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Research Article

Fuzzy logic based prediction of retaining wall stability

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ABSTRACT

In geotechnical engineering, retaining walls are widely employed to solve the problem of supporting horizontal loads occurring between two different soil levels. In the traditional retaining wall design, stability checks continue until a safe design is obtained according to selected wall dimensions and soil properties. This design method is a process that is time-consuming and based on trial and error. In this study, the stability control of the retaining wall, which is a complex engineering design, has been carried out with fuzzy logic methods. Adaptive network-based fuzzy inference systems (ANFISs) including Grid Partition (ANFIS-GP) and Substructive Clustering (ANFIS-SC) have been utilized as fuzzy logic methods. The sliding stability criterion of the cantilever retaining wall has been obtained by performing 1024 retaining wall designs which are created using different wall dimensions. Ninety percent and ten percent of the 1024 sliding safety factor values acquired through numerical analyses were respectively allocated to the training and testing phases. The prediction performances of the methods have been evaluated by considering the Root Mean Square Error (*RMSE*), Mean Absolute Error (*MAE*), and Coefficient of Determination (R^2) obtained for the sliding safety factors during the training and testing stages. Upon juxtaposing the actual and anticipated sliding safety factors for a dataset comprising 1024 observations, it has become evident that the ANFIS-SC methodology outperforms the ANFIS-GP approach in terms of predictive accuracy. Furthermore, this analysis culminated in the determination that the application of fuzzy logic methods stands as an efficacious and dependable means for checking the stability criteria of retaining walls.

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1. Introduction

Retaining walls, which are an engineering structure, are mainly employed in developing and expanding cities, on highway and railway transportation lines, in engineering structures such as bridges and roads, in coastal areas, and in irrigation canals. It is constructed as a vertical structural element in places where it is not possible to connect two different floors with a slope (Fig. 1). These structures are of vital importance in order to prevent negative situations that may affect the current structure during the operation process by ensuring the safety of work and worker health and stability, temporary or permanent as soon as the works and productions continue. In this mission, which is assigned to geotechnical engineers, a proactive approach is required to anticipate possible collapse scenarios and to analyze and implement designs that are safe against these scenarios. Lateral soil pressure theories put forward by the researchers are used to understand the natural behavior of the soil and to analyze the collapse scenarios correctly (Das and Sivakugan 2017).

Several parameters are decisive in the formation of lateral soil pressures affecting the retaining structures. These are the behavior of the soil under load, the engineering parameters such as the shear resistance of the soil, the physical properties of the soil, the groundwater condition, the geometry of the retaining structure drainage conditions, and external effects. In the case of transport or movement in the soil environment, stress

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changes and discharges occurring in the force balance of the system in the transport or movement region cause stability problems (Sağlamer 1985).

In geotechnical engineering, retaining structures are used to prevent the negative effects of the abovementioned stability problem. In the conventional stability control of the retaining wall, the repeated trial-and-error method is utilized according to the selected wall pre-sizing until the safe design is achieved. In traditional calculation methods, it is a problem that the designs made by trial and error based on experience take a long time and economic sections cannot be obtained. By making use of information technologies, the design processes can become faster and more reliable, and at the same time, it is possible to reduce the negative situations affecting nature by using the resources correctly by conducting interdisciplinary studies with the developing technology. In general, like all engineering structures, the traditional calculation methods of retaining walls take a long time and increase the workload of geotechnical engineers.

