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COMPARISON OF DYNAMIC PROPERTIES OF CLAYS OBTAINED BY DIFFERENT TEST METHODS

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ABSTRACT

For cohesive soils, an attempt for the classification of G_{max} considering two relevant parameters, namely confining pressure (σ_0') and plasticity index (*PI*), was carried out by hard k-means (HKM), fuzzy c-means (FCM) and Kohonen's self organizing map (SOM) methodologies. After determination of descriptive statistics of the experimental data, three different methods were applied to determine the ranges as well as representative values of G_{max} using the free parameters.

The first part of the study is a description and the analysis of experimental investigations conducted to determine the nonlinear stress-strain behaviors of clays when subjected to cyclic loadings at small strain levels. A series of torsional shear and cyclic triaxial shear tests were performed under undrained conditions to analyze the variations in the stress–strain properties of undisturbed saturated clay samples consolidated to specified confining pressure. The uniform cyclic sinusoidal loading at a 0.1 Hz frequency was applied to samples with different confining pressures. Test results are presented and evaluated in detail.

The second part of the study focuses on hard k-means (HKM), fuzzy c-means (FCM) and Kohonen's self organizing map (SOM) techniques to classify the complex mapping ranging from plasticity index and confining pressure input spaces to dynamic shear modulus output space.

Consequently, comparative results were presented in terms of the methods' clustering capabilities, and the benefit of such an analysis in soil dynamics was evaluated. Results indicate that the dynamic properties of clays are significantly affected by the testing technique and the initial conditions.

Keywords: Shear modulus, cyclic test, classification, fuzzy c-means, k-means, self organizing map.

INTRODUCTION

The deformational characteristics of soils, generally expressed by means of shear moduli and material damping ratios, are crucial parameters in determining the dynamic performance of geotechnical materials and the severity of ground shaking during earthquakes. Several researchers have attempted to understand the nonlinear deformation characteristics of soils, as well as the variations in shear modulus and damping ratios under cyclic loadings (Jamiolkowski et al, 1991; LoPresti et al., 1996). Evaluation of maximum shear modulus (G_{max}) is of great importance with respect to its usage in characterizing the stiffness of a particular soil. Apart from the empirical relationships derived for the determination of G_{max}, classification of this dynamic parameter by means of relevant factors may also

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be significant to understand the level of dynamic strength under certain conditions (Hardin and Drenevich, 1972; Hardin, 1979).

There are more than a few laboratory based methods that can be utilized to obtain maximum shear modulus, such as bender element, resonant column, cyclic simple shear, cyclic triaxial, and torsional shear tests. The main discrepancies among the testing methodologies come from the fact that they measure stress-strain variations at different strain levels and under different stress and strain boundary conditions as well as their accuracies are different from each other. Interpretation of laboratory studies lead to the conclusion that, soil stiffness expressed by G_{max}, is strongly influenced by cyclic strain level, void ratio, mean effective stress, plasticity index, overconsolidation ratio, and number of loading cycles. Although an easier way to estimate G_{max} is utilization of an empirical relationship, specific care should be devoted for the errors in interpreting shear wave velocity and anisotropic properties of soils.

Although numerous empirical relationships have been formulated and seem to be consistent with experimental observations, the measurement of dynamic soil properties (in laboratory or in-situ) is time-consuming and requires considerable computational effort. For this reason, it is desirable to develop a practical approach for the prediction of dynamic stress-strain parameters for soils. Numerous attempts have been made to estimate the maximum shear modulus of a specific types of soils using empirical expressions. However, only limited number of geotechnical engineers have been interested in the classification of soils with respect to dynamic soil properties. **(**Kokusho et al., 1982; Lanzo et al., 1997**)**

Studies considering the relationship between maximum shear modulus and confining pressure are also available in the literature. Results of these studies revealed that, shear modulus increases exponentially with the confining stresses with the exponent ranging from 0.58 to 0.01 (Saxena et al., 1988). A number of studies were carried out for the determination and modeling of G_{max} (Jovicic, 1996; Yamashita, 2001). Attempts on understanding this parameter using fuzzy logic and neural networks are also encountered in the literature. Akbulut et al. (2004) used neuro-fuzzy systems to model the shear modulus and damping ratio of sand as well as rubber mixtures. Romero and Pamukcu (1997) prepared samples having several particle size distributions, compacted to various densities, and tested under different confining pressures to determine the effects of the parameters on sample response. Ni et al.(1996) developed neural network model with six input variables (i.e. the standard penetration value, void ratio, unit weight, water content, effective overburden pressure, and mean effective confining pressure) to obtain shear modulus and damping ratio. The results revealed that the neural network model was successful in predicting shear modulus but not in damping ratio.

