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Published in:
Journal of Building Engineering

DOI:
10.1016/j.jobe.2021.103098

Published: 31/10/2021

Document Version
Peer reviewed version

Citation for published version (APA):
Kim, J-M., Yum, S-G., Park, H., & Bae, J. (2021). A deep learning algorithm-driven approach to predicting repair costs associated with natural disaster indicators: the case of accommodation facilities. *Journal of Building Engineering*, *42*, [103098]. https://doi.org/10.1016/j.jobe.2021.103098

A Deep Learning Algorithm-Driven Approach to Predicting Repair Costs Associated with Natural Disaster Indicators: The Case of Accommodation Facilities

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Abstract

It is well known that accurate and reliable maintenance and repair cost estimates are important to maintain a building in its optimal condition, especially during the operation and maintenance phase within the whole life cycle. However, due to emerging trends in buildings that are high-performance, large-scale, complex, and high-rise, it is difficult to achieve those cost estimates. In addition, the impact of climate changes that tend to occur more frequent and severe natural disasters has caused increasing damages to buildings, yet little is still specifically known about predicting the impact of natural disasters on repair costs of accommodation facilities accurately and reliably. This study fills this gap by developing and validating a deep neural network (DNN) model that can generalize repair cost trends associated with natural disaster factors, including peak ground acceleration, precipitation, wind speed, geographic profiles of adjacent water systems, drawing on 1,125 insurance claim payout records on accommodation facilities. The robustness of the developed DNN model was scientifically tested and validated using the root mean squared

error and the mean absolute error methods. Practical applicability of the proposed modeling framework was then demonstrated by creating predicted repair cost trends. This study contributes to the existing knowledge by proposing a deep learning method that predicts repair costs of accommodation facilities associated with natural disasters, while providing both facility managers and insurance companies with evidence-based reference to develop better-informed cost management strategies against potential natural disasters.

Keywords: Accommodation facilities; deep learning; deep neural network; repair cost; natural disaster

1. Introduction

As the height and size of buildings continue to rise, a new approach is needed to precisely estimate the maintenance and repair cost of a building during its life cycle so that it can be managed efficiently [1,2]. According to a report of the Intergovernmental Panel on Climate Change, the global average temperature is continuously rising and the severity and frequency of natural disasters such as extreme weather and meteorological disasters are expected to increase together [3, 4]. Therefore, predicting the cost of damage incurred by natural disasters in the future is very important in terms of building maintenance and repair. When estimating these future costs, simple structural repairs and replacements, complete replacements, and various factors should be comprehensively integrated [5]. In addition to increasing the severity and frequency of natural disasters, the cost of maintaining and repairing buildings is also increasing as new buildings become larger, more complex, and super tall [5,6]. Comprehensive factors such as natural disasters that can deteriorate functions of buildings should also be considered in order to solve these problems and effectively manage facilities. In general, asset management techniques have been applied to more efficiently manage maintenance and repair costs incurred in the operational phase because maintenance and repair costs account for the highest percentage of the total life-cycle cost of a building [7].

However, it is difficult to implement such asset management directly in enterprises and institutions because asset management not only differs depending on the type and function of the building, but also requires transparent information compatibility and long-term investment across all stages of a building's life cycle. To close this gap in reality, many studies have been conducted on facility management. However, few comprehensive studies have been conducted by considering natural disasters. Maintenance and repair management is also important for hotels that because they are representative facilities within the set of accommodation facilities. For the continuity of the business and service to customers, it is essential to restore fixtures or appliances against natural disasters [8]. However, despite a relatively long life and aging of a hotel building, the management method tends to be passive, not systematic [9]. Therefore, in this study, to calculate repair costs of accommodation facilities affected by natural disasters, a prediction model using deep learning algorithms was developed by adopting claim payout records of an international hotel chain over the past 12 years.

It is necessary to accurately and reliably estimate the cost of repair of accommodation facilities in order to reduce possible economic loss during the operation and maintenance stage. To respond this need, the key aim of this study is to generate and verify a deep learning algorithm model that could proficiently and precisely learn repair costs associated with natural disaster indicator, based on the high-precision insurance loss data. The insurance claim payout has high reliability since it has a standardized procedure in which the amount of loss is determined through objective loss analysis by an accredited loss assessor [10]. The developed model underwent a process of learning, testing, and verifying natural disaster factors and costs associated with facility repairs in the record of payment of insurance claims.

