Prediction of the Collapse Index by a Mamdani Fuzzy Inference System

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Abstract. Determination of collapse potential of collapsible grounds is an important problem for civil engineers. However, this requires extensive field and laboratory works. For this reason, prediction tools for this purpose are highly attractive for engineers. Considering this difficulty, development of a Mamdani fuzzy inference system for prediction of collapse index is the main purpose of the study. The fuzzy inference system developed in the study includes two inputs, one output and 25 lingusitic if-then rules. The performace of the fuzzy inference system is checked by various indices and these indices reveal that the fuzzy inference system has a significant prediction performance.

Keywords: fuzzy inference system, caliche, collapsible ground, collapse index.

1 Introduction

Economy and safety are two main componens of an engineering design. All civil engineering structures are constructed on natural ground. However, some grounds exhibit a considerable volume decrease under stresses. Collapsible grounds are characterized by considerable volume decreases under constant stress if they are saturated. Such type materials exhibit high strength when they are dry. However, if they are saturated, they can lose their strength because of their low unit weight and highly porous structure. Collapse occurs if the intergranular stress is higher than intergranular bonding strength provided by bridging. This collapse mechanism is triggered by increasing in stress or dennundation or both. Increasing in overburden thickness sourced from sedimentation, dynamic loadings created by earthquakes and surcharges of engineering structures are some causes of increases in stress [1]. To avoid a sudden failure of a structure, the collapse potential of a ground should be considered before construction on a collapsible ground. However, determination of collapse potential of a ground is highly difficult. For this reason, the purpose of the

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present study is to propose a Mamdani fuzzy inference system to predict the collapse index of a collapsible ground.

Before the preparation of the fuzzy inference system, an extensive field work to collect representative samples is carried out. In the second stage of the study, a series of laboratoru tests are performed on the samples collected from the field. Finally, a Mamdani fuzzy inference system is developed to predict the collapse index.

2 Collapse Mechanism and Data Structure

The sampling for laboratory tests is conducted on the clayey level of the caliche profile in the Adana Organized Industrial Site. A total of 20 undisturbed samples from the silty, sandy levels are extracted using 35x198 mm mould for oedometer tests to describe the collapse potential.

For the determination of collapse index (C_p) of solis, two types of laboratory tests are employed. One of them is double oedometer collapse test and the other one is single oedometer collapse test [2]. In the double oedometer collapse test, under different stress levels, the deformation differences of partially and fully saturated samples are determined. However, the purpose of the present study is to determine the volume decrease depending on saturation under constant stress. In addition, due to highly heterogenous nature of the geomaterial studied, preparation of two samples having similar void ratio for the double oedometer collapse tests is almost impossible. For these reasons, in this study, the single oedometer collapse test is preferred. In this procedure, the tests are conducted on one undisturbed sample having natural water content. During the single oedometer testing program, the procedure suggested by ASTM [3] is followed. At the end of the tests, the collapse index of the samples is determined by the following equation:

$$C_p=\Delta e_c/(1+e_1) \tag{1}$$

where; C_p is the collapse index; Δe_c, is the change of void ratio depending on saturation and e_1 is the original void ratio.

This equation may be used to determine the collapse potential, Ic, of soil at particular vertical stress or the collapse index, C_p, at an applied vertical stress of 200 kPa. C_p for smaller applied vertical stress may be estimated assuming that the soil does not swell after inundation at smaller applied vertical stress [3]. In other words, the parameter of C_p reflects the special conditions, because the samples are non-swell nature depending on increase in water content, and the constant load employed during the tests is 200 kPa. However, the term of collapse potential is a general concept. For this reason, instead of collapse potential, use of the term of collapse index reflecting a special condition is preferred in the study. In this study, after the dennundation under 200 kPa loading level, the tests are terminated as soon as the collapse occurred. Theoretically, the change in void ratio after the dennundation can be determined by combining the void ratio at the beginning (original void ratio) and the void ratio after the test. The list of the collapse index values obtained from the single oedometer tests and the inputs (fine content and void ratio) are given in Table 1.

