INTL JOURNAL OF ELECTRONICS AND TELECOMMUNICATIONS, 2021, VOL. 67, NO. 2, PP. 261-266
Manuscript received August 17, 2020; revised April, 2021 DOI: 10.24425/ijet.2021.135974

Development of Data-mining Technique for Seismic Vulnerability Assessment

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***Abstract*—Assessment of seismic vulnerability of urban infrastructure is an actual problem, since the damage caused by earthquakes is quite significant. Despite the complexity of such tasks, today's machine learning methods allow the use of "fast" methods for assessing seismic vulnerability. The article proposes a methodology for assessing the characteristics of typical urban objects that affect their seismic resistance; using classification and clustering methods. For the analysis, we use kmeans and hkmeans clustering methods, where the Euclidean distance is used as a measure of proximity. The optimal number of clusters is determined using the Elbow method. A decision-making model on the seismic resistance of an urban object is presented, also the most important variables that have the greatest impact on the seismic resistance of an urban object are identified. The study shows that the results of clustering coincide with expert estimates, and the characteristic of typical urban objects can be determined as a result of data modeling using clustering algorithms.**

***Keywords*—data analysis, seismic assessment, clustering, hkmeans, random forest**

I. Introduction

THE use of data mining methods to assess the seismic vulnerability of urban environment objects has proven its effectiveness. These methods are based on relatively small but reliable sets of basic characteristics of buildings, which are accessible even at the regional level [2]. In studies [1, 2, 3, 4, 5, 6] data mining methods were used to find the dependencies between the vulnerability of buildings and the range of their characteristics (building length, number of floors, total land area, etc.). In [8, 9, 10], the seismic vulnerability of historical centers is assessed based on a limited number of parameters and data collected after the earthquake.

No less interesting is the work [11], where the use of methods of data mining for clustering spatial data is pronounced clearly. The research were carried out with the aim of developing a spatial data cluster and analyzing the characteristics of each data cluster to develop the spatial zoning of the danger of damage to buildings caused by an earthquake in the city of Banda Aceh (Indonesia). Banda Aceh and the surrounding areas were spatially divided into two classes of potential building damage caused by an earthquake which are Based on the results of research. The authors presented a spatial picture of the danger of damage to buildings in the city of Banda Aceh at the end of this work. In the next research work [12], an analysis of seismic vulnerability on an urban scale (Konstantin, Algeria cities) which are based on the data mining method ARL (association rule learning), i.e. learning association rules. The use of the ARL method was to establish links between the attributes of the building (the number of floors or the age of the building) and the vulnerability classes of the European Macroseismic scale EMS98. As noted in the work, the using of this method helps to extract "hidden" connections between the elementary features of buildings and seismic vulnerability. At the same time, the ARL method allowed us to give an overall assessment of seismic risk in urban areas. According to the authors, this approach avoids the expensive process of compiling a cadastre of the characteristics of buildings in the field, which often hinders the assessment of seismic initiatives in weak and moderate seismically dangerous regions. In addition to everything else, the use of ARL in this research is related to seismic vulnerability in [1, 13]. Various methods for predicting the level of damage to buildings were made in the works [14, 15], one of which is the Bayesian network model. The assessment of the level of destruction is based on the Bayesian network and allows you to accurately establish a causal relationship between variables, and also reflects the relationship between states. In these works, a new method for assessing the level of damage to a building is presented. The data set is based on a building unit. Data obtained from the Padang Regional Agency for Disaster Management and the Indonesian Meteorological, Climatological and Geophysical Agency. As an example we can also give the work [16] along with all the works devoted to the assessment of seismic vulnerability. This work presents a deep learning approach, which is based on a recurrent neural network with long and short-term memory (LSTM), for modeling the response and predicting the structural seismic response. The proposed deep learning model makes it possible to predict both elastic and inelastic reactions of building structures based on trained data instead of classical numerical methods. This approach to forecasting nonlinear structural responses is relevant in the field of analysis of seismic fragility of buildings to assess reliability.

