Grouping & Optimization of Structural Design Using FCM Algorithm

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Abstract

The basis for grouping structural elements is a tradeoff between optimization in design and construction. The grouped elements should have common optimal design specifications that are structurally safe and convenient for construction. Fuzzy clustering provides flexibility to regroup the elements using membership values indicating their affinity to a cluster for the considered parameter. The proposed Fuzzy C-Means algorithm demonstrates grouping efficacy based on a dominant design parameter and also provides leverage for regrouping of an element considering other design or construction aspects. The method is evaluated by applying it to footings of four buildings with varying complexity, taking load on footing as basis for grouping. Distinct and homogeneous clusters are obtained with small computational effort, with further scope for regrouping members based on other parameters using their membership values for the parameter considered. The paper also proposes optimization methodology for rebar design of Reinforced Cement Concrete structures with fixed topology and cross-sectional dimensions.

1. Introduction

A large data set is divided into different groups based on similarity of information and each such subset formed is called as cluster. The process of clustering helps analyze the data sets more precisely and make decisions on their further application. Data clustering might find application in many fields of civil engineering, such as structural engineering, construction technology, geotechnical engineering, water resources engineering, land use-land cover classification, and the like. In structural engineering, clustering methods are adopted to group the components of a structure to optimize time and cost in design, procurement, construction technique, fabrication and erection, and finishing. Number of groups to be made in any construction project would be a trade-off between construction cost on the one hand and speed and ease of construction on the other (Barbosa and Lemonge, 2005; Barbosa et al., 2008).Grouping of structural elements is heuristic in nature, and structural design can be carried out by training Artificial Neural Networks with existing database (Biedermann and Grierson 1996).

Many researchers have used various grouping methods in structural engineering with different advantages. Rajeev and Krishnamoorthy (1988) used Genetic Algorithms (GA) and genetic modeling for the design optimization of reinforced concrete frames. Barbosa et al. (2008) achieved optimization as well as grouping for steel structural elements using GA search, while Chaudhari and Maity (2020) used GA for optimizing design of RCC footing as per IS-456(200). Lemonge et al. (2011) employed the adaptive penalty method (APM) to impose mechanical constraints in optimization of structural steel elements and to obtain their ideal grouping. An attempt was made by Ozbasaran and Yildirim (2020) to optimize truss design by Improved Crow Search algorithm, which is swarm intelligence based algorithm. Ant colony approach was adopted by Angelo et al. (2015) to optimize the structural design, using cardinality constraints. Whereas, Tapao and Cheerarot (2017) used Artificial Bee Colony (ABC) method for finding optimal design solutions without clustering. The procedure adopted by Walls and Elvin (2010) was non stochastic involving exhaustive permutation search but lacked flexibility of facilitating manual regrouping based on other influential variables. Huang et al. (2008) proposed use of Collaborative

Optimization (CO) architecture to obtain system level optimization by introducing fuzzy sufficiency degree for constraints and fuzzy satisfaction degree for objectives at discipline level. Kripka et al. (2015) achieved a considerable saving in the consumption of structural material by optimization of automatic grouping of reinforced concrete beams. Boscardina et al. (2019) resorted to harmony search method for structural optimization of building frames resulting in 5–7% cost reduction by automated grouping of the columns. GA technique was used to obtain optimum design with grouping of pile foundation by Liu et al. (2012). Differential evolution algorithm with cardinal constraints adopted by Carvalho et al. (2018) resulted in multi material optimization in the design of trusses. Simulated Annealing (SA) was carried out to optimize truss elements by Hasancebi and Erbatur (2002) and to optimize single RCC beam by Leps and Sejnoha (2003). The design optimization exercise in steel structures such as trusses and frames is more complex since the change in the cross section of an element results in the redistribution of member forces based on which the earlier grouping was done. Barbosa et al. (2008) required 1600 runs for optimization of a 78-bar truss.

Stochastic algorithms have been mostly used by researchers for optimization procedures which do not converge to a definite set of outputs during each run of these programs. Thus, several trial runs are required before arriving at optimum results. This poses problems for parallel validation of structural designs in project offices where multidisciplinary optimization is desired. Fuzzy C- Means (FCM) clustering has a non-stochastic but somewhat heuristic approach and gives the same output results for every run made, enabling the parallel validation of groupings for optimal design of structural elements. The emphasis of the present work is to obtain clustering using the influencing variables wherein the design solutions also get clustered resulting in the narrowing of search space. Grouping of the structural elements can be done based on the stress variables like bending moment, shear force, axial force and the like.

This paper proposes, *a priori* grouping of elements using FCM clustering to reduce the computational efforts, and then carrying out design optimization. The algorithm is applied for automatic grouping of column footings of four RCC structures, three residential and one school building of varied size and complexity. It is observed that the proposed method gives viable and spatially reasonable groupings with significant reduction in the number of iterations. The proposed method is based on application of FCM algorithm considering the load on the footing which is the most dominant design parameter.

2. Fuzzy C-means Clustering

Partitioning of dataset can be done by many clustering algorithms such as K-Means, PAM, CLARANS, FCM, DBSCAN, EM, CLIQUE (Saxena et al. 2017). Other nature inspired search algorithms like Artificial Bee Colony(ABC) (Zhang et al. 2010), Genetic Algorithm (Bezdek et al. 1994), Particle Swarm Optimization (Rana et al. 2011; Merwe and Engelbrecht 2003), Firefly Algorithm (Senthilnath et al. 2011), etc. can also be used for clustering. Most of these algorithms fall into category of hard clustering wherein the data set Y is subdivided into c clusters, the members of which are unequivocally hard partitioned. Whereas, in fuzzy c-partition of Y, the members in all the clusters will have some membership function with values between zero and one such that the sum of memberships for a member is unity (Bezdek et al. 1984). Members of data set *Y* are separated into *c* clusters in such a way that the intra-cluster distances are minimized, while simultaneously maximizing the inter-cluster distances.

The input to the FCM algorithm is given in the form of dataset, $Y = \left\{ y_1, y_2, y_3, \ldots\ldots. y_N \right\}$ with *n* similar features and *N* samples; number of clusters *c* decided *a priori* and weighting exponent *m* whose value of 1 suggests hard clustering and increasing value fuzzifies it. A value of 1.5 to 3.0 for *m*, generally works well for most data. After several iterations FCM converges to the output in the form of Fuzzy partition matrix(*U*). It is a *c*x*N* order matrix, each element of which corresponding to affinity of data point y_k in [*Y*] towards a particular cluster c_i and Vector of Cluster centers{*v*}which is a *c*x*n* order matrix. Every row of this matrix represents centroid of features of the cluster around which the data set *Y* is grouped with fuzziness.

Once all the datapoints of *Y* are partitioned into *c* number of tuples (Y_1, Y_2,..Y_c), following three conditions are met:

$$Y_i \neq \Phi; 1 \leq i \leq c$$

1

$$Y_i \bigcap Y_j = \Phi; i \neq j$$

2

$$\bigcup_{i=1}^{c} Y_i = Y$$

3

These conditions respectively state that none of clusters shall remain empty, no data point shall repeat itself in more than one cluster and union of all clusters should yield original dataset *Y*. Φ denotes empty set.

The objective function for minimizing the weighted sum of least-square errors is given by,

$$J(U, v) = \sum_{k=1}^{N} \sum_{i=1}^{c} u_{ik}^{m} \| y_k - v_i \|^2$$

4

Initially vectors of cluster centers are obtained by equation,

$$v_i = \frac{\sum_{k=1}^{N}\left(u_{ik}\right)^{m} y_k}{\sum_{k=1}^{N}\left(u_{ik}\right)^{m}}; 1 \le i \le c$$

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Subsequently, partition matrix U is computed using the v_i obtained as follows:

$${U}_{ik}={\left({\sum }_{j=1}^{c}{\left(\frac{{d}_{ik}}{{d}_{jk}}\right)}^{2/(m-1)}\right)}^{-1};1\le k\le N,1\le i\le c$$

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Computation of ${v}_{i}$ in Eq. (5) and U_{ik} in Eq. (6), being dependent on one another, undergo recursive improvement in successive iterations until objective function defined in Eq. (4) is satisfied or is run over a fixed number of iterations.

The degree of belongingness of k^{th} datapoint towards i^{th} cluster is obtained in membership function matrix U, element indexed U_{ik}.

