International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue III, March 2018- Available at www.ijraset.com

To Study the Seismic Behaviour of Multi Storeyed Building along with Planning at Various Zones using Hierarchical Agglomerative Clustering

Chandra Kumar Nimmana[1], Dr. Tirupati Naidu Gedala[2], Prasanna Kumar Gedela[3]
[1]*M.Tech Structures Student, Department of Civil Engineering, Aditya Institute Of Technology & Management,*
[2]*Associate Professor, Department of Civil Engineering, Aditya Institute Of Technology & Management*
[3]*Assistant Professor, Department of Civil Engineering, Aditya Institute Of Technology & Management*

Abstract: In governmental administration from the Centre to the State and State to the Districts and Districts to the villages, we often find hindrances due to non-optimal structural location of governmental offices. The inconvenient distances sometimes pose a bottleneck problem to smooth administration. However such problems can be avoided if we choose the Structural Administrative Offices location optimally. This first part of this research is to find the structural coordinate determination for optimal administrative offices stationing using Agglomerative Hierarchical Clustering. Needless to mention, such Hierarchy found is to be mimicked as the Hierarchy for Governmental Administration. From the Cluster Dendrogram, we can note the hierarchical gradation based on the distance between the cities which can be used for efficient governance.
After finding the Hierarchical gradation of the cities, the second factor of the research deals with the analysis of multi storied structure at different earth quake zones of the same cities. We then select the Best Administrative Station which is also safe against earth quakes and design multi storied structure at that location.
Keywords: Hierarchical Agglomerative Clustering

I. INTRODUCTION

In the following sections, the details of Hierarchical Agglomerative Clustering along with its various applications are discussed.

A. Measuring by Movements

Hierarchical Clustering of Cities in China Based on Aggregated Massive Positioning Data

The world is becoming linked more and more. A shift of researching focus can be observed recently, from “city as a system” to “systems of cities,” given the context of fast-changing communicating technologies such as high-speed railways (physical) as well as social media over the internet (nonphysical).

Flows play essential roles for a city network, indicating the trends of position and functions within the network. In [1], the authors adopt new type of aggregated positioning data of massive internet users in China to explore the spatial patterns of cities during the Spring Festival in 2015.

By introducing new clustering algorithm highlighting spatial constraints, models output hierarchic results with vary regional zones containing different number of cities. The higher layer of results with less members is not similar to the conventional delineation according to the conditions of physical and economic geography of China. Nevertheless, the very differences suggest hidden forces driving cities connected intensely across the administrative boundaries such as sharing mutual regional cultures or employment markets. These facts grounded for a general picture for the study on polycentric urban regions over the whole national territory.

B. A Survey of Recent Advances in Hierarchical Clustering Algorithms

It has often been asserted that since hierarchical clustering algorithms require pair wise inter object proximities, the complexity of these clustering procedures is at least O (N2). Recent work has disproved this by incorporating efficient nearest neighbour searching algorithms into the clustering algorithms.

A general framework for hierarchical, agglomerative clustering algorithms is discussed in [2], which opens up the prospect of much improvement on current, widely-used algorithms. This 'progress report' details new algorithmic approaches in this area, and reviews recent results.

C. Solving Travelling Salesman Problem Using Hierarchical Clustering And Genetic Algorithm

The Traveling Salesman Problem (TSP) is one of the most intensively studied problems in computational mathematics. To solve this problem a number of algorithms have been developed using genetic algorithms. But these algorithms are not so suitable for solving large-scale TSP. In [3], the authors propose a new solution for TSP using hierarchical clustering and genetic algorithm.

D. Grid-Based Hierarchical Clustering For Spatial Resource Allocation

The problem of allocating resources in spatial locations such as within an urban city or large regions in geographical sense has attracted much research efforts recently. Some applications include but not limit to city-planning for examples of building patrol stations in a city, establishing medical clinics or schools in a town, deploying guards for security patrol in a zone, and budgeting on the quantity of street lamps to lit up an urban area. These problems are generalized as spatial resource allocation, where they commonly share the characteristics of meeting certain demands by a limited amount of resources. The demands are usually distributed, unevenly in a confined spatial area. Traditionally clustering algorithms in data mining were used to solve these problems. In [4] the authors proposed a grid-based hierarchical clustering approach that was designed specifically for this kind of resource allocation decision-support. The grid-based feature makes the data extraction process which is usually from maps efficient. The hierarchy of clusters as outputs provides an advantage over normal clustering techniques because the resultant clusters can be zoomed in or out in different resolutions or abstractions at will.