The purpose of this study is to develop a methodology for assessing the importance of the influence of factors on the seismic resistance of urban objects using cluster analysis and classification methods. At the initial stage of the study, to ensure a better analysis, data pre-processing was carried out, which is a necessary step in the data analysis process. The following steps are not less important:

1) exploratory analysis and study of data structure by cluster analysis methods (*kmeans* and *hkmeans*);
2) building a classification model for predicting the seismic resistance of an object;

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3) identification of the influence degree of various building characteristics on its seismic resistance;
4) model accuracy assessment.
The structure of the operation is as follows: Section II presents a methodology for assessing the seismic resistance of typical urban objects based on data mining. Section III describes the progress and results of experimental work. Section IV sets out the main conclusions of the work.

II. Dataset and Characteristics

As a dataset for the study, we used the data provided in the reporting documentation of JSC "KAZRICA" (Kazakh research institute of construction and architecture) about urban objects with 19 characteristics that belong to certain subdistrict of Almaty [29]. Table 1 presents the features which were used for data analysis.

Table I
Dataset and Feature Names

№	Feature name		
1	object	11	foundations
2	location	12	bearing_struct
3	pr_develop_year	13	floor_struct
4	year_constr	14	wall_fence
5	type_pr	15	partitions
6	seism_cat_soils	16	height
7	space-plan_sol	17	total_area
8	floors	18	construct_vol
9	antiseism_activ	19	assessment
10	gen_char		

A data normalization process must be performed to improve the quality of data extraction. Otherwise, there is a risk of incorrect data output. A raw data undergoes normalization, as it is shown in Fig. 1.

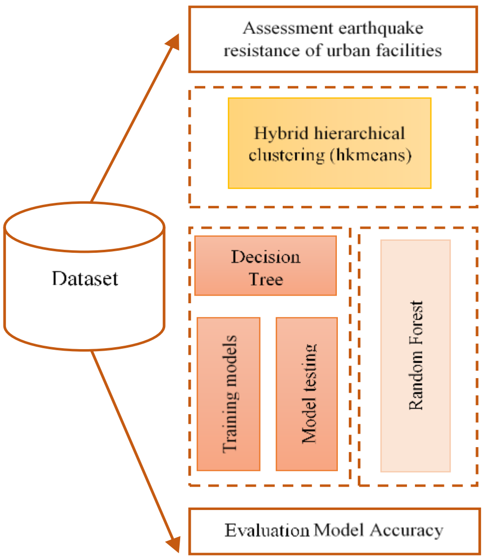


Fig. 1. The structure of the research information model

Then, *hkmeans*, Decision Tree and Random Forest clustering algorithms are applied to the processed dataset. Application of these methods is followed by the model accuracy assessment.
Structural model of the research problem is shown in Fig. 1.

III. Methods

K-Means Clustering

The main idea of the method is to determine k centroids, one for each cluster. The algorithm's goal is to minimize the target function, in the general case, the squared error function. Target function (1)

$$J = \sum_{j=1}^{k}\sum_{k=1}^{n}\left\|x_i^{(j)} - c^j\right\|^2 \qquad (1)$$

where $\left\|x_i^{(j)} - c^j\right\|^2$ is the selected measure of the distance between the data point $x_i^{(j)}$ and the center of the cluster c_j is a measure of the distance of n data points from their respective cluster centers.

Hierarchical Clustering

In hierarchical clustering, the main goal is to build a cluster structure. In this case, we apply the unification algorithm.
The distance between the clusters is taken as the measure used to determine which clusters should be combined and which to be divided [17, 18]. In the hierarchical unification algorithm each element from the set of X observations is taken as a separate cluster. Further, at each step of the algorithm, more similar pairs of elements are combined into one cluster. Cluster join condition is shown (2).

$$D = \min(\text{dist}(a,b)) \qquad (2)$$

where a and b belong to X.
The algorithm yields the structure of clusters, which is a graph. It ends when the required number of clusters is reached. [17].

