POLITECNICO
MILANO 1863

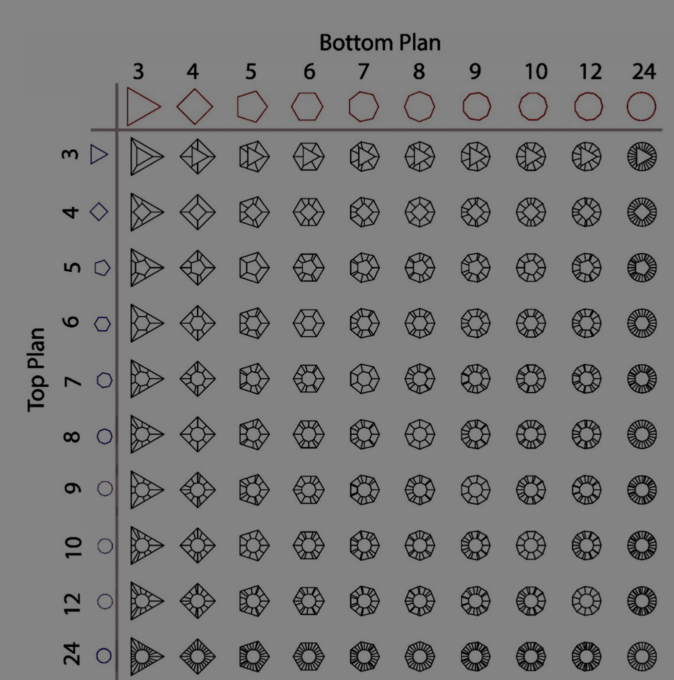
DIPARTIMENTO DI
INGEGNERIA CIVILE E AMBIENTALE

Architectural Form and Structural Efficiency:

Advanced Computation Design approach

Abstract

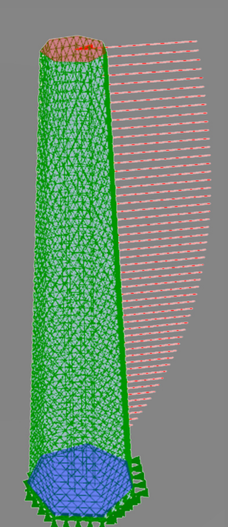
In this work, we exploit supervised machine learning (ML) to investigate the relationship be-tween architectural form and structural efficiency under seismic excitations. We inspect a small dataset of simulated responses of tall buildings, differing in terms of base and top plans within which a vertical transformation method is adopted (tapered forms). A diagrid structure with members having a tubular cross-section is mapped on the architectural forms, and static loads equivalent to the seismic excitation are applied. Different ML algorithms, such as **kNN, SVM, Decision Tree, Ensemble methods, discriminant analysis, Naïve Bayes** are trained, to classify the seismic response of each form on the basis of a specific label. Presented results rely upon the drift of the building at its top floor, though the same procedure can be generalized and adopt any performance characteristic of the considered structure, like e.g. the drift ratio, the total mass, or the expected design weight. This research activity puts forward a promising perspective for the use of ML algorithms to help architectural and structural designers during the early stages design of tall buildings.



Structural Modeling

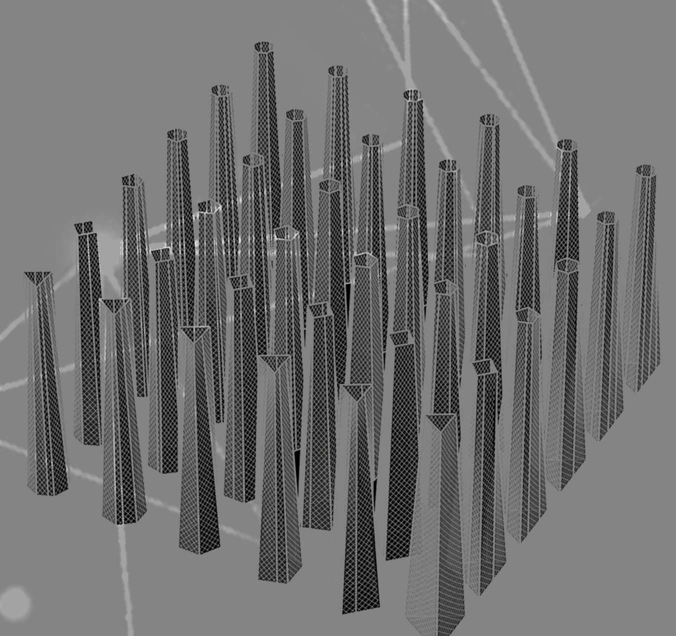
The result of architectural form generation process is the peripheral surface of the building. Further on, a structure should be added on to it. A structure of Diagonal Grid (DiaGrid) members is mapped on it with variations over the height and width of every module. The height of DiaGrid modules defined by the count of floors it covers which is assumed 2 floors height.

