}	Years elapsed since construction	7 – 49
	X_{12}	Walking time to the subway	1 – 15 min
	X_{13}	Officially assessed land price	495 – 5,620 $/m^2$
Nominal variable	X_{14}	Renovation scope 1: Interior 2: Interior + Equipment work 3: Interior + Exterior + Equipment work 4: Interior + Exterior + Equipment work + Extension of building	

Most of the 14 candidate factors (i.e., X_1 to X_{14} on Table 5.1) were developed by examining the factors influencing the monetary value of the existing and/or newly constructed office buildings. Therefore, attributes (i.e., the factors influencing the ROB monetary value) to be used in the MVP model were determined by using multivariate data analysis methods with the numerical data for the candidate factors obtained from 74 cases. The relationship between the numerical data on 14 candidate factors and the monetary value of each case were thereby analyzed by conducting correlation analysis and multiple regression analysis using IBM SPSS 23.0. As shown in Tables 5.2 and 5.3, the results of the two analyses showed that the gross floor area (X_1), site area (X_2), building area (X_3), number of floors (X_4), number of underground floors (X_5), floor area ratio (X_8), number of parking spaces (X_9), number of elevators (X_{10}), years elapsed since construction (X_{11}), and officially assessed land price (X_{13}) influenced the ROB monetary value. However, the gross floor area (X_1) comprehensively included the concept of the building area (X_3), number of floors (X_4), number of underground floors (X_5), and floor area ratio (X_8). In addition, the number of underground floors (X_4) could be overlapped with the number of parking spaces (X_9) because the underground floors were mainly used as parking lots. Therefore, the building area, number of floors, number of underground floors, and floor area ratio by this duplication were omitted from the attributes influencing the ROB monetary value.

Furthermore, as mentioned earlier, the renovation scope was added as the attribute influencing the ROB monetary value on account of its significance. Therefore, the attributes finally influencing the monetary value of ROB were deduced as the gross floor area, site area, number of parking spaces, number of elevators, years elapsed since construction, officially assessed land price, and renovation scope (see Table 5.4). Consequently, these seven attributes were regarded as the variables for implementing the MVP model.

Table 5.2 Correlation analysis between numerical variables and monetary value

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}
Monetary value	.977**	.782**	.857**	.806**	.375**	-.241*	.035	.424**	.928**	.933**	-.065	-.125	.360**

*p < 0.05, **p<0.01.

Table 5.3 The results of multiple regression analysis

	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Standard error	Beta		
Constant	76.841	29.536		2.602	.011
X_1	.011	.001	1.497	20.417	.000
X_2	-.020	.003	-.246	-6.835	.000
X_5	-25.348	3.927	-.148	-6.455	.000
X_{10}	-11.461	3.014	-.270	-3.803	.000
X_{13}	.012	.005	.047	2.439	.017
X_{11}	-1.448	.688	-.041	-2.104	.039

Table 5.4 Introduction of 74 cases with the estimated appraisal value of ICA

No.	Region	Data for applying ICA and equivalent estimated appraisal value							Estimated appraisal value (US $ million)
		Gross area (m^2)	Site area(m^2)	Number of parking spaces	Number of elevators	Years elapsed since construction	Officially assessed land price (US$/$m^2$)	Renovation scope	
1	GBD	29,784.84	4,588.62	185	4	25	997.5	3	115.27
2	GBD	16,130.55	1,105.89	97	3	22	2,066.0	1	82.00
3	GBD	16,436.44	949.90	124	4	26	3,287.0	4	83.56
4	GBD	8,172.74	1,153.10	40	1	24	2,385.0	4	50.70
5	GBD	13,808.56	1,259.41	72	3	24	3,670.0	4	75.09
6	GBD	212,379.55	13,156.70	1310	32	14	3,635.0	1	1658.39
7	GBD	22,856.83	1,367.31	158	5	16	3,710.0	1	124.95
8	GBD	66,202.68	3,587.22	515	12	16	3,710.0	1	460.60
9	GBD	2,986.76	400.40	14	1	7	1,236.0	4	16.03
10	GBD	2,562.25	795.00	16	1	36	1,715.0	4	10.58
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
70	YBD	17,362.80	1,696.20	100	2	32	1,211.0	3	59.60
71	YBD	21,612.57	2,247.30	116	4	30	1,790.0	2	84.59
72	YBD	33,770.44	8,925.90	188	5	32	685.0	1	114.80
73	YBD	14,861.48	1,536.45	122	4	23	922.0	1	67.95
74	YBD	26,184.26	2,999.00	134	3	31	676.2	1	84.49

※ GBD = Gangnam Business District; YBD = Yeouido Business District; CBD = Central Business District

5.3.2. Model algorithms

The MVP model algorithms that can predict the monetary value of the office building after renovation is shown in Figure 5.4. The basic concept of the MVP algorithms is to find the most similar case by comparing and analyzing among ROB cases and the new case, as in the CBR technique. Accordingly, DB was constructed based on 74 cases supplemented by ICA. The information, including the seven attributes for each case, were stored in the DB. In addition, Steps 1 to 3 were used for extracting a similar case from the historical cases in the DB with correspondence to the seven attributes of the new case. Step 4 was designed for converting the transaction price of the deduced similar case with consideration of the time value of money. A detailed explanation of each step is as follows.