The inter-cluster separability and intra-cluster homogeneity which are the measures of internal quality criteria (Saxena et al. 2017) are defined by Eqs. (7) and (8).

$$\text{Sum of Squared Error}\left(SSE\right)= \sum _{i=1}^{i}\sum _{\forall {x}_{k}\in {C}_{i}}{\left|\right|{x}_{k}-{\mu }_{i}\left|\right|}^{2}$$

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where C_i is the set of instances in cluster k; μ_i. is the vector mean of cluster i.

$$\text{Scatter Criteria} \left({S}_{i}\right)= \sum _{x\in {C}_{i}}(x-{\mu }_{i}){(x-{\mu }_{i})}^{T}$$

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3. Proposed Methodology For Optimization Using Fcm

The proposed FCM design procedure for optimization can be seen in the context of the currently practiced *a priori* grouping, wherein similarity in some parameters such as lengths, storey, spatial symmetry, etc. is used for member grouping (Breidman and Grierson 1996; Barbosa and Lemonge 2005; Barbosa et al. 2008; Lemonge et al. 2011). These parameters can be similarity of span in beams, size and number of stacks in columns, plan dimensions and depth in footings, stress variables in members, etc. After such grouping, the general approach to RCC design is to first carry out full scale design of one member selected arbitrarily from the group to find the reinforcement required for that member. Normally, the member loaded heavily is selected. The reinforcement thus obtained is copied to all other members in the group. The other members are then checked one by one to verify the adequacy of reinforcement. A member found unsafe is re-designed to get the correct reinforcement which is then copied again to all members in the group. This process continues until all members in the group have been satisfactorily checked. This method suffers from many drawbacks including subjectivity of deciding heavily loaded member, since members can be loaded in many ways with different magnitude, nature and direction of stress variables.

In the proposed methodology the optimization is achieved in two stages. In the first stage *a priori* grouping of structural elements using FCM is made considering internal forces developed in the members like support reactions, axial force, bending moment, etc. Clustering techniques adopted can effectively group structural elements that experience similar internal forces such that all members of a cluster exhibit the same structural behavior requiring same design. This will narrow down the design space required in the second stage. The membership values returned by FCM help the user to facilitate minor changes in the grouping if needed, considering parameters other than internal forces. In the second stage optimization, search for a common structural design that is most economical and satisfies the structural safety criteria of all the members of the group can be carried out.

This paper illustrates the methodology of grouping in detail along with case studies in the first stage. The second stage optimization for design search is presented in the form of flowchart and the details are discussed without performing the actual computations.

4. Implementation Of The Algorithm

In the proposed FCM algorithm, c is the number of cluster groups formed from the data set $[Y]$ containing n influencing stress variables pertaining to N structural elements. Each data-point as input vector$\{Y_k\}$ would yield an absolute optimum design vector $\{d_k\}$ where, k is indexing for the datapoint, $max\ k = N$. After splitting the entire dataset into c partitions, set of datapoints $[Y_i]$, where i is cluster number, $max\ i = c$, are formed. The final output of the search would be in the form of optimal design vector $\{d_i\}$, unknown initially, which satisfies required structural safety criteria for all the datapoints of $[Y_i]$. Several iterations can be programmed based on the desired convergence criteria. Strategy for iterations can be either stepwise increment or stepwise decrement.

The flow chart of the FCM algorithm for Stage I which is for grouping is enclosed as Fig. 1. Figures 2 (a) and (b) show the flow chart for Stage II implementation for design search with stepwise increment and stepwise decrement strategy respectively.

Further, $\{d_i\}$ shall have, as its elements the decision/design variables specific to the structural member under consideration. For example, shallow footing design problem will consider geometric dimensions and number as well as diameter of reinforcement bar in all the geometric directions as the variables (Kashani et al. 2019). Some of the design variables will have a finite set of discrete practically feasible values, as in the case of design variable '*bar diameter*', which shall have possible values of {8, 10, 12, 16, 20, 25, 30} in mm. In discrete optimization process, variable for bar diameter will be taken from this set only by enforcing cardinality constraints (Barbosa et al. 2008; Lemonge et al. 2011; Angelo et al. 2015). Kwak and Kim (2008) also emphasized on optimization of RCC structural elements with discrete variables for practicality. A set of exact stress variables will yield a single optimal design. Even if the stress variables deviate slightly from the centroid of identical elements of a set, the optimal design variables would still be close to the optimal common design of the group. This would narrow down the design search space, as optimal design variables $\{d_i\}$ would be close to any one of the design solutions.

Once the vector of stress variables $\{v_i\}$ at the cluster center is known from stage I, the initial optimal design solution $\{i\_d_i\}$ that optimally corresponds to $\{v_i\}$ is computed. However, the $\{i\_d_i\}$ so computed may not completely satisfy design safety requirements of all the elements of the cluster. There may be elements with individual stress variables greater than $\{v_i\}$. In such cases the search direction for a common stable design solution is only on the stepwise higher sides of $\{i\_d_i\}$, the process of which is shown in Fig. 2(a). If, on the other hand, optimal design solution $\{max\_d_i\}$ is computed for a vector $\{Y_{i\_max}\}$, for the highest input parameters in that group, obviously $\{max\_d_i\}$ will satisfy structural safety of all the individual members of the cluster. However, this might not be the optimal solution for entire group. In such cases the stable solution can be obtained only by stepwise decrement of individual variables of $\{max\_d_i\}$ until the search reaches the optimal design $\{d_i\}$. The flow chart of stepwise decrement strategy is shown as Fig. 2(b).

With the information on the variable of $\{v_i\}$ that influences a particular element of $\{i\_d_i\}$ the most $\{max\_d_i\}$ can be identified. Search algorithms can increment/decrement that variable alone to reach design solution quickly. For example, if safe bearing capacity (SBC) of soil is one of the variables in $\{v_i\}$ which directly influences '*width*' variable of $\{i\_d_i\}$, it can be decreased/increased to obtain optimum width of footing.

For the sake of modularity in programming one can consider the optimal design search of stage II as a function of '*design([Y_i])*', which takes cluster data points *[Y_i]* as input and gives $\{d_i\}$ as output. This function itself shall have necessary definition of optimality in terms of cost, time, fabrication effort, etc. Optimization of *design([Y_i])* can also be achieved by simple informed tree searches (Chiong et al. 2008) which can include simply checking design safety or checking with cardinality constraints for practical feasibility. The significant advantage of the proposed method is flexibility offered by FCM to make manual review of the decisions of *a priori* grouping done based on the magnitudes of stress variables resulting in narrowing of design search space. In the stage II of the algorithm (Fig. 2) structural design to find the optimal size and number of reinforcement bars can be performed on each group.

5. Models And Results

The proposed approach for first stage grouping is demonstrated on footing design of four models. Models 1 and 2 are residential buildings consisting of G+1 and G+2 floors having 12 and 16 columns respectively with symmetrical column positions. All the columns and beams are of size 230x300mm.

Slabs are 150 mm thick with the floor-to-floor distance of 3000 mm. Dead Load and Live Loads considered on slab are 2.5 kN/m^2 and 2.0 kN/m^2 in accordance with the provisions of Indian Standard codes of design (IS 456-2000 and IS 875-1987). Model 3 with 12 footings is similar to models 1 and 2 except that a marginal disturbance in the symmetry of columns and footings has been introduced deliberately so that the efficacy of the proposed method is tested for asymmetrical footing locations as well. The 4^{th} model considered being a public building, the columns and beams are 230x400mm, slabs are 150 mm thick, floor-to-floor distance is 3500 mm with Live Load of 3.0 kN/m^2 on the slabs. It has 68 column footings, placed symmetrically about the axis passing through the middle of the plan. This model would validate the applicability of the proposed method for grouping and optimization of large number of structural elements.

All the models have fixed geometric topology. As the vertical force on the footing is the predominant feature in footing design (Chaudhari and Maity 2020), the same is considered for clustering in all the models. Structural analysis software STAAD.Pro is used to obtain reactive forces on footings. The results are extracted in spreadsheet and FCM algorithm is executed in Python programming language. With the value of weighting component, *m*=2, results of clustering converged in less than 20 iterations in all the cases. The clustering algorithms facilitate search for optimal number of clusters by evaluating based on inter-cluster separability and intra-cluster homogeneity (Saxena et al. 2017). The application of FCM for clustering and their results for each of the 4 models are discussed in the following paragraphs.

Plan for residential building Model 1 is shown in Fig.3 (a). The result of grouping obtained by executing the FCM algorithm is enclosed as Fig. 3 (b). Clear and distinguishable partitions are obtained after only 10 iterations.

Model 1

The results of the FCM are presented in Table 1. It shows Forces on footings, membership values of the footing for each Cluster, grouping obtained as well as cluster center value of force for each cluster.

