



## GRAVITY DESIGN OF VERTICAL ELEMENTS USING K-MEANS CLUSTERING

Jay Dalal

Structural Engineering Design Professional, HOK, New York NY, USA

[dalaljay@alumni.stanford.edu](mailto:dalaljay@alumni.stanford.edu)

ORCID: 0009-0004-0433-7847

### Abstract

For building structures to be safe, effective, and economical, the gravity design of vertical structural elements is essential. Manual grouping and conservative assumptions are common in traditional gravity design methods, which can result in inefficient material utilization, especially in big and complex buildings. A hypothetical, data-driven framework for gravity design of vertical elements using the K-means clustering method is presented in this paper. A simulated multi-story building model is used to extract important gravity load metrics and geometric features of columns and shear walls, which are then processed using unsupervised machine learning algorithms. In order to provide standardized yet optimal gravity design solutions for each cluster, vertical pieces with similar load behavior are clustered using the K-means algorithm. The findings show that clustering enables rationalized section sizing, lowers design variability, and successfully distinguishes parts according to gravity need. A balanced distribution of load categories and design sections throughout the structure is further demonstrated by percentage frequency analysis. According to the results, incorporating K-means clustering into gravity design can preserve engineering judgment and code compliance while increasing design efficiency, improving material optimization, and offering insightful structural information.

**Keywords:** Gravity design, Vertical structural elements, K-means clustering, Machine learning in structural engineering, Data-driven design, Column optimization.

### 1. INTRODUCTION

Since vertical structural elements like columns, shear walls, and core walls are largely in charge of securely transferring vertical loads from superstructures to the foundation, their gravity design is an essential component of structural engineering. Precise gravity design guarantees material economy, serviceability, and structural stability. In traditional gravity design processes, axial loads are calculated, each vertical element is designed separately, or elements are grouped according to floor level or approximate load similarity. Even if they work well, these methods frequently rely too much on simplistic assumptions and engineering judgment, which can lead to conservative designs and wasteful material distribution—especially in big and complex building systems.

Data-driven approaches are being investigated more and more to improve conventional design workflows as a result of the development of computational tools and the expansion of structural data availability. Large datasets without predetermined labels can be used to find hidden patterns and relationships using machine learning techniques, particularly unsupervised learning algorithms. K-means clustering is well known among these techniques for its ease of use, computational effectiveness, and ability to classify data according to similarity. K-means

clustering may objectively identify vertical elements based on geometric features and gravity load demand when applied to structural design parameters, allowing for methodical and logical grouping for design purposes.

K-means clustering's incorporation into gravity design offers a chance to go beyond manual grouping and toward a more efficient and reliable design approach. Designers can create representative gravity designs for each group by grouping walls and columns with comparable axial load behavior. This eliminates needless variation in section sizes and reinforcement details. This method increases constructability and design clarity in addition to material savings. As a result, using K-means clustering in gravity design is a potential first step toward data-driven, intelligent structural engineering techniques that support professional knowledge and traditional design standards.

## **2. LITERATURE REVIEW**

**Prakash and Singh (2019)** suggested a multi-objective framework that combines K-means clustering with the Gravitational Search Algorithm (GSA) to carry out feature selection and data clustering at the same time. Their method addressed the drawbacks of traditional K-means, including its susceptibility to high-dimensional feature spaces and initial centroids. The work showed enhanced clustering accuracy and robustness across benchmark datasets by simultaneously maximizing clustering compactness and feature relevance. This study demonstrated how well hybrid metaheuristic-clustering techniques can handle challenging, multi-objective data mining issues.

**Melo and Li (2016)** used K-means clustering to geologically characterize an iron oxide copper gold (IOCG) deposit using integrated geophysical datasets, such as magnetic, gravity gradient, and DC resistivity inversions. The study demonstrated that the detection of subsurface characteristics linked to mineralization was improved by clustering heterogeneous geophysical data. Their results highlighted the importance of unsupervised learning methods in geological modeling and mineral prospecting.