Torsional and triaxial cyclic shear tests were conducted on undisturbed clayey samples under undrained conditions for different confining pressures in this study. The tests were performed under multi-stage cyclic loadings that were increased in each five cycles. Therefore, both initial values and modulus reduction curves of shear modulus as well as damping ratio increases were determined by means of cyclic torsional and triaxial shear tests.

Furthermore, an attempt to classify G_{max} by means of both mean effective stress (σ_0') and plasticity index (*PI*) was made using fuzzy c-means method, hard k-means algorithm, and self organizing maps Utilizing the methods, cluster centers were obtained by σ_0' and *PI* parameters, and a detailed comparison on the performances of employed methods were made. Results denoted that, all the classification methods depicted above are capable of making the desired clustering analysis; however, there are considerable discrepancies among the methods due to their precisions.

EXPERIMENTAL STUDY

Natural undisturbed inorganic clay samples were obtained from Kocaeli Region in the frame of a geotechnical investigation programme after the 1999 Kocaeli earthquake. Dynamic hollow cylinder (DHC) and dynamic triaxial test (DTT) systems were used in order to evaluate modulus and damping characteristics of the undisturbed clayey samples.

The tests were conducted according to JGS 0541-2000, JGS 0542-2000, JGS 0543-2000, JGS 0550-1998 standards. Undisturbed samples were trimmed 50mm diameter and 105mm in height in DTT. Hollow cylindrical samples were prepared by drilling and trimming with a special method. The hollow cylindrical samples are 140 mm in height. The outer diameter and the inner diameters are 70mm and 30mm, respectively.

Both testing systems has stress controlled dynamic loading and strain controlled static loading mechanisms. Also DTT apparatus were equipped with high sensitive displacement sensors and a load cell in the pressure chamber to completely eliminate the effect of mechanical frictions on the measured soil properties. For larger deformations, additional displacement gauges also introduced outside of the chamber in order to make reliable measurements for a wide strain range. It was possible to measure both small and large strains by using two kinds of displacement gauges in one unique test. In DHC apparatus vertical, torsional, and lateral stresses as inner and outer cell pressures can be applied independently to the specimen.

Undrained cyclic tests were conducted with a DTT and DHC in which cyclic loads were applied by a servo-pneumatic actuator at a frequency of 0.1 Hz. All tests were performed on undisturbed fine grained soil specimens under an isotropic effective confining pressure and a constant back pressure. Samples recovered under ground water table were chosen for the tests. Eight strips of saturated filtration sheets were introduced around the specimen to provide the faster completion of the primary consolidation and to make accurate measurement of the excess pore water pressure during the tests. The pore water pressure was measured at the base cap in both test apparatuses. Drainage during the stages of consolidation was allowed through the top and base cap of the specimens. By using these filtration sheets the 100 % completion of the primary consolidation is achieved in 3-4 hours in most of the test samples. The samples were isotropically consolidated in the cell and with a back pressure ranging between 200-300 kPa in order to assure the saturation. Average index properties are: natural water content ω_n=36 %, liquid limit w_L= 58%, plasticity index PI=21 and the specific gravity, G_s=2.71. The Skempton B values were between 98-100% indicating that specimens were fully saturated.

Multi stage cyclic loading was preferred as the number of available test specimens was limited. In multi stage loading following the consolidation of the specimen, a sequence of prescribed cyclic shear stress was then applied starting with relatively small amplitudes with each sequence having the same number of cycles. The amplitudes of cyclic stresses were increased in each sequence on the specimen under undrained conditions. The number of cycles, N was chosen as the third of every 5^{th} cycle and analyzed to obtain a representative cyclic stress-strain behavior. Two typical test results are given in Fig. 1.

