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Seismic loss assessment for buildings with multiple LOD BIM data

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ABSTRACT: Earthquake-induced economic loss of buildings is a fundamental concern for earthquake-resilient cities. The FEMA P-58 method is a state-of-the-art seismic loss assessment method for buildings. Nevertheless, because the FEMA P-58 method is a refined component-level loss assessment method, it requires highly detailed data as the input. Consequently, the knowledge of building details will affect the seismic loss assessment. In this study, a seismic loss assessment approach for buildings combining building information modeling (BIM) with the FEMA P-58 method is proposed. The detailed building data are automatically obtained from the building information model in which the building components may have different levels of development (LODs). The determination of component type and the development of the component vulnerability function when the information is incomplete are proposed. Finally, to demonstrate the rationality of the proposed method, an office building that is available online is selected, and the seismic loss assessments with multi-LOD BIM data are performed as case studies. The results show that, on the one hand, even if the available building information is limited, the proposed method can still produce an acceptable loss assessment; on the other hand, given more information, the accuracy of the assessment can be improved and the uncertainty can be reduced using the proposed method.

1. INTRODUXTION

Earthquake-induced economic losses of buildings are a fundamental concern for earthquake-resilient cities (Hwang and Lignos 2017). The Federal Emergency Management Agency (FEMA) proposed the FEMA P-58 method (FEMA 2012), which is a state-of-the-art seismic loss assessment method for buildings and has been used in many studies for the refined seismic performance assessment of buildings (Tian et al. 2016; Xu et al. 2018; Zeng et al. 2016).To render FEMA P-58 practical, FEMA proposed a database of fragility functions and consequence functions for 764 types of components (among which 322 components require certain user-defined parameters, and thus cannot be directly used) (FEMA 2012). Nevertheless, because the FEMA P-58 method is a component-level loss assessment method, it requires highly detailed input data. For example, FEMA P-58 provides 12 types of wall finishes (nine available for direct use). Given a certain wall finish, a series of data (e.g., surface material, wall height, connection details of the wall, etc.) are required to determine its corresponding type from the 12 candidates. Consequently, the knowledge of building details affects the seismic loss assessment. However, obtaining such knowledge is a critical challenge in the application of the FEMA P-58 method.

Building information modeling (BIM) can be a key technology in solving the problem above. The detailing of structural and non-structural components available in building information models is essential for building damage assessment to properly attribute damage characteristics (Perrone and Filiatrault 2017). In the building information model, building components with different levels of development (LODs) contain different amounts of effective information. Thus, when applying BIM to the FEMA P-58 loss assessment method of buildings, it is necessary to establish a uniform framework that can accommodate different LODs. Moreover, a higher LOD should lead to a more refined seismic loss assessment result using such a framework.

2. VULNERABILITY FUNCTIONS OF COMPONENTS WITH MULTIPLE LODS

2.1. Framework

In terms of the abovementioned problem, a solution is proposed as follows:

(1) Determine the potential fragility classification numbers.

If some key information of a component is insufficient, the classification process will stop at a branch node rather than at a leaf node of the classification tree. In this case, this study suggests the following steps to determine the type of component: (a) set all the available leaf nodes from the child nodes of the branch node as "potential fragility classification numbers"; (b) randomly select the fragility classification number of the component from the potential fragility classification numbers. A GWB partition component is used as an example (Figure 1). Assuming that the stud material of the GWB partition is "metal" and the height is "full height," the classification process stops at node 3 of the classification tree owing to incomplete information. Consequently, the component could be C1011.001a, C1011.001c, or C1011.001d. Because C1011.001a requires user-defined parameters, C1011.001c and C1011.001d are set as the potential fragility classification numbers. Subsequently, the component type is randomly selected from the two potential options with the probability of p_1 and p_2, respectively, where $p_1 + p_2 = 1$. This study assumes $p_1 = p_2 = 0.5$. However, when other prior knowledge is available, the values of p_1 and p_2 can be adjusted accordingly.

