Model for predicting price change patterns in multi-family houses post renovation work in South Korea

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ABSTRACT
Renovation work on deteriorated multi-family houses (MFHs) is often undertaken to improve their physical performance. However, due to uncertainties in economic benefits from renovation, many MFHs frequently withdraw their renovation plans in South Korea. Despite this problem, there has been little research on countering this issue. With this background, this study aims to develop a model for predicting the price change patterns (MPPCP) of deteriorated MFHs upon renovation in South Korea. An artificial neural network (ANN)-based MPPCP was developed to detect the relationship between project attributes and price change patterns due to renovations. By combining the parameters of the ANN method, 108 candidate models were identified and a final MPPCP was proposed after conducting simulation tests to verify the level of correct for the candidate’s models. The results of model application to actual MFH renovation cases show that the developed model can facilitate a project owner’s decision-making by estimating price change patterns for the deteriorated MFH in the project planning stage itself.

1. Introduction
1.1. Research background and objectives
According to a report by the Construction & Economy Research Institute of Korea (CERIK), in addition to physical deterioration of multi-family houses (MFHs), their social performance is experiencing rapid changes due to changes in lifestyle and population structure in South Korea (Yoon and Lee, 2012). Renovation and reconstruction are considered attractive solutions to counter this physical and social deterioration. From the point of view of low-carbon green construction, renovation is gaining much attention as it imposes less environmental burden.

However, in spite of the positive effect of less environmental pollution, the current status of renovations for deteriorated MFHs is poor. According to the Korea Remodeling Association (KRA), in 2011, only 3% (104,803 households) of 3,177,000 deteriorated households considered renovation and of these, 77% later cancelled their renovation plans (KRA 2011). According to Kim, Choi, and Kim (2010), Cho et al. (2012), and Kim et al. (2013), the reasons for abandoning MFH renovations in South Korea are primarily the uncertainty in economic profit after renovation and difficulty in securing the feasibility due to high building costs.

Economic benefit from renovation is very important to not only evaluate the success or failure of a project but also decide whether or not to undertake renovation work (Cho and Yoon 2016; Kim et al. 2018; Cho, Kim, and Kim 2019). However, most of the existing studies on the economic efficiency of MFH renovation projects analyzed economic efficiency only in terms of input cost, such as construction costs (Lee 2005; Lee et al. 2007; Han and Shin 2012; Yeon et al. 2014; Kim and Baik 2015). Some existing studies have been conducted for typical MFHs in estimating their price or in identifying the factors influencing the price. However, most of these studies have attempted to estimate the price for new and existing MFHs, mainly using the method based on the typical building appraisal methods compensated by referring to the transaction cases (Kim, Cho, and Kim 2016).

Therefore, due to the above limitation, it is highly difficult to evaluate the economic effect of renovations, which is one of the main concerns of property owners considering renovating their deteriorated MFHs; this is also a major reason for owners cancelling their renovation plans in South Korea. In this study, we aim to develop a method for evaluating the economic benefit, represented by changes in the monetary price of MFHs in South Korea, post renovation. It is expected that the results of this study would help facilitate decision-making with respect to renovation projects.

1.2. Research methodologies
The implementation procedure of the economic effect analysis model developed in this study is depicted in Figure 1. One of the main aspects in
developing the model lies in analyzing the relationship between attribute changes and price changes of a given MFH upon renovation. In other words, renovation work on a deteriorated MFH causes changes in its physical attributes and monetary value. Moreover, if the relationship between the two sets of changes can be structured using scientific and objective methodologies, it is possible to predict price changes in the MFH post renovation according to variations in the project’s attributes corresponding to the renovation plan. With this objective in mind, 120 MFH cases were selected to gather data required for analyzing changes in their attributes and monetary values after renovation; an artificial neural network (ANN) method was adopted to structure the relationship between the two changes objectively. As shown in Figure 1, the attribute change rate (△1) and corresponding price change rate (△2) were utilized as inputs and output variables for implementing ANN method. Through the above process, this research could propose an ANN-based model predicting price change of MFH post renovation works.

2. Analysis of price changes due to renovations

It is possible to analyse the economic effect of renovations on MFHs by evaluating trends in price changes of the MFH before and after renovation.