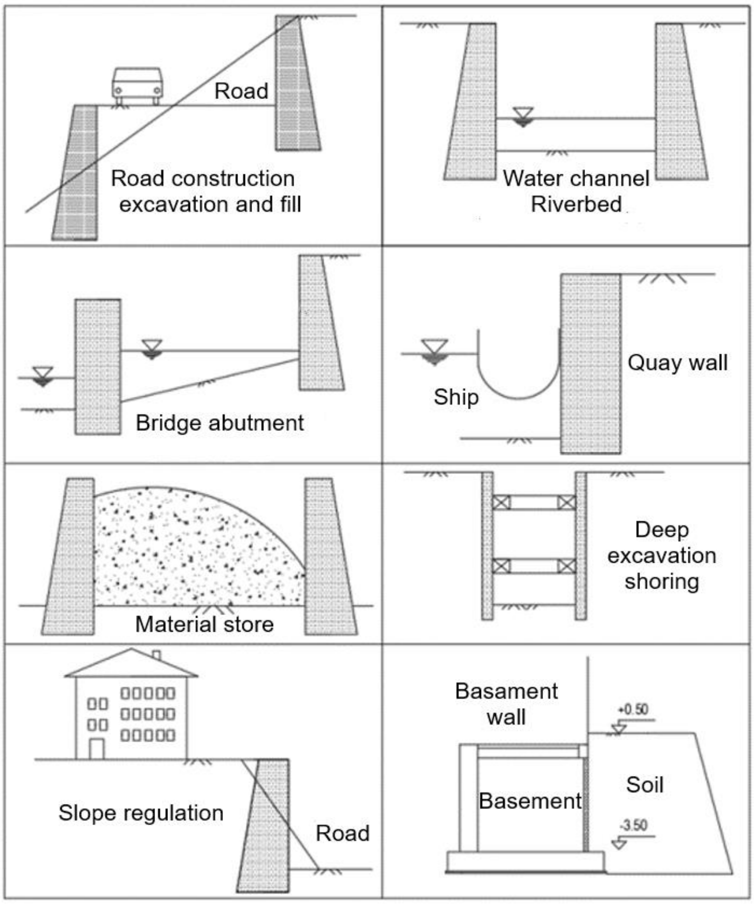

Fig. 1. Retaining structure applications (Uray 2020).

This phenomenon has drawn the attention of many researchers, and with the help of algorithms used for this problem, the processing power of computers has been emphasized and it has been stated that it is possible to obtain safe and fast results with multidisciplinary studies (Binici and Öztürk 2019; Uray et. al 2021, 2022). In addition, there are many studies in the literature on the variation of analysis results under different soil conditions and other variables in retaining wall design (Arama et al. 2020; Arslan et al. 2018; Dağdeviren and Kaymak 2018; Gandomi et al. 2015; Uray et al. 2019a; Yepes et al. 2008). Studies with methodologies such as the use of artificial neural networks, the use of heuristic optimization methods, the use of various optimization algorithms, and the realization of predictions with machine learning are included in the literature (Shahin et al. 2009; Manjunath et al. 2012; Önalp and Arel 2012; Gokkus et al. 2018; Uray et al. 2019b; Seyhan 2021; Mishra et al. 2021; Mustafa et al. 2022). Çıtakoğlu and Coşkun (2021) made predictions for the future by using the monthly total precipitation data between the years 1990–2015. They made the prediction model using traditional ANN and ANFIS, followed by wavelet transform ANN and wavelet transform ANFIS. The prediction performances of these models were evaluated according to statistical criteria. Predictions made using ANN and ANFIS methods did not yield the desired result. According to the coefficient of determination, Wavelet transform ANN (DD–ANFIS) and wavelet transform ANFIS (DD–ANFIS) models were found to be more successful in predicting future precipitation data (Citakoglu and Coskun 2021). Citakoglu et al. (2014) created a monthly average evaporation model using ANN and ANFIS models. Various combinations of long-term average monthly climate data such as wind speed, air temperature, relative humidity and solar radiation were used as input parameters in the models. It was observed that the ANFIS and ANN model gave more successful results compared to the results compared with the classical method (Citakoglu et al. 2014). Başakın et al. (2022) analyzed the monthly wind speed time series of Kırşehir province using independent, hybrid and ensemble models. Artificial neural networks, Gaussian process regression, support vector machines and multivariate adaptive regression lines are used as stand-alone machine learning models, while discrete wavelet transform is used as a preprocessing technique to create hybrid models. The results revealed that hybrid wavelet models outperform independent models (Başakın et al. 2022).

In the engineering discipline, effective, economical, and aesthetic design is essential, as well as minimizing the negative situations affecting nature by acting with the principle of sustainability. Providing a state of safety with economic sections is beneficial in this regard. In this study, the prediction of the sliding safety factor of the cantilever retaining wall against sliding was investigated employing two different fuzzy logic methods. The performance of the methods was examined by statistically evaluating the predicted sliding safety factor.

2. Method

2.1. Cantilever retaining wall

In the traditional solution method of the retaining structures, the preliminary design given in Fig. 2 may be started with the ratios specified in the regulations and standards. The wall size recommendations given in Fig. 2 are in the nature of a preliminary design guide taken into account in the trial-and-error method (ACI 318R-05 2005; TS 7994 1990).