Table 1. Forces, membership values and grouping for Model 1

Footing No	Force on footing (kN)	Membership values			Grouped to cluster
		Cluster1	Cluster 2	Cluster 3	
1	199.7	**0.98**	**0.01**	0.01	**1**
2	320.6	0.07	**0.91**	0.02	**2**
3	365.9	0.01	**0.98**	0.01	**2**
4	233.8	**0.98**	0.02	0	**1**
5	337.5	0.01	**0.99**	0	**2**
6	510.5	0.01	0.04	**0.95**	**3**
7	574.0	0.01	0.02	**0.97**	**3**
8	385.6	0.04	**0.91**	0.05	**2**
9	199.7	**0.98**	0.01	0.01	**1**
10	320.6	0.07	**0.91**	0.02	**2**
11	365.9	0.01	**0.98**	0.01	**2**
12	233.8	**0.98**	0.02	0	**1**
Cluster Center value of force (kN)		216.99	349.87	542.71	

FCM algorithm has grouped the 12 footings into 3 clusters based on the values of the forces ranging between 199.7 kN and 574.0 kN. The four corner footings with numbers 1, 4, 9 and 12are grouped in cluster 1 around the value of force 216.99 kN. The middle two footings experiencing heavy loads with numbers 6 and 7 are grouped in cluster 3 around the value of 542.72 kN. The remaining six footings with numbers 2, 3, 5, 8, 10 and 11are grouped in cluster 2 around the value of 349.87 kN. The efficacy of grouping can be ascertained from: (i) the high value of membership number of more than 0.91 for each element and (ii) the separating range between the central values of forces 216.99, 349.87 & 542.71 kN in cluster 1, 2 and 3 respectively. The same is pictorially depicted in Fig 4.

Model 2

Plan for residential building Model 2, having sixteen footings symmetrically placed is shown in Fig 5 (a). The results of grouping obtained by executing the FCM algorithm is enclosed as Fig. 5 (b). Clear and distinguishable partitions are obtained after only 10 iterations.

The results of the FCM are presented in Table 2. It shows Forces on footings, membership values of the footing for each Cluster, grouping obtained as well as cluster center value of force for each cluster.

Table 2. Forces, membership values and grouping for Model 2

Footing No	Force on footing (kN)	Membership values			Grouped to cluster
		Cluster1	Cluster 2	Cluster 3	
1	301.4	**0.94**	0.05	0.01	**1**
2	565.8	0.01	**0.99**	0	**2**
3	651.7	0.05	**0.84**	0.11	**2**
4	370.4	**1.00**	0	0	**1**
5	448.7	**0.7**	0.27	0.03	**1**
6	779.6	0.02	0.11	**0.87**	**3**
7	887.8	0.01	0.02	**0.97**	**3**
8	536.4	0.06	**0.92**	0.02	**2**
9	468.9	**0.52**	0.44	0.04	**1**
10	808.8	0.01	0.03	**0.96**	**3**
11	920.0	0.02	0.04	**0.94**	**3**
12	559.0	0.01	**0.98**	0.01	**2**
13	318.0	**0.96**	0.03	0.01	**1**
14	590.0	0	**1.00**	0	**2**
15	678.8	0.07	**0.70**	0.23	**2**
16	389.2	**0.98**	0.02	0	**1**
Cluster Center value of force (kN)		365.4	581.9	848.3	

FCM algorithm has grouped the 12 footings into 3 clusters based on the values of the forces ranging between 301.4 kN and 920.0 kN. The four corner footings with numbers 1, 4, 14 and 16 along with middle two footings of top row with numbers 5 and 9 are grouped in cluster 1 around the central value of force 365.4 kN. The middle four footings experiencing heavy loads with numbers 6, 7, 10 and 11 are grouped in cluster 3 around the cluster center value of 848.3 kN and remaining six footings with numbers 2, 3, 8, 12, 14 and 15 are grouped in cluster 2 around the value of 581.9 kN. Fig. 6 shows the efficacy of grouping indicating the intra cluster homogeneity and inter cluster distinctiveness pictorially.

In contrast to hard clustering techniques, FCM provides flexibility for manual intervention in the clustering and a base for adjusting the groupings in the form of membership values. In this example, the footings 5 and 9, which are grouped in cluster 1 due to the magnitude of the force on them, can be regrouped with the middle footings of other three end rows in cluster 2 due to the position similarity they possess with those members (Fig. 5(b)). The membership values of footing 5 and 9 to cluster 2 are 0.27 and 0.44 respectively. Therefore, from the consideration of symmetry, these footings can be manually regrouped to cluster 2. Similarly, those footings which possess some value of membership with clusters other than their grouping done by FCM can be readjusted manually based on variables not considered in FCM such as field considerations.

The results of the FCM are presented in Table 3 which shows forces on footings, membership values of the footing for each cluster, grouping obtained and the cluster center value of force for each cluster.

Model 3

Model 3 is a residential building with slight disturbance in the symmetry of footings as shown in Fig. 7 (a). The results of grouping obtained by executing the FCM algorithm are enclosed as Fig. 7 (b). Clear and distinguishable partitions are obtained after 10 iterations.

Table 3. Forces, membership values and grouping for Model 3

Footing No	Force on footing (kN)	Membership factor			Grouped to cluster
		Cluster1	Cluster 2	Cluster 3	
1	228.9	0.01	0.03	**0.96**	**3**
2	397.1	0	**1.00**	0	**2**
3	252.0	0	0	**1.00**	**3**
4	353.6	0.05	**0.74**	0.21	**2**
5	455.8	0.20	**0.75**	0.05	**2**
6	272.4	0	0.01	**0.99**	**3**
7	405.2	0	**1.00**	0	**2**
8	600.9	**0.94**	0.04	0.02	**1**
9	399.7	0	**1.00**	0	**2**
10	273.3	0	0.01	**0.99**	**3**
11	441.0	0.09	**0.87**	0.04	**2**
12	266.3	0	0	**1.00**	**3**
Cluster Center value of force (kN)		557.2	403.8	259.9	

FCM algorithm has grouped the 12 footings into 3 clusters based on the values of the forces ranging between 228.9 kN and 600.9 kN. One of the middle footings with number 8 is distinctly grouped due to its heavy loading. The four corner footings with numbers 1, 3, 10 and 12 along with one end footing in the 2nd row from bottom with number 6 are grouped in cluster 3 around the value of force 259.9 kN. The middle footings of each end row with numbers 2, 4, 7, 9 and 11 except footing number 6 but including footing number 5 are grouped in cluster 2 around the value of 403.8 kN. Fig. 8 shows the efficacy of the clustering obtained with the maximum and minimum values of member forces in each cluster.

It is evident from Fig. 3 (b) that footing numbers 4 and 6 are differently grouped with load on the footing as the sole criterion for grouping. From the considerations of factors like location proximity and symmetry, these footings can be grouped in a customary way, using the flexibility offered by FCM. However, the regrouping has to be done considering the membership values given by FCM from consideration of member force as it is a crucial factor. Footing 6 has a strong membership value of 0.99 towards cluster 3, hence adjusting it to other groups would be inappropriate. Whereas footing 4 has membership value of 0.21 to cluster 3. Hence, it can be regrouped to cluster 3. Again footing 5 has spatial proximity to footing 8 which is in cluster 1. Footing 5 has an affinity of 0.2 towards cluster 1. Hence, footing 5 can be regrouped to cluster 1 along with footing 8 so that the middle footings are now in one group. Such scenarios will be common when the building plan is asymmetrical, where regrouping may be necessary considering the variables other than the member force alone. This is the advantage of having membership values given by FCM over hard clustering techniques.

Model 4

Model 4 is a school building with large number of footings placed symmetrically, as shown in Fig. 9 (a) and (b). Each of the class rooms and other facilities are of size 9144x12192 mm with 3658 mm and 4572 mm corridors at two places each. FCM algorithm is run for 10 and 20 iterations respectively to obtain grouping for two exercises with number of clusters as 3 and 4 decided *a priori*. The result of grouping with 3 clusters is enclosed in pictorial form as Fig. 9 (a), whereas Fig. 9 (b) shows the grouping done with 4 clusters. Similarly, Tables 4 and 5 give the forces, membership values and grouping for the two cases of 3 and 4 clusters along with the respective cluster values of the forces.