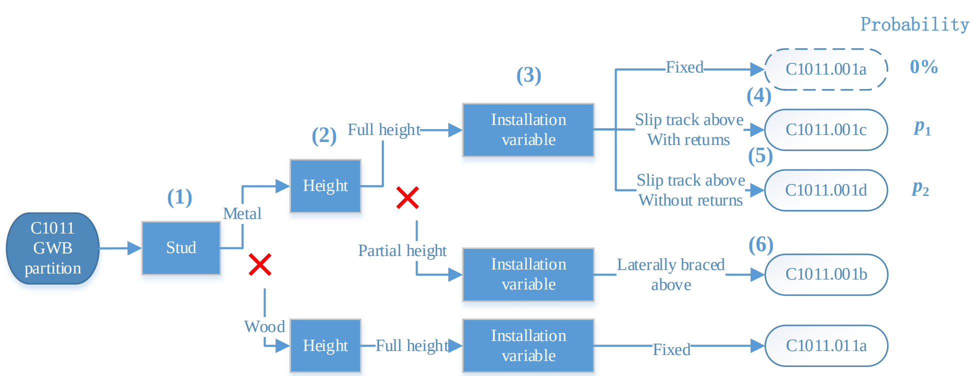


Figure 1: Determination of the component type when information is incomplete.

(2) Perform the Monte Carlo simulation

A large number of Monte Carlo simulations are performed to obtain the component vulnerability function. This approach is illustrated in Figure 2. The engineering demand parameter (EDP) is obtained every Δedp in a range of interest [0, upper limit]. For a given EDP = edp, a Monte Carlo simulation is performed, and each simulation is denoted as a "realization". In each realization, the component type is first randomly selected from the potential fragility classification numbers; subsequently, based on the corresponding fragility curves and *edp*, the probabilities of the occurring different damage states are calculated, and the damage state is randomly determined accordingly (it may be assumed as ds_i); finally, based on the consequence function corresponding to the damage state ds_i, the unit repair cost $l \mid edp$ is randomly determined. Through multiple realizations, multiple sample values of $l \mid edp$ can be obtained. Here, the random variable $l \mid edp$ does not obey the typical distributions (such as normal distribution), and the feature of the distribution varies with *edp*. For clarity, this study adopts the 10% quantile, median, and 90% quantile of $l \mid edp$ to reflect the feature of the distribution. Our numerical tests show that when the number of realizations is larger than 500, the distribution of $l \mid edp$ tends to be stable. Because the calculation time per realization is small (far less than 1 ms), the number of realizations is set as 1000 in this study.

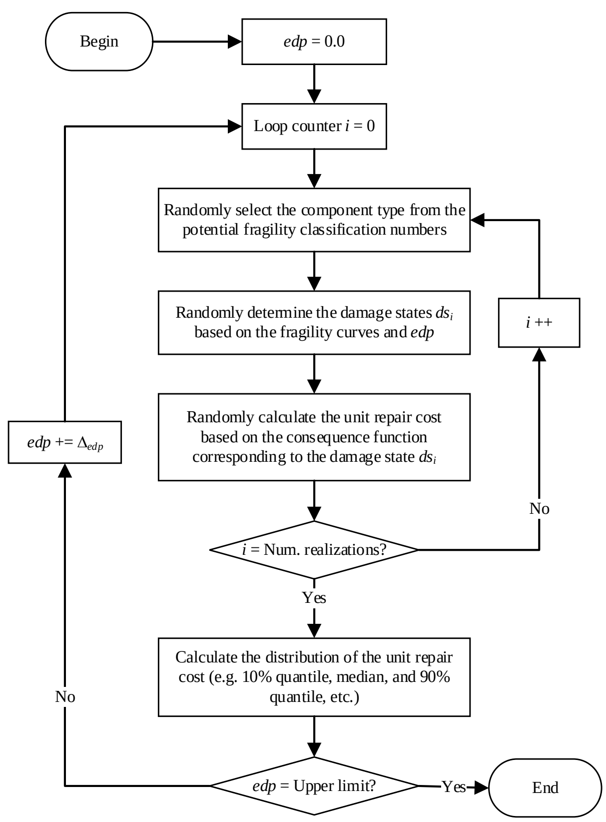


Figure 2: Flowchart to obtain the component vulnerability function using Monte Carlo simulation.

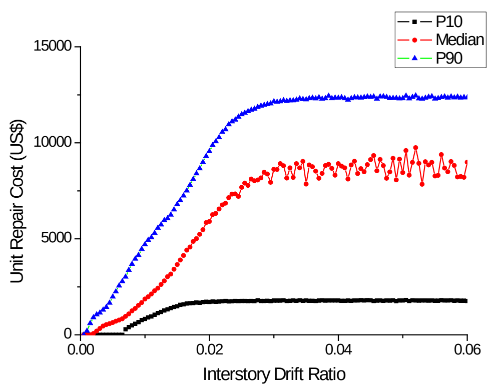
A building information model may contain components with different LODs. Consequently, the richness of available information is different for different components. A primary advantage of the proposed solution described above is that it accommodates different LODs using a uniform framework based on the FEMA P-58 method, and also exploits the available information. More information leads to less potential fragility classification numbers and less uncertainty of the vulnerability function.