Decision Tree

In the decision tree, the partition criterion and the stop condition will be determined in advance on the basis of entropy. When splitting, different subsets of the data set are created and each instance belongs to a single subset. Finite subsets are finite nodes, and intermediate subsets are called internal nodes. The average result of training data in the particular node is used to predict the result in each node of the sheet. In each node of the decision tree, the entropy is determined by (3).

$$E = -\sum_{i=1}^{c} p_i \times \log\left(p_i\right) \qquad (3)$$

where p_i represents the proportion of cases with class labels i, i={1 …c}.

Random Forest

Random forest consists of many trees. It allows a large number of weakly correlated classifiers to form a strong one.
The RF algorithm combines the ideas of bagging method (bagging, bootstrap aggregating) and random space method (RSM, random subspace method) [19, 20, 21].
A description of RF algorithm (Breiman, 2001) can be represented as follows. Let the training sample consist of N objects, the dimension of the attribute space is M, and the m parameter - the number of attributes; from which the selection of attributes for partitioning at the tree nodes occurs. All trees are built independently of each other as follows:

– a random subsample is generated with repetition (i.e., some objects will get into it several times) of the same size as the training sample (i.e., dimension N), it is also called a bootstrap sample;

– a decision tree that classifies the objects of this subsample is constructed. During the creation of next node of the tree, the attribute on the basis of which partition is performed is not selected from all M attributes, but only from randomly selected m parameter (selection of the best among these m attributes can be made using the Gini index);
– the tree is being built until there are no subsamples left and is not being cut.

Unlike the classic decision trees [24, 25] construction algorithms, when constructing each tree by the random forest method, at the stages of node splitting only a fixed number of randomly selected attributes of the training set is used (the second parameter of the method) and a complete tree is constructed (without cutting), i.e., each leaf of the tree contains observations of only one class. Classification is carried out by the classifiers voting, which are determined by individual trees, and the regression is assessed by averaging the regression estimates of all trees [26].

Random forest provides many benefits:
– It runs efficiently on large data bases.
– It can handle thousands of input variables without variable deletion.
– It gives estimates of what variables are important in the classification.
– It generates an internal unbiased estimate of the generalization error (oob error).
– It computes proximities between pairs of cases that can be used in locating outliers.
– It is relatively robust to outliers and noise.
– It is computationally lighter than other tree ensemble methods (e.g. Boosting) [27,28].

IV. Results

The optimal number of clusters k is determined using the Elbow method, where $k = 4$ (Fig. 2).

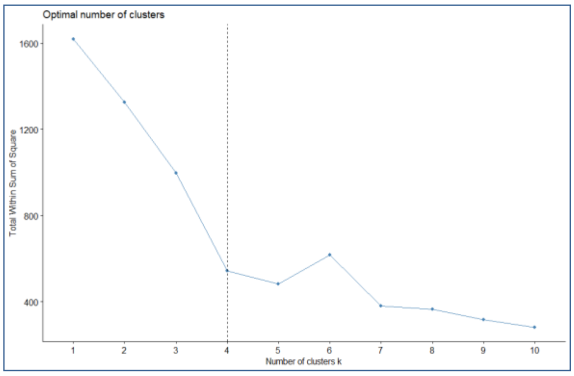


Fig. 2. Determination of the optimal number of clusters

For cluster data analysis, *kmeans* and *hkmeans* methods were used, the results of which are shown in Fig. 3a and Fig. 3b. In both cases, the Euclidean distance was used as a measure of distance.

Clustering using *kmeans* and *hkmeans* methods yields 4 clusters:
– cluster 1 groups earthquake-resistant large-panel buildings that contain objects built in 1975, 1978, 1986, 1987, 1993, 1994;
– cluster 2 contains earthquake-resistant frame-panel buildings with bored piles, where the load-bearing walls are brick walls. Cluster objects are constructions built in 1973, 1975, 1983;
– cluster 3 includes earthquake-safe frame-type objects built in 1972, 1985, 1992;
– cluster 4 contains non-earthquake-resistant brick buildings built in 1932, 1936, 1952, 1954, 1956, 1958 [22, 23].