Lateral loads, representing the equivalent static actions, are applied to the structure and a static linear analysis is made. The simplified approximate loads are studied in the initial phase of the research. Statically Equivalent Avenue for determining lateral loads is applied in the following manner. The equivalent loads are distributed on the floor slabs. In this research, a statically equivalent load of seismic was focused and all models which pass through architectural and structural phases were analyzed with same loads



Tall Building Moldels

144 potentially explorable forms were parametrically generated, based on previous research on form generation for tall buildings, consisting of regular geometries in symmetric axial, top, and base floor plans. The geometry plans constituted of simple polygons from 3-gon to 13-gon and 24-gon instead of circle. Overall forms were further generated by ascending from the base plan to the top, according to curvilinear and morph vertical transformations, by means of generative design.

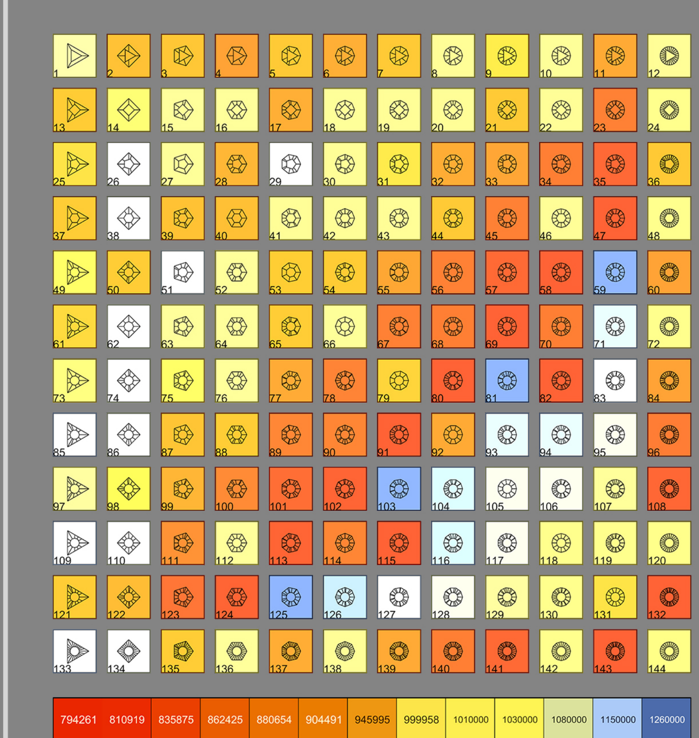


Structural Result: Drift

A graph, showing the top and base plan of each form, with a color representing the range of the structural parameter of interest, results insightful to compare the outcomes at a glance. Below figure shown such a graph in relation to the drift, for all the generated models. According to it, the green color qualitatively represents the tall buildings which are characterized by a lower drift, while the red color shows the tall buildings featuring a higher drift. It can be seen that, by increasing the side number of plans the structural efficiency is improved.

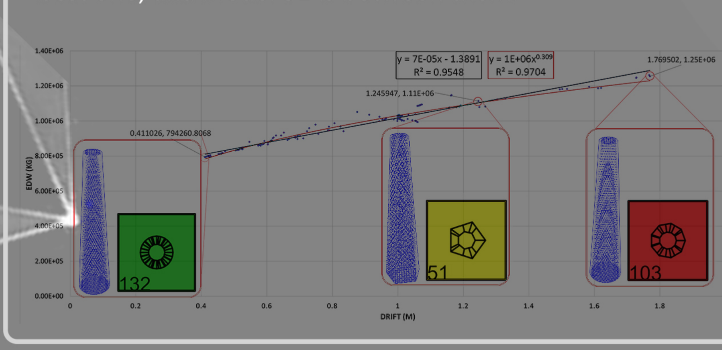
Expected Design Weight

Also, a novel structural efficiency factor is introduced as an "expected design weight," which represents the expected designed weight of the structural members of the building without going through a structural element design process. This factor can be used as an indication of the cost of the building structure for similar construction techniques in parametric design environments.