2.2. Vulnerability function of components

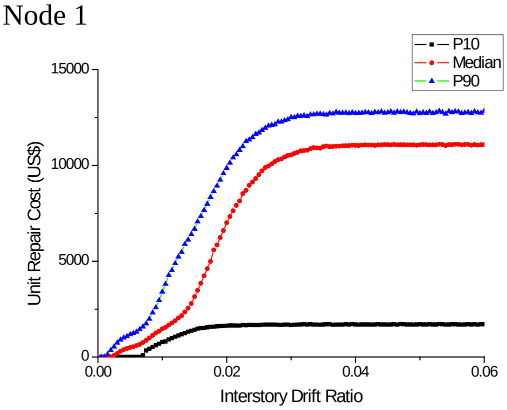
The GWB partition (C1011) is selected as an example to demonstrate the proposed method for components. The classification tree is shown in Figure 1. Six nodes in the classification tree are selected for illustration, and they are numbered 1 to 6 in the order of their depths. The vulnerability function for each node is subsequently calculated assuming that the component quantity is 10, and the unit repair cost is used. The result is shown in Figure 3. When the EDP is larger than 0.04, the unit repair cost tends to be stable, except for the median value of nodes 1 and 3. Taking the repair cost of node 3 when interstory drift ratio = 0.06 (denoted as $l_3 \mid 0.06$) as an example: the repair costs of the two potential fragility classification numbers of node 3, i.e., C1011.001c (Figure 3d) and C1011.001d (Figure 3e), differ significantly from each other. Consequently, the probability density function of $l_3 \mid 0.06$ contains multiple peaks, and the density at the median is low (Figure 4a), thus implying that the slope at the median value of the empirical distribution function of $l_3 \mid 0.06$ is small (Figure 4b). This leads to significant fluctuations.

When the interstory drift ratio is 0.06, both C1011.001c and C1011.001d reach their highest damage states with almost 100% probability. However, according to the FEMA P-58 database, for C1011.001c, three damage states exist; and for C1011.001d, only two damage states exist. Because the repair cost at damage state 3 is much larger than the repair cost at damage state 2, the repair cost of C1011.001c is much larger than the repair cost of C1011.001d.

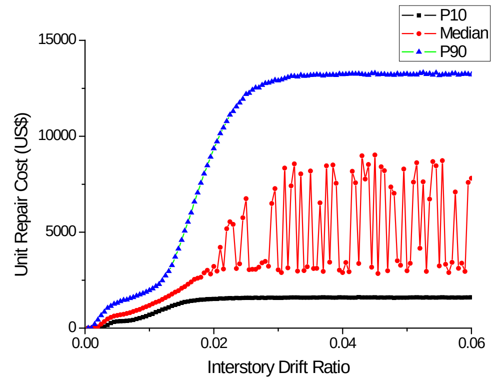
According to the detailed descriptions of the interior partition by the BIMForum (2017), components with an LOD of 200 should accurately define the type of material, with flexible layouts, locations, heights, and elevation profiles. Components with an LOD of 300 should contain specific geometries and locations; components with an LOD of 350 or higher should contain members at any interface with wall edges. Therefore, for the component with an LOD of 200, the classification process reaches nodes with a depth of 2 (such as node 2 in Figure 1). For the component with an LOD of 300, the classification process reaches nodes with a depth of 3 (such as node 3 in Figure 1). Components with an LOD of 350 or higher contain all the required information, and thus the classification process can reach the leaf node (such as nodes 4 to 6 in Figure 1).