As it is shown in Figure 3, the *hkmeans* method, which demonstrated a clear separation between clusters, rather than the *kmeans* method, is more successful in managing the clustering task. The *kmeans* method turned out to be very sensitive to the selection of the initial centers of the clusters, thereby failing to cope with the task when the object belongs to different clusters equally or does not belong to any.

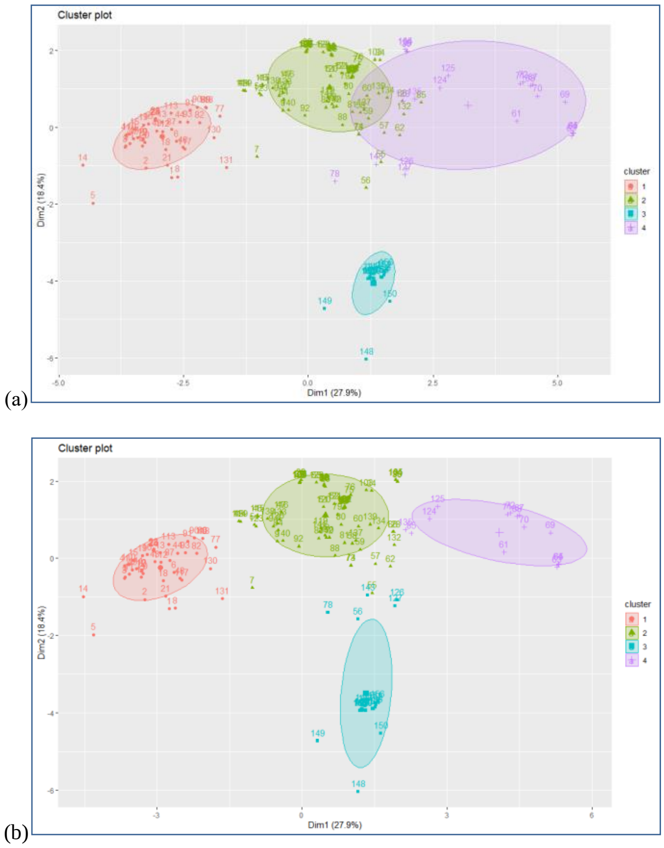


Fig. 3. Comparison of results of the constructed clusters by methods: (a) k-means (b) hkmeans

The purpose of each cluster and their interpretation is verified through the decision tree and random forest methods.

To implement verification by the decision tree method, the initial data set was divided into training (70%) and test (30%) samples. Using the k-fold cross-validation method, the training set was tested several times and branches with the smallest dispersion were selected. As a result, the decision tree algorithm determined three branches with the lowest dispersion. As can be seen from Fig. 4, if the value of the wall_fence parameter is <3.5 (wall fence), then the object is considered earthquake-resistant, otherwise the foundation of the object should be checked where if foundations <4.5, then the object is not earthquake-resistant, otherwise it is considered earthquake-safe. The classification accuracy of the constructed decision tree was 91.3%.

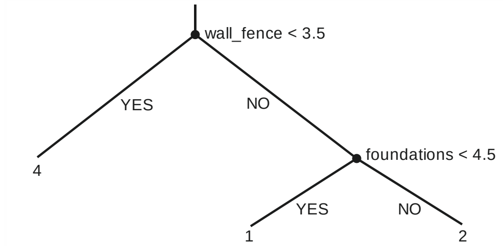


Fig. 4. Forecast decision tree model

Random forest was applied to refine the constructed model of the decision tree and identify the most crucial characteristics that affect the forecast model of seismic resistance of the objects.

In this problem, the model type - regression, number of trees - 500, no. of variables tried at each split - 5, mean of squared residuals - 0.08. Minimum depth distribution values are presented in Table II. The distribution of the minimum depth for the first ten variables in accordance with the average minimum depth calculated using the upper trees is shown in Fig. 5a.