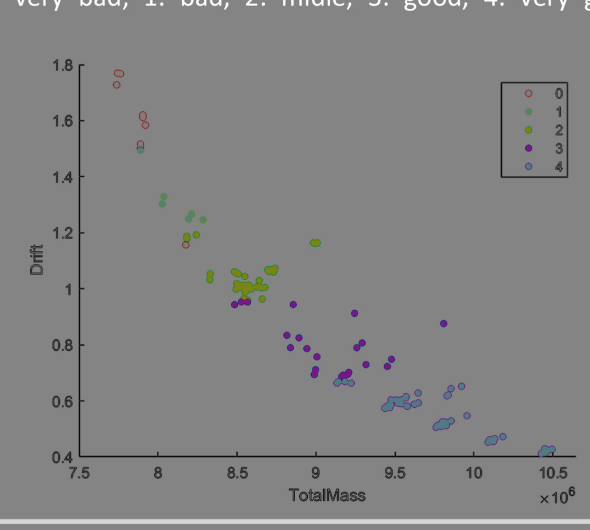
Comparison

After comparing 144 models regards the Drift, and Expected Design Weight parameter, we can collect both of them in one diagram. According to which the models that have highest Drift (not favorable) also have the highest Expected Design weight (not favorable), and vice versa. For example form 103 is the worst model , and model 132 is the best one, and model 51 is between them.



Classification: Define Label

A qualitative label has been defined for the drift, exploiting its values ranging from a 34 cm to 158 cm within the dataset. Tall buildings whose drift was near 34 cm have been considered "very good" in their structural behavior; a drift increase would be linked to a diminished structural efficiency. Five classes have been defined for classification (0: very bad, 1: bad, 2: midle, 3: good, 4: very good)



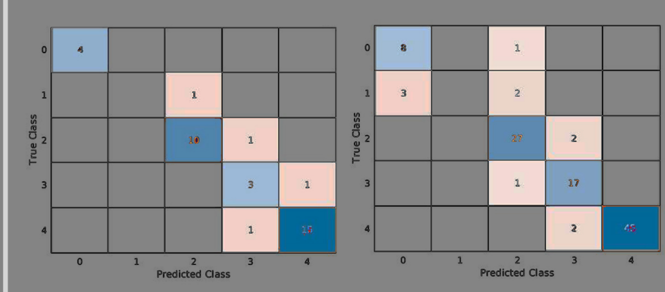
Classification Learner Algorithm

In this work, a small data set has been considered: out of the 144 architectural forms, 75% (108 forms) have been used for training, and 25% percent (36 forms) have been instead used for testing. First, a randomization algorithm has been applied to split the dataset into the training and testing sets, without any bias. Different ML algorithms, such as **kNN, SVM, Decision Tree, Ensemble methods, discriminant analysis, Naïve Bayes** are trained, to classify each form on the basis of a specific label