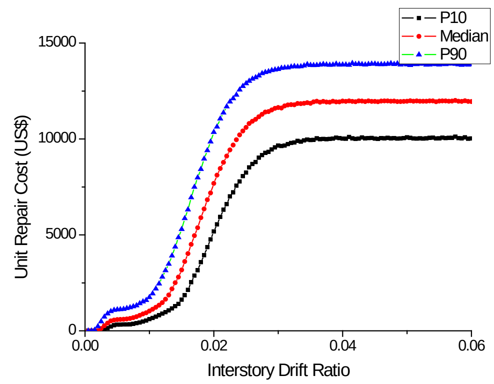
(a) Node 1



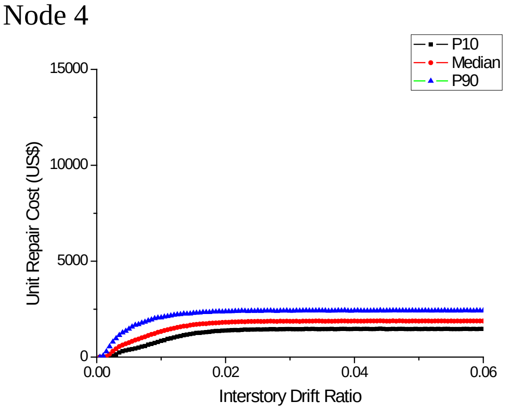
(b) Node 2



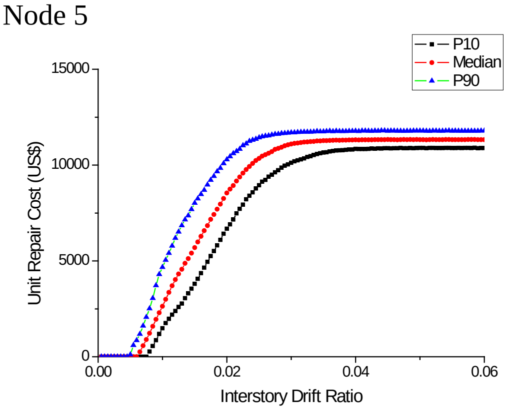
(c) Node 3



(d) Node 4

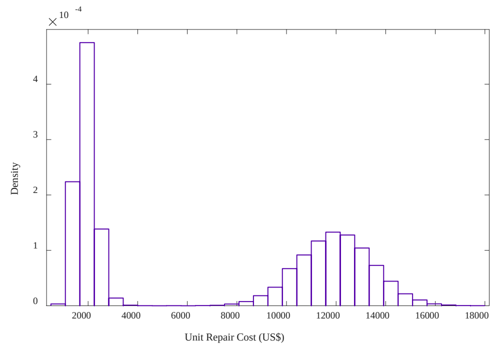


(e) Node 5

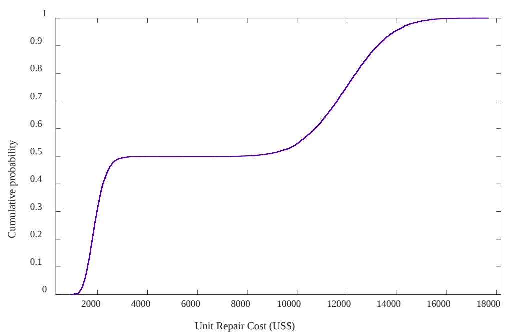


(f) Node 6

Figure 3: Vulnerability functions of nodes 1 to 6 from the classification tree of GWB partition.



(a) Probability density distribution histogram



(b) Empirical cumulative distribution function

Figure 4: Sample attributes of node 3 of the GWB partition when interstory drift ratio = 0.06 (setting number of realizations = 10,000 to obtain 10,000 samples).

The information provided by BIM can reduce the uncertainty caused by the component type as well as the component quantity. For example, for a LOD 200 partition, if its quantity is unknown, it can be estimated according to the normative quantities given in Appendix F of FEMA P-58 (FEMA 2012). For example, a 900 m^2 office building contains approximately 10 units of partition walls (1 unit = 1,300 square feet) with a dispersion of 0.2. After considering the uncertainty of the quantity, the vulnerability function of node 2 in Figure 1 is calculated, as shown in Figure 5. Comparing with Figure 3b, it can be found that if the exact component quantity is available, the uncertainty of the repair cost can be significantly reduced.

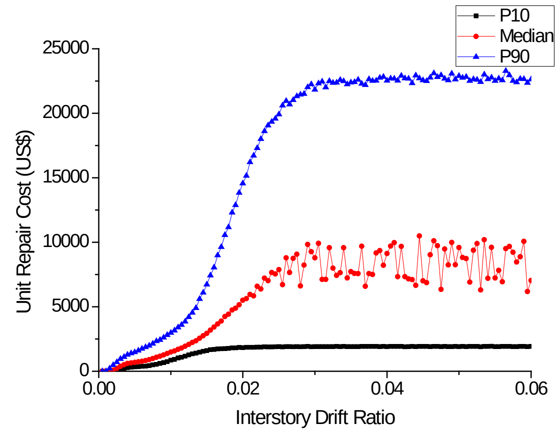
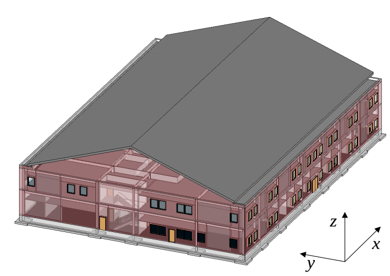


Figure 5: Vulnerability functions of node 2 from the classification tree of GWB partition considering the uncertainty of component quantity.