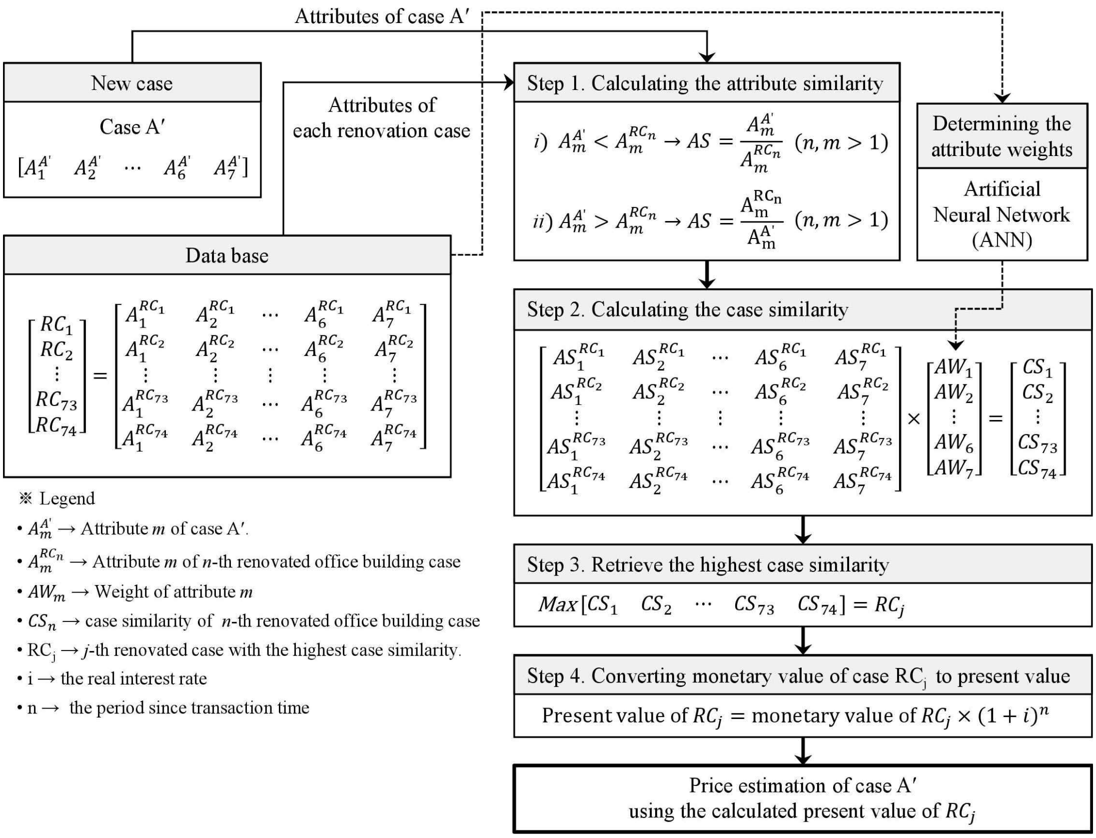

Figure 5.4 Monetary Value Prediction (MVP) algorithms

5.3.2.1. Calculating the attribute similarity

As shown in MVP algorithms of Figure 5.4, Step 1 calculates the similarity between the attribute value of each case in the DB and the one for the new case. The process of calculating the attribute similarity is based on the nearest-neighbor retrieval method, which is widely used to retrieve the similar case. It compares the attributes of the renovated case and the new case, which can be expressed as Eq. 5.1.

$$AS = \frac{Min(AV_{new\ case}, AV_{renovated\ case})}{Max(AV_{new\ case}, AV_{renovated\ case})} \tag{5.1}$$

Where, AS = Attribute Similarity,

$AV_{new\ case}$=Attribute Value of new case,

$AV_{renovated\ case}$ Attribute Value of renovated case.

5.3.2.2. Calculating the case similarity

In Step 2, the case similarity can be calculated using the calculated attribute similarity and attribute weight. The cumulative sum based on the value of each case (attribute similarity × attribute weight) is divided by the cumulative sum of the attribute similarity. However, the cumulative sum of the attribute similarity can be omitted as Step 1 in this study. The case similarity of each case was calculated by applying this calculation process, which can be expressed as Eq. 5.2.

$$CS = \frac{\sum_{i=1}^{n}(AS_i \times AW_i)}{\sum_{i=1}^{n} AW_i} \tag{5.1}$$

Where, CS = Case Similarity,

AS = Attribute Similarity,

AW = Attribute Weight.

5.3.2.3. Retrieve the similar case

The attribute similarity and the case similarity were calculated by Steps 1 and 2, and the result can enable identifying the similarity between the cases in the DB and the new case. In Step 3, by comparing the similarity of each case, the case with the highest case similarity (i.e., RC_j) is retrieveed using the Eq. 5.3, and, consequently, the monetary value of the retrieved case RC_j can be regarded as the potential monetary price of the new case.

$$HCS = Max(CS_1,\ CS_2,\ \cdots,\ CS_n) \tag{5.3}$$

Where, HCS = the highest case similarity

CS = Case similarity

n = the number of cases

5.3.2.4. Convert to present value

Since the monetary value of RC_j extracted from Step 3 is a price that was evaluated in the past, it is necessary for such monetary value to be revised with the current value by considering the time value of money in Step 4. The present worth (PW) measure can be applied to convert the past transaction price into the present transaction price. In other words, the PW measure converts or discounts all costs and benefits into their present-day equivalent, and it can be defined as Eqs. 5.4 and 5.5 (Carmichael, 2014). As shown in Eq. 5.4, the value (C_j) of the extracted monetary value of RC_j can be calculated as the equivalent present value (P_j) by considering the real interest rate i and n years for the time difference between the transaction cases and the present.