KNN | Ensemble
SVM | Discriminant
Decision Tree | Naïve Bayes

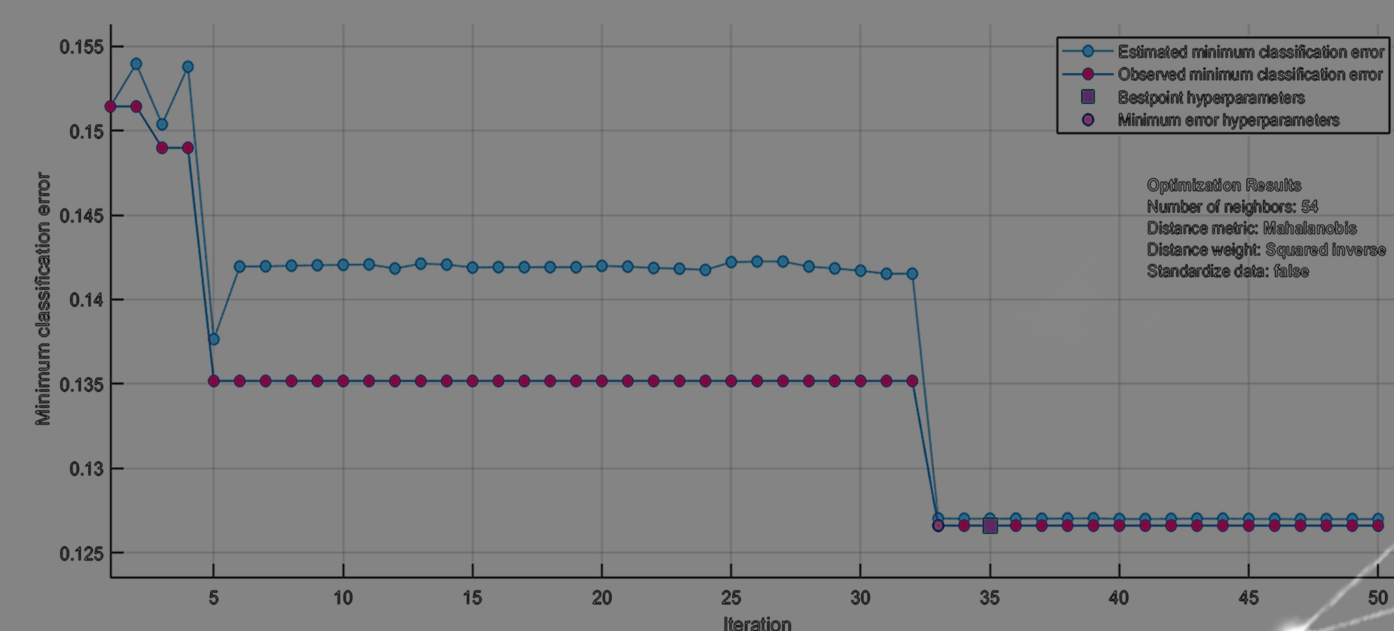
Applying Classification

First, it has been tested whether supervised ML classification can be used in this case study. By means of a very simple implementation of the kNN algorithm, the accuracy for training has resulted to be 91.7%, while the accuracy for testing has been 83.3%. It has been thus proved that the classification algorithm can correctly predict the structural response of tall buildings, in case the label is appropriately chosen. According to the confusion matrix for training and testing depicted below, it can be understood that each class does not have the same number of observations .



Bayesian HyperParameter Optimization

Instead of tuning each classification algorithm parameter manually, it would be better to define them within an optimization process. We have inspected three types of optimiza-tions: grid search, random search, and Bayesian optimization. Each of these optimization approaches has a specific property, see e.g. for further details. The Bayesian optimization approach has been used because it can lead to better results in a shorter time and through fewer iterations; moreover, it is the only approach that efficiently exploits the iteration results according to the Bayes rule. In Figure 4, the Bayesian optimization is showed for the kNN algorithm, for 50 iterations: at iteration 35 the optimum result has been already attained, with a minimum classification error of about 12.5%, so with an accuracy for the training dataset of 87.5%. The four tuned hyperparameters of kNN are also reported in the graph.



Decision tree Classifier

Decision tree works with the number of splits, and a criterion for them. The number of splits has been varied from 1 to 107; the criterion for split has been selected among the Gini's diversity index, Twoing rule, maximum deviance reduction. The com-puting time has varied from 17.4 s to 45 s, the accuracy from 86.1% to 93.5% for training, and from 77.8% to 100% for testing. The accuracy for testing of four models out of the five considered has attained the 100% result. It has resulted the best algorithm.

Model No.	Accuracy Training	Accuracy Testing	Total Misclassification cost	Training time	Maximum Number of Split	Split Criterion	Surrogate Decision Split	Optimizer	Acquisition Function	Iteration	Feature selection	PCA
2	93.5	100.0	7	29.7	5	Twoing rule		Bayesian	Expected Improvement per second plus	40	all	Disabled
5	93.5	100.0	7	17.4	4	Gini's diversity index	On, using max 10 surrogate	Random Search		40	all	Disabled
6	93.5	100.0	7	18.8	7	Gini's diversity index	Find all	Random Search		40	all	Disabled
9	86.1	77.8	15	30.76	42	Gini's diversity index	Find all	Random Search		40	all	95% Variance 1 kept off
11	93.5	100.0	7	45.0	5	Gini's diversity index	off	Random Search		40	1. Model No	Disabled

