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Development of a Regional Seismic Response Model Using Building Clustering

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ABSTRACT

This paper presents a framework for regional seismic response estimations that uses machine learning driven building clustering and the relatively novel concept of indicator buildings. A robust database of buildings is required to provide detailed structural and site information to develop typologically similar building clusters and allow for an informed selection of the indicator buildings that are used to estimate the seismic response of all buildings in a cluster. Here, the framework is applied to a database of buildings consisting of over 400 buildings in the central business district of Wellington, New Zealand. First, key structural and site parameters are extracted from the building database and building clusters are generated using the k-prototype clustering methodology. Next, indicator buildings within each cluster are selected and modelled using ETABS. To provide more accurate estimations of drift across all buildings in the cluster, supplementary models were generated by modifying the stiffness of the base indicator building models to represent the structural period range across all buildings in each cluster. A case study was undertaken using the 2016 Kaikoura earthquake, and the response of the models are utilized to propose a linear regression model estimating seismic response of all buildings in the database.

Introduction

This paper outlines the development of a framework for selecting and modeling representative indicator buildings within typologically similar clusters in a building portfolio to provide a regional seismic response model. The framework requires a detailed database of buildings and uses an unsupervised machine learning methodology to cluster buildings into typologically similar groups based on relevant structural and site characteristics. Buildings closest to the center (or mean) of the clusters are selected as candidates to serve as indicator buildings, which are modeled and used to estimate the seismic response of all buildings within the cluster. Indicatory buildings have been previously used following earthquakes to limit structural inspections of damaged buildings following aftershocks [1]. Here the objective is to select indicator buildings before the occurrence of ground shaking to allow for the development of numerical models that can be used for scenario planning pre-event and can provide situational awareness post-event.

Wellington, the capital city of New Zealand, has been selected as the case study for this research due to the high risk of seismic damage in this city and the existence of a comprehensive building inventory, herein referred to as the Wellington Building Inventory (WBI) [2], [3]. This paper proceeds with introducing WBI and the key structural and site parameters which have been used for clustering. Next, building clustering and

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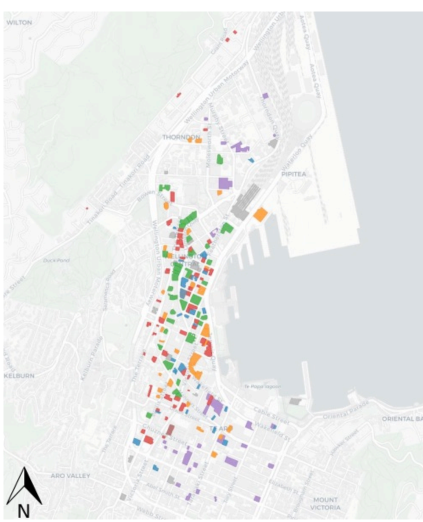
indicator building selection using unsupervised machine learning methodology, k-prototype, is discussed. Finally, the undertaken case study for the 2016 Kaikoura earthquake and the developed seismic response model is presented.

Wellington Building Inventory

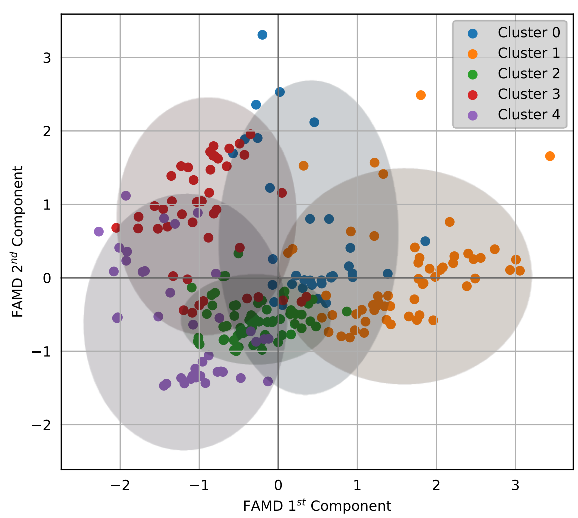
The WBI consists of eleven building databases that have been consolidated into a single easy-to-use database consisting of over 400 buildings in the central business district in Wellington, shown in Fig. 1 (a) [3]. This research focuses on buildings in the WBI that are five or more stories and primarily use reinforced concrete for the lateral load resisting system, which results in approximately 270 buildings. Amongst the various available data for each building in the database, the structural and site characteristics affecting the seismic response of buildings are of primary interest here. In particular, these parameters include: primary lateral load resisting system (LLRS), floor system (FS), year of construction, height, and site conditions including site subsoil class (adopted from [4]) and strong motion station (adopted from [5]), as well as detailed structural drawings which are available for most buildings in the database, and facilitate the creation of detailed building models for seismic response analysis.