2.1. Analysis of price changes due to renovations

Generally, the price of an MFH is influenced by various factors, including location, convenience of transportation, and educational environment (Choi and Song 2006; Jin et al. 2012; Kim, Cho, and Kim 2016). As price changes due to renovation must be measured, the factors above should be controlled while assessing price changes. In other words, price change assessment due to renovations may follow the concept of “relative price” for the renovated MFH on the similar comparative cases, which aims at excluding other price-influencing factors.

Therefore, a comparative case with location and size similar to those of the renovation case should be
selected; the price of the renovation case should be assessed relative to the comparison case at three time points (before renovation, after renovation, and present). From the obtained results, one can be sure that the relative price change between the price of the renovated MFH and that of the comparative MFH is due to renovations. The relative price ratio can be calculated using Equations (1–1), (1–2), and (1–3). \( R_{k} \) and \( CC_{j} \) denote renovation case \( k \) and comparative case \( j \) for \( RC_{k} \), respectively.

\[
R_{k}^{p_{BR}} = \frac{P_{RC_{k}}^{BR}}{P_{CC_{j}}^{BR}} \times 100 \quad (1-1)
\]

\[
R_{k}^{p_{AR}} = \frac{P_{RC_{k}}^{AR}}{P_{CC_{j}}^{AR}} \times 100 \quad (1-2)
\]

\[
R_{k}^{p_{P}} = \frac{P_{RC_{k}}^{P}}{P_{CC_{j}}^{P}} \times 100 \quad (1-3)
\]

Here, \( R_{k}^{p_{BR}} \) = price rate of renovation case \( RC_{k} \) on comparative case \( CC_{j} \) before renovation, \( R_{k}^{p_{AR}} \) = price rate of \( RC_{k} \) on \( CC_{j} \) after renovation, and \( R_{k}^{p_{P}} \) = price rate of \( RC_{k} \) on \( CC_{j} \) at present, \( RC_{k} = \) renovation case \( k \), and \( CC_{j} = \) comparative case \( j \) for \( RC_{k} \).

Using the above method, it is possible to analyse price change patterns for an MFH upon renovation; furthermore, the economic effect of renovation can be grasped objectively. As shown in Figure 2, if the price after renovation is higher than that before renovation, it can be considered that renovations have a positive influence on the monetary value of the MFH.

### 2.2. Collection of renovation cases and comparative cases

A total of 17 renovated MFH cases, all of which were located in Seoul, were considered in this study. As shown in Table 1, in most of these cases, the house- hold unit area increased upon renovation, which took about 1 to 2 years. In some cases, vertical expansion was conducted by increasing the number of floors; most of these structures were constructed around 1970 and about 25 years later, they required renovations for improving building performance in terms of energy, physical appearance, and economic performance. Furthermore, as described above, comparative

![Figure 2: Example of positive price changes due to renovation.](image)

Table 1. Renovation cases.