Ensemble classifier

The ensemble classifier algorithm exploits several learning algorithms to reach a final prediction. One of the most famous ensemble classifiers is the bootstrap aggregating (Bagging) one. the ensemble method has been selected among Bag, AdaBoost, RUS Boost. The computing time varied from 72 s to 129.4 s, with an accuracy from 85.2% to 98.1% for training, and from 94.4% to 100% for testing. After the tree, ensemble turns out to be the best classification algorithm.

Model No.	Accuracy	Total Misclassification cost	Training time	Ensemble method	Maximum number of splits	Number of learners	Learning rate	Number of predictors to sample	Optimizer	Acquisition Function	Iteration	Feature selection	PCA
1	98.1	2	123.3	RUSBoost	38	71	.94	Select All	Bayesian	Expected improvement per second plus	40	all	Disabled
2	97.2	3	128.3	RUSBoost	23	324	.46	Select All	Grid Search		Grid Div.= 10	all	Disabled
3	98.1	2	72.0	AdaBoost	3	20	.10	Select All	Random Search	Expected improvement per second plus	40	all	Disabled
4	96.3	4	80.3	RUSBoost	14	12	.98	Select All	Bayesian	Expected improvement per second plus	40	1. Model No	Disabled
5	98.1	2	105.9	RUSBoost	25	65	.85	Select All	Bayesian	Expected improvement per second plus	40	1. Model No 2. Total length of Diagrid Members 3. Max Normal Force	Disabled
6	85.2	16	129.4	RUSBoost	106	124	0.07	Select All	Bayesian	Expected improvement per second plus	40	1. Model No 2. Total length of Diagrid Members 3. Max Normal Force	95% Variance 1 kept off
7	88	13	99.2	Bag	66	61	1		Bayesian	Expected improvement per second plus	40	all	95% Variance 1 kept off

Conclusion

In this work, the relation between architectural form and structural efficiency of tall buildings has been studied via a data-driven approach. Several architectural and struc-tural model generation methods could be used to get insights into which architectural de-tail or modification may increase the structural efficiency, moving in the direction of morphing or smart structures. A novel view has been provided by adopting machine learning tools to learn the links between shape and structural response under seismic ex-citations, by also reducing the computing time: a sample dataset has been used to predict the performance of new architectural forms of tall buildings.

It has been proven that supervised machine learning can be successfully applied to this case study. Moreover, among the six investigated classification algorithms, even though each of them provides advantages and disadvantages, the ensemble and the deci-sion tree classifier algorithms have attained the best results

Model	Train Acc.	Test Acc.	Model	Train Acc.	Test Acc.	Model	Train Acc.	Test Acc.
KNN			SVM			Tree		
model 1	91.7	94.4	1	95.4	94.4	2	93.5	100
3	91.7	94.4	2	95.4	94.4	5	93.5	100
8	91.7	97.2	3	95.4	94.4	6	93.5	100
9	91.7	94.4	4	95.4	94.4	9	86.1	78
10	88.0	97.2	5	95.4	91.7	11	93.5	100
16	88.0	97.2	6	86.1	91.7			
17	96.3	97.2	7	91.7	91.7			

Model	Train Acc.	Test Acc.	Model	Train Acc.	Test Acc.	Model	Train Acc.	Test Acc.
Naïve Bayes			Discriminant			Ensemble		
1	90.7	91.7	1	93.5	86.1	1	98.1	100.0
2	92.6	88.9	2	85.2	83.3	2	97.2	97.2
4	92.6	88.9	3	94.4	91.7	3	98.1	100.0
5	82.4	83.3	4	95.4	91.7	4	96.3	97.2
7	91.7	88.9	5	85.2	83.3	5	98.1	100.0
						6	85.2	94.4
						7	88.0	94.4

Authors:
S. Pooyan Kazemi S.
PhD student
Politecnivo di Milano

Aldo F. Ghisi
Associate Professor
Politecnico di Milano
Stefano Mariani
Associate Professor
Politecnico di Milano

Advanced Computing, Big Data

CS³ 2021