Furthermore, as shown in Eq. 5.5, the real interest rate i can be calculated by considering the nominal rate of interest and the inflation rate. As shown in Table 5.5, this study calculates the real interest rate i used in the MVP algorithms by collecting i) the annual deposit interest rates of the Bank of Korea to apply the nominal interest rate and ii) the inflation rate of construction materials by Statistics Korea. Since most of the cases constructed in the DB of this study were from 2012 to 2016, the interest rate and inflation rate were collected over the past ten years based on 2016. According to the above data and as a result of applying Eq. 5.5, the average real interest rate of 2.78% over the past ten years was applied in this study.

$$P_j = C_j(1+i)^n \tag{5.4}$$

Where, P_j = present value

C_j = the extracted monetary value of RC_j

i = the real interest rate

n = the analysis period since transaction time.

$$i = \frac{(1+j_1)}{(1+j_2)} - 1 \tag{5.5}$$

Where, j_1 = nominal rate of interest

j_2 = the inflation rate

Table 5.5 Discount rate

Year	Nominal interest rate[a](%)	Inflation rate[b](%)	Discount rate (%)
2007	6.55	2.50	3.95
2008	7.17	4.70	2.36
2009	5.65	2.80	2.77
2010	5.51	2.90	2.54
2011	5.76	4.00	1.69
2012	5.40	2.20	3.113
2013	4.64	1.30	3.30
2014	4.26	1.30	2.92
2015	3.53	0.70	2.81
2016	3.37	1.00	2.35
Mean	5.18	2.34	2.78

[a] Annual deposit interest rate of the Bank of Korea

[b] Inflation rate of construction materials from Statistics Korea

5.3.3. Determining the attribute weight based on Artificial Neural Network

5.3.3.1. Literature review

The CBR technique conducts a comparison and analysis between the attributes of the new case and that of each case in the DB. In this process, the attribute weights are determined by reflecting the relative importance of each attribute, and the prediction accuracy of the CBR technique is greatly influenced.

Doğan et al. (2006) compares the performance of three optimization techniques (namely Feature Counting (FC), the Gradient Descent Method, and Genetic Algorithms (GA)) in generating attribute weights that were used in a spreadsheet-based CBR prediction model. The model was tested by data pertaining to the early design parameters and unit cost of the structural system of 29 residential building projects. The results indicated that GA-augmented CBR performed better than CBR used in association with the other two optimization techniques.

Doğan et al. (2008) compares the performance of three different decision tree-based methods of assigning attribute weights, to be used in the CBR prediction model. The generation of the attribute weights considered the presence, absence, and positions of the attributes in the decision tree. The results indicate that the attribute weights were generated by considering the information gain of all the attributes, and performed better than the attribute weights generated by considering only the appearance of attributes in the tree.

An et al. (2007) proposed a CBR model using the Analytic Hierarchy Process (AHP), which includes experience in all cost estimation processes by eliciting the domain knowledge from experts for determining the weights of attributes. In this model, AHP is used to systematically elicit domain knowledge from the experts. The results show that the AHP-based CBR model is more accurate, reliable, and explanatory than the FC-based CBR model, and the GDM-based CBR model. The AHP-based CBR model, considered to be an effective construction cost estimation model, adopts the estimator's experience in the cost estimation process, and emphasizes the use of experience and previous cases to obtain the cost of a new construction project.

Park et al. (2010) proposed a CBR cost prediction model using genetic algorithms for attribute weighting. The prediction model of construction cost was applied to the preliminary stage (such as the planning and planning design stage), and used data from the public apartment building sector. The verification result for the validity of model is superior to the Association for the Advancement of Cost Engineering (AACE)-defined estimation timing accuracy. The prediction performance was higher than the model using the MRA and FC method.

Ji et al. (2011) developed methods for measuring similarity and assigning weight values for CBR modeling, and suggested a CBR cost estimation model for the budgeting of apartment buildings in Korea. When combined with the suggested methods (i.e., the Euclidean distance-based similarity function and weight values optimized by genetic algorithms), the proposed model was found to be superior to its counterparts. The proposed method can enhance the value of a case-based reasoning method by improving the explanatory power of the similarity measurement and by mitigating the output distortion provoked by sudden changes of features.

As previously described, many studies focused on techniques for applying optimal attribute weights using various methods. However, there have been problems with existing applied methods. Because AHP is based on subjective factors such as expert knowledge and experience. It has the problem that the attribute weight changes according to the expert (An and Kang, 2005). FC does not reflect the difference in importance between attributes, because it gives equal weight to all attributes. GDM has the problem of performing an unnecessary search process in order to converge to the local minimum when the curvatures of different directions are different (Yau and Yang, 1998). Although MRA assumes linearity when estimating the relationship between dependent and independent variables, most of the regression models fail to meet the assumptions and, hence the reliability of the results is low (Kim, 2006). If there is a very strong linear relationship between the independent variables, the usual interpretation of the regression coefficient causes a problem of colinearity (Kim et al, 2004).

In this study, an artificial neural network (ANN) is applied for the estimation of attribute weights. ANN does not need to find complex mathematical relations among attributes. It not only has no limit on the number of attributes influencing the monetary value, but also can learn by oneself and reduce error through the repeated learning of the cases, even if the number of data is few or irregular (Bode, 1988; Bode, 2000). Because these advantages counter the disadvantages of the existing methods, the ANN method was used to determine the attribute weights in this study.

5.3.3.2. Artificial Neural Network theory.

The ANN created intelligence by imitating neurons of the human brain. In other words, the intelligent form that the human brain appears in is embodied by simplifying the connection between the biological neuron, which represented the human brain, and mathematical modeling.

As shown in Figure 5.5, neurons are composed of nerve fibers such as the cell body, dendritic, and axon. The dendritic receives the neural excitement transmitted from adjacent neurons into a cell body, and the axon transmits the neural excitement through synapse. A neuron accepts the neural excitement transmitted from many other neurons connected to it. When the neural excitement is increased and exceeds the threshold value, the neuron is ignited and transmits the neural excitement to the surrounding other neurons through axon (Kwon, 2013).