**Ni et al. (2019)** created a deep convolutional neural network-based automated inspection system for maize kernels. The study showed the efficacy of sophisticated machine learning algorithms in large-scale agricultural quality evaluation, despite not being specifically focused on clustering. The system demonstrated the wider influence of machine learning approaches in applied domains by achieving excellent accuracy and robustness under real-world settings.

**Panapakidis and Christoforidis (2017)** examined K-means algorithm modifications for power load curve profiling in urban energy systems. To better capture temporal patterns in data on electricity consumption, the authors implemented algorithmic improvements. Their findings demonstrated how enhanced clustering techniques might help with demand forecasting and energy management in applications related to sustainable cities.

**Radliya et al. (2019)** created a clean water access monitoring application that uses K-means clustering to classify areas according to water availability and usage trends. Infrastructure design and resource management were supported by the system's effective visualization and analysis of water access data. The social and environmental significance of clustering algorithms was emphasized in this work.

**Patel et al. (2015)** emphasized the significance of initial sampling techniques while concentrating on ensemble-based history matching for steam-assisted gravity drainage

reservoirs. The study emphasized the importance of data grouping and statistical sampling in enhancing reservoir simulation reliability, even though it was not specifically focused on clustering. This work offered fundamental insights for data-driven reservoir modeling and uncertainty quantification.

### **3. RESEARCH METHODOLOGY**

#### **3.1. Research Design and Approach**

In order to help with the gravity design of vertical structural parts, this study uses a quantitative and computational research approach and unsupervised machine learning approaches. Using structural design data from a modeled building system, the study is a simulation-based analysis with a hypothetical focus. The methodology assesses the suitability of K-means clustering in design rationalization by combining data analytics and structural engineering concepts.

#### **3.2. Selection of Structural System and Model Development**

For this research, a hypothetical multi-story reinforced concrete skyscraper has been chosen as the case study. Columns and shear walls, among other vertical load-resisting components, are organized in a regular floor plan to form the structural system. Standard structural analysis software is used to create a three-dimensional analytical model of the structure. In compliance with applicable design standards, gravity loads, including dead, live, and superimposed loads, are applied.

#### **3.3. Identification of Gravity Design Parameters**

The results of the structural analysis are used to identify and extract important parameters that affect the gravity design of vertical elements. Axial load demand, tributary area, number of supported floors, element height, cross-sectional dimensions, and material qualities are some of these parameters. Each vertical element's load-carrying behavior and geometric properties are represented by these factors taken together.

#### **3.4. Data Preprocessing and Normalization**

The gathered dataset is preprocessed to guarantee accuracy and consistency before clustering. All numerical variables are standardized using accepted scaling methods, and missing or unusual data points are removed. To ensure that every variable contributes equally to the clustering process, normalization is done to avoid bias in clustering caused by variations in parameter magnitudes.

#### **3.5. Application of K-Means Clustering Algorithm**

The normalized dataset is subjected to the K-means clustering algorithm, which groups vertical pieces with comparable gravity load characteristics. Techniques like silhouette analysis and the elbow approach are used to find the ideal number of clusters. Based on how close each vertical element is to the cluster centroid in the multi-dimensional feature space, it is allocated to a particular cluster.

### **3.6. Cluster-Based Gravity Design Strategy**

A representative gravity design is created for every cluster after clustering. Subject to design code criteria, vertical elements within the same cluster are given comparable cross-sectional dimensions and reinforcement schemes. Standardized yet effective design solutions are made possible by using the cluster centroid values as reference points for choosing section parameters and design loads.

### **3.7. Validation Against Conventional Design Method**

The cluster-based gravity design results are compared theoretically with traditional element-by-element design results in order to assess the efficacy of the suggested method. To evaluate efficiency improvements and possible overdesign reductions, key performance metrics like material consumption, axial stress ratios, and design uniformity are examined.