In this manner, 52 samples having different PI values were tested using both torsional and triaxial test apparatus in order to obtain maximum dynamic shear modulus. All the test results obtained under different effective confining pressure are illustrated as G_{max} versus PI in Fig. 2.

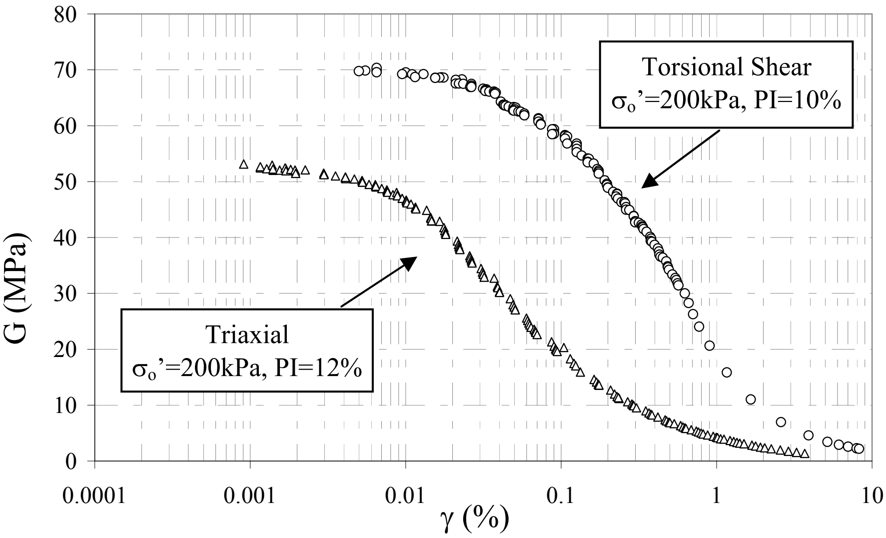

Figure 1. Typical cyclic torsional shear and triaxial test results

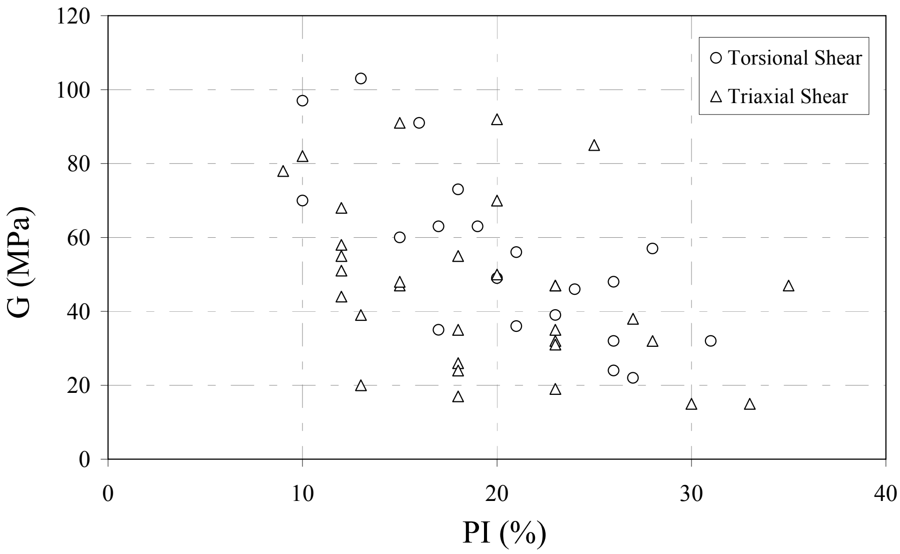

Figure 2. Scatter plots of maximum shear modulus vs. plasticity index for general test data

CLUSTERING TECHNIQUES

Hard k-means algorithm

Clustering (or classification) is essentially to partition the finite data into a number of clusters by understanding the underlying structure. In order to classify the data with respect to similar features and attributes, it is required to define a similarity measure describing the distance between pairs of feature vectors. Therefore, a clustering technique determines optimum partitions due to a certain dissimilarity function that measures global error extent between data points and cluster centers in feature space. Hard k–means (HKM) algorithm, also referred to as c-means algorithm, partitions the $n \times m$ dimensional data matrix, $\mathbf{x}$, into c clusters by minimizing the dissimilarity function (J) that is defined as (Ross, 1995):