2. Literature Review

Facility management consists of a professional methodology for ensuring the functioning of real estate and built environments. This technology not only considers the economics of the facility, but also includes durability, safety, maintenance, and repair [11]. Teicholz [7] has compared facility management in four countries (i.e., Australia, Canada, Korea, and the U.S.), focusing on the operation and management phase which accounts for the majority (about 85%) of the building's lifecycle. However, only Australia puts an emphasis on cost in a building's lifecycle.

Lee and Jung [12] have reviewed the existing literature on facility management and classified it into 19 categories according to function such as functions necessary for facility management. Facility management is divided into technology and general management, environment, security, documentation, materials, energy, services, human resources, schedule, mobility, space, cost, outsourcing, assets, regulations, quality, communication, and equipment. For the introduction of new technologies in facility management, studies are also being actively conducted. Williams et al. [13] have studied the perception of the use of Building Information

Modeling (BIM) in facility management through interviews and surveys. Through their research, they found that it was important to educate facility experts and use BIM to facilitate exchange of information on facility management in order to advance facility management. Yu et al. [14] have presented a methodology of a computer-based model for facility management functions. Foster [15] has focused on operational and administrative costs. Among the costs, the focus was on energy which accounted for 25% of operating costs. In the operation and management phase, a strategy to reduce energy costs was proposed.

Maintenance and repair cost has been recognized as an important factor for improving the resilience of structures. American Society for Testing and Materials (ASTM) has developed a standard to quantify and systematize the cost of each phase of the building life cycle for more accurate estimate of maintenance cost [16, 17]. In addition, many studies have focused on the cost of the design and construction process, which is the initial stage of the building, and developed and improved the methodology of maintenance and repair cost assessment. For example, Pettang et al. [18] investigated a matrix-based framework for selecting cost-effective materials considering operating and administrative costs, labor costs, and material costs in the construction cost of a project. This matrix-based framework can assist construction stakeholders in decision-making during material scenarios. Günaydın and Doğan [19] proposed a new cost estimation approach focusing on the early stages of construction using an artificial neural network (ANN). Kim et al. [7] found that efficient management is possible by developing a construction cost estimation model through three methods (i.e., artificial neural networks, case-based reasoning, and regression analysis). However, their study was also focused on the cost-effectiveness of early stages of a construction project without focusing on operation and management costs known to account for the most in the life cycle cost of a building. Rahman et al. [20] presented a decision framework for the effect of aging on buildings. They considered various factors (i.e., durability, energy, resilience, environment, and cost effectiveness) in their evaluation and reported that operational and management stages such as material changes should be considered for building performance.

Another aspect of research on the maintenance and repair cost of a building is energy consumption. Continuous technological development and use of high-quality building materials can make buildings more energy-efficient and ultimately reduce environmental impact as well as maintenance costs [6]. Gluch and Baumann [21] proposed the use of lifecycle cost of a building in a model for green decision making. Hasan [22] evaluated and used the life cycle cost of a building to optimize the insulation performance and wall thickness of a building. Morrissey et al. [23] conducted a survey to explain relationships among the initial construction cost, thermal characteristics, and energy cost of a new building. Kneifel [24] investigated relationships among carbon emissions, building life cycle costs, and energy consumption through studies that explain the effectiveness of efficient design of commercial buildings.

Some studies have found that natural disaster factors should be included in the assessment of the maintenance cost of a building. Change et al. [25] calculated the lifecycle cost of infrastructure systems based on data for the Northridge earthquake (1994) and the Kobe earthquake (1995). Their study showed that when estimating the maintenance cost of an infrastructure system, the damage caused by natural disasters had a lot of uncertainty, making it difficult to assess. In addition, they suggested that damage caused by natural disasters can be calculated through systematic research and models and that the vulnerability can be reduced through management. Wei et al. [26] also suggested that for the long-term building performance evaluation and maintenance and repair cost, the cost of potential damage from earthquakes should be included in the life cycle cost. Similarly, Wei et al. have argued that the cost of potential seismic damage should be added to the lifecycle cost when evaluating long-term building performance. Despite these studies, it is difficult to include natural disasters in a building's life-cycle cost assessment. The reason is that natural disasters inherently have a lot of uncertainty in terms of severity and frequency. Such uncertainty makes it difficult to estimate damage [6, 9]. Therefore, this study proposed a cost assessment method that included not only the maintenance cost generally incurred in buildings, but also damages caused by natural disasters.