E. Hierarchical Simplification of City Models to Maintain Urban Legibility

For 3D global visualization systems such as Google Earth, it is important to be able to render city-sized collections of relatively simple building models at fast speeds without losing spatial coherence. Since traditional mesh simplification algorithms are not designed for collections of simple models, in [5], the authors introduce a method of simplification through merging of similar objects. We incorporate the concept of “urban legibility” from architecture and city-planning as a guideline for simplifying city models. The author’s algorithm can be broken down into five steps. Hierarchical clustering, cluster merging, polyline simplification, and hierarchical texturing are performed during pre-processing, while at runtime, the levels-of-detail (LOD) process selects the appropriate models to render. It is author’s belief that many applications can benefit from their algorithm. Google Earth (and other 3D geographical information systems) as well as any spatial data visualization applications (including scatter plots) can all use logical, simplified clusters to represent large amounts of spatial information.

F. Analysis of Dendrogram Tree for Identifying and Visualizing Trends in Multi-attribute Transactional Data

Most of the data collected by organizations and firms contains multi-attribute and temporal data. Identifying temporal relationships (e.g., trends) in data constitutes an important problem that is relevant in many business and academic settings. Data mining techniques are used to discover patterns in such data. Temporal data can take many forms, most commonly being general transactional (multi)attribute-value data, for which time series or sequence analysis methods are not particularly well suited. In [6] the authors present the clustering algorithm with performance and implementation of dataset based on distances in miles between US cities.

G. An Overview on Clustering Methods

Clustering is a common technique for statistical data analysis, which is used in many fields, including machine learning, data mining, pattern recognition, image analysis and bioinformatics. Clustering is the process of grouping similar objects into different groups, or more precisely, the partitioning of a data set into subsets, so that the data in each subset according to some defined distance measure. [7] covers about clustering algorithms, benefits and its applications. It concludes by discussing some limitations.

H. Automatic Extraction of Clusters from Hierarchical Clustering Representations

Hierarchical clustering algorithms are typically more effective in detecting the true clustering structure of a data set than partitioning algorithms. However, hierarchical clustering algorithms do not actually create clusters, but compute only a hierarchical representation of the data set. This makes them unsuitable as an automatic pre-processing step for other algorithms that operate on detected clusters. This is true for both dendrograms and reach ability plots, which have been proposed as hierarchical clustering representations, and which have different advantages and disadvantages. In [8], the authors first investigate the relation between dendrograms and reach ability plots and introduce methods to convert them into each other showing that they essentially contain the same information. Based on reachability plots, the authors then introduce a technique that automatically determines the significant clusters in a hierarchical cluster representation. This makes it for the first time possible to use hierarchical clustering as an automatic pre-processing step that requires no user interaction to select clusters from a hierarchical cluster representation

I. Hierarchical Visual Feature Analysis for City Street View Datasets

The visual appearance of city neighborhoods helps us to mentally map urban spaces. For instance, from the visual features of a city or neighborhood, we gain perspectives on local identity as might be described by their functions, demographics, or affluence. An effective way to summarize and present this information would be useful, e.g., for urban design and planning. The authors explore whether these perspectives can be automatically learned from street-level imagery using a deep neural network and build a visual analytics tools to explore what is learned. Starting with a dense geo-sampling of city Google Street View data, the authors train a neural network to learn visual features. Then, the authors cluster these features using unsupervised learning to build a similarity hierarchy of visual appearance. Existing approaches for exp loring this kind of geographically-embedded cluster data often have difficulty in addressing the need to compare across both the visual hierarchy and the geography of the different neighborhoods. To improve this situation, the authors develop a visualization scheme which allows users to keep track of both the geographical and semantic interpretations of the data. In doing so, the authors aim to provide an exploration tool to aid in the visual study of urban environments.

II. HIERARCHICAL AGGLOMERATAIVE CLUSTERING ALGORITHM OVERVIEW

A. Hierarchical Agglomerative Clustering Method

In data mining and statistics, hierarchical clustering (also called hierarchical cluster analysis or HCA) is a method of cluster analysis which seeks to build a hierarchy of clusters. Agglomerative Clustering is a type of Hierarchical Clustering.

1) *Agglomerative:* This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy.

In general, the merges and splits are determined in a greedy manner. The results of hierarchical clustering are usually presented in a dendrogram.

It produces a set of nested clusters organized as a hierarchical tree. It Can be visualized as a dendrogram. The Clusters are represented by a tree-like diagram that records the sequences of merges or splits which is known as a Dendrogram.