For random forests with many variables with a large number of missed observations, we should always consider adding the min_no_of_trees option so that only those variables that were used to split at least into the declared number of trees will be taken into account. This allows us to avoid choosing variables that were accidentally used for splitting. However, in our case, we can simply increase the k parameter to build all the trees (Fig. 5b).

TABLE II
MINIMUM DEPTH DISTRIBUTION

№	tree	variable	minimal_depth
1	1	bearing_struct	0
2	1	floors	2
3	1	foundations	1
4	1	gen_char	2
5	1	height	2
6	1	location	3
7	1	partitions	3
8	1	seism_cat_soils	9
9	1	space.plan_sol	1
10	1	type_pr	4

Using only relevant trees to calculate the mean does not change it for variables that do not have missing values. In addition, the change does not affect the order of the variables in this case.

In the next stage of the study, we studied the importance indicators of the variable through calculating the following measures: accuracy_decrease (classification), gini_decrease (classification), mse_increase (regression), node_purity_increase (regression), which extracted them from our random forest object.

Accuracy_decrease (classification) and mse_increase (regression) measures are based on a decrease in the predictive accuracy of the forest. The gini_decrease (classification) and node_purity_increase (regression) measures are based on changes in node purity after splitting into a variable. The mean_minimal_depth, no_of_trees, no_of_nodes, times_a_root, p_value measures are based on the structure of the forest.

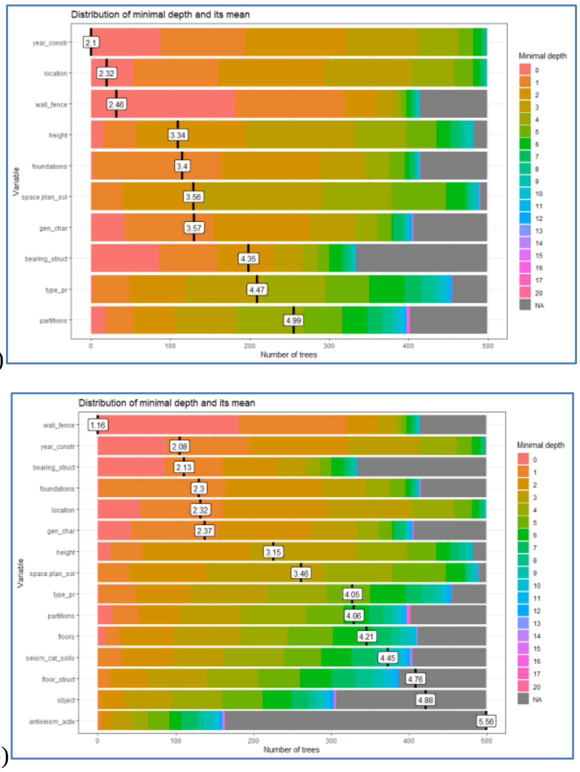
(a)
(b)


Fig. 5. Graphs of calculating the average minimum depth: (a) top_trees (b) relevant_trees

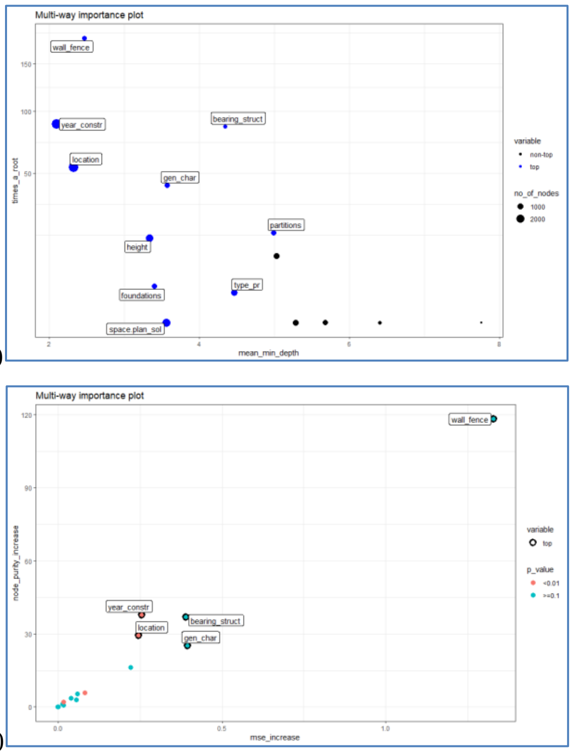
(a)
(b)