Table 4. Forces, membership values and grouping for Model 4 (for 3 clusters)

Footing No	Force on footing (kN)	Membership values			Grouped to cluster
		Cluster1	Cluster 2	Cluster 3	
1	1656.007	0.971	0.023	0.006	1
2	3022.592	0.002	0.996	0.002	2
3	2937.319	0.001	0.998	0.001	2
4	2964.307	0.000	1.000	0.000	2
5	2971.341	0.000	1.000	0.000	2
6	2973.037	0.000	1.000	0.000	2
7	2973.035	0.000	1.000	0.000	2
8	2971.392	0.000	1.000	0.000	2
9	2962.029	0.000	1.000	0.000	2
10	2934.087	0.001	0.998	0.001	2
11	3022.931	0.002	0.995	0.002	2
12	1656.029	0.971	0.023	0.006	1
13	2006.872	0.971	0.024	0.005	1
14	3995.488	0.003	0.014	0.983	3
15	5160.246	0.075	0.171	0.754	3
16	4202.513	0.001	0.005	0.994	3
17	3849.708	0.016	0.084	0.900	3
18	3850.793	0.016	0.083	0.901	3
19	3850.592	0.016	0.083	0.901	3
20	3852.991	0.016	0.081	0.903	3
21	4202.513	0.001	0.005	0.994	3
22	5028.393	0.064	0.153	0.783	3
23	3998.715	0.003	0.013	0.984	3
24	2006.759	0.971	0.024	0.005	1
25	2650.456	0.133	0.828	0.039	2
26	3767.904	0.027	0.157	0.816	3
27	1912.497	0.996	0.003	0.001	1
28	1811.221	0.998	0.001	0.000	1
29	3879.863	0.013	0.063	0.924	3
30	3849.970	0.016	0.084	0.900	3
31	3849.914	0.016	0.084	0.900	3
32	3881.031	0.013	0.063	0.925	3
33	1989.690	0.978	0.018	0.004	1
73	1841.007	1.000	0.000	0.000	1
35	3771.568	0.027	0.153	0.820	3
36	2650.376	0.133	0.828	0.039	2
37	1320.031	0.875	0.092	0.032	1
38	3002.215	0.001	0.998	0.001	2
39	2972.292	0.000	1.000	0.000	2
40	2972.299	0.000	1.000	0.000	2
41	3002.389	0.001	0.998	0.001	2
42	1307.542	0.872	0.095	0.033	1
43	3705.406	0.037	0.231	0.733	3
44	5013.655	0.063	0.151	0.786	3
45	3735.466	0.032	0.193	0.774	3
46	4887.643	0.053	0.131	0.816	3
47	2006.590	0.971	0.024	0.005	1
48	2651.354	0.132	0.829	0.039	2
49	4120.117	0.000	0.000	1.000	3

50	2141.379	0.877	0.104	0.018	1
51	3144.503	0.018	0.952	0.031	2
52	1633.141	0.965	0.027	0.008	1
53	3279.093	0.040	0.845	0.115	2
54	2344.830	0.592	0.363	0.045	1
55	2748.529	0.056	0.920	0.024	2
56	2890.453	0.006	0.990	0.004	2
57	5014.342	0.063	0.151	0.786	3
58	3705.160	0.037	0.231	0.732	3
59	4887.481	0.053	0.131	0.816	3
60	3735.457	0.032	0.193	0.774	3
61	2650.964	0.133	0.828	0.039	2
62	2006.529	0.971	0.024	0.005	1
63	4120.295	0.000	0.000	1.000	3
64	2141.182	0.878	0.104	0.018	1
65	3144.018	0.018	0.952	0.031	2
66	1632.353	0.965	0.027	0.008	1
67	3279.047	0.040	0.845	0.115	2
68	2357.324	0.571	0.383	0.046	1
Cluster Center value of force (kN)		1855.964	2969.085	4118.474	

Fig. 10 shows the efficacy of grouping the members into 3 clusters. It can be seen that the *a priory* decision of having 3 groups has missed a large gap between members with force 4202.5 kN and 4887.48 kN within cluster 3. Hence, this may be non optimal grouping leading to unoptimized common design.

Since the numbers of footings are more, FCM was run for 3 groupings with 10 iterations and 4 groupings with 20 iterations to get clear distinct classification. In both the cases results showed symmetry.

Table 5. Forces, membership values and grouping for Model 4 (for 4 clusters)

Footing No	Force on footing (kN)	Membership values				Grouped to cluster
		Cluster1	Cluster 2	Cluster 3	Cluster 4	
1	1656.007	0.969	0.021	0.003	0.007	1
2	3022.592	0.005	0.983	0.002	0.010	2
3	2937.319	0.000	1.000	0.000	0.000	2
4	2964.307	0.001	0.998	0.000	0.001	2
5	2971.341	0.001	0.997	0.000	0.001	2
6	2973.037	0.001	0.997	0.000	0.002	2
7	2973.035	0.001	0.997	0.000	0.002	2
8	2971.392	0.001	0.997	0.000	0.001	2
9	2962.029	0.001	0.999	0.000	0.001	2
10	2934.087	0.000	1.000	0.000	0.000	2
11	3022.931	0.005	0.983	0.002	0.010	2
12	1656.029	0.969	0.021	0.003	0.007	1
13	2006.872	0.961	0.029	0.003	0.007	1
14	3995.488	0.003	0.012	0.014	0.971	4
15	5160.246	0.003	0.006	0.975	0.017	3
16	4202.513	0.015	0.053	0.136	0.796	4
17	3849.708	0.000	0.001	0.001	0.998	4
18	3850.793	0.000	0.001	0.001	0.999	4
19	3850.592	0.000	0.001	0.001	0.999	4
20	3852.991	0.000	0.001	0.000	0.999	4
21	4202.513	0.015	0.053	0.136	0.796	4
22	5028.393	0.000	0.000	0.999	0.001	3
23	3998.715	0.003	0.013	0.015	0.969	4
24	2006.759	0.961	0.029	0.003	0.007	1
25	2650.456	0.105	0.837	0.012	0.045	2
26	3767.904	0.003	0.017	0.008	0.973	4
27	1912.497	0.994	0.004	0.000	0.001	1
28	1811.221	0.999	0.001	0.000	0.000	1
29	3879.863	0.000	0.000	0.000	1.000	4
30	3849.970	0.000	0.001	0.001	0.998	4
31	3849.914	0.000	0.001	0.001	0.998	4
32	3881.031	0.000	0.000	0.000	1.000	4
33	1989.690	0.969	0.023	0.002	0.006	1
34	1841.007	1.000	0.000	0.000	0.000	1
35	3771.568	0.003	0.015	0.007	0.975	4
36	2650.376	0.105	0.837	0.012	0.046	2
37	1320.031	0.856	0.090	0.017	0.036	1
38	3002.215	0.003	0.990	0.001	0.006	2
39	2972.292	0.001	0.997	0.000	0.002	2
40	2972.299	0.001	0.997	0.000	0.002	2
41	3002.389	0.003	0.990	0.001	0.006	2
42	1307.542	0.852	0.093	0.018	0.037	1
43	3705.406	0.008	0.046	0.016	0.930	4
44	5013.655	0.000	0.000	0.999	0.000	3
45	3735.466	0.005	0.030	0.012	0.953	4
46	4887.643	0.001	0.003	0.986	0.010	3
47	2006.590	0.961	0.029	0.003	0.007	1
48	2651.354	0.104	0.838	0.012	0.045	2

49	4120.117	0.010	0.037	0.069	0.883	4
50	2141.379	0.848	0.118	0.009	0.025	1
51	3144.503	0.023	0.893	0.011	0.072	2
52	1633.141	0.962	0.025	0.004	0.009	1
53	3279.093	0.040	0.701	0.028	0.231	2
54	2344.830	0.538	0.385	0.019	0.057	1
55	2748.529	0.040	0.928	0.006	0.026	2
56	2890.453	0.002	0.995	0.000	0.002	2
57	5014.342	0.000	0.000	0.999	0.000	3
58	3705.160	0.008	0.046	0.016	0.930	4
59	4887.481	0.001	0.003	0.986	0.011	3
60	3735.457	0.005	0.030	0.012	0.953	4
61	2650.964	0.105	0.837	0.012	0.045	2
62	2006.529	0.961	0.029	0.003	0.007	1
63	4120.295	0.010	0.037	0.069	0.883	4
64	2141.182	0.848	0.118	0.009	0.025	1
65	3144.018	0.023	0.894	0.011	0.072	2
66	1632.353	0.962	0.025	0.004	0.009	1
67	3279.047	0.040	0.701	0.028	0.231	2
68	2357.324	0.516	0.405	0.020	0.059	1
Cluster Center value of force (kN)		1844.3	2936.3	4991.9	3876.4	

The application of FCM algorithm to Model 4 shows that the proposed method is suitable to clustering in structures having fairly large number of structural elements as well, which can be grouped into small numbers of clusters as 3 and 4. Fig. 11 shows the efficacy of clustering into 4 groups in terms of intra cluster homogeneity and inter cluster distinctiveness. The range of mean plus or minus two standard deviations in the magnitude of the loading on the members within the clusters showed only a single outlier accounting for less than 5% in both the cases of 3 clusters and 4 clusters indicating that the elements are normally distributed within the cluster. Further, the inter cluster distances are seen to be distinct in both the cases.

Observation of Table 4 shows majority of members have membership values near to unity indicating very strong affinity to a particular group based on force criterion. However, some elements like footings with numbers 16,21,53,54,67 and 68 are having some considerable affinity towards clusters other than to which they have been grouped. In these cases, manual intervention is quite possible to shift these elements to other clusters if there are considerations other than the member force on which the primary clustering has been done by the FCM algorithm. Footing numbers 51 and 65 are grouped in cluster 2. If they are to be re-grouped they should go to cluster 4 based on the membership number of 0.072 they have with cluster 4. This can be done for design purpose. However, field considerations might dictate them to be grouped in Cluster 1 manually, since all their neighboring members are in Cluster 1 even though they have membership number of 0.023.