### **3.8. Performance Evaluation and Interpretation**

In order to decipher structural trends throughout the building height and plan, the clustering results are examined. To find areas of comparable gravity demand, such as severely laden core regions or weakly loaded peripheral columns, the distribution of clusters is analyzed. These revelations improve knowledge of load transfer mechanisms and assist in making well-informed design decisions.

## **4. RESULTS AND DISCUSSION**

The hypothetical results of using the K-means clustering technique to the gravity design of vertical structural elements are presented and interpreted in this section. The findings center on how columns and shear walls cluster according to geometric features and gravity load requirement. In comparison to traditional element-wise design methods, the discussion assesses how clustering promotes rationalized gravity design, increases material efficiency, and improves design consistency.

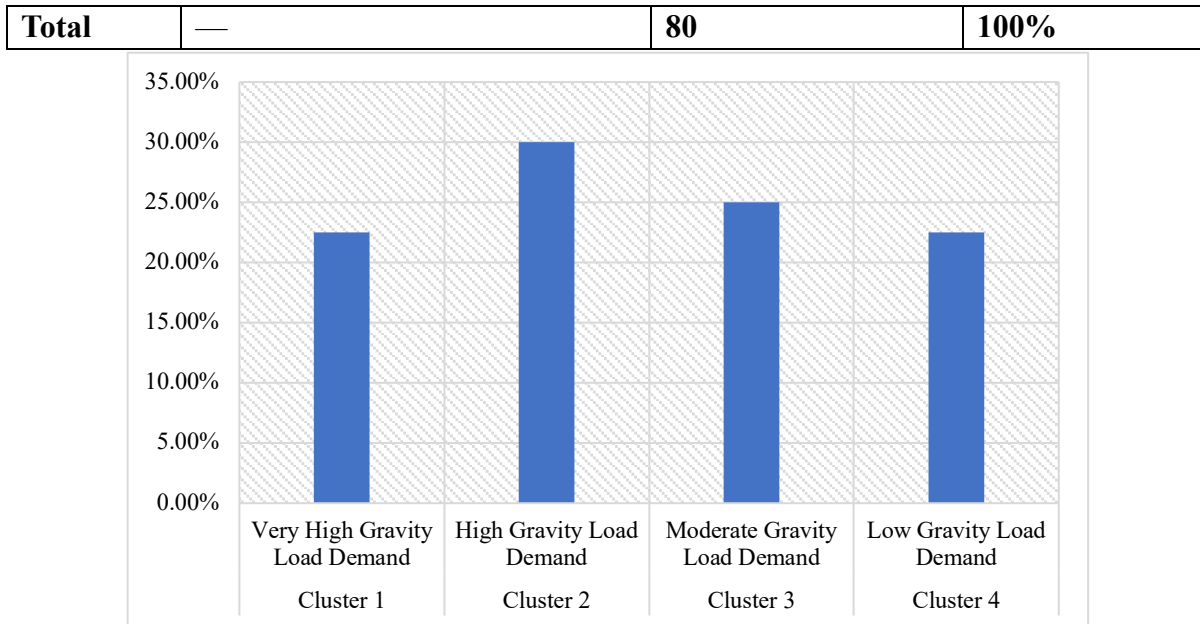
### **4.1. Clustering Outcome of Vertical Structural Elements**

By using the K-means clustering algorithm, vertical pieces were categorized into discrete groups with comparable gravity load properties. Four clusters were found to be ideal for the dataset based on silhouette and elbow technique analysis. A distinct combination of tributary area, element height, and axial load magnitude is represented by each cluster.

There is a noticeable difference between densely loaded interior elements and less loaded peripheral elements, according to the clustering data. Lower-story elements were mostly classified into clusters with larger loads, whilst upper-story elements were put into clusters with lower axial demands.