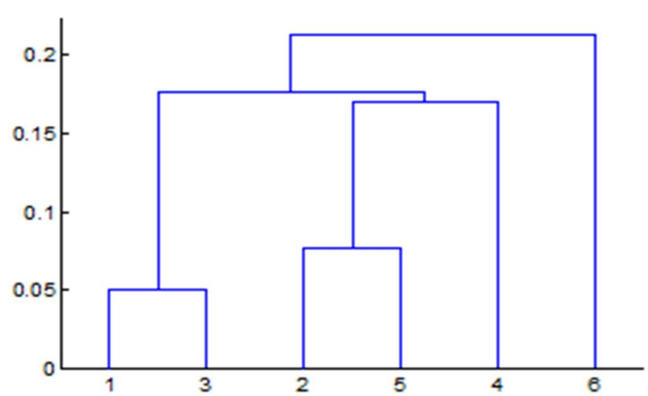

Fig 1- Example of Dendrogram for the dataset of first 6 numbers

B. Strengths of Hierarchical Clustering

There are no assumptions on the number of clusters. Any desired number of clusters can be obtained by ‘cutting’ the dendogram at the proper level. Hierarchical clusterings may correspond to meaningful taxonomies. For Example, in biological sciences (e.g., phylogeny reconstruction, etc), web (e.g., product catalogs) etc.

The Two main types of hierarchical clustering are:

C. Agglomerative

We start with the points as individual clusters. At each step, merge the closest pair of clusters until only one cluster (or **k** clusters) left.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue III, March 2018- Available at www.ijraset.com

D. Divisive

We start with one, all-inclusive cluster. At each step, split a cluster until each cluster contains a point (or there are **k** clusters). Traditional hierarchical algorithms use a similarity or distance matrix. Here, we Merge or split one cluster at a time.

E. Complexity of Hierarchical Clustering

A Distance matrix is used for deciding which clusters to merge/split. It is at least quadratic in the number of data points. It is not usable for large datasets

F. Agglomerative clustering algorithm

It is the most popular hierarchical clustering technique

1) *Basic algorithm*

a) Compute the distance matrix between the input data point
b) Let each data point be a cluste
c) Repea
d) Merge the two closest clusters
e) Update the distance matri
f) Until only a single cluster remains

The *Key* operation is the computation of the distance between two clusters. Different definitions of the distance between clusters lead to different algorithms

G. Distance Between Two Clusters

Each cluster is a set of points.

We define distance between two sets of points in the following fashions:

1) Single-link distance between clusters C_i and C_j is the minimum distance between any object in C_i and any object in C_j

The distance is defined by the two most similar objects

$$D_{sl}(C_i, C_j) = \min_{x,y} \{d(x,y) | x \in C_i, y \in C_j\}$$

It is determined by one pair of points, i.e., by one link in the proximity graph.

2) Complete-link distance between clusters C_i and C_j is the maximum distance between any object in C_i and any object in C_j

The distance is defined by the two most dissimilar objects

$$D_{cl}(C_i, C_j) = \max_{x,y} \{d(x,y) | x \in C_i, y \in C_j\}$$

3) Group average distance between clusters C_i and C_j is the average distance between any object in C_i and any object in C_j

$$D_{avg}(C_i, C_j) = \frac{1}{|C_i| \times |C_j|} \sum_{x \in C_i, y \in C_j} d(x,y)$$

Centroid distance between clusters C_i and C_j is the distance between the centroid r_i of C_i and the centroid r_j of C_j

$$D_{centroids}(C_i, C_j) = d(r_i, r_j)$$

Ward's distance between clusters C_i and C_j is the difference between the total within cluster sum of squares for the two clusters separately, and the within cluster sum of squares resulting from merging the two clusters in cluster C_{ij}

$$D_w(C_i, C_j) = \sum_{x \in C_i} (x - r_i)^2 + \sum_{x \in C_j} (x - r_j)^2 - \sum_{x \in C_{ij}} (x - r_{ij})^2$$

$\mathbf{r_i}$: centroid of $\mathbf{C_i}$
$\mathbf{r_j}$: centroid of $\mathbf{C_j}$
$\mathbf{r_{ij}}$: centroid of $\mathbf{C_{ij}}$
Ward's distance for clusters is

Similar to group average and centroid distance
Less susceptible to noise and outliers
Biased towards globular clusters
Hierarchical analogue of k-means
It can be used to initialize k-means
Hierarchical Clustering: Time and Space requirements
For a dataset X consisting of n points
O(n^2) space; it requires storing the distance matrix
O(n^3) time in most of the cases
There are n steps and at each step the size n^2 distance matrix must be updated and searched
Complexity can be reduced to O(n^2 log(n)) time for some approaches by using appropriate data structures

III. HIERARCHICAL AGGLOMERATAIVE CLUSTERING RESULTS

A. Data Pre-Processing [10]

We have considered 99 cities of India and recorded their Latitudes and Longitudes. Using the formulae* stated below, we computed the Distances between each of the 99 cities to each of the 99 cities. That is, we have calculated 99X99=9801 distances. We have used R program to compute the same.