6. Conclusions

Grouping of structural elements to form clusters with identical design variables facilitates ease of design of structures and in most cases their construction as well. The grouped elements should have common design and construction specifications that provide optimization in both the processes simultaneously. Available genetic algorithms for the grouping and optimization of structural elements are computationally intensive and provide hard clustering where each element is unequivocally assigned to a particular group. In contrast fuzzy clustering method provides flexibility. In FCM clustering, fuzzy partition matrix is obtained assigning membership values to each element towards a few clusters for the design variable considered. This can be used to regroup elements to achieve advantage of both design optimization and construction cost efficiency. The approach proposed in this paper minimizes the combinatorial search process to limited numbers by clustering the elements based on internal forces generated in the structural members. The methodology is applied to four building structures of different sizes and configurations, considering footing design as objective. Using only 10 or 20 iterations, each cluster obtained has fairly homogeneous members showing strong affinity with a large separating range from other clusters. For simple and symmetrical configuration of structures, predictable groupings are obtained requiring no further manual intervention from design or construction point of view as shown in Models 1 and 2. For structures with large number of elements and asymmetry in configuration, the membership numbers obtained facilitate manual regrouping of some elements based on other design and field considerations as shown in model 3 and 4. Possibilities of re-grouping of a few elements and the basis on which they can be done so are also demonstrated.

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Availability of data and material (The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request)

Code availability (Developed custom code in Python programming language)

Figures

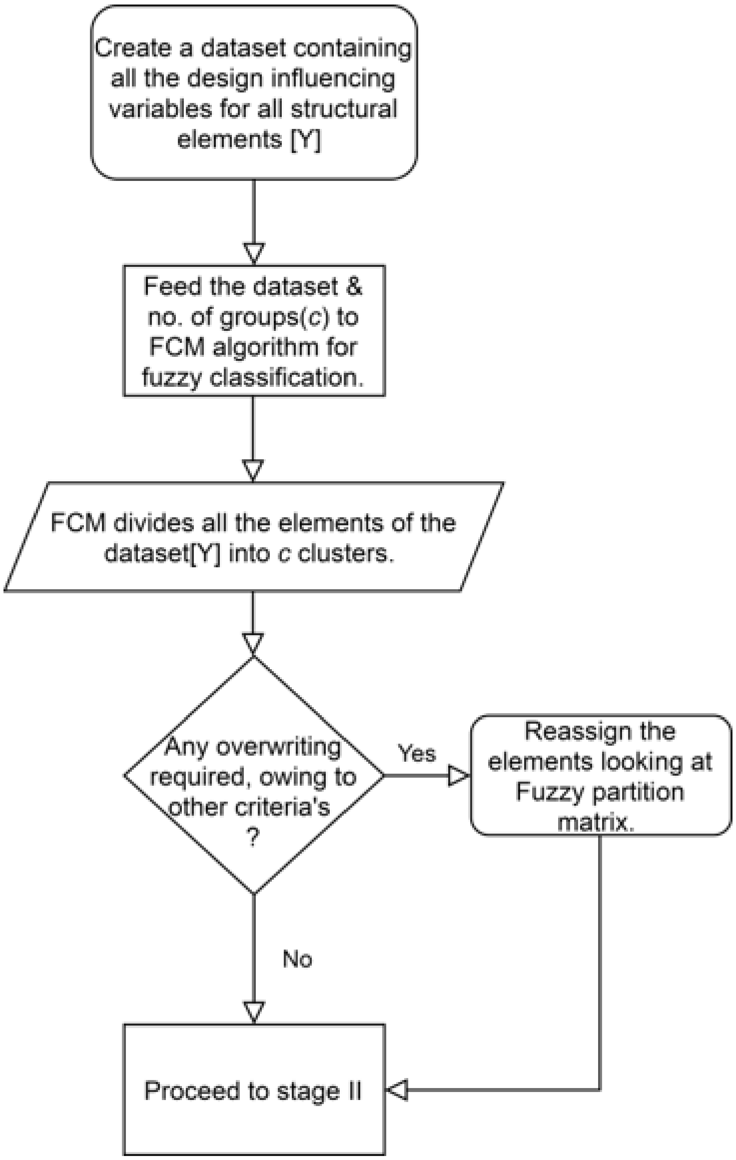


Figure 1

Flow chart of FCM algorithm for grouping (Stage I)

Figure 2

FCM algorithm for design search (Stage II) (a) Stepwise increment strategy (b) Stepwise decrement strategy