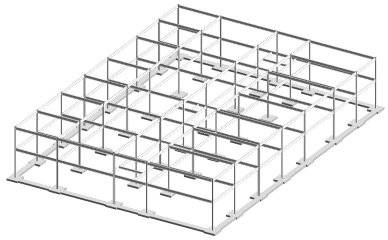
3. CASE STUDY

3.1. The example models

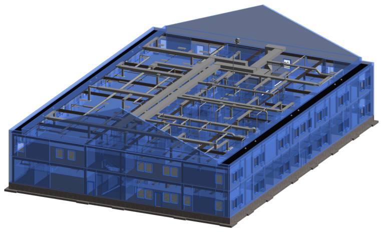
Currently, many software platforms are available for BIM. For clarity, the BIM software mentioned in this work is the widely used Autodesk Revit 2018 (Autodesk 2018). The Revit model of a two-story steel moment frame office is selected as an example to illustrate the proposed method. This office building is a benchmark model proposed by East and Bogen (2012), and it includes architectural, structural, and mechanical, electrical, and plumbing (MEP) models (Figure 6). No other design information is available for the benchmark model. Consequently, it is assumed in this study that the seismic design category (ASCE 2010) of the building is C. This attribute is included in the classification tree for many components (e.g., heating, ventilation, and air conditioning (HVAC) ducts, ceilings, pipes, diffusers, etc.).



(a) Architectural model



(b) Structural model



(c) MEP model (only displaying the HVAC)

Figure 6: Revit models of the benchmark office building.

To investigate the uncertainty of building seismic loss owing to the completeness of data, three virtual building information models are established based on the benchmark model, as shown in Table 1. To control the source of uncertainty and discuss the analysis results more clearly, it is assumed that the type and quantity of structural components of the three virtual buildings are deterministic and identical. The structural information is obtained from the benchmark model (Figure 6b) through the Revit application programming interface (API).

Building A is identical to the benchmark model except that all the non-structural components are removed. Consequently, the types and quantities of non-structural components of Building A are indeterministic. The quantity of non-structural components is assumed to follow a lognormal distribution (FEMA 2012), where the median and dispersion are estimated according to the normative quantities given in Appendix F of FEMA P-58 (FEMA 2012).

Building B is identical to the benchmark model except that all the attributes of the non-structural components are removed. Consequently, the types of non-structural components of Building B are indeterministic, and the potential fragility classification numbers for each component are identical to those of Building A. Meanwhile, the quantities of non-structural components of Building B are deterministic, which are obtained by extracting the building information using the Revit API. One exception is the wall finish component because it has to be modeled in Revit as an attribute of the GWB partition component rather than an independent element. Therefore, the quantity of wall finish components in Building B is also indeterministic, and its median and dispersion are identical to those of Building A.

Building C is identical to the benchmark model except that all the necessary component information is added, such that the leaf nodes of the classification trees for all the components can be reached. Consequently, the types and quantities of non-structural components of Building C are deterministic.

Table 1:The three models for the case study.

Label	The type and quantity of structural components	The type of non-structural components	The quantity of non-structural components
Building A	Deterministic	Indeterministic	Indeterministic
Building B	Deterministic	Indeterministic	Deterministic (except for wall finish)
Building C	Deterministic	Deterministic	Deterministic

3.2. Structural analysis

The application of BIM in the structural domain is an important topic of research. There are numerous studies on the automatic generation of structural analysis models based on building information models (Hu et al. 2016; Oti et al. 2016). Consequently, the related topics are not discussed in detail herein. Instead, the Industrial Foundation Class (IFC) (buildingSMART 2018) building model format is exported from Revit and subsequently imported to ETABS 2016 software (Computers and Structures Inc 2018) to establish the structural analysis model directly. Basically, the location of structural components such as the beams and columns can be imported correctly (as shown in Figure 7), while other properties, such as the materials, sections, and plastic hinges, require manual adjustment. The widely used El-Centro ground motion record at the design basis earthquake (DBE) hazard level is selected as an example.