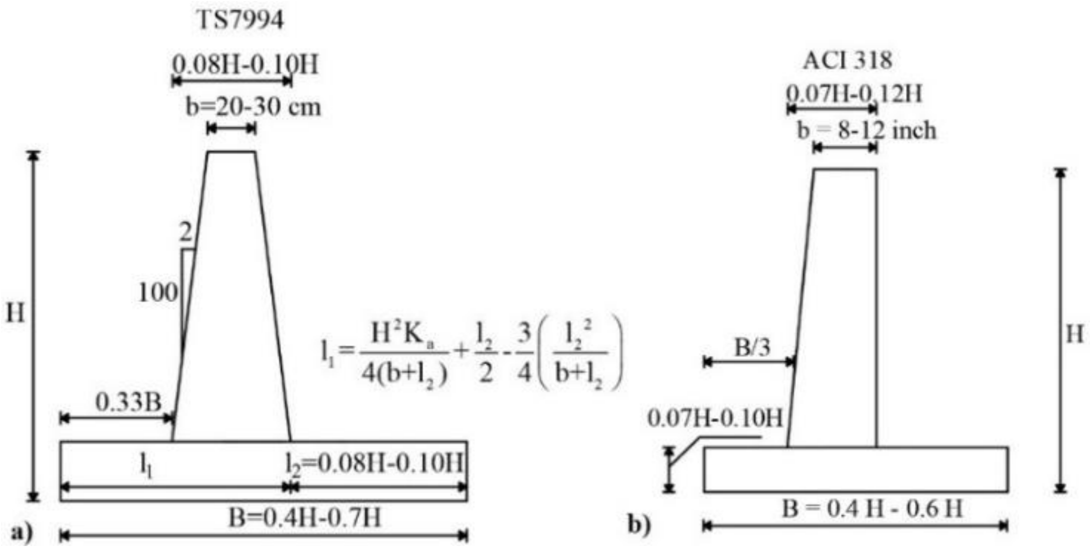

Fig. 2. Cantilever retaining wall preliminary design guides (Uray et al. 2021).

After pre-sizing the retaining wall design, investigations are made against sliding, overturning, bearing capacity, and slope stability, and the safety factors (F_s) are determined. In cases where the safety factor is not sufficient (F_s <1.50), the designer repeats the operations until it is satisfied (Das and Sivakugan 2017). The sliding behavior of the retaining wall, which is effective in determining the sliding safety factor considered in this study, is shown in Fig. 3.

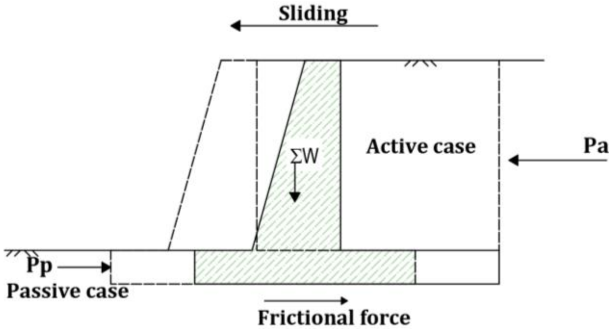

Fig. 3. Sliding behavior in retaining wall (Uray 2020).

The stability criteria of the cantilever retaining wall should be checked by considering soil properties obtained from the results of experiments and examinations conducted in the field and laboratory and design geometry. First of all, the lateral soil pressures affecting the retaining structure should be calculated by the designer with the theories in the literature. In this study, the lateral soil pressures considered in determining the sliding safety factor were determined according to the Rankine theory (Rankine 1857). In Rankine theory, calculations are made by regarding the stresses that occur when a soil medium reaches a state of plastic equilibrium. In elastic equilibrium, the soil is at rest; in the plastic case, it is in the case of active and passive thrust. For these three cases, the lateral soil pressures (σ_0, σ_a, σ_p) affecting the retaining structure can be calculated by multiplying the vertical stress (σ_v) with the coefficients of earth pressure at rest (K_0), active earth pressure (K_a), and passive earth pressure (K_p) given by Eqs. (1)–(3) (Orhan 2020), respectively.

$$K_0 = 1 - \sin\phi, \sigma_0 = K_0 \sigma_v \quad \text{(at rest)} \tag{1}$$

$$K_a = \cos\beta \frac{\cos\beta - \sqrt{(\cos\beta)^2 - (\cos\phi_{fs})^2}}{\cos\beta + \sqrt{(\cos\beta)^2 - (\cos\phi_{fs})^2}}, \sigma_a = K_a \sigma_v \quad \text{(active case)} \tag{2}$$

$$K_p = \tan^2\left(45 + \frac{\phi}{2}\right), \sigma_p = K_p \sigma_v \quad \text{(passive case)} \tag{3}$$

There, ϕ corresponds to the internal friction angle of the soil from which the horizontal soil thrust is determined, and β corresponds to the slope of the soil.