Many studies in the past have explained effects of natural disasters in the operation and maintenance phases of buildings. Error of load due to natural disaster in the design stage of a building can cause problems due to the cost of damage caused by a natural disaster in the operation and maintenance stage [27, 28, 29]. Harvard's Center for Multifamily Research has described a monetary relationship between natural disasters and residential buildings. It was found that damage from hurricanes and earthquakes contributed to the cost of residential buildings the most [30]. According to the 2013 US Housing Survey, the cost due to natural disasters was $15.8 billion in 2011 and 2012 alone in the United States [30]. Earthquakes during natural disasters have a profound impact on buildings and infrastructure systems in the operation and maintenance phases. Ayyub [31] reported that earthquakes among natural disasters have the most profound negative impacts on buildings and infrastructure systems. They also have a huge impact on the economy, society, and the environment. Wei et al. [26] described the impact of earthquakes on buildings and infrastructure systems as well as the cost of earthquake damage over the life cycle of the building. Hurricanes can also cause significant damages to buildings and infrastructure systems during operation and maintenance phases. Among various properties of a hurricane, the maximum wind speed radius, the maximum wind speed, the forward speed are main indicators that can measure the damage to an infrastructure system [32, 33, 34, 35]. The rainfall accompanying hurricanes is also a key indicator of the hurricane damage [36, 37]. Flooding can also have a huge impact on buildings. As the water system has been reorganized due to recent rapid urbanization, damage to buildings and infrastructure systems is also increasing as floods increase rapidly [38, 39]. Brody et al. [36] underscored the importance of an effective flood control system to reduce flood damage and pointed out that flooding of the water system during rainfall is the trigger of a flood damage. Therefore, the difference in distance and altitude from the water system can be an important factor indicating the risk related to a flooding [40].

3. Research Method: A Five-Step Approach

As stated earlier, this study attempted to propose a modeling framework that can exactly learn several natural disaster indicators known to have a great influence on the repair and maintenance cost of accommodation facilities. It is well acknowledged that repairs are intended to restore fixtures and appliances broken or damaged. Hence, it is obvious that claim payout records on repairs are directly linked with the types of natural disaster. Given the significance of knowing accurately and reliably about those repair costs, the goal of this study was achieved by following a five-step approach:

1) Insurance claims payouts related to accommodation maintenance and repair records were gathered from 2007-2018 by an international hotel chain.
2) This study collected natural disaster information based on details of maintenance and repair history.
3) A deep learning algorithm model was generated based on the learning performance of network scenarios that learned the maintenance cost of accommodations from the multi-contextual natural disaster indicators collected in phased 2. This study adopted Python 3.7 with Keras and Scikit-Learn libraries.
4) To verify the developed model, multiple regression analysis models were individually developed using IBM Statistical Package for Social Sciences (SPSS) V23.
5) The root-mean-square error and mean absolute error value of the developed learning model and multiple regression analysis model were calculated, compared, and verified.

4. Data Collection and Classification

This study collected data on the repair cost of a major international hotel chain distributed around the world among accommodation facilities. This international hotel chain is the leading hotel chain, owning more than 5,000 real estate properties and more than 24 brands worldwide. This study collected a total of 1,125 financial loss data caused by repairs for this hotel chain from 2007 to 2018. Despite being distributed all over the world, this international hotel chain holds similar characteristics of facilities to highlight its uniqueness, such as space functional characteristics, exterior design, and construction quality and method. Moreover, since it is a single hotel chain, there are similarities in the management manual of the building and the cost of operation and management. In this sense, it was assumed that the baseline of project costs is relatively similar. However, repair costs affected by natural disasters still remain questionable due to various location of facilities associated with different external conditions. To avoid biased results in this study, the collected repair costs were log-transformed for two different purposes: (1) the validation to compare the robustness of the developed DNN with the traditional multiple regression analysis method; and (2) the normalization of costs considering various facilities profiles in different locations and weather conditions across the world.