| Renovation cases | Number of floors (before renovation) | Location | Area of unit households (m²) | Year of construction | Renovation period |
|------------------|--------------------------------------|----------|-----------------------------|---------------------|------------------|
| \( RC_{1} \)     | 12(12)                               | SC. gu, Seoul | 89.84                       | 1978                | 2005.07 – 2006.12 |
| \( RC_{2} \)     | 12(12)                               | SC. gu, Seoul | 121.07                      | 1978                | 2005.07 – 2006.12 |
| \( RC_{3} \)     | 12(12)                               | SC. gu, Seoul | 155.44                      | 1978                | 2005.07 – 2006.12 |
| \( RC_{4} \)     | 5(5)                                 | MP. gu, Seoul | 57.86                       | 1971                | 2006.02 – 2007.03 |
| \( RC_{5} \)     | 12(10)                               | MP. gu, Seoul | 89.79                       | 1989                | 2011.03 – 2012.12 |
| \( RC_{5} \)     | 12(12)                               | YS. gu, Seoul | 147.74                      | 1972                | 2004.07 – 2005.12 |
| \( RC_{7} \)     | 12(12)                               | YS. gu, Seoul | 186.12                      | 1972                | 2004.07 – 2005.12 |
| \( RC_{8} \)     | 13(12)                               | YS. gu, Seoul | 89.09                       | 1976                | 2007.06 – 2008.08 |
| \( RC_{9} \)     | 11(10)                               | YD. gu, Seoul | 88.03                       | 1978                | 2008.07 – 2010.07 |
| \( RC_{10} \)    | 13(12)                               | YD. gu, Seoul | 68.27                       | 1978                | 2008.07 – 2010.07 |
| \( RC_{11} \)    | 13(12)                               | YD. gu, Seoul | 106.56                      | 1978                | 2008.07 – 2010.07 |
| \( RC_{12} \)    | 5(5)                                 | MP. gu, Seoul | 59.50                       | 1971                | 2002.06 – 2003.07 |
| \( RC_{13} \)    | 16 (15)                              | GN. gu, Seoul | 110.39                      | 1989                | 2011.12 – 2014.02 |
| \( RC_{14} \)    | 15(12)                               | GN. gu, Seoul | 110.20                      | 1991                | 2011.06 – 2014.01 |
| \( RC_{15} \)    | 19(18)                               | GN. gu, Seoul | 110.14                      | 1992                | 2012.02 – 2014.03 |
| \( RC_{16} \)    | 11(10)                               | GN. gu, Seoul | 92.40                       | 1987                | 2010.08 – 2013.08 |
| \( RC_{17} \)    | 11(10)                               | GJ. gu, Seoul | 65.65                       | 1987                | 2010.08 – 2013.08 |
MFH cases were selected for each renovated MFH case selected using a 2-step criterion as follows (see Figure 3). In Step 1, an MFH located in the same administrative district as the renovation case was selected to control the effect on price by location, which has a highly significant effect on MFH price (see (a) in Figure 3). If the area of the administrative district is too wide, MFHs located within a radius of 1 km from the renovated MFH are selected as comparative candidates (see (b) in Figure 3). In the second step, because price is also influenced by the household unit area of the MFH, a case with similar unit area was selected from among the candidates screened in the first step as the comparative case (see (c) in Figure 3).

In accordance with the above criteria, 103 comparative MFH cases were collected for 17 renovated MFH cases (see Table 2). As shown in the table, each comparative case had an area similar to that of the household unit area of the renovation case. For example, the household unit area of $RC_7$ was 186.12 $m^2$ while that of comparative cases $CC_{7^1}$ to $CC_{7^4}$ was 177.62, 147.48, 180.20, and 196.71 $m^2$, respectively. A minimum of two comparison cases (for $RC_{11}$ and $RC_{12}$) were selected for each renovation case while the maximum was 10 (for $RC_{13}$).

Although comparative cases in similar areas were selected in most cases, some comparative cases (i.e., $CC_{3^7}$, $CC_{3^7}$, and $CC_{3^8}$) exhibited significant differences in a unit area. Despite the area difference, because they were located very close to the renovation case, it is meaningful to compare their price data with that of renovation cases. Price data at the three selected time points were collected through the Declared price of real estate in Korea inquiry system (Ministry of Land, Infrastructure, and Transport, 2016).

2.3. Analysis of price change patterns due to renovation work

In this study, we collected price data at three time points (before renovation, after renovation, and present) for selected renovation and comparison cases. Using this data, the impact of renovation on MFH prices can be assessed. Table 3 shows an example of such evaluation for Renovation Case 1. The table shows price information on renovation case $RC_1$ and its comparative cases $CC_1$ to $CC_4$ at the three selected time points as well as the price ratio of $RC$ to $CC$, which can be used to analyse relative price change trends upon renovation. As shown in the table, a total of four relative price changes could be observed (i.e., changes in the prices of the renovation and comparative cases. The price change of $RC_1$ as compared to $CC_{1^7}$ to $CC_{1^4}$ shows that its current relative price is greater than its
Table 2. Comparative cases for each renovation case.