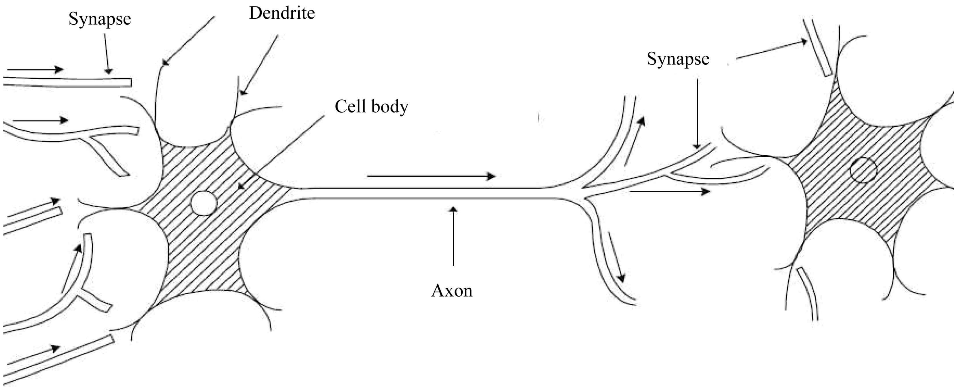

Figure 5.5 Biological neuron (Kim, 2009)

The ANN is implemented by imitating the information processing and transmission process of these biological neurons. As shown in Fig. 5.6, each neuron receives the output of many different neurons as input. This is modeled by the neurons of the brain receiving input signals from other neurons or outside. As the synapse in the brain gives the weight to the input signal, the neural network also gives the weight to input signal. The input values given the weight are summed, and the summed value calculates the output value using the transfer function. The neural network uses the threshold value of each transfer function to determine whether the neurons in the brain are sufficient to export the summed signal. The point in which two neurons exchange information is called a connection, and is similar to the synapse of the brain (Kim, 2004).

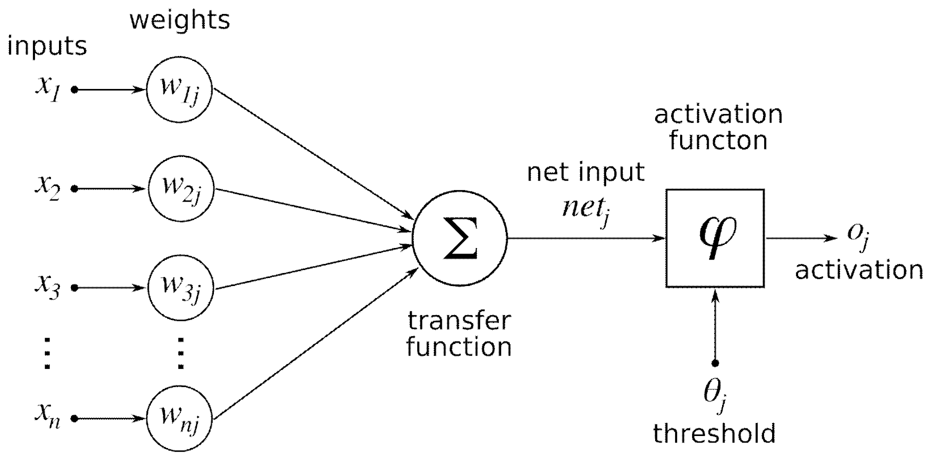

Figure 5.6 Neural network neuron

The ANN consists of the interconnected artificial neurons. The neurons composed of each group, as shown in Figure 5.7, are divided into three layers (input, hidden, and output). There is a single-layer perceptron composed of the input and output layer, and a multi-layer perceptron in which at least one hidden layer exists between the input and the output layer. Here, the neurons in the input layer receive the information from the outside, and export the information to the hidden or output layer. The neurons in the hidden layer are located between it and the output layer. Because neurons are interconnected with neurons in different layers, the input and output values cannot be identified. The neurons in the output layer provide the results of the neural network obtained from the neuron of the hidden layer to the outside users. The constructed neurons are connected by a single line from neurons in each layer to neurons in another layer. Through this connection, a neuron sends the information to the neuron of another layer, and the other neurons receive information.

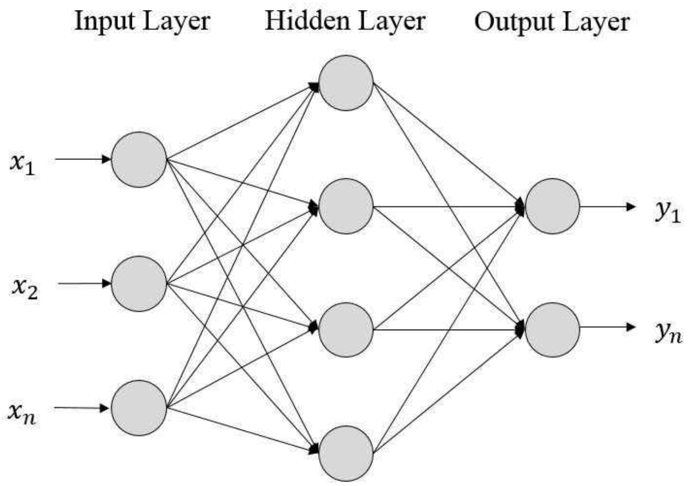

Figure 5.7 Neural network structure

The ANN can be classified according to the role of transfer functions and learning algorithms. It is classified as a feedback network if some neurons are affected by the next connected neuron, or feed-forward networks if they are not affected. It is classified according to whether the activation function is linear or nonlinear. Because the result obtained from the learning process according to the learning algorithm is known, it is classified as supervised learning compared with the target value, and as unsupervised learning without the target value.

5.3.3.3. Artificial neural network design

In this study, the ANN algorithm applied to determine the attribute weights used an error backpropagation algorithm, which is generally used in the engineering and management fields of the construction industry.

According to Hegazy et al. (1994), ANN design contains two methods: the empirical method and genetic algorithms. This study designed neural networks using the empirical method, which utilized parameters applied in existing studies. Parameters were established to develop the optimization model using ANNs. As shown in Table 5.6, the parameters were composed of the transfer function, number of hidden layers, number of nodes in the hidden layer, learning rate, and momentum.