Fig. 6. Important variables extraction: (a) multi-way importance plot (top 10 variables) (b) multi-way importance plot (top 5 variables)

The result of important variables extraction is presented below in Fig. 6. As can be seen from Fig. 6a, by default, the top 10 variables in the graph are highlighted in blue and marked, they are selected using the sum of the ranks based on the importance indicators. The superiority of wall_fence, bearing_struct, year_constr, location, gen_char is evident in all three cases. Next, we present a graph of importance for several directions for another set of indicators of importance: grow of a mean squared error. We also set the marked variables to five so that only the top five variables are highlighted (Fig. 6b). In both graphs wall_fence, bearing_struct show the structure of the forest on the importance of variables.

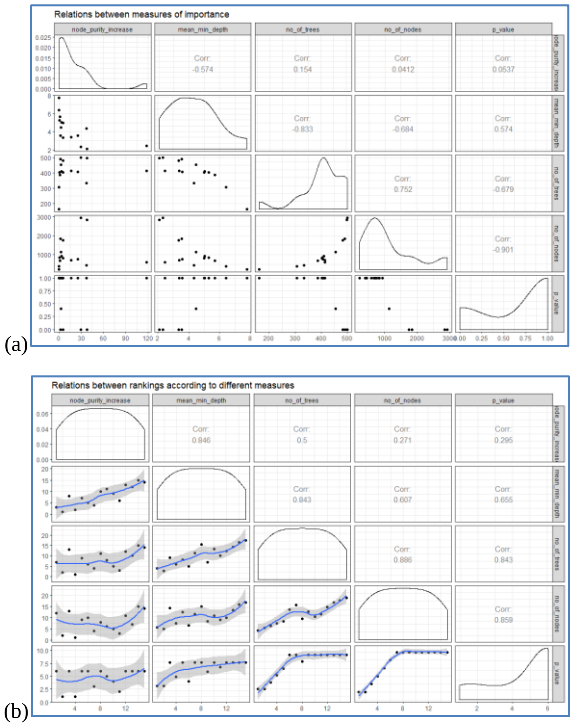


Fig. 7. Comparison of measures: (a) Compare measures using ggpairs (b) Compare different rankings

As can be seen from Fig. 6a, by default, the top 10 variables in the graph are highlighted in blue and marked, they are selected using the sum of the ranks based on the importance indicators. The superiority of wall_fence, bearing_struct, year_constr, location, gen_char is evident in all three cases.

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In both graphs wall_fence, bearing_struct show the structure of the forest on the importance of variables.

Measures comparison result Fig. 6a, 6b offer many options for selecting variable importance, so this does not allow us to choose the most informative schedule for the analysis. In this regard, we studied the relationship between various importance measures, then selected the three that are least consistent with each other, and used them on a graph of versatile importance to select the top variables Fig. 7a, 7b.

Comparing the ranking in the above graph, we see that the two pairs of measures almost exactly coincide in their variables ranking: mean_min_depth against mse_increase and mse_increase against node_purity_increase.

After choosing the set of the most important variables, we investigated the interactions with respect to them, i.e. splitting that appear in the maximum subtrees with respect to one of the selected variables (assessment). Thus, the 5 most important variables were extracted in accordance with the average minimum depth and number of trees: "location", "year_constr", "height", "space.plan_sol", "wall_fence". At the next stage, we constructed a graph (Fig. 8) containing information on the average conditional minimum depth of variables for each element of variables.