| Ren. Cases, $RC$ (Household unit area, m²) | $RC_{1}$ | $RC_{2}$ | $RC_{3}$ | $RC_{4}$ | $RC_{5}$ | $RC_{6}$ | $RC_{7}$ | $RC_{8}$ | $RC_{9}$ | $RC_{10}$ | $RC_{11}$ | $RC_{12}$ | $RC_{13}$ | $RC_{14}$ | $RC_{15}$ | $RC_{16}$ | $RC_{17}$ |
|--------------------------------------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Household unit area of each $CC$          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |
| $CC_{1}$                                   | 80.33    | 133.31   | 159.47   | 59.94    | 122.68   | 145.19   | 177.62   | 84.65    | 84.93    | 73.86    | 114.96   | 59.99    | 114.59   | 89.36    | 89.36    | 84.92    | 75.55    |
| $CC_{2}$                                   | 105.04   | 116.13   | 177.52   | 59.65    | 84.84    | 114.69   | 174.48   | 84.88    | 82.65    | 60.83    | 162.21   | 59.25    | 128.03   | 138.51   | 84.53    | 59.94    |          |
| $CC_{3}$                                   | 84.96    | 128.50   | 164.55   | 59.98    | 114.96   | 180.20   | 84.75    | 59.40    |          |          |          |          |          |          |          |          |          |
| $CC_{4}$                                   | 84.94    | 129.76   | 134.76   | 84.97    | 140.07   | 196.71   | 84.78    | 94.96    |          |          |          |          |          |          |          |          |          |
| $CC_{5}$                                   | 124.81   | 147.26   | 59.21    | 134.90   | 84.96    | 82.77    | 68.88    |          |          |          |          |          |          |          |          |          |          |
| $CC_{6}$                                   | 114.74   | 164.73   | 84.98    | 149.09   | 84.86    | 84.87    |          |          |          |          |          |          |          |          |          |          |          |
| $CC_{7}$                                   | 134.04   | 157.56   |          | 84.82    |          |          |          |          |          |          |          |          |          |          |          |          |          |
| $CC_{8}$                                   |          | 163.36   |          |          |          |          |          |          |          |          |          |          |          |          |          |          |          |

For example, as shown in Table 3, the four combinations (see Figure 4) the relative price before renovations, which means the price of each renovation case at three time points, the relative price before renovations was expressed as $U_{1}^{*}$, $U_{2}^{*}$, $U_{3}^{*}$, and $U_{4}^{*}$ (see Union cases in Table 3), expressed as follows.

- Pattern I: $U_{1}^{*}$, $U_{2}^{*}$, and $U_{3}^{*}$ (Equation 3-1).
- Pattern II: $U_{1}^{*}$, $U_{2}^{*}$, and $U_{4}^{*}$ (Equation 3-2).
- Pattern III: $U_{1}^{*}$ and $U_{2}^{*}$ (Equation 3-3).
Table 3. An example showing the calculation of price ratio for each union case.

| Price data of RC | Price data of CC | Price ratio of RC on CC (%) | Union cases |
|------------------|------------------|----------------------------|-------------|
| $P_{RA}$ | $P_{RA}$ | $P_{RA}$ | $P_{RA}$ | $P_{RA}$ | $P_{RA}$ | $P_{RA}$ |
| $RC_1$ | 308.5 | 584.0 | 536.0 | 222.0 | 442.0 | 355.0 | 139 | 132 | 151 | $U_1$ |
| $RC_2$ | 394.0 | 672.0 | 586.0 | 222.0 | 442.0 | 355.0 | 78 | 87 | 91 | $U_2$ |
| $RC_3$ | 367.5 | 625.0 | 481.0 | 222.0 | 442.0 | 355.0 | 84 | 93 | 111 | $U_3$ |
| $RC_4$ | 381.0 | 649.0 | 523.0 | 222.0 | 442.0 | 355.0 | 81 | 90 | 102 | $U_4$ |

Figure 4. Three deduced price change patterns and union cases following each pattern. (a). Pattern I. (b). Pattern II. (c). Pattern III.

3. Development of a model for predicting price change patterns after renovation on MFHs

The derived patterns provide information that helps in deciding whether or not to perform renovations on deteriorated MFHs. If an MFH for which renovation is being considered follows Pattern I or II in terms of price change, renovations may be undertaken. However, if Pattern III is predicted, it may be better not to proceed with renovation for that MFH. Keeping these aspects in mind, this study intends to develop a model that can predict price change patterns after renovating a deteriorated MFH. Using this model, MFH owners will be able to evaluate the pattern of price changes in the renovation planning stage itself, which would help in better decision-making.

3.1. Network architecture

The model for predicting price change patterns (MPPCP) in MFHs upon renovation includes the following processes, as described earlier in Figure 1 – (1) inputting attribute values of the target MFH corresponding to the renovation plan and (2) predicting price change patterns of the MFH due to renovation. To yield this output, the MPPCP model is required to analyse the relationship between property value (i.e., attributes) due to renovation and price change patterns. During the process of identifying the relationship, this study first attempted to analyze it using multivariate data analysis methods (e.g., regression analysis, decision tree method, etc.) that are implemented based on mathematical analysis, but there was a limitation to mathematically generalizing the
relationship. Therefore, the authors focused only on developing a method to predict the price change patterns of renovated MFHs using 19 attributes. In this context, a methodology for defining complex nonlinear relationships with 19 input variables (attributes) and 3 output variables (price change patterns) was required to achieve the research goal.