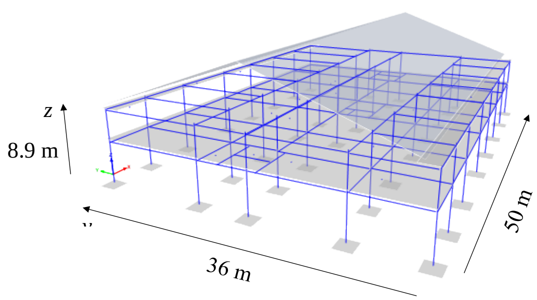
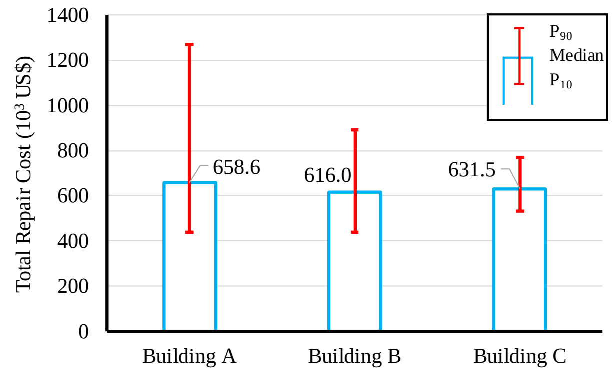


Figure 7: Structural analysis model established in the ETABS software by importing the IFC-format model exported from Revit.

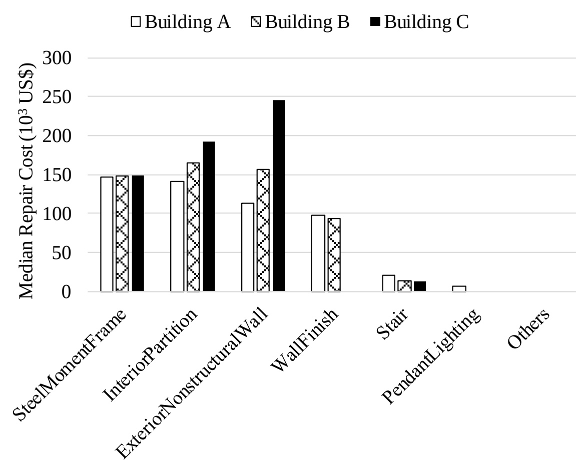
3.3. The seismic loss assessment results

The seismic loss assessment results of the three building examples are shown in Figure 8. Comparing the results of Buildings A, B, and C (Figure 8a), it can be found that as more information is given, the uncertainty of the total seismic loss tends to decrease (the dispersions are 0.38, 0.28, and 0.14, respectively). In addition, even if the only available information are the seismic design category and structural information of the building (i.e., Building A), a preliminary estimation of the seismic loss can be obtained using the proposed method.

In the case study, the estimated median seismic loss of Buildings A, B, and C are close to each other. It is noteworthy, however, that this is a coincidence. Figure 8b further illustrates the median loss of different components within the buildings. As shown, for Buildings A and B, the median losses of the external non-structural wall are much lower than that of Building C, while the median losses of the wall finish are much higher than that of Building C. These errors are due to insufficient information. Specifically, the error of the repair cost of the external wall is primarily due to insufficient wall type information, while the error of the repair cost of the wall finish is primarily due to insufficient quantity information.



(a) Total seismic loss



(b) Median loss of each component

Figure 8: Seismic loss assessment results for the three example buildings.

4. CONCLUSIONS

In this work, a seismic loss assessment approach for urban buildings combining BIM with the FEMA P-58 method was proposed. Based on the classification trees of the components, the determination of the component type and the development of the component vulnerability function with incomplete information were proposed. An office building that is accessible online was selected, and the seismic loss assessments with multiple LODs and BIM data were performed as case studies. The conclusions are as follows:

(1) The FEMA P-58 loss assessment method required highly detailed data for input. The proposed Monte Carlo approach enabled the calculation of the vulnerability function of the components even when the available information was insufficient for a precise classification. Furthermore, if more information was provided, the nodes with higher depths in the component classification tree could be reached, and the uncertainty of the estimated repair cost tended to decrease.

(2) The case study results showed that, on the one hand, even if the available building information was limited, the proposed method could still produce an acceptable loss assessment; on the other hand, given more information, the accuracy of the assessment could be improved and the uncertainty could be reduced using the proposed method.

This study provided a useful reference for the automation of the refined seismic loss assessment of buildings.

5. ACKNOWLEDGEMENT

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