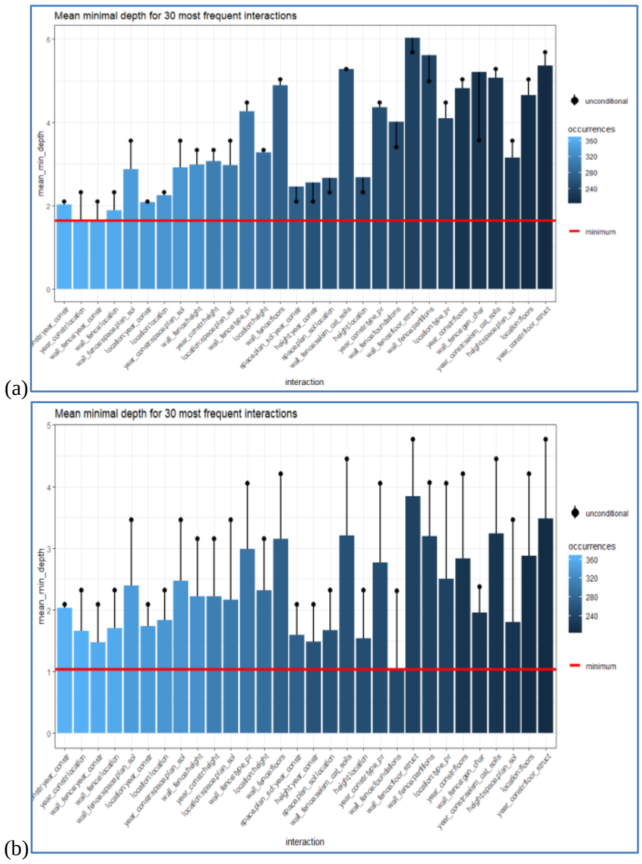

Fig. 8. Average conditional minimum depth of variables for each element of variables: (a) top_trees (b) «related_trees»

Interactions are ordered by decreasing number of occurrences - the most frequent of them: year_constr:location, wall_fence:year_constr, wall_fence:location, wall_fence:space.plan_sol, also takes place with a minimum average conditional minimum depth (Fig. 8a).

Comparing the graphs, it can be seen that in addition to the frequent ones, some of the less frequent ones are highlighted, such as wall_fence:foundadions (Fig. 8b).

As a result of the study, the accuracy of the random forest model was 95.06%.

V. Discussion

In the course of the study, the application of the *hkmeans* clustering method allowed us to obtain clusters (k = 4) with similar object variables and define the objects to a specific group. Compared to the conventional k-means clustering method, *hkmeans* showed a more accurate clustering result. To determine the optimal number of clusters, the Elbow method was used. For a more in-depth study of the resulting clusters and their interpretation, a decision tree was applied. To identify important characteristics, we used the random forest method, which allowed us to calculate the importance of variables. Thus, dependencies between the characteristics of objects were identified. These characteristics turned out to be the location, year of construction, based on which typical design of the object is determined. Space-planning decisions, which also affect the general characteristics of an object are no less important. Based on the general characteristics of the urban object, random forest has identified the wall_fence variable as the most significant one. Also, to ensure the reliability of the obtained results, the accuracy of the constructed model was evaluated.

VI. Conclusions

This article proposed a methodology for assessing the importance of factors which affect the seismic resistance of urban objects. An exploratory study of the data set was carried out through the cluster analysis. The results of cluster analysis coincided with experts' estimates. The application of cluster analysis revealed groups of urban objects with certain characteristics of building structures. For a detailed study of the structure of the obtained clusters, a classification model for assessing the seismic resistance of urban objects was built. Also, to clarify the relationship between the characteristics and determine their importance, the random forest method was used. The proposed methodology can be used to assess the seismic resistance of objects in the urban environment and in determination of strategies for planning urban infrastructure related to seismic risks.

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