Table 5.6 ANN structure and learning algorithm parameters

Parameter	Contents
Input·Output data type	Continuous type
Transfer function	Sigmoid function
Number of hidden layer	1
Number of nodes in hidden layer	Number of input variables = 7 Number of input variables × 0.75 = 5 Number of input variables × 2 + 1 = 15
Learning algorithm	Back-propagation algorithm
Connectivity	Connect all nodes
Learning rate	0.3, 0.6, 0.9
Momentum	0.7, 0.8, 0.9
Stopping rules	Choose automatically

Based on a study by Hegazy et al. (1994), the number of hidden layers was set to one for all models. The number of nodes in the hidden layer applied the three criteria presented in Hegazy et al. (1994): i) 75% of the number of input variables, ii) the same number of input variables, and iii) the number of input variables 2 + 1. In addition, the learning rate and momentum were set at 0.3, 0.6, 0.9 and 0.7, 0.8, 0.9 respectively. Based on the above parameters, the ANN model was constructed. The 90 collected cases were used to construct the ANN model, and, as shown in Table 5.7, it was divided into training datasets, cross-validation datasets, and verification datasets for model accuracy and validity. The 16 cases with actual transaction prices among the 90 cases were divided for verification datasets, and 61 cases among the remaining 74 cases were divided for the training dataset.

Table 5.7 Division of ANN dataset

Type of dataset	Cases	Rate
Training datasets	61	67.78%
Cross-validation datasets	13	14.44%
Verification datasets	16	17.78%
Total	90	100%

As shown in Table 5.8, 27 models of the ANN were constructed using the 61 cases of training datasets and the set parameters. Each model is distinguished by the number of nodes in the hidden layer, learning rate, and momentum. The 27 ANN models were compared with the accuracy of each model by applying 16 validation cases.

Table 5.8 Error rate of ANN model

ANN model	Number of node units	Learning rate	Momentum	Error rate	Rank
1	5	0.3	0.7	0.187	5
2	5	0.6	0.7	0.730	27
3	5	0.9	0.7	0.215	12
4	5	0.3	0.8	0.122	1
5	5	0.6	0.8	0.160	2
6	5	0.9	0.8	0.230	14
7	5	0.3	0.9	0.211	11
8	5	0.6	0.9	0.254	21
9	5	0.9	0.9	0.210	10
10	7	0.3	0.7	0.237	17
11	7	0.6	0.7	0.240	18
12	7	0.9	0.7	0.190	6
13	7	0.3	0.8	0.232	15
14	7	0.6	0.8	0.241	19
15	7	0.9	0.8	0.194	7
16	7	0.3	0.9	0.220	13
17	7	0.6	0.9	0.276	24
18	7	0.9	0.9	0.261	23
19	15	0.3	0.7	0.208	9
20	15	0.6	0.7	0.249	20
21	15	0.9	0.7	0.254	21
22	15	0.3	0.8	0.293	25
23	15	0.6	0.8	0.166	3
24	15	0.9	0.8	0.207	8
25	15	0.3	0.9	0.300	26
26	15	0.6	0.9	0.167	4
27	15	0.9	0.9	0.232	15

As shown in Table 5.8, the 27 ANN models that were constructed based on the combination of set parameters showed an accuracy ranging from 27% (Model 2, error rate 0.730) to 87.8% (Model 4, error rate 0.122). The results of the five models with high accuracy were selected from the 27 models, and the attribute weights of each model are shown in Table 5.9. Examining the attribute weights of each model, Models 1, 4, 5, and 26 were not appropriate for the attribute weights because these models have a high weight in one attribute (i.e., gross floor area (X_1)) and a low weight in the other attributes. On the other hand, Model 23, unlike the other models, did not focus on one attribute (i.e., the weights of attributes were decentralized) and had a model accuracy of 83.4% (error rate: 0.166) with a relatively high accuracy. Therefore, the attribute weight of the CBR model applied the attribute weights of ANN Model 23.

Table 5.9 Attribute weighs for each condition

ANN model	Attribute weights of the each variables						
	Gross area (X_1)	Site area (X_2)	Number of parking spaces (X_9)	Number of elevators (X_{10})	Years elapsed since construction (X_{11})	Officially assessed land price (X_{13})	Renovation scope (X_{14})
1	0.630	0.031	0.079	0.137	0.056	0.002	0.065
4	0.685	0.047	0.094	0.078	0.023	0.036	0.036
5	0.760	0.018	0.071	0.031	0.037	0.048	0.036
23	0.378	0.123	0.178	0.205	0.024	0.043	0.050
26	0.567	0.025	0.120	0.158	0.040	0.032	0.059

5.3.4. Spreadsheet for the model

Along with some modifications on the developed spreadsheet by Doğan et al. (2006) and Jin et al. (2012), an MVP spreadsheet model was developed, as shown in Fig. 5.8. Row 1 presents the seven attributes defined in this study, and Row 2 provides the attribute weights of each attribute determined through ANN. Rows 4 to 7 present cases constructed in the case DB and the attribute values of each case, while Row 8 shows the attribute values for the new case. Rows 10 to 13 are the results in the attribute similarity and case similarity between the DB and new case. Row 15 lists the case with the highest degree of similarity calculated in Rows 10 to 13, and H15 extracts the monetary value of the case (RC_j). Finally, Row 18 shows the information required to convert the extracted monetary value of RC_j to its present value, and H18 extracts the monetary value converted to the current value of RC_j. By using the extracted and converted monetary value, the price of the office building according to the renovation of the new case could be developed.