In this study, the design variables of cantilever retaining wall are top stem thickness (X_1), toe extension (X_2), bottom stem thickness (X_3), heel extension (X_4), base thickness (X_5) and they demonstrated in Fig. 4.

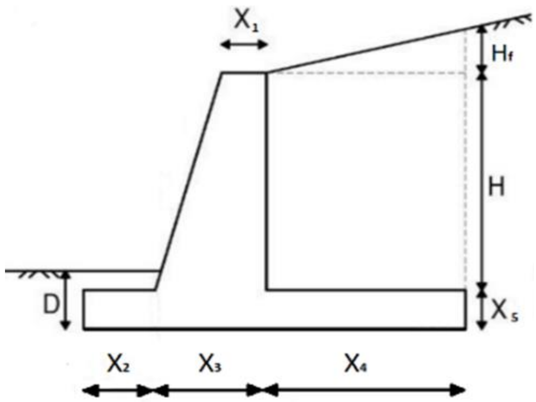

Fig. 4. Cantilever retaining wall design.

In the stability of the retaining wall against sliding, there is a balance between the sliding forces and the forces resisting sliding. A collapse scenario occurs when the forces resisting the slide are defeated. Since it is desired to stay on the safe side in the analysis, the ratio of the forces resisting slip (F_{sr}) given in Eq. (4) to the sliding forces (F_{sw}) given in Eq. (5) is defined as the sliding safety factor (F_{ss}) (Fig. 5). The mathematical expression of the sliding safety factor (F_{ss}) is given by Eq. (6).

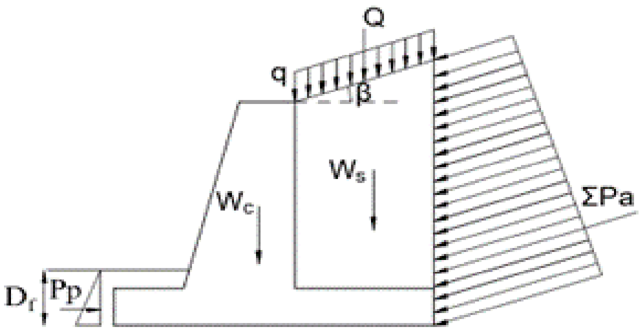

Fig. 5. Loads acting on the retaining wall.

$$F_{sr} = \Sigma V \tan\left(\frac{2}{3}\phi_{fb}\right) + \frac{2}{3} c_{fb}(X_2 + X_3 + X_4) + P_p$$

$$\Sigma V = W_c + W_s + Q + \Sigma P_{ay} \tag{4}$$

$$F_{sw} = \Sigma P_{ax} \tag{5}$$

$$F_{ss} = \frac{F_{sr}}{F_{sw}} \quad (F_{sw} = \Sigma P_{ax}) \tag{6}$$

W_c and W_s are the weight of the wall and the weight of the backfill soil above the heel extension, respectively. The active lateral soil force (P_a) formed by the soil supported by the retaining wall and the passive lateral soil force (P_p) formed along the base depth at the front of the wall are given by Eqs. (7) and (8), respectively.

$$P_a = 0.5 K_a \gamma_{bs} (X_4 \tan\beta + H + X_5)^2$$

$$P_{ax} = P_a \cos\beta, \;\; P_{ay} = P_a \sin\beta \tag{7}$$

$$P_p = 0.5 K_p \gamma_{fs} {D_f}^2 + 2 c_{fs} \sqrt{K_p} D_f \tag{8}$$

In this study, the sliding safety factors of the cantilever retaining wall was determined by taking into account the mathematical expressions and the geotechnical and slope properties of the soil environment given in Table 1.

Table 1. Cantilever bearing wall design parameters.