Building Clustering

Unsupervised Machine Learning was used to cluster buildings in the WBI into typologically similar building clusters based on the previously mentioned structural and site characteristics. A total of seven parameters from the WBI were used to generate the clusters, including both numerical and categorical data types, namely year and height which are numerical, and LLRS, FS, soil type, and strong motion station which are categorical. To allow for clustering of the mixed data, a k-prototype clustering method was applied to cluster mixed numerical and categorical data types [6]. The Elbow Method was used to determine the optimum number of clusters, and suggested five clusters was the optimum number for the given dataset [7]. The results of k-prototype clustering is illustrated in the map of Fig. 1 (a), showing clustered buildings in different colors as well as not-clustered buildings in gray. Moreover, Factor Analysis of Mixed Data (FAMD) method was used to reduce the seven dimensions consisting mixed numerical and categorical values into two component and visualize the 2D reduced dimension of clustered building [8]. Fig. 1 (b) shows the distribution of buildings on the FAMD reduced 2D plane. The buildings are colored according to the results of k-prototype method.



(a)



(b)

Figure 1. (a): Distribution of clustered buildings on Wellington map, where gray footprints represent the buildings not clustered due to insufficient structural data, and (b): Buildings distribution on FAMD reduced 2D space.

Indicator Building Selection and Modeling

To select an indicator building from each cluster, the spatial distance of all buildings to their respective cluster centroid was calculated based on k-prototype dissimilarity function and hence, all building were ranked according to their distance to the cluster centroid [6]. The five top-ranked buildings from each cluster were selected initially as candidate for cluster indicator buildings. From the top five ranked buildings in each cluster, the selection of an indicator building was primarily based on the floor plans, structural systems, and building period.

Ground Floor and Typical Floors layouts were drawn for the top five ranked buildings in each cluster. Common features were identified between the five floor plans considering floor area, plan/vertical irregularity, and column/beam/shear wall layout. Although it is unlikely that one building can effectively represent all key features in a cluster, the most representative building between the five candidate buildings was chosen based on these characteristics. The selected building in each cluster was modelled in CSI ETABS to provide a linear finite element response model of each indicator building. A demonstration of the procedure is shown in Fig. 2 for Cluster 0, where Fig. 2 (a) shows the Ground Floor layouts, Fig. 2 (b) shows the selected indicator building from the top-five ranked buildings within the cluster, and Fig. 2 (c) represents a rendered sketch of the building model in CSI ETABS.

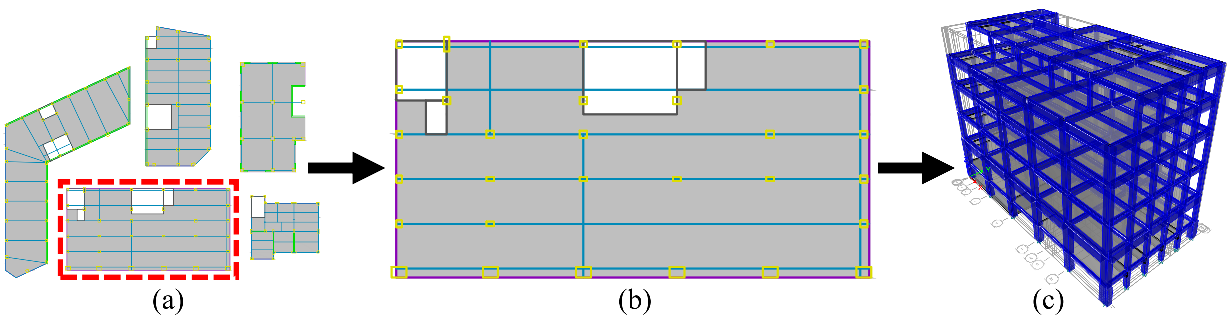


Figure 2. Cluster 0 (a): top five ranked buildings floor plans, (b): the selected indicator building floor plan, and (c): the rendered sketch of ETABS model for indicator building.