Table 1. The parameters used in the fuzzy inference system [1]

No	i	e_0	C_p
L1	27	0.354	1.77
L2	66	0.417	2.58
L3	53	0.427	2.53
L4	65	0.529	2.73
L5	12	0.345	1.62
L6	47	0.411	2.22
L7	64	0.476	2.68
L8	18	0.348	1.82
L9	55	0.489	3.13
L10	82	0.720	3.79
L11	77	0.599	3.38
L12	52	0.400	2.82
L13	39	0.453	2.32
L14	28	0.312	1.67
L15	54	0.604	2.68
L16	45	0.439	2.32
L17	42	0.381	2.27
L18	48	0.478	2.47
L19	52	0.537	2.78
L20	46	0.410	2.37

i : fine content (%); e_o: void ratio; C_p: collapse index.

3 Fuzzy Inference System

Sometimes, due to the difficulties encountered during sample collection and preparation, some projects can be prepared employing limited number of tests. To overcome these limitations, some empirical relationships for indirect determination of the collapse index are investigated by Zorlu and Kasapoglu [1]. However, the empirical equations developed by Zorlu and Kasapoglu [1] are based on regression techniques. To determine the collapse index by regression equations requires numerical data. However, the linguistic based fuzzy inference systems can be used by not only numerical data but also linguistic terms such as "low", "high" etc. For this reason, a Mamdani fuzzy inference system to predict the collapse index is developed in the present study. An interesting and perhaps the most attractive characteristic of fuzzy models compared with other conventional methods commonly used in geosciences, such as statistics, is that they are able to describe complex and nonlinear multivariable problems in a transparent way [4]. In literature, commonly two different types of fuzzy inference system are used. These are the Mamdani and the Takagi-Sugeno-Kang algorithms. Among them, particularly the Mamdani algorithm is mostly preferred in engineering geology studies [5]. This algorithm was first developed by Mamdani and Assilian [6] to use in a steam machine control. They put forward their expert opinion on the use of this machine using "if-then" rules. Considering the conventional mathematical techniques, integration of this expert opinion to an indirect model evidently seems to be impossible [5]. Alvarez Grima [5] mentioned that the Mamdani algorithm constitutes one of the most efficient techniques to solve the complex engineering geological problems. The main reason for this evaluation is that the materials studied in engineering geology are commonly natural, and hence they involve a high level of uncertainty. In this study, as the previous studies related to the engineering geology and geology [7-12], the Mamdani fuzzy inference system is considered to introduce a prediction model for the collapse index. The model includes two inputs (the fine content, i and the void ratio, e) and one output (the collapse index, C_p).

For inference in a rule-based fuzzy model, the fuzzy propositions need to be represented by an implication function called a fuzzy if-then rule or a fuzzy conditional statement [5]. A fuzzy set is a collection of paired members consisting of members and degrees of “support” or “confidence” for those members. A linguistic variable whose values are words, phrases or sentences are labels of fuzzy sets [13]. In literature, many methods such as intuition, rank ordering, angular fuzzy sets, genetic algorithms, inductive reasoning, soft partitioning, etc. exist for the membership value assignment [e.g. 14-16]. Although, a fuzzy model is built generally by using expert knowledge in the form of linguistic rules, recently, there is an increasing interest in obtaining fuzzy models from measured data [4]. Designing membership functions is the most difficult, laborious and critical stage of building a fuzzy model, particularly when the available data is limited [5]. In such a case, the best alternative is simply to partition the numerical domain of the fuzzy input/output variables into a specified number equally spaced membership functions [17]. In this study, the fuzzy sets of the membership functions are obtained from the data partition. The type of membership functions used to represent the fuzzy terms of the inputs and the outputs are piecewise triangular membership functions. Before obtaining the membership functions, to provide standardization among the inputs and the outputs, all data is normalized in a close interval of [0, 1] using the following equation:

$$X_{norm} = (X - X_{min})/(X_{max} - X_{min}) \tag{2}$$

Table 2. Linguistic “if-then” rules used in fuzzy inference system

If	Fine content is VL and void ratio is VL	*then*	Collapse potential is VL
If	Fine content is VL and void ratio is L	*then*	Collapse potential is VL
If	Fine content is VL and void ratio is M	*then*	Collapse potential is L
If	Fine content is VL and void ratio is H	*then*	Collapse potential is M
If	Fine content is VL and void ratio is VH	*then*	Collapse potential is H
If	Fine content is L and void ratio is VL	*then*	Collapse potential is VL
If	Fine content is L and void ratio is L	*then*	Collapse potential is L
If	Fine content is L and void ratio is M	*then*	Collapse potential is L
If	Fine content is L and void ratio is H	*then*	Collapse potential is M
If	Fine content is L and void ratio is VH	*then*	Collapse potential is H
If	Fine content is M and void ratio is VL	*then*	Collapse potential is L
If	Fine content is M and void ratio is L	*then*	Collapse potential is L
If	Fine content is M and void ratio is M	*then*	Collapse potential is M
If	Fine content is M and void ratio is H	*then*	Collapse potential is M
If	Fine content is M and void ratio is VH	*then*	Collapse potential is H
If	Fine content is H and void ratio is VL	*then*	Collapse potential is L
If	Fine content is H and void ratio is L	*then*	Collapse potential is M
If	Fine content is H and void ratio is M	*then*	Collapse potential is H
If	Fine content is H and void ratio is H	*then*	Collapse potential is H
If	Fine content is H and void ratio is VH	*then*	Collapse potential is VH
If	Fine content is VH and void ratio is VL	*then*	Collapse potential is M
If	Fine content is VH and void ratio is L	*then*	Collapse potential is M
If	Fine content is VH and void ratio is M	*then*	Collapse potential is H
If	Fine content is VH and void ratio is H	*then*	Collapse potential is VH
If	Fine content is VH and void ratio is VH	*then*	Collapse potential is VH

Where; X_{norm} is the normalized value of the measured variable; X is the measured variable; X_{min} is the minimum value of the measured variable in the data; X_{max} is the maximum value of the measured variable in the data.

The graphs of the membership functions are given in Figure 1. In the fuzzy inference system, a total of 25 linguistic rules are used (Table 2). The control surface of the model is given in Figure 2. In the model, "min" and "max" are employed as "and" and "or", respectively. The final output of the Mamdani fuzzy model is also a fuzzy set. However, numerical values are commonly desired in practice. For this reason, a defuzzification procedure is required. Defuzzification is briefly defined as the transformation of a fuzzy