Then, through a solid review of previous studies, five different types of natural disaster indicators affecting repair costs were collected, such as precipitation, distance to water system, elevation difference, peak ground acceleration, and wind speed. The distance to the adjacent water system and the difference in elevation from the water system were calculated using Google Maps, based on the location information of each hotel. Maximum amount of daily precipitation, peak ground acceleration, and wind speed were then collected by the National Oceanic and Atmospheric Administration (NOAA). The collected natural disaster factors and claim payout records on repair costs were then mapped with the corresponding accommodations. Table 1 describes the variables used in this study, while descriptive statistics of variables are shown in Table 2. To achieve more conservative prediction results, the maximum values of weather and seismic conditions were extracted from historical records with regard to the corresponding accommodation locations.

Table 1. Variable Descriptions

Variable	**Description**
Repair cost	Log-transformed costs used for repairs in the corresponding accommodation (log USD)
Maximum precipitation	Maximum amount of daily precipitation (mm/day)
Distance to water system	Distance to adjacent water system (m)
Elevation difference	Elevation difference with water system (m)
Peak Ground Acceleration	Peak Ground Acceleration (PGA) value (g)
Wind speed	Maximum wind speed sustained over 10 minutes (m/s)

Table 2. Descriptive Statistics

Variable (unit)	**N**	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
Repar cost (log-transformed dollar amount)	1125	10.81	1.92	3.61	17.87
Maximum precipitation (mm/day)	1125	234.33	74.85	91.17	496.24
Distance to water system (m)	1125	1921.44	1648.08	0.00	6095.51
Elevation difference (m)	1125	396.68	3558.11	-37.00	32764.00
Peak Ground Acceleration (g)	1125	0.95	0.98	0.01	6.98
Wind speed (m/s)	1125	36.97	5.46	25.87	54.77

5. Developing a Deep Neural Networks-Driven Learning Model

Deep learning algorithms are generally neural networks with multiple layers and various structures. They are widely applied in prediction and recognition industries and research. Deep learning algorithm is also a machine learning technique using a type classification approach or a regression method [41]. The general training framework for deep learning models is the same as that for other types of neural networks. However, many data sets can be trained more efficiently than the other types of neural networks through several hidden layers [42]. Deep learning algorithms can be categorized according to their structure and processing method: deep neural network (DNN), recurrent neural network (RNN), generative adversarial network (GAN), auto encoder (AE), and convolutional neural network (CNN) [43].

A DNN model was adopted to learn the maintenance cost of accommodation facilities in consideration of the nonlinearity of the data set collected in this study. DNN has been used for prediction and cataloging in many academic and industrial fields because DNN is trained to model complex nonlinear relationships through several layers [44, 45]. The learning performance of the developed model was evaluated based on the root-mean-square error (RMSE) and the mean absolute error (MAE) as representative indicators of the magnitude of the error by comparing actual and predicted results of an artificial neural network model [46]. RMSE is an index that measures the average value of the error size and MAE is an index that is performed by giving equal and linear weights to all errors. Both values are interpreted as decreasing the prediction error as the error value approaches zero.

5.1. Pre-Processing and Setting

A z-score normalization method was used for data preprocessing of collected data. Data preprocessing was performed to adjust the range or units of quantities that were problematic to match. Preprocessed input data were distributed into three groups: training data, verification data, and test data. Training data were used for learning the algorithm. Verification data were used for determining whether or not the learning performance was optimal. Test data were used to evaluate whether the developed model was trained for its purpose. Considering the amount of collected data, 70% and 30% of all data were used as training data and test data, respectively. Of the training data, 30% were used as validation data.

The DNN model uses a backpropagation algorithm to update weights of neural network nodes. Since each combination depended on input and output variables, it was necessary to find the optimal combination through the trial-and-error method. To find the optimal combination, it was necessary to determine the network structure scenario and hyper parameters. In a network structure scenario, numbers of layers and nodes are specified while activation function, optimizer, dropout, and so on are determined by hyper parameters [47]. In the present study, the network structure scenario was set to have three hidden layers in consideration of the dressiness of the data. The activation function was a method of adjusting the weight of each node for optimal learning. The optimizer was related to the speed and stability of learning. The epoch specified the number of lessons and the batch specified the grouping of data for efficient computation [47, 48]. Dropout was a normalization penalty to prevent overfitting. Overfitting meant that the performance was degraded due to an increase in prediction errors caused by excessive learning of the model's training data.