According to Patel and Jha (2016) and Kim (2004), the artificial neural network (ANN) theory can be effectively applied when a complex nonlinear relationship exists between several input and output variables. In addition, it is not necessary to identify a mathematical relationship between variables that affect the output variable, and there is no limit to the number of input variables; thus, there is no need to select appropriate variables (Kim 2004). For these reasons, the ANN method is widely used in the field of construction management, and this research developed the MPPCP model using the ANN method.

To develop the ANN-based MPPCP model, input and output variables should be defined. As described earlier, the input variable is set to the attribute value of MFH due to renovation and the output variable is set to the price change pattern described in Equations 3–1, and 3–3. To set the input variables, it is necessary to define the attributes that affect the price of the renovated MFH. Kim, Cho, and Kim (2016), which is a previous study of this research, proposed 19 parameters that affect the price of the renovated MFH in two stages. First, dozens of candidate influencers were derived through an analysis of 23 previous studies dealing with factors influencing the price of general MFHs. Then, a correlation analysis was conducted to identify the relationship between these candidates and price of the renovated MFH; 19 parameters were found to have a significant influence on the price of the renovated MFH. By adopting these parameters, 19 factors that influence the price of renovated MFHs were selected as input variables; these include (1) household unit area, (2) gross floor area, (3) building footprint, (4) number of unit houses, (5) number of floors, (6) years elapsed since construction, (7) type of heating system, (8) reputation of the construction company, (9) number of parking lots, (10) unit plan, (11) administrative district, (12) number of rooms in a household unit, (13) number of convenience facilities near the MFH, (14) distance to the nearest metro station, (15) educational environment, (16) distance to the neighbourhood park, (17) distance to the bus stop, (18) distance to the general hospital, and (19) view from each unit.

To use the above-stated 19 attributes as model input variables, the ratio of relative attribute values was calculated in the same way the relative price ratio was calculated for price change pattern analysis. In other words, if an arbitrary attribute $i$ chosen from the list of 19 attributes given above is referred to as $m_i$, the attribute value of the union case $m_iU_k$ (i.e., the attribute value of renovation case $RC_k$ with the comparative case $CC_j$) can be estimated using Equation (4).

$$m_iU_k = \frac{m_iRC_k}{m_iCC_j} \times 100$$

### 3.2. Design parameters and training criteria

To develop MPPCP using ANN, the structure of ANN and various parameters that determine said structure are defined, as shown in Table 5. To determine the values of these parameters, empirical methods and genetic algorithms can be used (Hegazy, Fazio, and Moselhi 1994). In this study, we used empirical methods. In addition, to operate the ANN, the activation function must be determined. The activation function serves to activate the input signal value in a certain

**Table 5.** ANN model parameters and implementation design.

| Parameters                      | Setting                  | References                  |
|---------------------------------|--------------------------|-----------------------------|
| Transfer function (Activation function) | Sigmoid transfer function | Kim 2004                   |
| Number of Hidden layers         | 1 or 2                   | Hegazy, Fazio, and Moselhi 1994 |
| Number of units in the hidden layers | 17, 19, 39              |                             |
| Connectivity                    | All units connected      |                             |
| Learning algorithm              | Error back-propagation algorithm |                |
| Learning rate                   | 0.3, 0.6, 0.9            | Cho, Seo, and Kang 2002     |
| Momentum                        | 0.7, 0.8, 0.9            | Shin, Cho, and Lee 2007     |
| Training options                | Auto setting value (SPSS 23) | SPSS ver. 23               |
| Stopping rules                  | Auto setting value (SPSS 23) | SPSS ver. 23               |