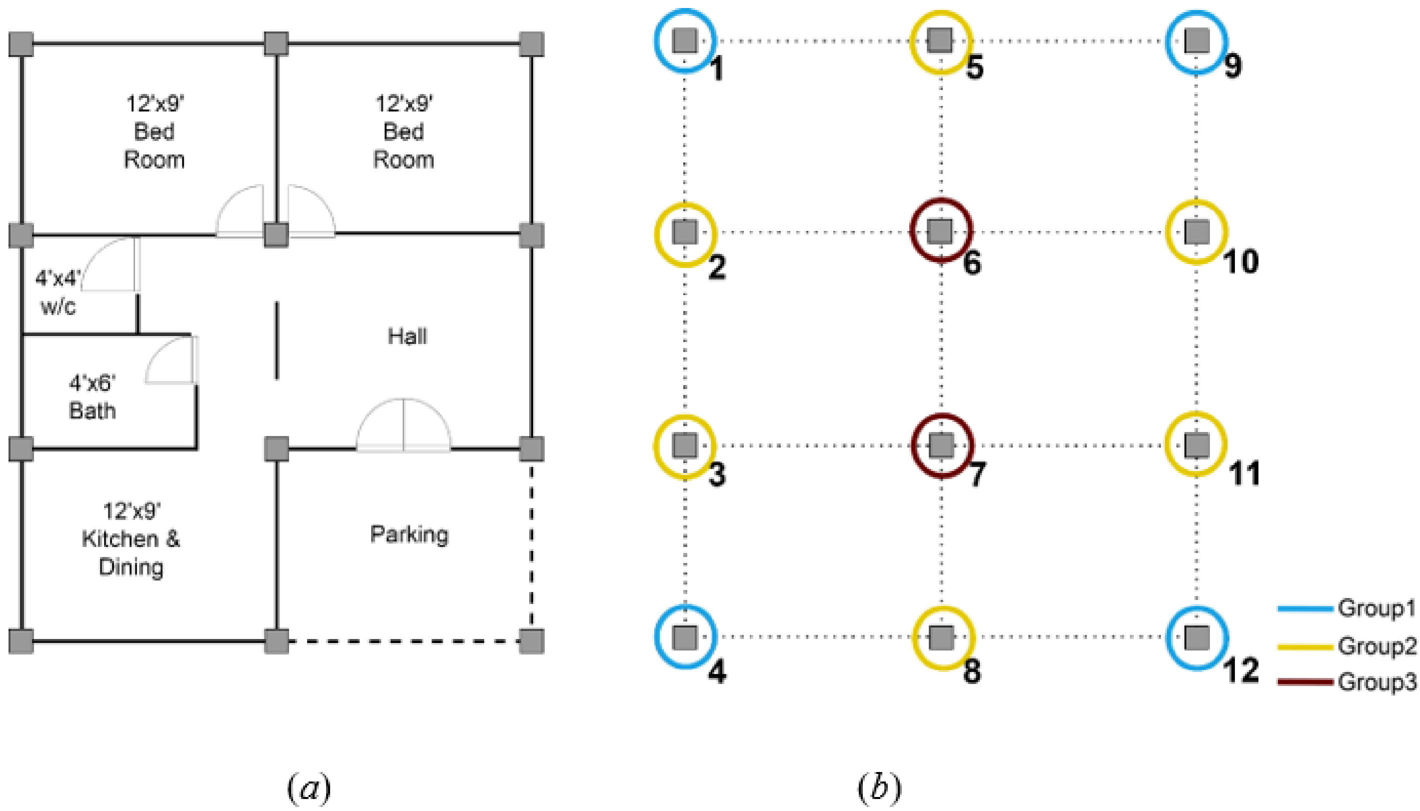


Figure 3

(*a*) Plan for model 1 and (*b*) Grouping results of footings in FCM algorithm

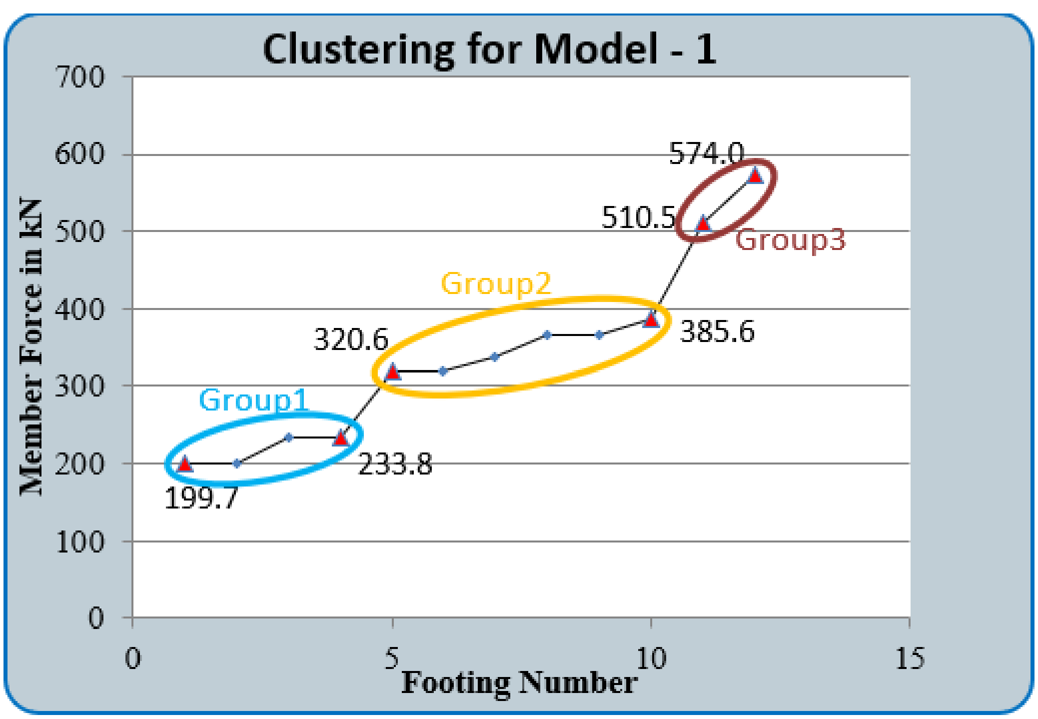


Figure 4

Results of clustering achieved for Model 1

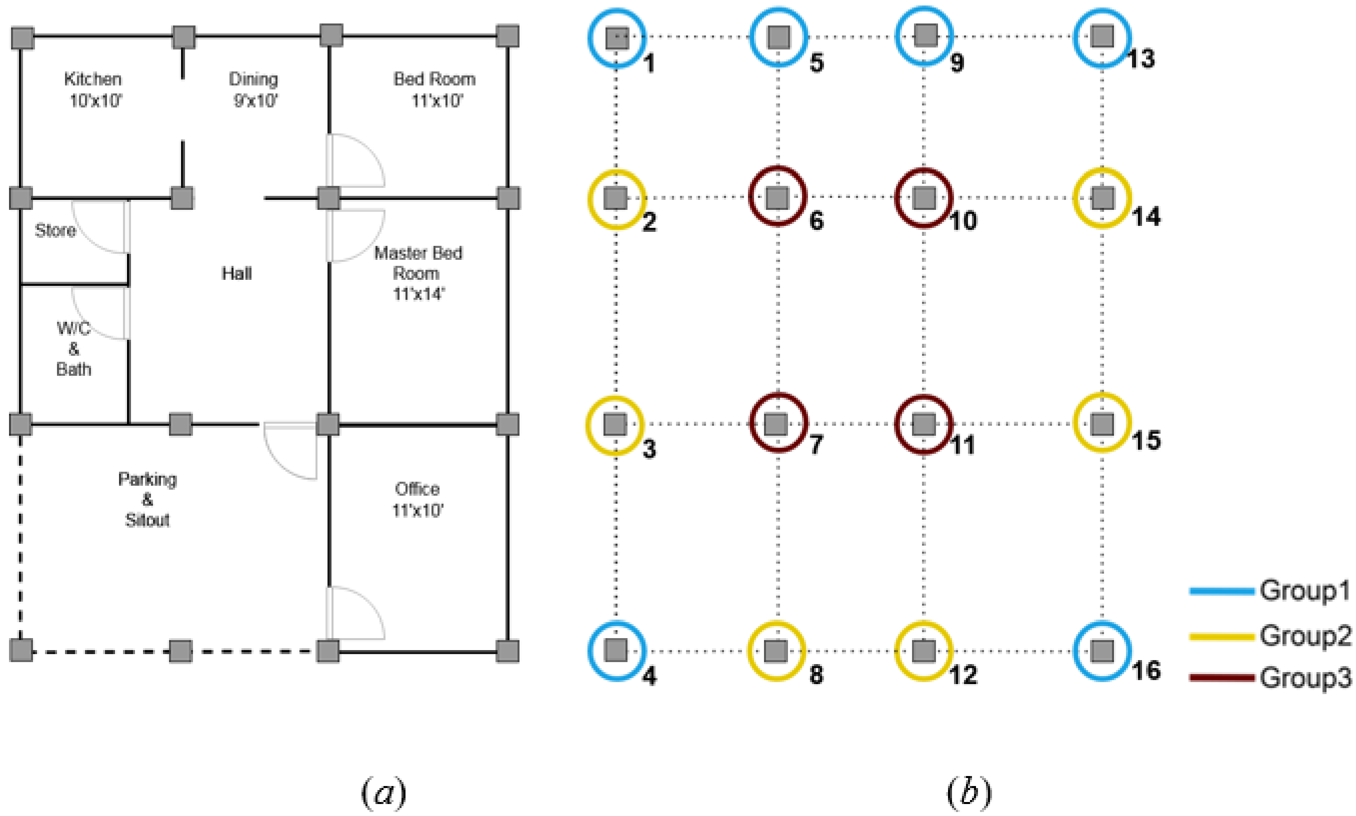


Figure 5

(a) Plan for model 2 and ***(b)*** Grouping results of footings in FCM algorithm