B. Computation Of The Distance Between Two Pairs Of Latitude And Longitude [10]

The website
https://www.movable-type.co.uk/scripts/latlong.html
allows one to calculate the distance between two pairs of latitude and longitude.
Alternately, we have written an R program to compute the same using the formulae

Haversine Formula	$a = Sin^2\left(\frac{\Delta\varphi}{2}\right) + Cos(\varphi_1)Cos(\varphi_2)Sin^2\left(\frac{\Delta\lambda}{2}\right)$ where $\Delta\varphi = (\varphi_2 - \varphi_1)$ and $\Delta\lambda = (\lambda_2 - \lambda_1)$
	$c = 2a\tan 2\left(\sqrt{a}, \sqrt{1-a}\right)$
	$d = Rc$
where	φ is Latitude, λ is longitude, R is earth's radius (mean radius = 6,371km); note that angles need to be in radians to pass to trig functions!

Table 1- Formulae for Computing the distance between Latitudes and Longitudes of two different locations

https://docs.google.com/spreadsheets/d/1Rdo8659_NHs7V0u1GBt1qBOhFyiIgPi4vasgEc4SCVQ/edit#gid=1055903115

C. Results of the Hierarchical Clustering Algorithm

The aforedetailed Agglomerative Hierarchical Clustering Algorithm (printed in the red colour) yielded the following results: It basically hierarchically graded the 99 cities.
Please see the link below for a clearer view of the Cluster Dendrogram.
https://drive.google.com/file/d/1jQtVXal2s3ai4eMoA83Af9hppSAJDRJZ/view?ths=true

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue III, March 2018- Available at www.ijraset.com

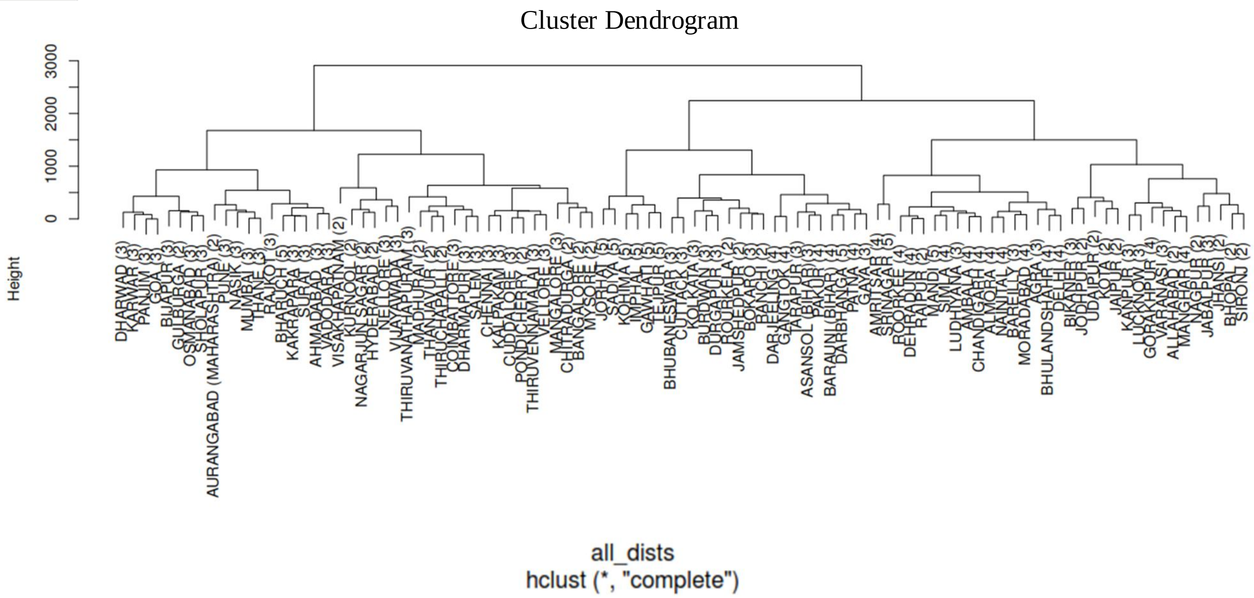

Figure 2 – The Summarized Output of the Hierarchical Agglomerative Clustering Algorithm

The detailed Agglomerative Hierarchical Clustering yielded the following results:
It had basically graded hierarchically the 99 cities.
After getting the output of dendrogram, by considering all the factors the best cities in India are listed below:

List of Indian cities	Seismic zone categories
1.Ahmadabab(Gujarat)	5
2.Visakhapatnam(Andhra Pradesh)	2
3.Patna(Bihar)	4
4.Hyderabad (Telangana)	2
5.Vadodara(Gujarat)	4
6.Kurnool(Andhra Pradesh)	2
7.Nagarjun sagar (Telangana)	2
8.Amritsar(Punjab)	4
9.Srinagar(Jammu &Kashmir)	5