**Table 4.** Example of attribute ratios for each union case.

| Patterns | Union cases | $m_1$ | $m_2$ | $m_3$ | $m_4$ | $m_5$ | $m_6$ | $m_7$ | $m_8$ | $m_9$ | $m_{10}$ | $m_{11}$ | $m_{12}$ | $m_{13}$ | $m_{14}$ | $m_{15}$ | $m_{16}$ | $m_{17}$ | $m_{18}$ | $m_{19}$ | $m_{20}$ | $m_{21}$ | $m_{22}$ | $m_{23}$ | $m_{24}$ | $m_{25}$ | $m_{26}$ | $m_{27}$ | $m_{28}$ | $m_{29}$ | $m_{30}$ | $m_{31}$ | $m_{32}$ | $m_{33}$ | $m_{34}$ | $m_{35}$ | $m_{36}$ | $m_{37}$ | $m_{38}$ | $m_{39}$ | $m_{40}$ | $m_{41}$ | $m_{42}$ | $m_{43}$ | $m_{44}$ | $m_{45}$ | $m_{46}$ | $m_{47}$ | $m_{48}$ | $m_{49}$ | $m_{50}$ | $m_{51}$ | $m_{52}$ | $m_{53}$ | $m_{54}$ | $m_{55}$ | $m_{56}$ | $m_{57}$ | $m_{58}$ | $m_{59}$ | $m_{60}$ | $m_{61}$ | $m_{62}$ | $m_{63}$ | $m_{64}$ | $m_{65}$ | $m_{66}$ | $m_{67}$ | $m_{68}$ | $m_{69}$ | $m_{70}$ | $m_{71}$ | $m_{72}$ | $m_{73}$ | $m_{74}$ | $m_{75}$ | $m_{76}$ | $m_{77}$ | $m_{78}$ | $m_{79}$ | $m_{80}$ | $m_{81}$ | $m_{82}$ | $m_{83}$ | $m_{84}$ | $m_{85}$ | $m_{86}$ | $m_{87}$ | $m_{88}$ | $m_{89}$ | $m_{90}$ | $m_{91}$ | $m_{92}$ | $m_{93}$ | $m_{94}$ | $m_{95}$ | $m_{96}$ | $m_{97}$ | $m_{98}$ | $m_{99}$ | $m_{100}$ |
|---------------------------------|--------------------------|-----------------------------|
neuron to the input value of the neuron in the hidden layer or the output layer. We found the sigmoid function to be suitable for our study as the input and output variables are nonlinear. In addition, because the sigmoid function is in the range of 0 to 1, it is possible to solve the problem of one neuron dominating the entire operation of the neural network (Kim 2004).

Next, it is necessary to determine the number of hidden layers. In this study, as the input and output variables are not complicated, it is considered that sufficient learning can be achieved by determining the number of hidden layers by one or two. According to the criteria laid down by Hegazy, Fazio, and Moselhi (1994) for determining the number of nodes in hidden layers, in this investigation, we developed three alternatives in the number of nodes as follows – (i) the number of input variables (i.e., 19 nodes), (ii) the number corresponding to 75% of the number of input variables (i.e., 17 nodes), and (iii) twice the number of input variables and then plus one (i.e., 39 nodes).

Finally, it is necessary to set the learning rate and momentum constant. In general, it is not known whether certain values of learning rate and momentum constant guarantee proper neural network learning (Cho, Seo, and Kang 2002). Therefore, to generate various alternatives to derive the optimal ANN model, the learning rate and momentum were determined according to the criteria applied by Cho, Seo, and Kang (2002) and Shim, Cho, and Lee (2007). The learning rate was set at 0.3, 0.6, and 0.9 while the momentum constant was set at 0.7, 0.8, and 0.9. In addition, the error back-propagation algorithm was applied to the learning of the ANN model developed in this study. This algorithm is based on the Delta rule that learns in the direction of decreasing the error value using the sigmoid function, which is in the range of 0 to 1, it is possible to solve the problem of one neuron dominating the entire operation of the neural network (Kim 2004).

Based on the set parameters, an ANN-based MPPCP was constructed. In general, to operate a prediction model using ANN, it is necessary to divide the collected data into two groups – (i) a set of learning data for constructing a neural network structure and (ii) a data set for model verification. At this time, a data set must be formulated to prevent excessive learning along with a cross-validation data set (Kim 2004). Therefore, we classified 100 union cases into case sets for learning, cross-validation, and testing. In this study, because there are many types of input variables (i.e., 19 MFH attributes) but the amount of data is relatively small, (i) the proportion of the learning case set was relatively high for normalization of learning and (ii) the proportion of verification case sets was also increased as there are three types of output variables (i.e., Patterns I, II, and III). Accordingly, the collected union cases for learning, cross-validation, and verification were set at 73%, 11%, and 16%, respectively. Meanwhile, for the operation of the model, Patterns I, II, and III are coded nominally as 1, 2, and 3, respectively.