	A	B	C	D	E	F	G	H
1	Attribute Weights		AW_1	AW_2	…	AW_{m-1}	AW_m	
2	Attributes		A_1	A_2	…	A_{m-1}	A_m	
3		Case No.	Input- Value of each attribute					Output- Monetary value
4	Case Base	RC-01	$A_1^{RC_1}$	$A_2^{RC_1}$	…	$A_{m-1}^{RC_1}$	$A_m^{RC_1}$	C_1
5		RC-02	$A_1^{RC_2}$	$A_2^{RC_2}$	…	$A_{m-1}^{RC_2}$	$A_m^{RC_2}$	C_2
6		…	…	…	…	…	…	…
7		RC-n	$A_1^{RC_n}$	$A_2^{RC_n}$	…	$A_{m-1}^{RC_n}$	$A_m^{RC_n}$	C_n
8	New Case	A'	$A_1^{A'}$	$A_1^{A'}$	…	$A_{m-1}^{A'}$	$A_m^{A'}$	
9		Case No.	Weighted Attribute Similarities					Case Similarities
10	Similarities	RC-01	$AS_1^{RC_1}$	$AS_2^{RC_1}$	…	$AS_{m-1}^{RC_1}$	$AS_m^{RC_1}$	CS_1
11		RC-02	$AS_1^{RC_2}$	$AS_1^{RC_2}$	…	$AS_{m-1}^{RC_2}$	$AS_m^{RC_2}$	CS_2
12		…	…	…	…	…		=SUM(C10:G10)
			=MIN(C$8,C4)/MAX(C$8,C4)*C$2/SUM($C$2:$F$2)					
13		RC-n	$AS_1^{RC_n}$	$AS_1^{RC_n}$	…	$AS_{m-1}^{RC_n}$	$AS_m^{RC_n}$	CS_n
14		Case No.	Input- Value of each attribute					Output- Monetary value
15	Retrieved Case with the Highest Case Similarity	RC-j	$A_1^{RC_j}$	$A_2^{RC_j}$	…	$A_{m-1}^{RC_j}$	$A_m^{RC_j}$	C_j
			=VLOOKUP($B$15,$B$4:$H$7,2,FALSE)					
		=INDEX($C$10:$H$13,MATCH(MAX($H$10:$H10$13),$H$10:$H$10,0),1)						
16								
17		Case No.	Input-					Output- Present value
18	Present value	RC-j	C_j	Transaction time		Interest rate (i)	n	P_j
						= 2016-D18		$= C18(1+E18)^{F18}$

Figure 5.8 Modified Spreadsheet for MVP algorithms

5.4. Model validation

A validation for the models developed in this study was conducted to determine the predicted value accuracy of post-renovation office buildings. As described in Section 1.2, the 16 cases with complete data sets were used for the validation of the developed model by comparing the actual transaction value (i.e., (a) in Table 5.10) and the value predicted by the MV model II (i.e., (c) in Table 5.10).

In the validation process of the MVP model II, because the timing of the two values (i.e., the value predicted by the MVP model was the value converted into the present value by considering the time value of money, whereas the actual transaction value was the value estimated for each case in the past) differed, it was limited to the accurate validation of the MVP model. Therefore, the actual transaction value was converted to the value of the present time by using the PW measure applied in Step 4 of the MVP model. Consequently, MVP model validation was conducted by comparing the converted transaction value (i.e., (b) in Table 5.10) and the value predicted by the MVP model II (i.e., (c) in Table 5.10).

As shown in Table 5.10, the case similarity by applying the MVP model II ranged from 78.05% at the minimum to 91.29% at the maximum, and the average case similarity was 84.78%. Because the error rate of the model ranged from 1.69% at the minimum to 34.74% at the maximum, and the average error rate was 14.12%, it revealed that the model could predict the monetary value relatively accurately. Generally, given that the prediction accuracy in the very early project phase was approximately 90% on account of the limited information, the MVP model II with the average error rate of 14.12% was applicable for clients considering renovation in the process of estimating the monetary value of the post-renovation office building.

Table 5.10 Application result of the developed MVP model II

(Estimation price: US million $)

No.	Transaction price (a)	MVP model II			
		Case similarity	Converted transaction price (b)	Estimation price (c)	Error rate (d)
1	159.50	82.38%	16394	128.43	21.66%
2	160.00	80.66%	164.45	167.23	1.69%
3	132.10	80.10%	135.77	167.23	23.16%
4	193.00	84.08%	215.39	219.61	1.96%
5	83.00	78.05%	90.12	86.84	3.64%
6	55.70	80.28%	57.25	43.74	23.59%
7	87.50	86.50%	89.93	84.28	6.28%
8	400.00	82.96%	411.13	424.49	3.25%
9	64.50	91.17%	66.29	72.06	8.70%
10	650.00	90.31%	668.08	436.02	34.74%
11	202.50	91.29%	208.13	156.53	24.79%
12	109.00	90.43%	115.15	94.80	17.67%
13	197.90	80.89%	220.86	167.23	24.28%
14	250.00	83.34%	250.00	219.61	12.16%
15	170.80	91.08%	170.80	156.53	8.36%
16	231.00	82.99%	244.03	219.61	10.01%
Average		84.78%	-	-	14.12%

$d = \{|b-c| \div b\} \times 100\%$

6. Discussion

6.1. Comparison of the developed models and existing approach

To investigate the benefits and disadvantages of the developed MVP model, as shown in Table 8, a comparison between the existing appraisal approach (i.e., ICA, income capital approach), the MVP model I (i.e., a prediction model developed by MRA), and the MVP model II (i.e., a prediction model developed by CBR) was conducted in terms of seven categories: view of accuracy, required data, accessibility of the required data, evaluation method, reflection of the market, renovation scope, and possibilities for future development.