$$J(\mathbf{U}^*, \mathbf{v}^*) = \min[J(\mathbf{U}, \mathbf{v})] = \min\left[\sum_{k=1}^{n}\sum_{i=1}^{c}\chi_{ik}(d_{ik})^2\right] \tag{1}$$

where, **U** is $m \times n$ dimensional partition matrix, **v** is $c \times m$ dimensional cluster center matrix, n is the number of data points, c is the number of clusters, **d** is $c \times n$ dimensional similarity matrix, **U*** is partition matrix with optimal values, **v*** is cluster center matrix involving optimal cluster centers, and χ is characteristic function calculating the partition matrix (**U**) matrix as follows:

$$\mathbf{U} = \{\chi_1, \chi_2, \chi_3 ......\chi_i\} \quad \text{and} \quad \chi_i(x_k) = \begin{cases} 1 & x_k \in i^{th} \ cluster \\ 0 & x_k \notin i^{th} \ cluster \end{cases} \tag{2}$$

Utilizing the Euclidean distance measure to characterize the similarity, the elements of **d** are calculated by:

$$d_{ik} = d(x_k - v_i) = \|x_k - v_i\| = \sqrt{\sum_{j=1}^{m} (x_{kj} - v_{ij})^2} \qquad \text{(for, } i = 1 \text{ to } c \text{ and } k = 1 \text{ to } n\text{)} \tag{3}$$

in which, m is the number of features, x_k is k^{th} data point and v_i is the centeroid of i^{th} cluster that can be presented by:

$$v_i = \{v_{i1}, v_{i2}, ..., v_{im}\} \qquad \text{(for, } i = 1 \text{ to } c\text{)} \tag{4}$$

In addition, cluster centers are calculated as follows:

$$v_{ij} = \frac{\sum_{k=1}^{n} \chi_{ik} \times x_{kj}}{\sum_{k=1}^{n} x_{ik}} \qquad \text{(for, } i = 1 \text{ to } c \text{ and } j = 1 \text{ to } m\text{)} \tag{5}$$

Fuzzy c-means algorithm

Fuzzy c-means (FCM) algorithm was presented by Ross (1995) as the extension of hard k-means technique with the advantage of fuzzy set theory. In fuzzy set theory, the crisp boundary in classical set theory that separates the inclusion and the exclusion decision is shifted with the transition region, by means of changing the binary membership with gradual membership on the real continuous interval [0, 1]. Thereby in fuzzy approach, uncertain belonging of a point to a set is described by partial membership (Zahid et al., 2001).

Fuzzy c-means algorithm permits a data point's belonging to one or more clusters utilizing membership value concept. Therefore, elements of the partition matrix consist of membership values varying within the interval [0, 1], and a data point can partially belong to a cluster (Ross, 1995). Basically, fuzzy c-means algorithm calculates fuzzy partition matrix to group some of data points into c clusters. Therefore, the aim of this algorithm is to cluster centers (centeroids) that minimize dissimilarity function (J_m), which is given by (Lanhai, 1998):

$$J_m(\mathbf{U}^*, \mathbf{v}^*) = \min[J_m(\mathbf{U}, \mathbf{v})] = \min\left[\sum_{k=1}^{n}\sum_{i=1}^{c} (\mu_{ik})^{m'} \times (d_{ik})^2\right] \tag{7}$$

where, μ_{ik} is the membership value of the k^{th} data point in the i^{th} cluster, m' is weighting parameter varying in the range $[1, \infty]$, **U** is fuzzy partition matrix, **v** is cluster center matrix, and **d** is similarity matrix given in Eq.3 (as in hard k-means algorithm). In addition, cluster centers are calculated using following formulation (Ross, 1995):

$$v_{ij} = \frac{\sum_{k=1}^{n} \mu_{ik}{}^{m'} \times x_{kj}}{\sum_{k=1}^{n} \mu_{ik}{}^{m'}} \qquad \text{(for, } i = 1 \text{ to } c \text{ and } j = 1 \text{ to } m\text{)} \tag{8}$$

where, x is fuzzy variable describing data point. In essence, fuzzy partitioning is performed through an iterative optimization utilizing following formulation:

$$u_{ik}(s+1) = \frac{1}{\left[\sum_{j=1}^{c} \left(\frac{d_{ik}(s)}{d_{jk}(s)} \right)^{\frac{2}{m'-1}} \right]} \tag{9}$$