Supplementary Models

Supplementary models were generated by modifying the stiffness of the base indicator building models to represent the structural period range across all buildings in each cluster. This was done using statistical analyses on cluster period distributions and adjusting the stiffness modification coefficients in the base indicator building models. Estimated building periods were calculated for all buildings in the WBI using approximate methods from NZS 1170.5 Commentary [9]. The mean and standard deviation of building periods in each cluster were calculated, and the stiffness modification coefficients on the primary structural elements in the models were modified to create three supplementary models which are geometrically identical to the base model but with varying periods. The targeted periods included the mean period of all buildings within the cluster as well as the mean plus one standard deviation and the mean minus one standard deviation. These models were created to generate response estimates for a range of periods in each cluster for more accurate response estimation of all building in each cluster.

Case Study

The 2016 Kaikoura Earthquake was an M_w 7.8 earthquake that had an epicenter approximately 200 km from Wellington [2]. The nearest location of fault rupture occurred approximately 50 km South of Wellington and caused significant structural damage to many buildings [2]. Time series acceleration data for this earthquake was obtained from several strong motion stations (SMSs) in Wellington [5]. A linear time history analysis was conducted for each of four models in each cluster, where the time history data used for each building was assigned based on site period rather than geographic distance to the SMS. Using the maximum drift and acceleration of four different models in each cluster, two methods were utilized to estimate the response parameters of all buildings within the cluster. In Method I, the maximum drift from the indicator building in each cluster was applied to all buildings in that cluster. In Method II, a linear regression model was developed based on the response parameters and periods of four models in each cluster. The developed model was used to estimate the maximum drift and maximum acceleration of all buildings in each cluster according to building periods. Fig. 3 shows the results for Method I (a), and Method II (b) for drift of all buildings in the WBI for the Kaikoura earthquake. This comparison corroborates the response underestimation of Method I. Preliminary analysis indicates that these drift estimates are consistent with response and damage observed during the earthquake. Ongoing work is being done to validating this mythology.

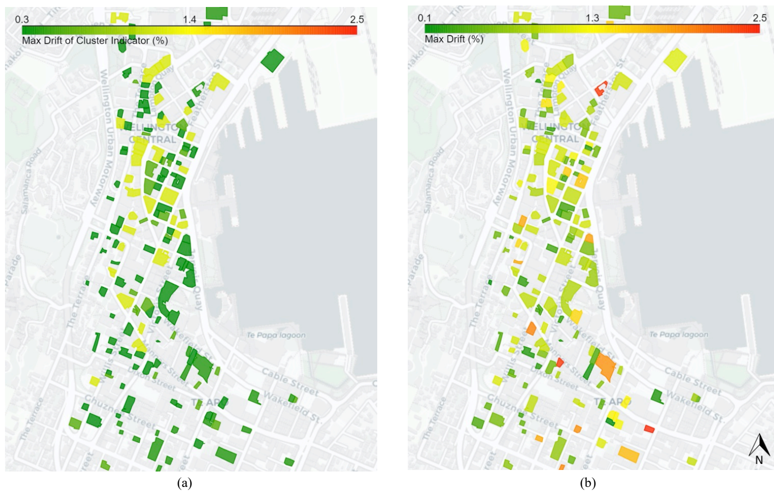


Figure 3. Drift maps using two methods; (a) Method One: drifts driven from indicator buildings (b) Method Two: drifts driven from linear regression response model.

Conclusions

This paper presents a methodology to develop regional seismic response model for buildings in a portfolio that uses unsupervised machine learning methods to cluster buildings and select representative indicator buildings. The Wellington Building Inventory was selected as the case study of this paper due to the availability of a robust database of buildings within the central business district. The buildings were initially clustered into five similar vulnerability archetype clusters using the k-prototype method. Next, an indicator building from each cluster was selected and elastic models were developed in CSI ETABS to enable seismic response estimation. Moreover, three supplementary models were created in each cluster to match the mean, mean plus, and mean minus standard deviation of the periods in each cluster. The 2016 Kaikoura earthquake was selected as the case study event to develop a linear regression model for seismic response of all buildings in the database. Using the developed models, maximum drift of all buildings were estimated according to the building period. Ongoing work by the two last authors focuses on developing detailed non-linear macro models for the top five ranked buildings in each cluster to improve the accuracy of response models and further validate this methodology. Moreover, the top five indicator buildings are going to be instrumented to enable verification of the response models with the results of ambient vibration measurements. The response models can be utilized to estimate the regional seismic damage and loss of the building portfolio in the future.

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