Table No. 2 Final list of the cities from Dendrogram

Cities of Zone 2 are:
Visakhapatnam (Andhra Pradesh)
Hyderabad (Telangana)
Nagarjun sagar (Telangana)
Kurnool (Andhra Pradesh)

D. Analysis Of The Multistoreyed Building Based On Earth Quake Zones Data

1) *Modelling of structure:* In the present study the seismic effect is considered in zone-I, zone-II, zone-III, zone-IV and zone-V by modeling a G+15 RCC structures having material properties M30 grade for concrete and Fe415 for reinforcing steel and structures dimensions are length = 8x6 = 48m, width = 5x6 = 30m and heights of G+15 is 50m from the foundation or footing top and the support considered are fixed base the plans and elevations of the structures are shown in the figures.

The data required for analysis and design are tabulated below:

Materials	M30, Fe415
Loadings	Dead, live, seismic(earthquake)
Height of building	G+15
Foundation depth	2.0m
Floor to floor height	3.0m
Zones	1,2,3,4,5
Software	STAAD.Pro
Columns	230x450mm
Beam size	230x500mm
Geometry of Building	Symmetric
Length(L)	8x6 = 48m
Width(w)	5x6 = 30m

E. Loads and load Combination Considered for Analysis

1) DL
2) LL
3) EL+X
4) EL-X
5) EL+Z
6) EL-Z
7) WL+X
8) WL-X
9) WL+Z
10) WL-Z
11) DL+LL
12) DL+EL+X
13) DL+EL-X
14) DL+EL+Z
15) DL+EL-Z
16) DL+LL+EL+X
17) DL+LL+EL-X
18) DL+LL+EL+Z
19) DL+LL+EL-Z
20) 1.5DL+1.5LL
21) 0.9DL+1.5EL+X
22) 0.9DL+1.5EL-X
23) 0.9DL+1.5EL+Z
24) 0.9DL+1.5EL-Z

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 6.887
Volume 6 Issue III, March 2018- Available at www.ijraset.com

25) 1.5DL+1.5EL+X
26) 1.5DL+1.5EL-X
27) 1.5DL+1.5EL+Z
28) 1.5DL+1.5EL-Z
29) 1.2DL+1.2LL+1.2EL+X
30) 1.2DL+1.2LL+1.2EL-X
31) 1.2DL+1.2LL+1.2EL+Z
32) 1.2DL+1.2LL+1.2EL-Z
33) DL+WL+X
34) DL+WL-X
35) DL+WL+Z
36) DL+WL-Z
37) DL+LL+WL+X
38) DL+LL+WL-X
39) DL+LL+WL+Z
40) DL+LL+WL-Z
41) 0.9DL+1.5WL+X
42) 0.9DL+1.5WL-X
43) 0.9DL+1.5WL+Z
44) 0.9DL+1.5WL-Z
45) 1.5DL+1.5WL+X
46) 1.5DL+1.5WL-X
47) 1.5DL+1.5WL+Z
48) 1.5DL+1.5WL-Z
49) 1.2DL+1.2LL+1.2WL+X
50) 1.2DL+1.2LL+1.2WL-X
51) 1.2DL+1.2LL+1.2WL+Z
52) 1.2DL+1.2LL+1.2WL-Z

The heights of the multi storied buildings along with their seismic zones are mentioned below in the table as follows:

Building	*Zone*
G+15	I
G+15	II
G+15	III
G+15	IV
G+15	V

Table No. 3 Building zones and heights and considered in analysis and design

The zone factors for various seismic zones are listed in the table below:

Zone	Zone factor
II	0.1
III	0.16
IV	0.24
V	0.36

Table No 4. Zones with respect to zone factors

F. Displacement Of Structure In Different Zones Along Length Direction

The plot of the displacement of the structure in different zones along the length direction is shown below:

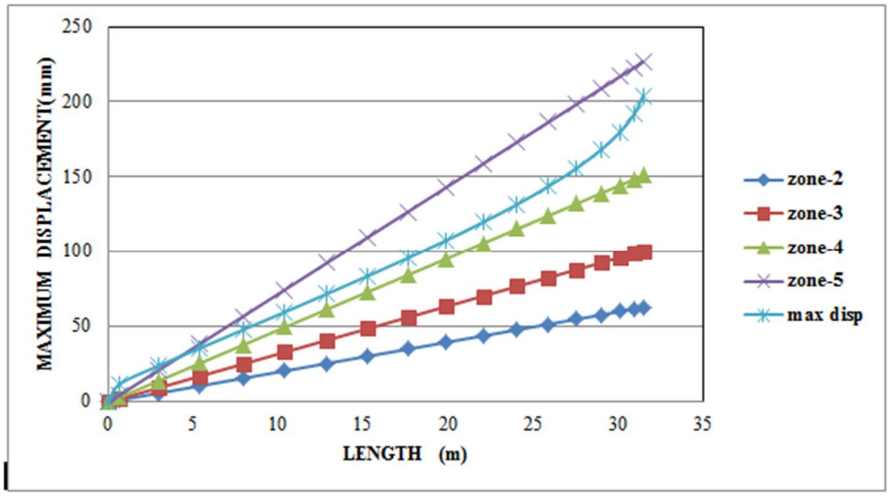

Fig 3: Displacement of structures in different zones along length direction

G. *Variation of Bending Moments for different zones*

The variation of bending moments for different zones is shown below:

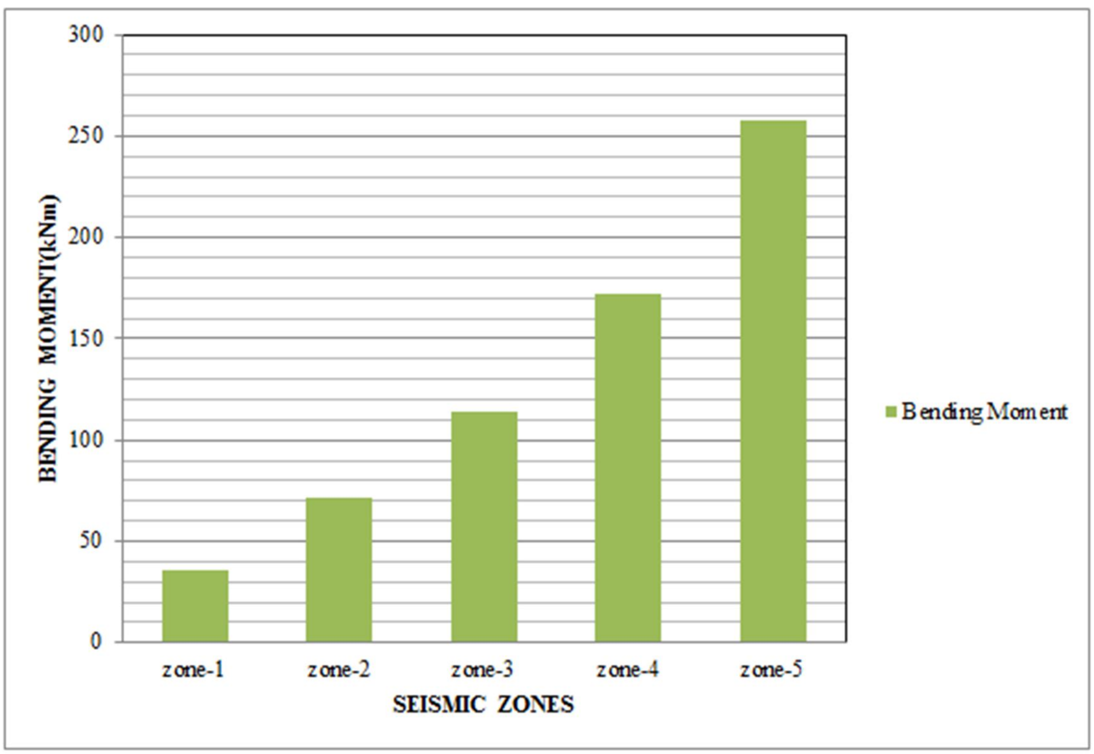

Fig 4: Variation of bending moment for different zones

H. *From the Above Figure, it was Observed That*

1) The maximum bending moment for structure-1, structure-2, structure-3, structure-4, and structure-5 are 35.79kNm, 71.51kNm, 114.42kNm, 171.64kNm, and 257.46kNm respectively.
2) The bending moments are increased as 199.80%, 319.69%, 479.57% and 719.36% in structure-2, structure-3, structure-4, and structure-5 when compared with structure-1.

I. Variation of Shear Forces for different zones

The variation of shear forces for different zones is shown below:

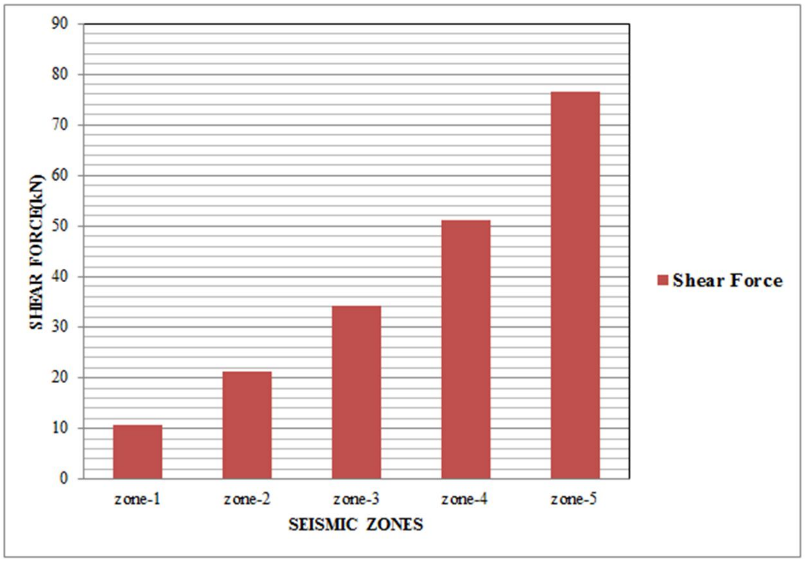

Fig 5: Variation of shear forces for different zones

J. Variation of Support Reactions for different zones

The variation of Support Reactions for different zones is shown below:

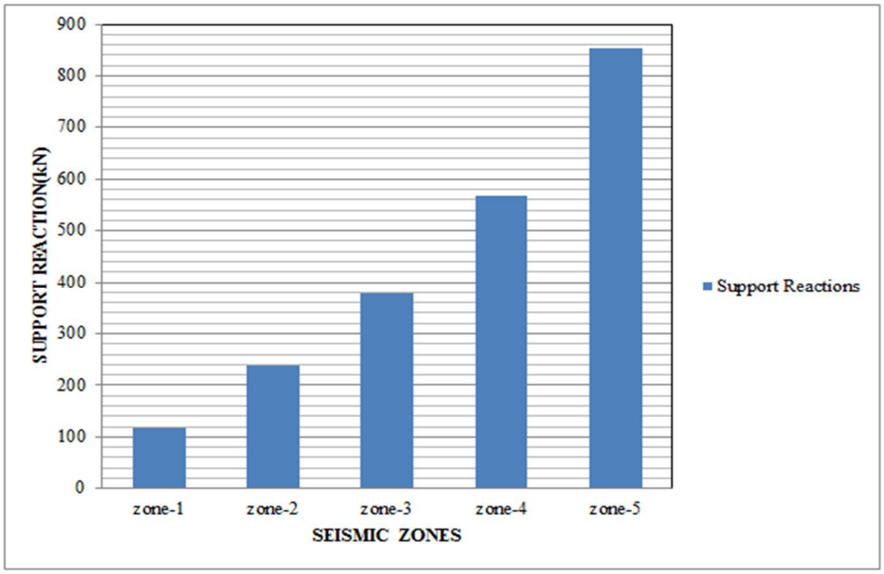

Fig 6: Variation of support reactions for different zones

1) *From the above figure, it was observed that:*

a) The maximum support reaction for structure-1, structure-2, structure-3, structure-4, and structure-5 are 118.48kN, 236.97kN, 379.15kN, 568.73kN, and 853.10kN respectively.

b) The support reactions are increased as 200%, 320%, 475% and 725% in structure-2, structure-3, structure-4, and structure-5 when compared with structure-1.

It is observed that with increase in the seismic zone, the storey displacements, bending moments, shear forces and support reactions also increase.

Types	Displacements(mm)	bending moment (kNm)	Shear force(kN)	Support reactions(kN)
Zone1	66.79	35.76	10.64	118.48
Zone2	133.59	71.51	21.29	236.97
Zone3	213.74	114.42	34.06	379.15
Zone4	320.61	171.64	51.09	568.73
Zone5	480.92	257.46	76.64	853.10

Table 5: Final results of each zones

From the above table, it is observed that with increase in the seismic zone, the storey Displacements, bending moments, shear forces and support reactions are increased.

II. CONCLUSIONS

From the Cluster Dendrogram, we can note the hierarchical gradation based on the distance between the cities. Such a hierarchical gradation can be used for efficient governance. Furthermore,

A. The results suggest that dendrograms seem to be the most effective cluster analysis technique for selection of city for administrative offices which can be used for optimal effective governance in Zone-2 and the cities suggested from the dendrogram are as follows:

1) Visakhapatnam (Andhra Pradesh).
2) Hyderabad (Telangana).
3) Nagarjun sagar (Telangana).
4) Kurnool (Andhra Pradesh).

B. The maximum storey displacements for the structure in Zones- 1,2,3,4 & 5 are observed as 66.79mm, 133.59mm, 213.74mm, 320.61mm, and 480.92mm along width direction.

C. The maximum storey displacements for the structure in Zones- 1,2,3,4 & 5 are observed as 31.47mm, 62.95mm, 100.73mm, 151.09mm, and 226.64mm along length direction.

D. The max storey displacement, drift as per IS; 1893-2002 is 0.004X3000 = 12mm,for G+15 structure the maximum displacement is 200mm.