In this study, the dropout was determined to be 0 and 0.2 considering the amount of training data and simulated to find the optimal combination. ReLu (Rectified Linear Unit) function was used as the activation function and Adaptive Moment Estimation (Adam) method was used as the optimizer. The ReLu function was developed to solve the problem of slope loss of the existing Sigmoid function. The input value changes when the input value is greater than or less than 0 [49]. The Adam Method is one of the most widely used algorithms since its development in 2015 [50]. The number of epochs was specified to be 1,000 and the batch was definite at 5.

5.2. Model Selection

Table 3 shows MAE and RMSE values of each network structure with dropouts of 0 and 0.2. Based on our results, the model with the minimum MAE and RMSE was selected as the final model. As the number of hidden layer nodes increased, the MAE and RMSE values also increased. The number of hidden layer nodes became the minimum at 200-200-200 and the result value increased again. When the dropout value was 0, the loss function was generally lower than that when the dropout value was 0.2. If the number of hidden layer nodes was 200-200-200 and the dropout was 0.0, both MAE and RMSE had minimum values. Consequently, the 200-200-200 network architecture with the dropout value of zero was selected as the final deep learning model.

Table 3. Results of Learning Scenarios

Network Architecture Scenario	**Dropout (0)**		**Dropout (0.2)**	
	MAE	**RMSE**	**MAE**	**RMSE**
5-5-5	2.419	2.982	2.937	2.370
10-10-10	3.052	4.410	4.480	5.333
25-25-25	3.680	5.261	4.332	5.733
50-50-50	4.529	5.531	5.854	6.972
100-100-100	1.637	2.266	6.056	7.272
200-200-200	1.599	2.252	5.286	6.655

300-300-300	1.635	2.254	5.040	6.356
400-400-400	2.128	2.819	6.095	7.302
500-500-500	1.696	2.376	7.025	8.174

Table 4. Configuration of the Selected Network Structure and Hyper-parameters

Group	Composition	Detail
Network Structure	Number of Hidden Layer	3
	Number of Nodes in the Hidden Layers	200-200-200
Hyper-parameters	Optimizer	Adaptive Moment Estimation Method
	Activation Function	Rectified Linear Unit Function
	Dropout	0.0
	Batch Size	5
	Epoch	1000

6. Illustrative Result of the Developed Model

Based on the predicted outputs obtained from the final network model, the illustrative result demonstrates how the developed learning model can be used to capture the predicted repair cost trends associated with the input variables used in this study, such as peak ground acceleration, maximum precipitation, wind speed, distance to water system, and elevation difference.

As depicted in Figure 1, ranges of the log-transformed predicted cost values were classified into two different groups of peak ground acceleration ranges. To provide a consistent and clear snapshot of cost trends, under each peak ground acceleration range, two different sub-groups were then made by weather conditions and water system aspects. More specifically, the weather condition group includes maximum precipitation and wind speed, while the other consists of distance to water system and elevation difference with water system.