Self organizing maps

The self organizing map (SOM), also referred to as Kohonen map, is an unsupervised learning methodology reducing the dimensionality of the data utilizing self-organizing neural network methodology (Haykin, 1996). Basically, SOMs classify input vector with respect to the grouping in the input space. Neighbouring neurons in SOM learn to recognize neighbouring sections of the input space; therefore, it is possible to teach both distribution and topology of input vectors. Basically, the user-defined dimension of input vector and two-dimensional output layer forms the architecture of the SOM. There exists a relation between the adjacent neurons, which forms the topology of the output space. Particularly, rectangular and hexagonal lattices are common topologies in use. The algorithm is extensively explained by Kohonen (1990).

In order to focus on the algorithm, let x be the normalized input vector randomly selected from the input space, and w_{ij} denotes the assigned synaptic weights (connections) between input and output layers. Output of the neuron j can be summarized as:

$$O_j = \sum_{i=1}^{n} w_{ij} X_i \tag{13}$$

where, **O**, **w** and, **X** denote output vector, weight matrix, and input vector, respectively. All output values of output neurons are set to 0; exceptionally, the winning neuron is set to 1. The node with its weight vector closest to the input vector is considered as the winner and its weights are adjusted. In case of a node wins the competition, the neighbors' weights are also changed, as well as further the neighbor is far from the winner, the smaller its weight change. This process is repeated for each input vector for a number of iterations. Obviously, different winners can be produced from different inputs. Using the Euclidean measure of distance, the following formulation can be employed in the algorithm:

$$\mathrm{d}_{\mathrm{j}} = \left\| \mathrm{X}_{\mathrm{j}} - \mathrm{w}_{\mathrm{ij}} \right\| \tag{14}$$

where, **d** is lateral distance vector. The most common neighborhood function is the Gaussian neighborhood function that is used to determine the topological neighborhood as given below:

$$\mathrm{h}_{\mathrm{ij}} = \mathrm{e}^{\left(-\frac{\mathrm{d}_{\mathrm{ij}}{}^2}{2\sigma^2} \right)} \tag{15}$$

where, h_{ij} is topological neighborhood and σ is the parameter of neighborhood width. Furthermore, weights of neighboring neurons are recalculated utilizing the following equation:

$$w_{ij}(p+1) = w_{ij}(p) + \eta(p)\, h_{ij}(p)\left[X_j(p) - w_{ij}(p)\right] \tag{16}$$

where, p is the iteration step, and η denotes learning rate parameter decreasing as the iteration continues. As a consequence, the algorithm is terminated when the map is thought to have converged to a stable state as soon as the assignment of the various input values to the respective winning unit remains constant. If no noticeable changes are observed in the feature map, new input pattern is selected and the process is restarted.

CLASSIFICATION OF THE G_{max} BY CONFINING STRESS USING HKM, FCM AND SOM

The main objective of this study is to emphasize the feasibility of defining G_{max} intervals for plasticity and confining pressure values using three different clustering techniques that are fundamentally different from the confidence interval theory. Additionally, two different dynamic testing procedures, namely cyclic triaxial and torsional shear tests, were compared under the light of this philosophy.

The information of experimental study performed to obtain necessary data were reported elsewhere (Altun, 2003; Okur and Ansal, 2000). Obviously, the aim is to determine whether a data pattern belonging to the same cluster on the G_{max}-PI plane has the same confining pressure. The experimental results from 52 samples tested summarized in Figure 3. The minimum and maximum values of the plasticity index are 9% and 35%, respectively. Accordingly, maximum and minimum values for G_{max}/σ_0' parameter are pronounced as 0.15 and 0.39. As can be derived from Figure 2 easily, G_{max} values observed at confining pressures of 100 and 300kPa are widely scattered. As a result of this, initial application of the classification algorithms in G_{max}-*PI* plane yielded unacceptable results. Afterward, classification trials were made using the normalized G_{max}/σ_0' values. Corresponding normalized data points are shown in Figure 3. Accordingly, clustering in terms of normalized G_{max} by confining pressure was found to be more successful than the first trial shown in Figure 3.