Parameter	Symbol	Value	Unit
Wall stem height	H	6	m
Surcharge load	q	0	kPa
Backfill slope	β	10	°
Internal friction angle of backfill soil and base soil	ϕ_{fs} and ϕ_{bs}	30	°
Unit weight of backfill soil and base soil	γ_{bs} and γ_{fs}	18	kN/m³
Friction angle between foundation base and soil	δ	2/3 ϕ_{bs}	°
Cohesion of backfill soil and base soil	c_{bs} and c_{fs}	0	kPa
Foundation depth	D_f	X_5	m

2.2. Fuzzy logic methods

In this section, data set, fuzzy logic methods, and evaluation criteria were given with implementation details of models for predicting the sliding safety factor (F_{ss}) of cantilever retaining wall. A data set consisting of 1024 different wall designs was prepared for the prediction of F_{ss} of the cantilever retaining wall. In the preparation of the data set, the design variables given in Fig. 4 were considered. 1024 (4^5) different wall designs (combinations) including all values of 5 design variables and 4 different values given in Table 2 were created. By utilizing safety factor dataset of these designs, the sliding safety factors were predicted by fuzzy logic methods.

Table 2. Cantilever retaining wall design parameters.

X_1 (m)	X_2 (m)	X_3 (m)	X_4 (m)	X_5 (m)
0.30	0.50	0.30	0.50	0.50
0.35	1.50	0.35	1.50	0.75
0.40	2.50	0.40	2.50	1.00
0.45	3.50	0.45	3.50	1.25

In prediction analysis, 1024 data set was randomly sorted and 922 (90%) and 102 (10%) of them were used as training and as test data, respectively. In the analyzes, two different iterations were tried and the effect of iteration on the modeling was also examined. The iterations used are ten (10) and one hundred (100). Looking at the correlation relationship between the inputs and F_{ss}; it is seen that they are 0.031 with X_1, 0.179 with X_2, 0.405 with X_3, 0.980 with X_4, and 0.005 with X_5.

Root Mean Square Error (*RMSE*), Mean Absolute Error (*MAE*) and Coefficient of Determination (R^2) were used as evaluation criteria. *RMSE*, *MAE*, and R^2 evaluation criteria are given in Eqs. (9)–(11), respectively.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(F_{ss_e} - F_{ss_o}\right)^2} \tag{9}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|F_{ss_e} - F_{ss_o}\right| \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(\sum F_{ss_o} - F_{ss_e}\right)^2}{\sum_{i=1}^{N}\left(\sum F_{ss_o} - \bar{F}_{ss_e}\right)^2} \tag{11}$$

In formulas, F_{ss_o}, F_{ss_e}, and N correspond to the observed F_{ss} value, pedicted F_{ss} value, and the number of data, respectively.

In Fig. 6, the implementation of ANFIS-GP and ANFIS-SC models for predicting F_{ss} are demonstrated.