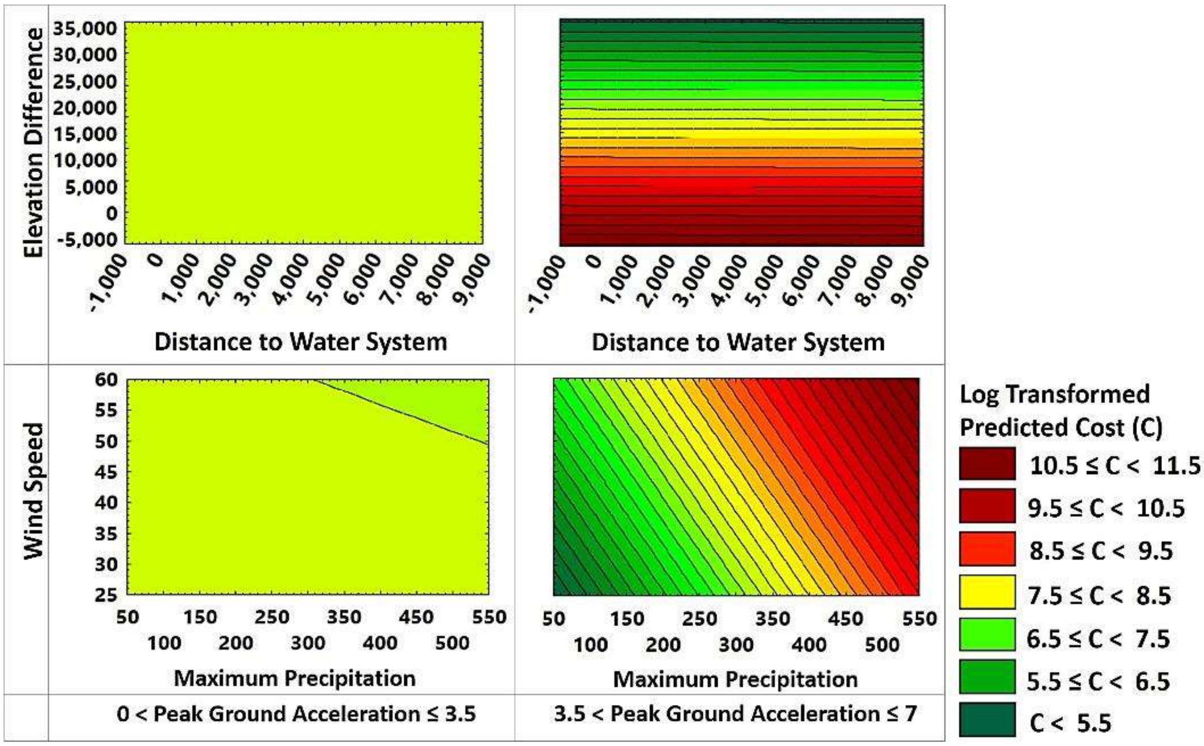

Figure 1. Illustrative result of predicted cost trends

As shown in the trend results, various repair cost trends were achieved under the higher range of peak ground acceleration (i.e., 3.5 < peak ground acceleration ≤ 7). In addition, higher values of wind speed and maximum precipitation tend to cause more repair costs. It is noteworthy that elevation difference with water system would be more critical, compared to distance to the system. This result could reflect that elevation difference would affect flooding during rainfall. To demonstrate the illustrative results of predicted repair costs, the following hypothetical conditions were applied:

- 3.5 < peak ground acceleration ≤ 7
- Maximum precipitation: 400 mm/day
- Wind speed: 45 m/s

- Distance to water system: 15,000 m
- Elevation difference with water system: 5,000 m

Based on the applied conditions, log-transformed cost ranges can be read by two sub-groups of weather conditions and water system aspects under the applied peak ground acceleration range, as shown in Figure 1:

- Weather condition group: 8.5 ≤ Log-transformed dollar amount < 9.5
- Water system aspects: 7.5 ≤ Log-transformed dollar amount < 8.5

Given this scenario result, it is expected that weather conditions are more critical than water system aspects, which cause a larger amount of cost. To consider various risk conditions under this scenario, the predicted repair cost range could be achieved by integrating the two results of ranges: 7.5 ≤ Log-transformed dollar amount < 9.5.

7. Validation of the Developed Model

For scientific verification of the final DNN model, a Multiple Regression Analysis (MRA) model was added and results of these two models were compared. In general, the MRA method is a method mainly used for quantitative prediction models. After constructing the MRA model, MAE and RMSE values of the MRA model were calculated and compared with results of the DNN model. As this study underscores the DNN model development, the traditional MRA modeling process and result were omitted.

The results of model validation are summarized in Table 5. In the DNN model, verification data results showed MAE of 1.649 and RMSE of 2.316 and test data results showed MAE of 1.506

and RMSE of 2.119. When comparing calculated results of these two data, it was found that the problem of overfitting of the final model was negligible as there was no significant difference between these two results. Results also showed an MAE of 10.780 and an RMSE of 7.793 in the MRA model. Comparing results of these two models, it could be seen that the DNN model had significantly lower prediction error rates of MAE 86.0% and RMSE 72.8% than the MRA model.

Table 5. Validation Results

	Validation		**Test**	
	MAE	**RMSE**	**MAE**	**RMSE**
DNN	1.649	2.316	1.506	2.119
MRA	-	-	10.780	7.793
DNN/MRA (%)			-86.0%	-72.8%

8. Discussion

This study suggested a modeling framework by generating a deep learning algorithm model that learned the repair cost of accommodation facilities considering various natural disaster factors. The developed model was scientifically tested and validated through RMSE and MAE by comparing results of multiple regression analysis methods generally used in conventional quantitative prediction studies. As a result of comparing the two models (i.e., DNN and MRA models), it was found that the DNN model had lower prediction error rates than the MRA model. The validation results confirmed that the non-parametric DNN model is more suitable than the parametric MRA model for predicting non-linear characteristics of natural disaster factors and repair cost of accommodation facilities. Therefore, the proposed analytical modeling framework is effective in learning repair costs of accommodation facilities, against natural disasters.