Three algorithms described above were applied to classify the G_{max} values in terms of the plasticity index and the confining pressure. Solutions obtained using HKM, FCM and SOM methodologies are summarized in Figures 3. In essence, all the methods explained above are capable of clustering the data of the range of four particular percentages of G_{max}. As mentioned before, fuzzy c-means method utilizes the partial membership concept that quantifies the belonging of a data point to any cluster. Uncertainty existing in experimental data can be handled using fuzzy approach better. Smoothed membership values belonging to the three classes are given in Figure 3. It should be noted that particular artificial membership functions for each cluster cannot be identified easily as shown in Figure 4. In addition, clustering outcomes of FCM and HKM algorithms depend on the initial cluster centers; therefore, the algorithms were applied many times in order to obtain the final clusters.

Additionally, the solutions of FCM methodology, which is more successful for clustering than the other algorithms, are given in Fig. 4. Clustering outcomes obtained using three different algorithms for triaxial and torsional shear test data are separately illustrated in Fig. 5 and Fig. 6, respectively. The cluster centers calculated by HKM, FCM and SOM for all test data are tabulated in Table 1. In Table 2 and 3, the cluster center obtained by three clustering methodology for triaxial and torsional shear test data are given.

It should be noted that the main objective of this study is to determine threshold values for G_{max} measurements for predefined number of classes. Because a precise estimation of G_{max} value is not possible due to soil heterogeneity and anisotropy, to characterize an interval for specific plasticity and confining pressure measurements can be used in several generalization studies. Namely, representative G_{max} value can be predicted by plasticity data, which can be simply obtained, using such an approach. Apart, as an alternative to confidence interval theory in statistics, different approach is presented in this study. Consequently, the testing techniques were compared in this manner.

In essence, there are two directions of this study that can be considered as an accumulation in soil science. First of them, an idea about self-classification of widely used dynamic test results is presented in order to make a generalization. In detail, soil parameters are generally known to be heterogeneous, and it is hard to determine precise values characterizing the behavior. Therefore, parameters are usually treated with certain confidence intervals and safety factors. From this point of view, an innovative generalization method is proposed as an alternative to traditional statistics-based procedures. Moreover, the approach can also be utilized for conditions in which several G_{max} estimations are required by means of plasticity index and previous G_{max} measurements. Therefore, a representative G_{max} value can be calculated by simply obtained plasticity index value for a certain soil on which dynamic tests previously performed. Second consideration of this study is to compare the results of torsional shear and cyclic triaxial tests. In order to achieve this, different tests performed on specific clay samples are considered by classifying representative values using the clustering techniques. Results denoted that there are worth mentioning discrepancies among the results of clustering analyses, and the best one should be preferred carefully.

Table 1. Cluster centers obtained using the three algorithms for all test data

Percentage of G_{max} (%)	HKM		FCM		SOM	
	PI (%)	G_{max}/σ_0'	PI (%)	G_{max}/σ_0'	PI (%)	G_{max}/σ_0'
0-25	11.500	0.2808	11.834	0.2757	14.195	0.2624
25-50	15.714	0.2441	18.144	0.2415	17.392	0.2489
50-75	19.154	0.2424	24.027	0.2240	22.887	0.2246
75-100	26.350	0.2093	31.133	0.1789	26.792	0.2106

Table 2. Cluster centers obtained using the three algorithms for triaxial test data

Percentage of G_{max} (%)	HKM		FCM		SOM	
	PI (%)	G_{max}/σ_0'	PI (%)	G_{max}/σ_0'	PI (%)	G_{max}/σ_0'
0-25	12.500	0.2423	12.040	0.2496	14.059	0.2392
25-50	18.750	0.2300	18.000	0.2198	17.517	0.2303
50-75	24.000	0.2034	23.500	0.2085	23.291	0.2082
75-100	33.000	0.1578	32.000	0.1596	27.584	0.1839

Table 3. Cluster centers obtained using the three algorithms torsional test data

Percentage of G_{max} (%)	HKM		FCM		SOM	
	PI (%)	G_{max}/σ_0'	PI (%)	G_{max}/σ_0'	PI (%)	G_{max}/σ_0'
0-25	11.000	0.3604	27.013	0.2332	14.035	0.2844
25-50	17.000	0.2826	10.580	0.3639	17.781	0.2565
50-75	21.800	0.2413	16.725	0.2756	22.522	0.2271
75-100	27.333	0.2302	21.224	0.2376	25.566	0.2185