**Table 1: Percentage Frequency Distribution of Vertical Elements by Cluster**

<b>Cluster ID</b>	<b>Load Characteristic Description</b>	<b>Number of Elements</b>	<b>Percentage (%)</b>
Cluster 1	Very High Gravity Load Demand	18	22.5%
Cluster 2	High Gravity Load Demand	24	30.0%
Cluster 3	Moderate Gravity Load Demand	20	25.0%
Cluster 4	Low Gravity Load Demand	18	22.5%



**Figure 1: Percentage Frequency Distribution of Vertical Elements by Cluster**

The rather even percentage distribution shows that vertical pieces were successfully separated by the K-means algorithm without being overly concentrated in one cluster. This supports the viability of cluster-based standardized design by confirming that gravity load differences across the structure are gradual rather than abrupt.

**4.2. Cluster-Based Gravity Design Characteristics**

Based on centroid values, a representative gravity design was allocated to each discovered cluster. Column size, axial stress ratio, and reinforcement need were among the design criteria. In order to minimize needless variance in cross-sectional dimensions, elements within the same cluster shared comparable design qualities.

Clusters 1 and 2 were dominated by lower-story interior columns, necessitating longer sections and higher reinforcement ratios. Cluster 3 and Cluster 4, on the other hand, were mainly composed of upper-story and perimeter columns, which permitted smaller section sizes without sacrificing safety.

**Table 2: Percentage Frequency of Gravity Design Section Categories Across Clusters**

Section Category	Typical Column Size Range (mm)	Number of Elements	Percentage (%)
Category A	$\geq 700 \times 700$	16	20.0%
Category B	$600 \times 600 - 650 \times 650$	26	32.5%
Category C	$450 \times 450 - 550 \times 550$	22	27.5%
Category D	$\leq 400 \times 400$	16	20.0%
<b>Total</b>	—	<b>80</b>	<b>100%</b>

Approximately 60% of vertical pieces are found in moderate-to-high-capacity sections (Category B and C), according to the frequency distribution of section types. The effectiveness of clustering in preventing overdesign for lightly loaded elements while preserving sufficient capacity for strongly laden zones is demonstrated by this result.

### **4.3. Comparison with Conventional Gravity Design Approach**

The cluster-based strategy demonstrated a discernible decrease in section variability when hypothetically compared with traditional gravity design techniques. While clustering offers a data-driven foundation for grouping items with similar load behavior, traditional design sometimes leads to cautious sizing because of manual grouping assumptions.

The clustering strategy also minimized repetitious design tests, enabling engineers to focus on representative designs for each cluster rather than individual items. As a result, the structural system's design is more consistent and productive.

### **4.4. Structural Insights from Cluster Distribution**

The spatial distribution of clusters indicated substantial structural characteristics. Low-load clusters were dispersed around the building's perimeter and upper floors, but high-load clusters were primarily centered in the building's core and lower levels. This demonstrates that the clustering results are consistent with the basic gravity load transfer mechanisms found in buildings with multiple stories.

These kinds of insights can help designers make decisions early on, allowing for proactive material allocation and vertical load path optimization.

### **4.5. Implications for Gravity Design Optimization**

The findings show that semi-automated decision-making can be supported while maintaining engineering control by including K-means clustering into gravity design. The method encourages uniformity in detailing, increases material efficiency, and improves design rationalization. Despite being speculative, the results point to a high likelihood of practical implementation in major construction projects.

## **5. CONCLUSION**

This study shows that using K-means clustering into the gravity design of vertical structural elements offers a methodical and data-driven substitute for traditional design techniques based on the hypothetical findings. The suggested strategy improves design consistency, eliminates needless variation in section sizing, and promotes more effective material use by classifying columns and shear walls based on comparable geometric properties and gravity load demands. Clustering results in a rational and balanced distribution of design categories that are in line with the structure's actual load transfer behavior, as confirmed by the percentage frequency analysis. The results show that K-means clustering can be a useful decision-support tool for structural engineers, allowing optimized gravity design while maintaining compliance with established design codes and engineering judgment, despite the study's limitations to gravity load considerations and its hypothetical nature.

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