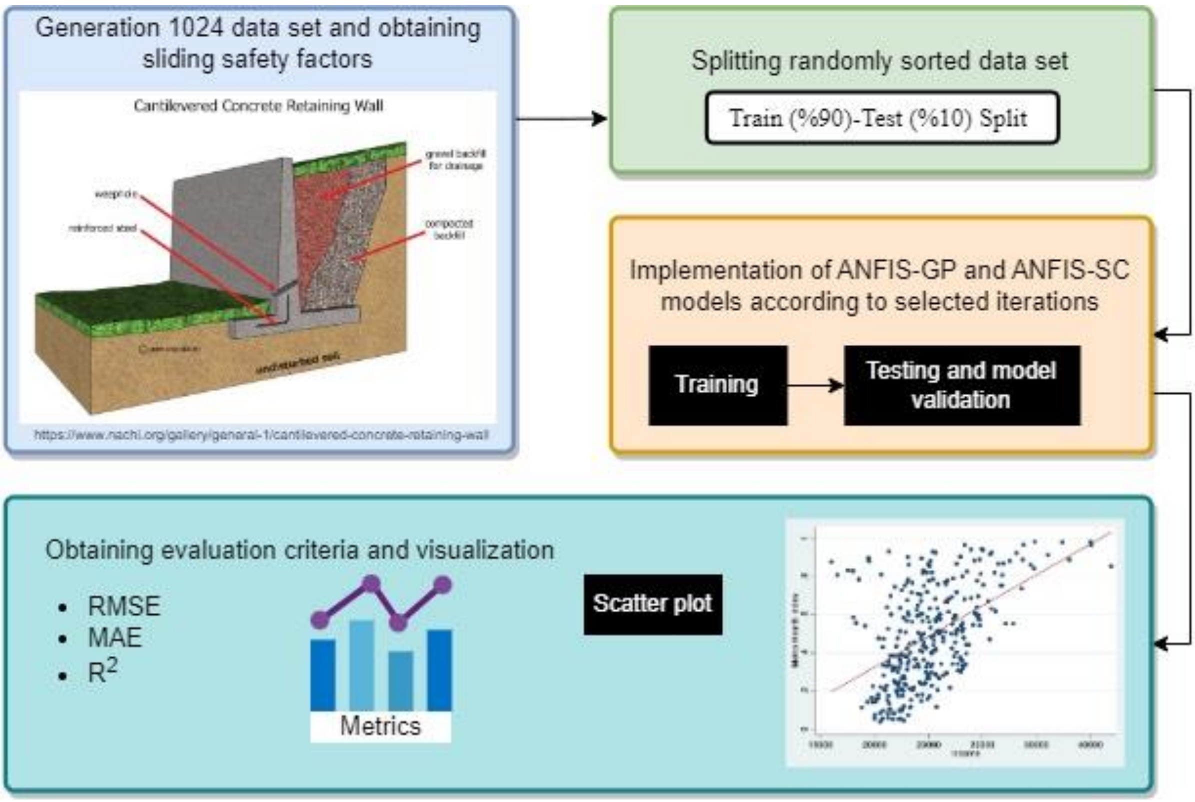

Fig. 6. Fuzzy logic based prediction of retaining wall stability.

Table 3 contains the inputs used in the study and the corresponding datasets.

Table 3. Inputs and datasets used in the study.

Inputs	Data Sets
1 input	X_1
2 input	$X_1 + X_2$
3 input	$X_1 + X_2 + X_3$
4 input	$X_1 + X_2 + X_3 + X_4$
5 input	$X_1 + X_2 + X_3 + X_4 + X_5$

2.2.1. Grid partition (GP)

When the GP fuzzy inference system is desired to be used, the learning of the model is basically based on the grid partitioning method. The Grid Partition method divides the data set into rectangular sub-areas, called grids, according to the previously determined number and types of membership functions to be used. In the subspace, each input is divided into membership functions of identical shape. The system creates fuzzy rules based on input-output training, optimizing data providing fast learning processes and computation time. When using this model; Membership functions of all antecedent variables can be defined. The basic logic of the system is to create rules by calculating all combinations of membership functions for the input variables to be used in the model to be created (Benmouiza and Cheknane 2019; Fattahi 2016; Hekim and Orhan 2011; Kaya 2018).

2.2.2. Substructive clustering (SC)

SC is applied when there is no clear idea about the number of centers for the distribution of data. It is one of the fuzzy clustering methods. It is similar to Mountain Clustering proposed by Yager and Filev (1994). However, since the grid is not used, the number of possible cluster centers depends only on the number of data, not on the dimensionality or distribution of the data (Yager and Filey 1994). The data point with the largest number of close neighbors is chosen as the cluster center. It positions other data points accordingly, where each point is a potential cluster center based on its own characteristics. It continues like this until the end. In this method, which is a good approach especially since it is independent of the initial condition, cluster centers are not determined except for data points. Therefore, the detected cluster centers may not be suitable for every data space (Fattahi 2016; Hekim and Orhan 2011; Kaya 2018; Priyono et al. 2005).

3. Findings and Discussion

Tables 4 and 5 show the test results of the models performed for 10 and 100 iterations using the GP and SC methods. In Figs. 7–10, the scatter plots prepared for each input set in 10 and 100 iterations of the GP and SC methods are given. Charts show observations and predictions of test data. In addition, the regression line and equation of the best-performing model in the form of $y=ax+b$ and the coefficient of determination are given in the figures.

Table 4. Test results using 10 iterations.

Criteria	Algorithm	Inputs (10 iteration, test)					
		1 input	2 input	3 input	4 input	5 input	Avr.
RMSE	GP	0.324	0.319	0.321	0.016	0.004	0.197
	SC	0.324	0.322	0.331	0.017	0.001	0.199
	Avr.	0.324	0.320	0.326	0.016	0.002	0.198
MAE	GP	0.289	0.286	0.287	0.011	0.004	0.175
	SC	0.289	0.289	0.298	0.011	0.002	0.178
	Avr.	0.289	0.287	0.292	0.011	0.003	0.177
R^2	GP	0.001	0.026	0.015	0.998	0.999	0.408
	SC	0.007	0.011	0.002	0.997	0.999	0.403
	Avr.	0.004	0.018	0.009	0.997	0.999	0.406

Table 5. Test results using 100 iterations.