### 4. Model validation and discussion

#### 4.1. Evaluation of the ANN model

The input and output variables of case learning and cross-validation sets were input to the ANN model. By controlling each parameter, a total of 108 model candidates were constructed. After stopping the learning of the model, based on 16 union cases for model verification, the level of correct between actual patterns and the model-predicted patterns were calculated. As shown in Table 6, 108 model candidates were developed through a trial and error method for each parameter. Of these, candidates 8, 10, 31, 37, and 51 exhibited a 93.80% of

| Model candidates | # of Hidden layers | # of units in the hidden layers | Learning rate | Momentum | Lev. of correct (%) | Remark |
|------------------|--------------------|---------------------------------|---------------|----------|--------------------|--------|
| 1                | 1                  | 17                             | 0             | 0.3      | 0.7                | 87.50  |
| 8                | 1                  | 17                             | 0             | 0.6      | 0.9                | 93.80  | Model 1 |
| 9                | 1                  | 17                             | 0             | 0.9      | 0.9                | 75.00  |
| 10               | 1                  | 19                             | 0             | 0.3      | 0.7                | 93.80  | Model 2 |
| 31               | 2                  | 17                             | 17            | 0.3      | 0.8                | 93.80  | Model 3 |
| 37               | 2                  | 17                             | 19            | 0.3      | 0.9                | 93.80  | Model 4 |
| 51               | 2                  | 17                             | 39            | 0.9      | 0.8                | 93.80  | Model 5 |
| 107              | 2                  | 39                             | 39            | 0.9      | 0.9                | 81.30  |
| 108              | 2                  | 39                             | 39            | 0.9      | 0.9                | 81.30  |
the level of correct and thus these five candidates were named as Models 1 to 5. Subsequently, additional analysis was performed to find the best prediction model among the five chosen models. In order to find the optimal model among these, in this study, the receiver operating characteristic (ROC) and level of correct according to variation of data set number were further evaluated. Recently, in many previous studies adopting ANN method, ROC curve analysis can be used to fine a model with best classifier performance.

Figure 5(a) shows an example ROC curve. These curves are commonly used to analyse the trade-off between sensitivity and specificity of classifiers across different classification thresholds. In general, the more accurate an ANN-based model is, the farther away the ROC curve is from the 45° diagonal, as shown in Figure 5(a). Thus, for a very good model, the ROC curve appears close to a square. The area under the ROC curve (AUC) can be used to characterise the overall discrimination of a classification model. The closer the value of AUC is to 1, the better is the distinction between different classes (Shenfield, Day, and Ayesh 2018; Yu, Ye, and Xiang 2016). With this background, with cases extracted randomly from 100 union cases, this study evaluated how accurately the five models classified the patterns of the extracted cases and compared them to their actual patterns using the AUC analysis method. Based on the composition ratio (i.e., 73% for learning, 11% for cross-validation, and 16% for verification) of the 100 union cases used for developing the models, as shown in Table 7, 10 simulations were carried out to verify how the developed five models distinguish the extracted cases according to their actual patterns; in these simulations, the number of data sets for each ANN implementation was varied randomly. Figure 5(b) shows the ROC curve of Model 2 and its corresponding AUC under the seventh simulation condition in Table 7. As shown in the figure, under the seventh simulation condition, the AUC value was 0.993 for pattern I, 0.998 for pattern II, and 0.867 for pattern III, which confirms that classification by pattern using Model 2 is preferable. Using the same process, it was found that the average AUC value for each model during 10 simulations was over 0.9 in all the models as shown in the table. According to the testing criterion set by Tserng et al. (2011) (if AUC ≥ 0.9, it implies an outstanding discrimination), this result implies that pattern classification by all the tested models is highly desirable.

In addition to AUC analysis, based on randomly extracted cases for model verification on each simulation, the level of correct between actual patterns and model-predicted patterns was calculated. As shown in Table 7, for example, Model 1 predicted patterns with 76.5% accuracy for simulation test 1 wherein the model was implemented 17 times based on 17 random verification cases. Furthermore, Model 1 shows an average accuracy of 69.1% during 10 simulations. Similarly, the average level of correct was 69.1% for Model 1, 72.2% for Model 2, 66.6% for Model 3, 69.9% for Model 4, and 71.1% for Model 5.