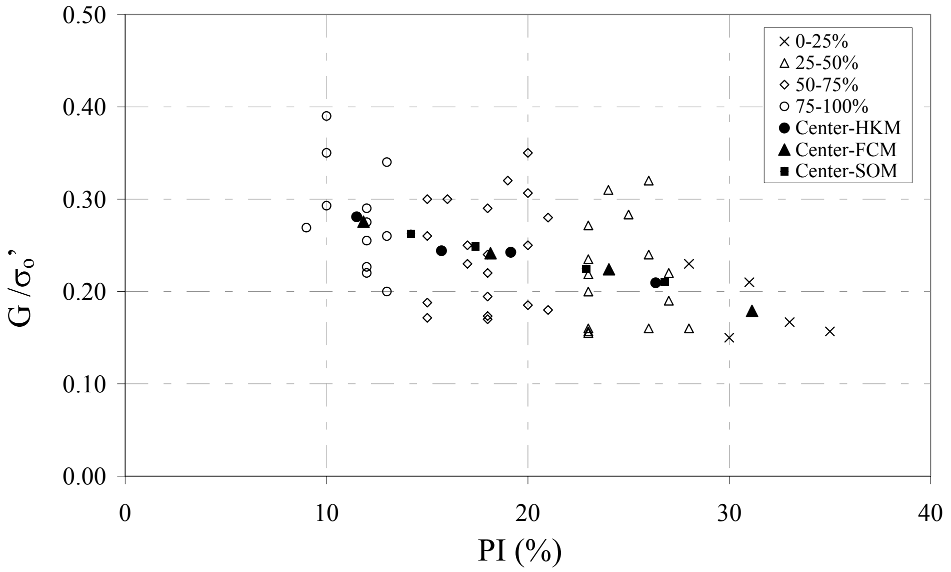

Figure 3. Solution by three algorithms for general data

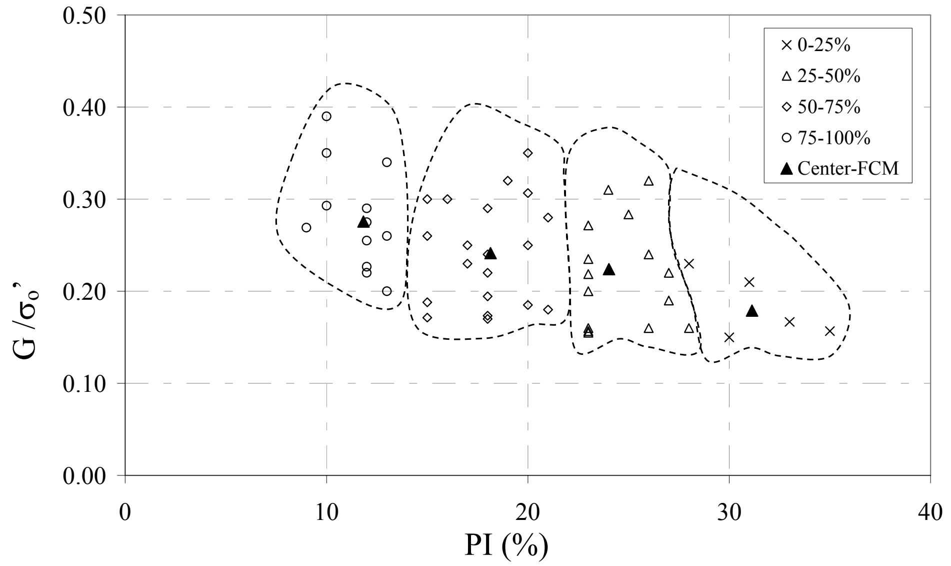

Figure 4. Solution by fuzzy c-means method for general test data

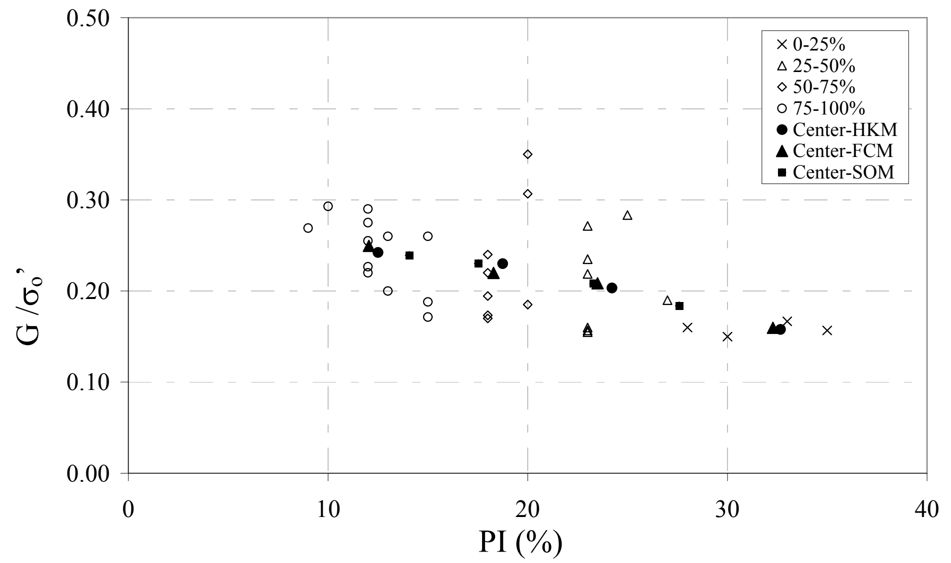

Figure 5. Solution by three algorithms for triaxial test data

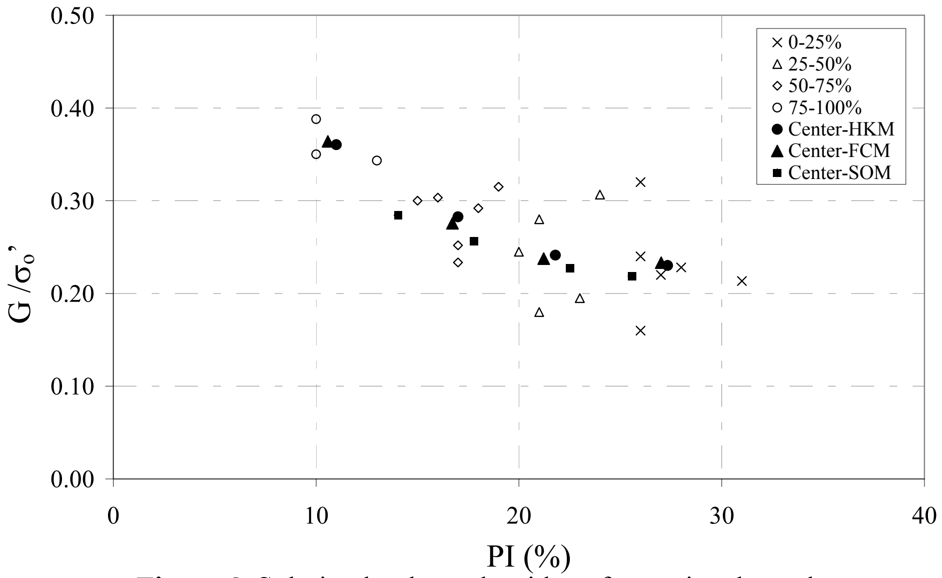

Figure 6. Solution by three algorithms for torsional test data

CONCLUSIONS

In this study, three unsupervised clustering algorithms were employed to determine the thresholds of G_{max} values of fine grained soils considering plasticity index and confining pressure parameters. The clusters were arranged by the algorithms so that the G_{max} values stays under four different ranges constituting each cluster. Following conclusions were drawn from this study:

1. It was concluded in the investigation that, the normalization of G_{max} data with initial confining pressure (σ_0') is required to achieve successful clustering outcomes.
2. FCM, HKM and SOM methodologies were utilized to cluster maximum shear modulus of clay soils by means of plasticity index. The algorithms were gave different outcomes as a cluster center to handle existing uncertainty in the input data.
3. Although the methodologies in this study are capable of clustering the maximum shear modulus of soils by means of the plasticity index, analogous study should be performed on larger databases involving different soil types. Moreover, this approach can be applied successfully on further geotechnical engineering problems involving uncertain and ambiguous data.

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