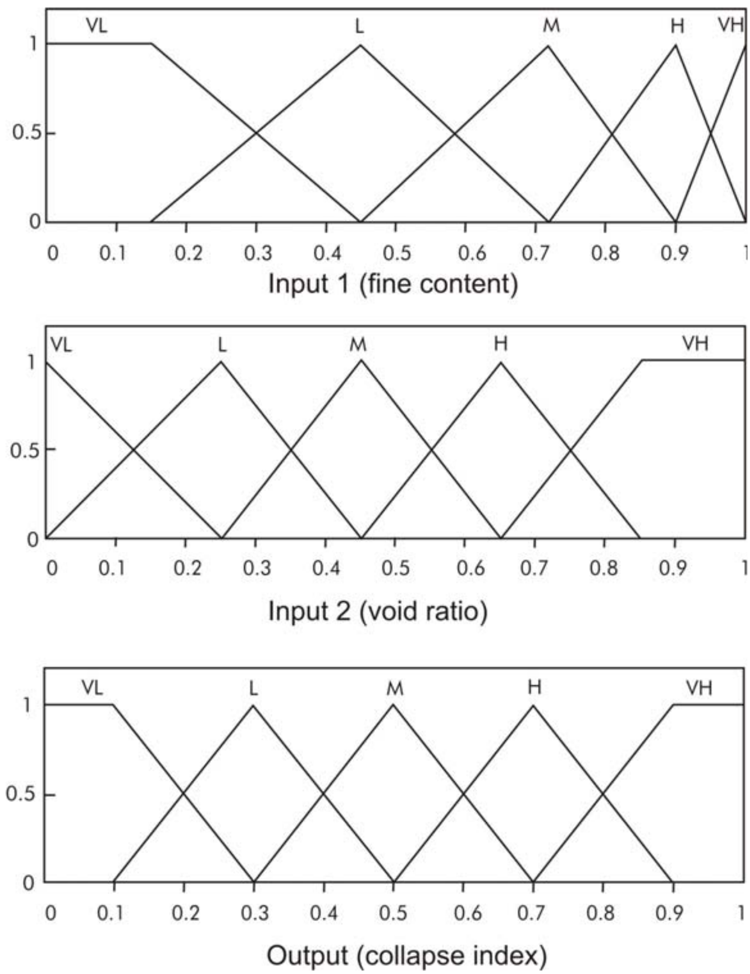

Fig. 1. Input and output fuzzy membership functions

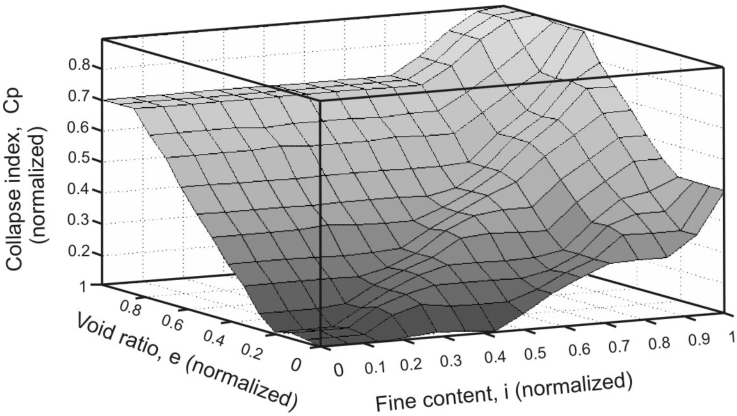

Fig. 2. Control surface of the fuzzy inference system

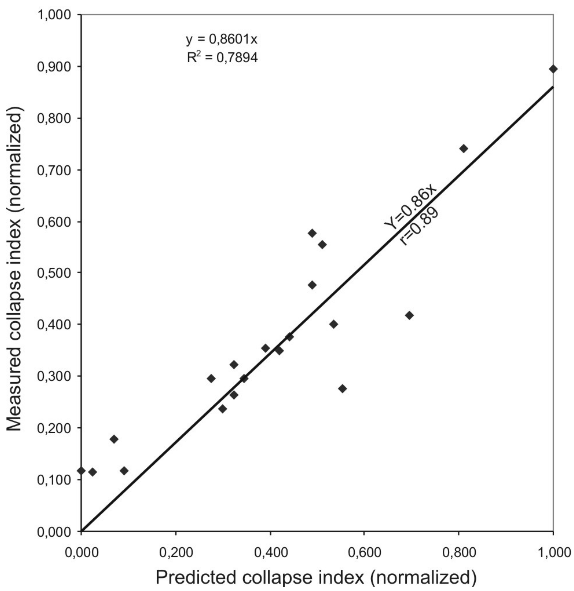

Fig. 3. Graph of cross-correlation between the predicted and the measured collapse indices

set into a numerical value. In literature, many defuzzification methods are proposed [18]. However, the center of gravity (COG) method is mostly preferred among them because the calculation stage is simple and it produces plausible results. By running the FIS constructed for the description of the collapse index, the collapse index of each specimen is predicted. The prediction performance of the constructed model is assessed by some prediction indices such as variance account for (VAF) and root mean square error (RMSE). Theoretically, if VAF and RMSE are equal to 100% and 0 respectively, the model produces excellent results. The VAF and RMSE values for

20 specimens are calculated as 57.2% and 0.11 respectively. The coefficient of cross-correlation between the predicted and the measured collapse potential is obtained as 0.89 (Figure 3).

4 Results and Discussion

The following results and discussions can be drawn from the present study:

Even though its crucial importance for the safety of structures, the direct determination of collapse potential of collapsible grounds is highly difficult. For this reason, indirect determination of such feature is an attractive subject for civil engineers especially. In literature, some limited studies to indirect determination of the collapse index exist. However, these approaches are based on regression techniques. Considering this lack, in the present study, a Mamdani fuzzy inference system is developed. The performance analyses show that the developed inference system has a sufficient prediction capacity for civil engineering projects. Moreover, the fuzzy inference system can be used by employing "if-then" linguistic rules.

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