E. The maximum storey displacements is found to be within limits along length direction for the structure in seismic zones-1, 2, 3 and 4 and where as in limits along width direction for the structure in seismic zones-1 and 2.

F. From the above statements, the maximum storey displacements are found to be within the limits along width and length directions for structures in Zone 1 and 2.

G. The maximum storey displacements are increased 100.01%, 220.01%, 380.02% and 620.04% in structure in Zones- 2, 3, 4 and 5 when compared with structure in Zone-1 respectively.

H. The maximum bending moment for the structure in Zones- 1,2,3,4 & 5 are observed as 35.79kNm, 71.51kNm, 114.42kNm, 171.64kNm, and 257.46kNm.

I. The maximum bending moments are increased 99.97%, 219.96%, 379.978% and 619.96% in the structure in Zones- 2, 3, 4 & 5 when compared with structure in Zone-1.

J. The maximum shear force for the structure in Zones- 1,2,3,4 & 5 is observed as 10.64kN, 21.29kN, 34.06kN, 51.09kN, and 76.64kN respectively.

K. The maximum shear forces are increased 100%, 220.02%, 380.17% and 625.30% in the structure in Zones- 2, 3, 4 & 5 when compared with structure in Zone-1.

L. The maximum support reaction for the structure in Zones- 1,2,3,4 & 5 is observed as 118.48kN, 236.97kN, 379.15kN, 568.73kN, and 853.10kN.

M. The shear forces, support reactions are increased 100%, 220.01%, 380.02% and 680.03 % in the structure in Zones- 2, 3, 4 & 5 when compared with structure in Zone-1.

N. From the above statements, the increase in maximum displacements, bending moment, shear forces and support reactions for the structure in Zones-2,3,4&5 when compared to Zone-1 are identical.

O. Hence, the city with earthquake zone number 2 is considered as the best city for Administrative Station which is safe against earth quakes for multi storied structures at that location.

IV. ACKNOWLEDGMENT

The authors are grateful for the encouragement, advice and support offered by Prof G.T.P. Naidu, (HOD, Department Of Civil Engineering, Aditya Institute Of Technology & Management (AITAM), K. Kotthuru, Tekkali, Andhra Prdesh State India). The authors also are grateful to the former HOD Prof Ch. Kannam Naidu (AITAM). The authors also express their gratitude to Prof Murali Monangi (formerly at AITAM).

REFERENCES

[1] 'Measuring by Movements: Hierarchical Clustering of Cities in China Based on Aggregated Massive Positioning Data', Dong Li, Menghe Wu, Bingruo Duan, Yuheng Cai, Big Data Support of Urban Planning and Management pp 63-77

[2] 'A Survey of Recent Advances in Hierarchical Clustering Algorithms', F.Murtagh, THE COMPUTER JOURNAL, VOL. 26, NO. 4,1983

[3] 'Solving Travelling Salesman Problem Using Hierarchical Clustering And Genetic Algorithm', S N S KalyanBharadwaj.B, Krishna Kishore.G, SrinivasaRao.V, (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 2 (3) , 2011, 1096-1098, ISSN 09759646

[4] **'**Grid-Based Hierarchical Clustering For Spatial Resource Allocation**',** Liyang Liu, Simon Fong and Andy Ip, IADIS International Conference e-Society 2011.

[5] **'**Hierarchical Simplification of City Models to Maintain Urban Legibility**',** Remco Chang, Thomas Butkiewicz, Caroline Ziemkiewicz, Zachary Wartell http://graphics.cs.cmu.edu/nsp/papers/ChangSketch06.pdf

[6] 'Analysis of Dendrogram Tree for Identifying and Visualizing Trends in Multi-attribute Transactional Data', D.Radha Rani, A.ViniBharati, P.LakshmiDurgaMadhuri, M.PhaneendraBabu, A.Sravani, International Journal of Engineering Trends and Technology- Volume3Issue1- 2012

[7] 'An Overview On Clustering Methods', T. SoniMadhulatha, IOSR Journal of Engineering Apr. 2012, Vol. 2(4) pp: 719-725

[8] **'**Automatic Extraction of Clusters from Hierarchical Clustering Representations**',**Jörg Sander, Xuejie Qin, Zhiyong Lu, Nan Niu, Alex Kovarsky http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.642.4559&rep=rep1&type=pdf

[9] 'Hierarchical Visual Feature Analysis for City Street View Datasets', Lezhi Li, James Tompkin, PanagiotisMichalatos, and HanspeterPfister https://vadl2017.github.io/paper/vadl_0106-paper.pdf

[10] IS 1893:1984,"Criteria for earthquake resistant design of structures", Bureau of Indian Standards, New Delhi, India.

[11] IS 456: 2000,"Plain reinforced concrete-code of practice", Bureau of Indian Standards, New Delhi, India.