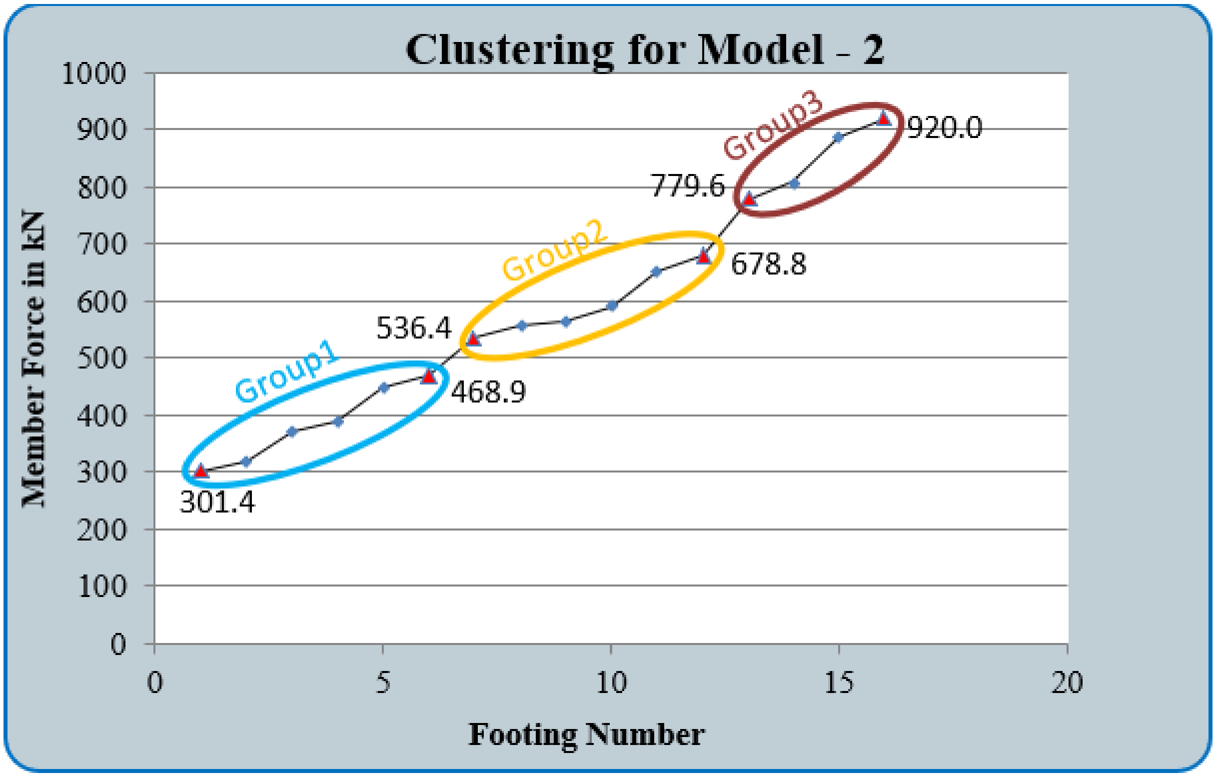


Figure 6

Results of clustering achieved for Model 2

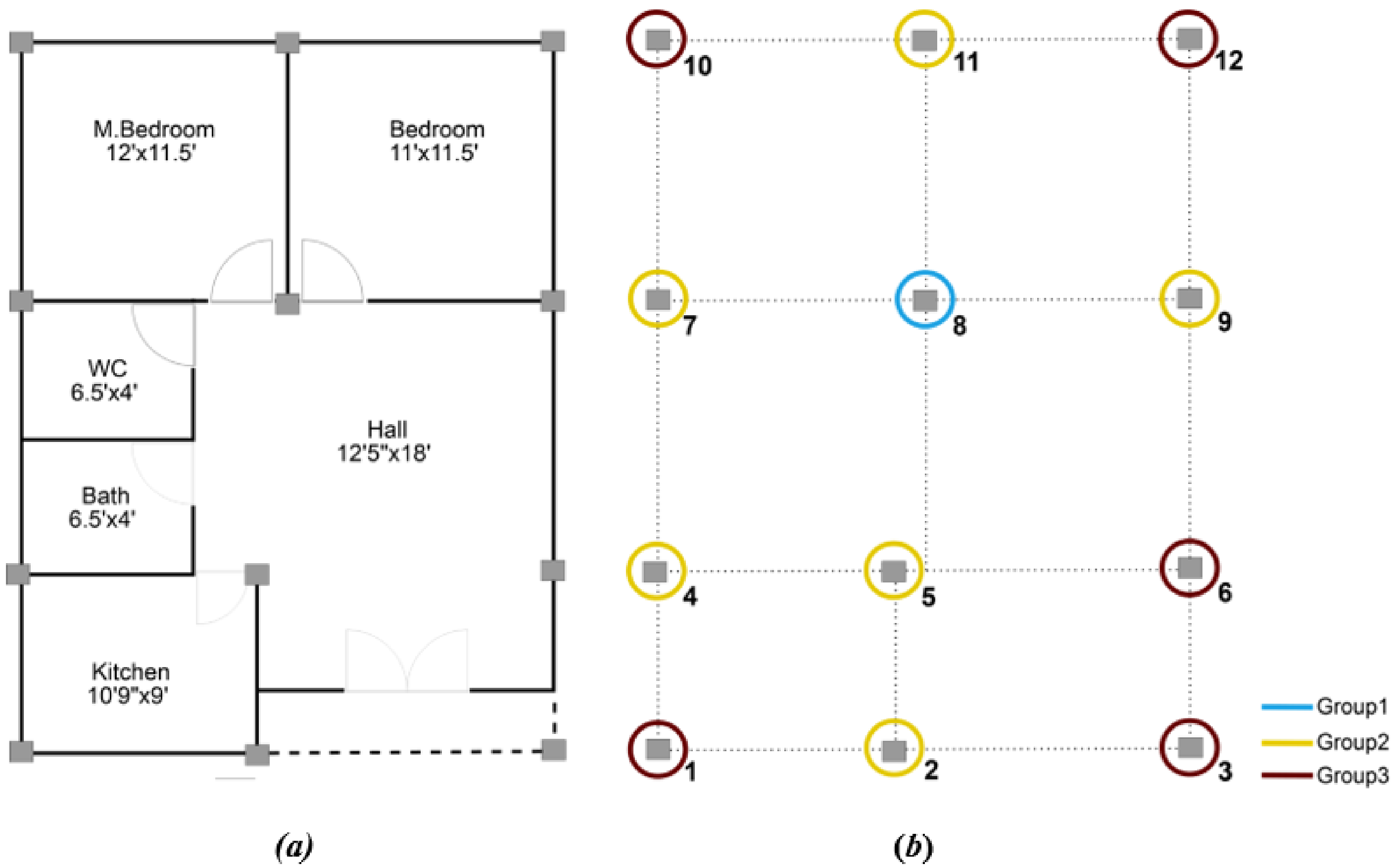


Figure 7

(*a*) Plan for model 3 and (*b*) Grouping results of footings in FCM algorithm

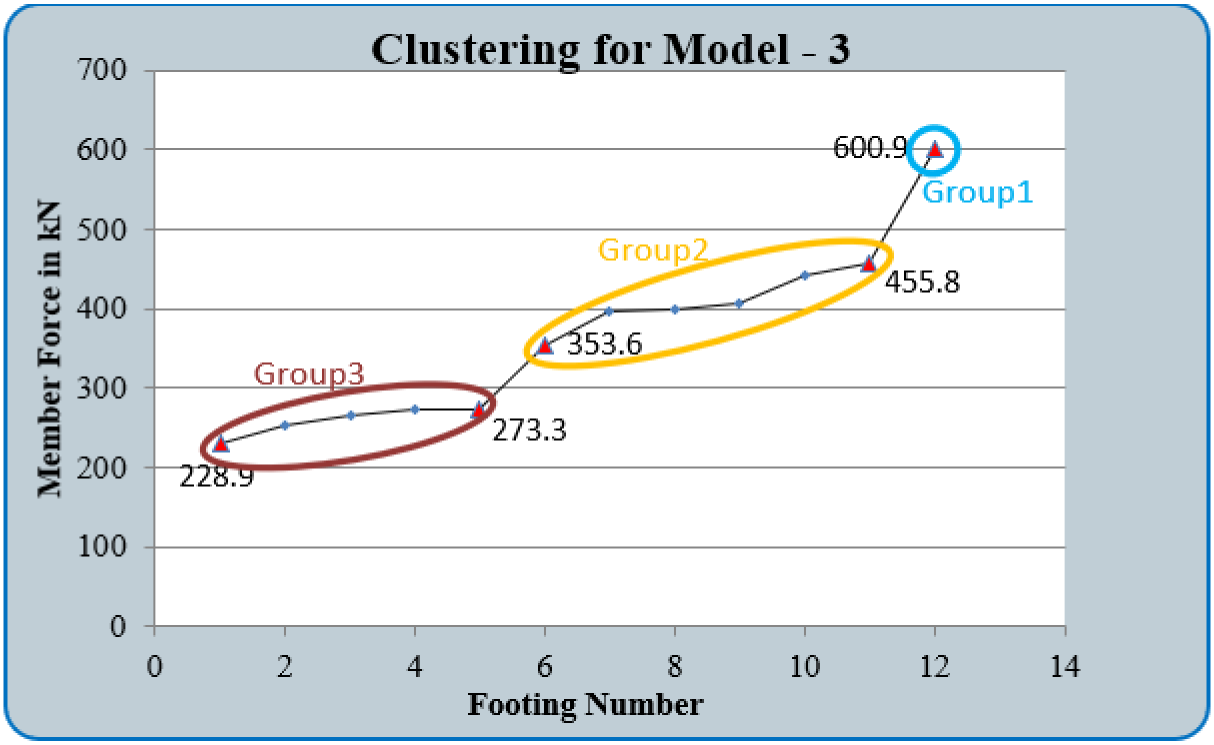
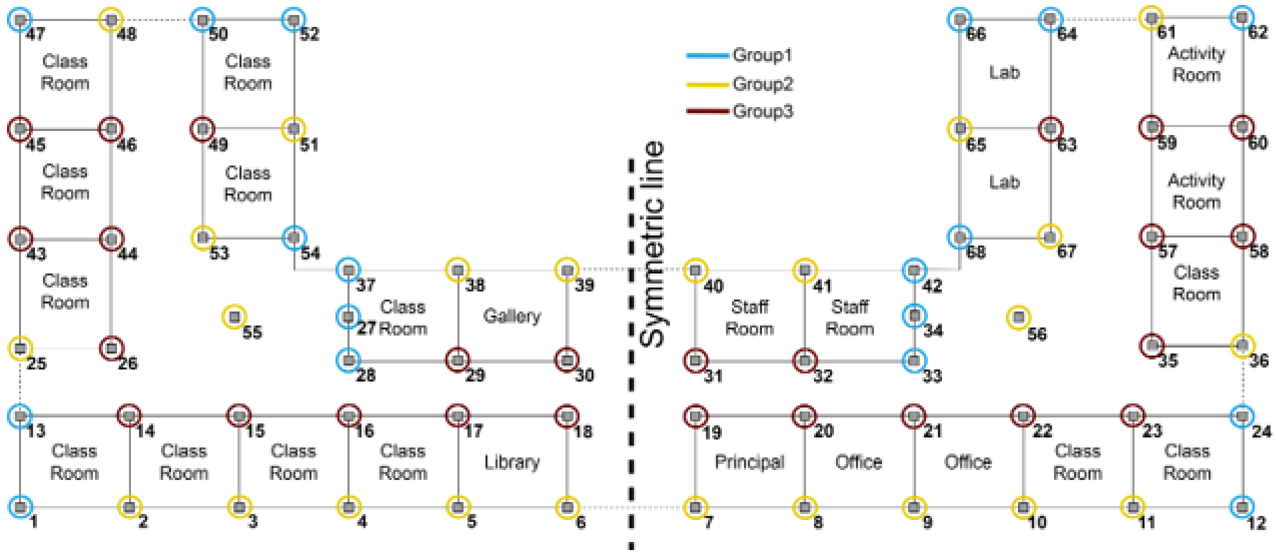
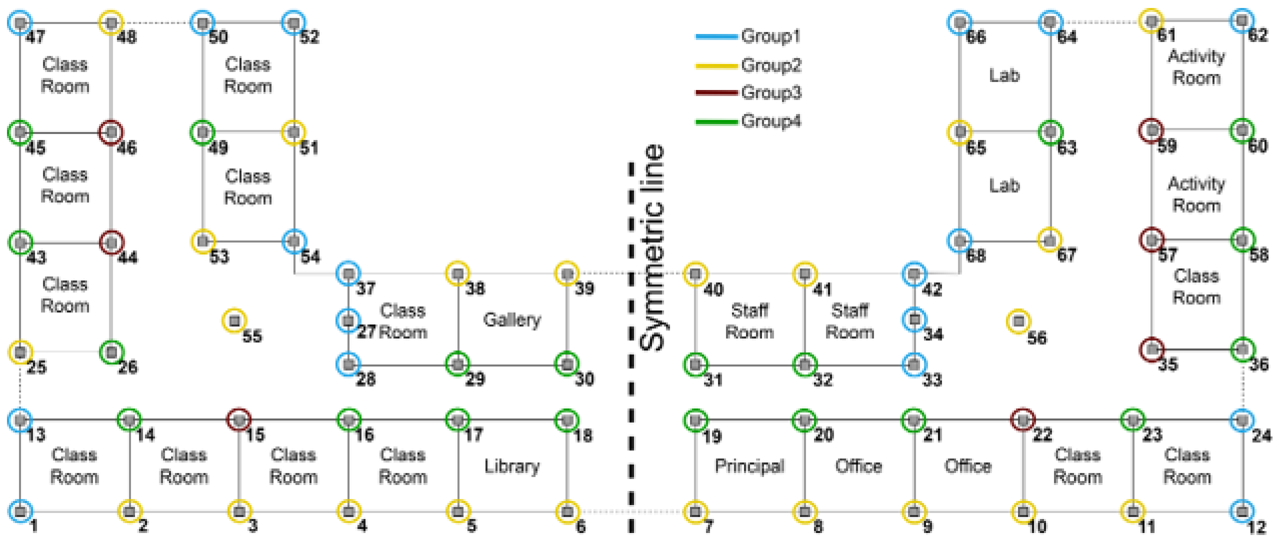