Based on the validated learning model, the practical applicability was demonstrated using the illustrative results of predicted repair cost trends. The trend results showed that repair cost could occur under the higher range of peak ground acceleration (i.e., 3.5 < peak ground acceleration ≤ 7). Based on the hypothetical scenario result, it was found that weather conditions would be more critical than water system aspects, which cause larger amounts of repair costs. More specifically, higher values of wind speed and maximum precipitation tend to cause more repair costs. It is noteworthy that elevation difference with water system would be more critical, compared to distance to the system. Through the illustrative result of generalized trends in repair costs, it will be possible to reinforce facility management of accommodation facilities by identifying potential financial losses caused by potential natural disasters. To this end, building and facility managers could refer to historical natural disaster data or weather forecast to practically adopt the proposed illustrative trends in repair costs against unexpected natural disaster events.

Nevertheless, it should be noted that the only one international hotel chain's claim payout records were adopted in this study, due to the difficulty in collecting large volumes of data. Therefore, further research is needed to compare and verify the results obtained from this study by collecting additional data from other hotel chains in the future. Furthermore, in order to more accurately predict repair costs using a deep learning algorithm model, it is necessary to add the amount of data through database construction and additional research considering additional natural disaster variables. Moreover, since this study was focused on hotels among accommodation facilities, additional research studies that secure data for various types of accommodation facilities such as resorts, pensions, and inns are needed.

9. Conclusion

It is well acknowledged that accurate and reliable maintenance and repair cost estimates are crucial to maintain a building in its optimal condition, especially during the operation and maintenance phase within the whole life cycle. However, due to emerging trends in buildings that are high-performance, large-scale, complex, it is difficult to achieve those cost estimates. In addition, the impact of climate changes that tend to occur more frequent and severe natural disasters has caused increasing damages to buildings, yet little is still known about predicting the impact of natural disasters on repair costs of accommodation facilities accurately and reliably. This study attempted to fill this gap by developing and validating a deep neural network model that can generalize repair cost trends associated with natural disaster factors, including peak ground acceleration, precipitation, wind speed, geographic profiles of adjacent water systems, drawing on 1,125 insurance claim payout records on accommodation facilities.

To select the most feasible deep neural network, a total of 18 network alternatives (i.e., 9 different network architectures by 2 different dropout values) were trained and tested. By comparing the accuracy of the network alternatives using the MAE and RMSE methods, the number of 200-200-200 nodes in three hidden layers with the dropout value of zero was selected as the final network model that learns and generalize maintenance and repair costs. The final model showed remarkably lower prediction error rates than the MRA model used in many general prediction techniques. More specifically, the developed DNN model held 86.0% less than the MRA's MAE value, while 72.8% less than RMSE of the MRA model. Therefore, the validation results conclude that the DNN model was more suitable for predicting nonlinear characteristics of repair costs of accommodation facilities than the traditional MRA model, associated with the applied natural disaster factors. The practical applicability of the learning outcomes was then demonstrated by the illustrative result of generalized trends in repair costs, linking with the input variable groups (i.e., weather conditions and water system aspects under two different peak ground acceleration ranges).

To summarize, this study developed a modeling framework to predict repair cost ranges of accommodations using deep learning algorithms based on historical claim payout records of accommodations, linking with natural disaster factors. Using the proposed modeling framework, the staff of lodging facilities will be able to predict repair costs or evaluate costs efficiently through addition and modification of model variables. Additionally, main findings of this study can be used as reference for future predictive research on repair cost predictions for other types of properties, such as residential and commercial buildings. Furthermore, through the developed modeling framework, the insurance industry will be able to calculate damage forecasts, expected maximum losses, premiums, and so on due to increasing natural disasters. In addition, the facility management industry will be able to manage assets more efficiently by predicting and reducing potential losses due to natural disasters.

Funding: This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2021R1C1C2003316). ※MSIT: Ministry of Science and ICT.

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