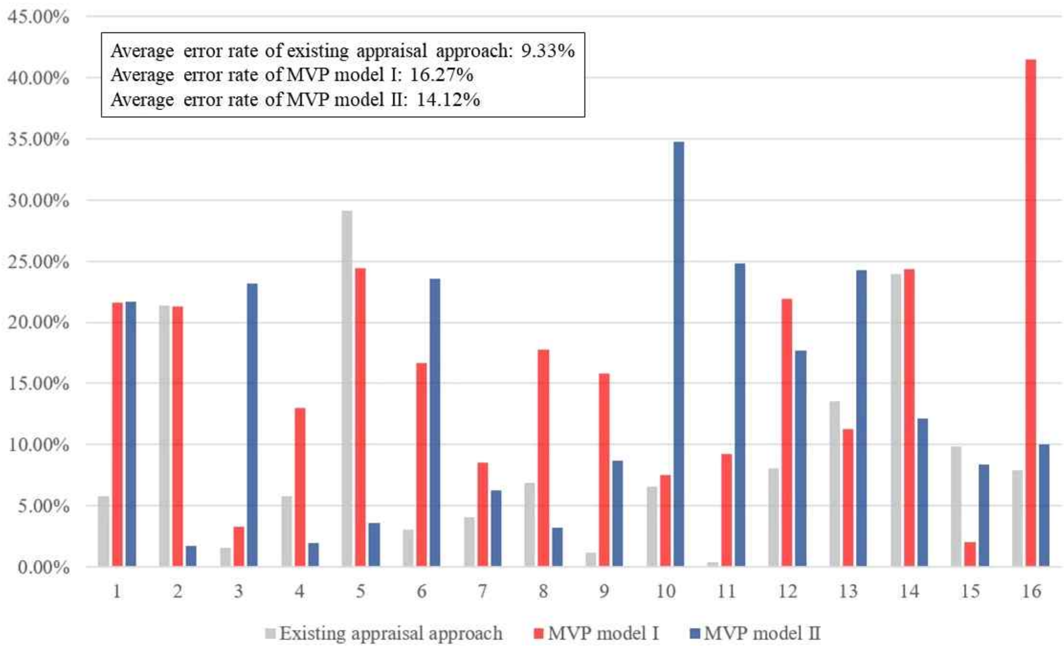

Fig. 6.1 Error rates of model applications

Table 6.1 Comparison result between existing appraisal approach MVP model I and II

(Estimation price: US million $)

No.	Transaction price (a)	Existing appraisal approach		MVP model I		MVP model II			
		Estimation price (b)	Error rate (c)	Estimation price (b)	Error rate (c)	Case similarity	Converted transaction price (d)	Estimation price (e)	Error rate (f)
1	159.50	150.21	5.82%	125.05	21.60%	82.38%	163.94	128.43	21.66%
2	160.00	194.26	21.41%	194.07	21.29%	80.66%	164.45	167.23	1.69%
3	132.10	130.00	1.59%	136.41	3.27%	80.10%	135.77	167.23	23.16%
4	193.00	204.13	5.76%	167.95	12.98%	84.08%	215.39	219.61	1.96%
5	83.00	107.20	29.16%	103.30	24.46%	78.05%	90.12	86.84	3.64%
6	55.70	54.01	3.03%	65.01	16.71%	80.28%	57.25	43.74	23.59%
7	87.50	91.06	4.06%	80.06	8.51%	86.50%	89.93	84.28	6.28%
8	400.00	427.50	6.87%	328.76	17.81%	82.96%	411.13	424.49	3.25%
9	64.50	65.25	1.16%	74.71	15.82%	91.17%	66.29	72.06	8.70%
10	650.00	692.96	6.61%	698.84	7.51%	90.31%	668.08	436.02	34.74%
11	202.50	201.66	0.41%	221.22	9.25%	91.29%	208.13	156.53	24.79%
12	109.00	100.19	8.08%	85.14	21.89%	90.43%	115.15	94.80	17.67%
13	197.90	171.03	13.58%	175.64	11.25%	80.89%	220.86	167.23	24.28%
14	250.00	190.07	23.97%	189.16	24.34%	83.34%	250.00	219.61	12.16%
15	170.80	187.62	9.85%	174.31	2.06%	91.08%	170.80	156.53	8.36%
16	231.00	212.79	7.88%	135.11	41.51%	82.99%	244.03	219.61	10.01%
Average		-	9.33%	-	16.27%	84.78%	-	-	14.12%

$c = \{|a-b| \div a\} \times 100\%$

$f = \{|d-e| \div d\} \times 100\%$

As shown in Table 6.1 and Figure 6.1, the three methods were applied to 16 cases with the actual transaction value, and the results of each method were compared in terms of accuracy. The results of the existing appraisal approach showed 9.33% of the average error rate. Meanwhile, in order to compare the accuracy with other models, the price of the square root value predicted by the MVP model I was converted to the actual price. And, validation result of the MVP model I showed the error rate from 2.06% at the minimum to 41.51% at the maximum, and the average error rate was 16.27%. Therefore, it was revealed that MVP model II could predict more accurately than the MVP model I; however, the existing appraisal approach could more accurately predict than the MVP model II.

When comparing the amount of data required for predicting the monetary value, the existing appraisal approach required ten types of data－operation profit, operation cost, loss for vacancy, deposit, monthly lease income, monthly operating cost, lease area, Treasury bond interest ratio, vacancy ratio, capitalization ratio－and the MVP model I required four data types－gross floor area, number of underground floors, years elapsed since construction, and officially appraised land price. On the other hand, the MVP model II required seven data types－gross floor area, site area, number of parking spaces, number of elevators, years elapsed since construction, officially appraised land price, and renovation scope. In addition, when comparing the degree of effort to acquire the above information, some information required for the existing appraisal approach, such as Treasury bond interest ratio, vacancy ratio, and capitalization ratio, could be obtained from the information released by the government and real estate company; however, it was difficult to understand or acquire the above data. On the other hand, the information for the MVP model I and II was related to attributes or characteristics that would be changed for post-renovation work for a particular office building. Thus, they could be easily accessed by the client who owns the building.