Figure 8

Results of clustering achieved for Model 3



(a)



(b)

Figure 9

(*a*) Plan & grouping results of footings in FCM algorithm for 3 groups to model 4

(b) Plan & grouping results of footings in FCM algorithm for 4 groups to model 4

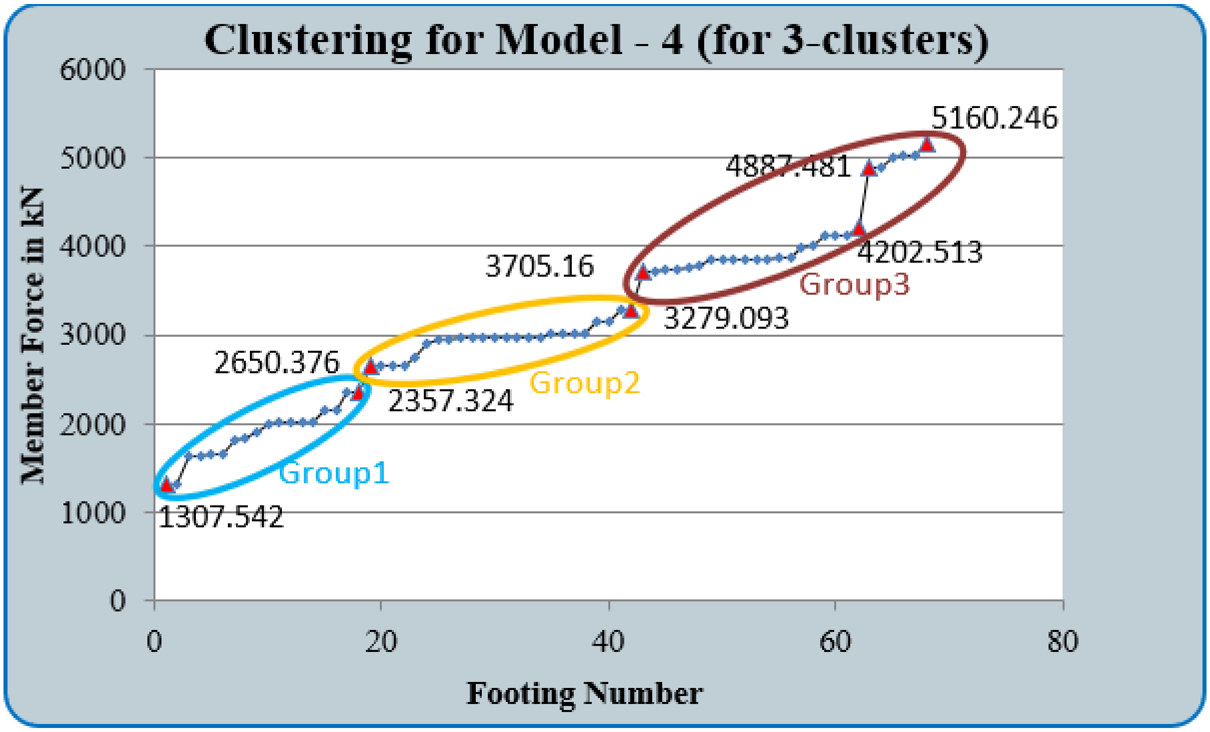


Figure 10

Results of clustering achieved for Model 4 (for 3 clusters)

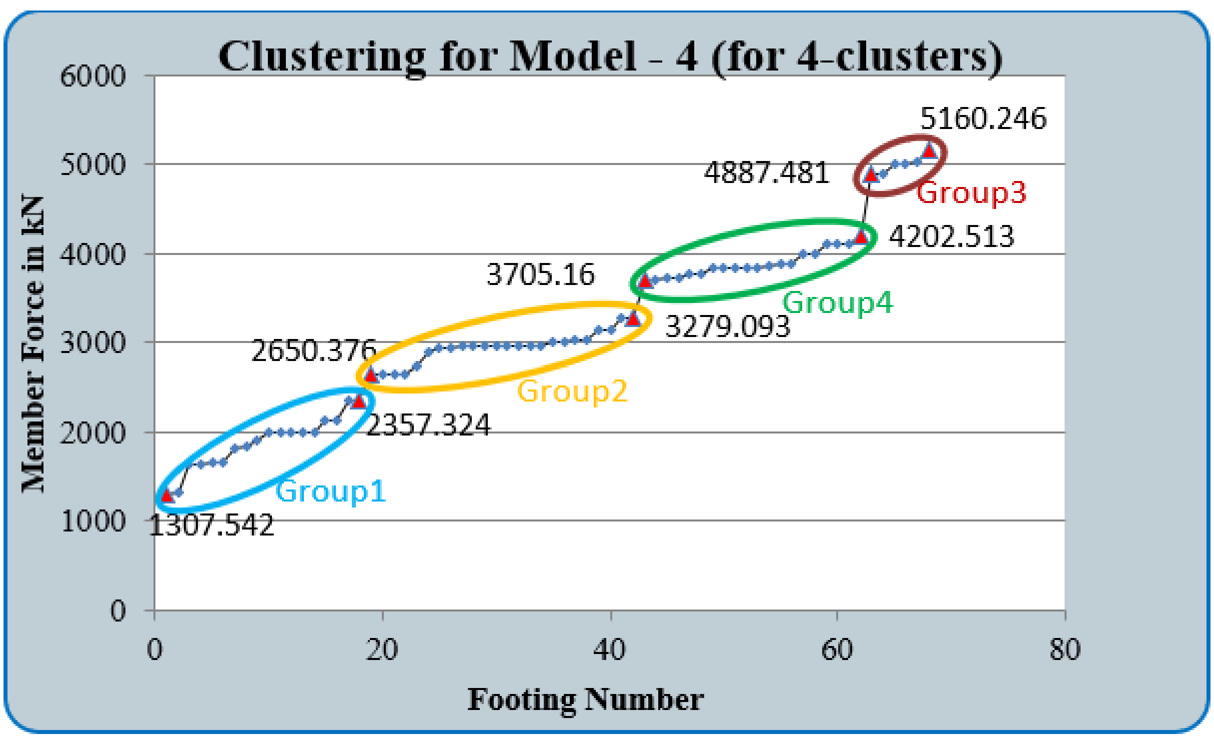


Figure 11

Results of clustering achieved for Model 4 (for 4 clusters)