Because Model 2 shows outstanding pattern discrimination ability (AUC analysis) and its accuracy of prediction for random cases is superior to that of other models (72.2% of accuracy), Model 2 was finally selected as the MPPCP. Table 8 shows the parameters and performances of the proposed model.

### 4.2. Model application and discussion

To evaluate the applicability of the MPPCP, this study applied the chosen model on an MFH planning actual
renovation works. The MFH considering renovation work was built in 1992 in Seoul, South Korea. To apply the MPPCP model, 10 comparative cases of similar size were selected.

To implement MPPCP, it is necessary to calculate various attribute values of the renovation case and use them against those of comparison cases as model input values. Using Equation 4, the relative ratio values for 19 attributes of 10 union cases, which combine the renovation and comparative cases, are derived (Table 9). After providing the input values of each case to the MPPCP, it predicted price change patterns, as listed in Table 9. As can be seen in the table, the model predicted that Cases 1, 3, and 9 follow Pattern I and the remaining 7 cases follow Pattern II. Therefore, it can be inferred that (i) the MFH undergoing renovations is currently lower in price as compared to the 10 comparative cases, (ii) renovations on the MFH will result in a higher price as compared to the prices of the comparative cases, and (iii) the price will continue to increase in the future (Pattern I) or the increased price will be maintained (Pattern II).

Meanwhile, 10 cases could be divided into two groups: a group including cases 1, 3, and 9 that predicted Pattern I and another group predicting Pattern II. In order to identify which attributes can significantly influence the pattern prediction, the average value of each attribute in the two groups was evaluated. As a result, “m₆ (years elapsed since construction),” “m₁ (household unit area),” and “m₉ (number of parking lots)” were detected as the critical attributes, because the difference in the average values for the three attributes between the two groups were evaluated as significant. For example, the average value of m₆ for group 1 was about 141.33% (i.e., (192 +156 +76)/3), while the average value of m₆ for group 2 was 79.14% (i.e., (83 +78 +69 +74 +100 +76 +74)/7). The gap for this attribute was remarkable, and it could be interpreted that the years elapsed since the MFH’s construction increased; the renovation of such an MFH could be expected to yield economic benefit. Similarly, if the MFH has a relatively small house unit area (m₁, 47.00% of group 1 and 75.57% of group 2) and number of parking lots (m₉, 77.33% of group 1 and 133.71% of group 2) compared to the surrounding cases, such an MFH could be regarded a good candidate for renovation in terms of economic value increase.
Based on the above application results, this research enables decision-makers to grasp the economic effect of MFH renovation and it is expected that they would be able to decide whether or not to carry out renovations.

5. Conclusion

Interest in the renovation of deteriorated MFHs has been growing in recent years. However, many MFH owners cancel their renovation plans as economic advantages after renovation are often not guaranteed. Although the economic effects of a renovation project are very important for its success or failure and in making decisions on the fate of the project, existing literature on this topic is minimal. Therefore, in this study, we developed a model (MPPCP) that can predict the economic effects of renovation on older MFHs. The effects of renovation were evaluated based on price changes at three time points (before renovation, after renovation, and present) and price changes due to renovation were measured by measuring relative price changes with respect to surrounding comparison cases.

The MPPCP developed in this study was based on the ANN technique. To develop the model, 17 renovation cases and 103 comparison cases were considered for retrieving attribute data and price data. From the collected data, (i) the price change pattern of renovation cases at three time points was analysed and (ii) relative attribute values corresponding to 19 parameters after renovation were calculated. Furthermore, the relationship between price change patterns and these attributes was derived using the ANN method. During the process of applying the ANN method, parameters required to apply the ANN were designed to generate model candidates and finally 108 candidate models were detected by combining various parameters that define the ANN method. From these candidates, five models with relatively high prediction accuracy were selected. Subsequently, by analysing AUC and the level of correct for randomly retrieved verification cases, the final model MPPCP with the highest prediction accuracy was derived.

After applying the selected model to the deteriorated MFH which is currently planning a renovation, it is shown that the price change pattern of the MFH after the renovation is well predicted positively. Using the MPPCP presented in this study, it is possible to predict price change patterns that would be experienced by MFHs upon renovation. Such prediction can be done at the renovation planning stage, which would be of great help to the MFH owner in coming to a decision. In future, based on additional collections of renovation cases and their comparative cases, a model for predicting price changes, and not only price change patterns, due to renovations should be developed.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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