When comparing the methods in terms of the evaluation and reflection of the market, the existing appraisal approach predicted the price of the office building based on the profit generated in the future. Because the profit generated by the office building depended on various conditions, such as the current market value, building location characteristics, vacancy rate, and surrounding commercial area, the profit would be subjectively rendered according to the appraisers having differences in terms of the application of the above conditions. Thus, this method indirectly reflected the market characteristics. The MVP model I estimated the prices using statistical methods based on multiple characteristics influencing the value of the office buildings. It was thus expressed as an objective evaluation; however, the approach did not reflect the market conditions. On the other hand, the MVP model II provided an objective estimation result because it was implemented based on the actual case and the converted transaction value data. In addition, the model directly reflected the market characteristics because it predicted based on the transaction value of a similar building.

Finally, because the existing appraisal approach predicted based on the generated profit individually evaluated by an appraiser, it was not difficult for this approach to reflect the renovation work scope, which surely affected the building value, and improve the estimation performance owing to its characteristic. MVP model I could be improved by adding cases; however, an additional analysis based on expanded data set would be required. On the other hand, the MVP model II reflected the renovation scope, which could significantly influence the changes of the monetary value of the office building after renovation. This is because the variable was one of those used for implementing the MVP model II. In addition, because the MVP model II was theoretically developed based on the case-based methodology, it was possible to improve the accuracy of the model simply by adding the cases to the DB.

Table 6.2 Comparison between three methods

Category	The existing appraisal approach	MVP model Ⅰ	MVP model Ⅱ
Level of accuracy	9.33%	16.27%	14.12%
Required data	More than 10 types	4 types of data	7 types of data
Accessibility of required data	Difficult to get the required information	Easy to identify	Easy to identify
Evaluation method	Subjective approach by individuals	Objective approach by statistical model	Objective approach by actual cases
Reflection of the market	Indirect	None	Direct
Renovation scope	None	None	Existence
Possibilities for future development	None	Medium	High

One of the most important decision making factors for conducting office-building renovation work is the change in the monetary value of the office building after the renovation. Therefore, it is expected that the ability to predict changes in monetary value using the proposed MVP model II at an early project stage can significantly influence the client decision-making process.

7. Conclusion

7.1. Research conclusion

Recently, renovation projects for deteriorated office buildings have been undertaken on account of their related physical, economic, and environmental problems. Owing to the increase of interest in building renovation work, it has become critical to estimate the change in the post-renovation office-building value. Studies on estimating this post-renovation monetary value remain insufficient to date; furthermore, the existing appraisal approaches present difficulties in terms of applicability and usability. Thus, the proposed MVP model was designed to assist a building owner / client to more easily and accurately predict the price of the office building after renovation work.

This study developed the two MVP models. The MVP model I developed by applying the MDA method, which widely used in statistical analysis method, and the MVP model II developed by applying the CBR technique, well-known for artificial intelligence technique. In the process of developing the MVP model I, (i) the result of analyzing the existing studies was used to derive the 13 factors influencing the price of office buildings, and it was applied as independent variables of MRA, which is the one of MDA methods, (ii) the developed MVP model I can predict the price of post-renovation office building by applying the only four variables (i.e., gross area, number of underground floors, years elapsed since construction, and officially appraised land price).

In the process of developing the MVP model II, (i) correlation analysis and multiple regression analysis by using the 13 factors were used to derive the seven input variables (i.e., gross floor area, site area, number of parking spaces, number of elevators, years elapsed since construction, officially appraised land price, and renovation scope) of the model, (ii) the main framework of the MVP model II was developed by applying the basic principle of the CBR technique, and (iii) the weights of each attribute, which are keys to extracting the similar transaction cases, were estimated by using the ANN technique. In addition, 90 cases of actually conducted renovation work and completed transactions were collected for constructing the MVP model DB, and 74 cases among those were used to develop the model, while 16 cases were used to verify the model.

The results of applying the developed MVP model I and II to 16 verification cases showed 16.27% and 14.12% of the average error rate. Meanwhile, to investigate various aspects, such as usability, applicability, and accuracy of the MVP model, the existing appraisal approach (i.e. ICA) was applied to 16 verification cases and the results were compared. By comparing the three methods in terms of accuracy, the existing appraisal approach showed the most accuracy compared to the developed MVP model I and II (i.e., 9.33% for the existing appraisal approach; 16.27% for MVP model I; 14.12% for MVP model II). However, when considering the other aspects, including the amount of data, accessibility of required data, evaluation method, reflection of the market, renovation scope, and possibilities for future improvement, the proposed MVP model II was evaluated as the most suitable for easily and accurately predicting the price of the office building after the renovation at the planning stage of the project. Therefore, this study selected the developed MVP model II as a model to predict the price of post-renovation office buildings.

By applying the developed MVP model, it is expected that the owner of the deteriorated office building can easily engage in the decision-making process concerning the renovation work. Moreover, model is expected to contribute to promoting the office-building renovation market. Similarly, the developers and contractors can be supported by applying the MVP model II developed in the study. Meanwhile, this study can be a cornerstone related to the future research, which will focus on the effect according to the renovation work in terms of economy; this is because there have been few studies on the economic value changes owing to the renovation work.

7.2. Limitations of research and future directions

The monetary value prediction (MVP) model of post-renovation office buildings proposed in this study requires the following improvements:

1) It was very difficult to collect the cases that meet 2 conditions: (i) cases of office buildings that have already completed renovation, and (ii) cases with historical data of transaction time and price. Therefore, this study estimated the transaction price for some cases, by applying the existing appraisal approach (i.e., ICA). Although ICA can predict the price of the office building relatively accurately, it is necessary for the cases in DB to be compensated with the actual transaction price data, to develop a more accurate MVP model.

2) The renovation scope among the seven input variables using the proposed MVP model in this study was defined as a nominal variable, because it is one of the most important factors in the price change of office buildings. However, the renovation scope, which was defined in four scopes, is outline level. Therefore, it is necessary to add information (such as more detail renovation scope and construction cost and time) to identify the renovation scope for each case, for a more accurate estimation of the renovation scope.

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