Criteria	Algorithm	Inputs (100 iteration, test)					
		1 input	2 input	3 input	4 input	5 input	Avr.
RMSE	GP	0.324	0.319	0.322	0.016	0.003	0.197
	SC	0.324	0.323	0.333	0.018	0.003	0.200
	Avr.	0.324	0.321	0.327	0.017	0.003	0.198
MAE	GP	0.289	0.287	0.289	0.011	0.002	0.175
	SC	0.289	0.290	0.299	0.012	0.002	0.178
	Avr.	0.289	0.288	0.294	0.011	0.002	0.177
R^2	GP	0.001	0.025	0.012	0.998	0.999	0.407
	SC	0.007	0.007	0.004	0.997	0.999	0.403
	Avr.	0.004	0.016	0.008	0.997	0.999	0.405

In the study conducted by Uray et al. (2019b), prediction models that provide sliding, overturning, and slope stability safety factors by using Multilayer Artificial Neural Networks, Generalized Regression Artificial Neural Networks, and Radial Based Artificial Neural Networks were submitted. According to the study, the model developed with Artificial Neural Networks can be used reliably in predictions of safety factors of the cantilever retaining wall. On the other hand, the prediction models of sliding, overturning, and slope stability safety factors were obtained by utilizing machine learning algorithms for cantilever retaining walls and creating a mathematical model based on regression that provides to calculation of the safety factors (Seyhan 2021). Looking at the results; observed that the correlation coefficient value is quite close to one. Thus, it has been revealed that the obtained mathematical model can be an important and practical solution for finding the value of safety factors in retaining structures.

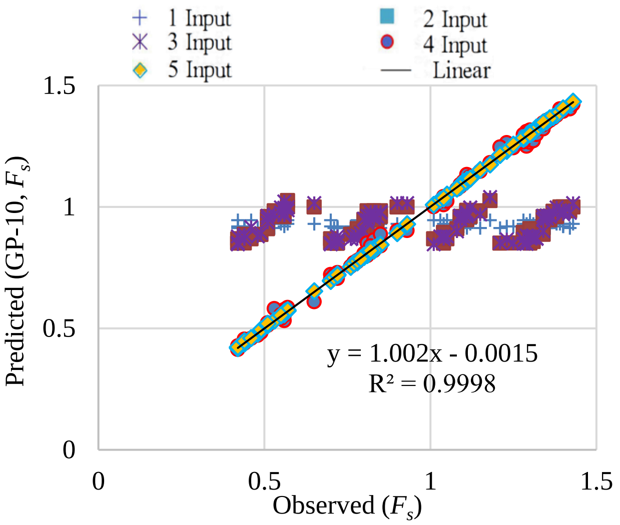

Fig. 7. Scatter plot for 10 iterations of the GP method.

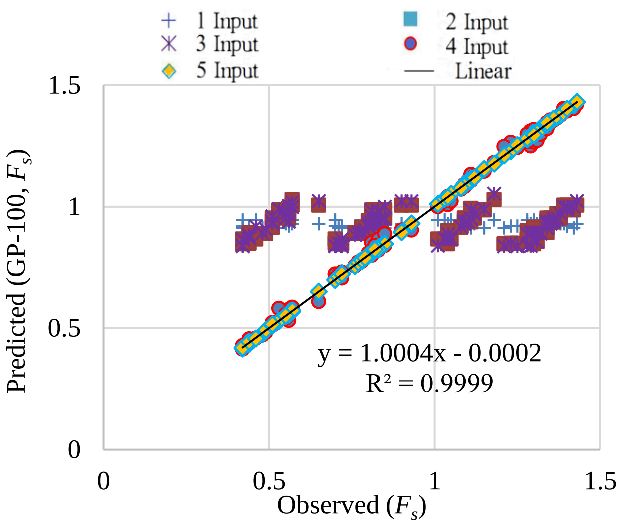

Fig. 8. Scatter plot for 100 iterations of the GP method.

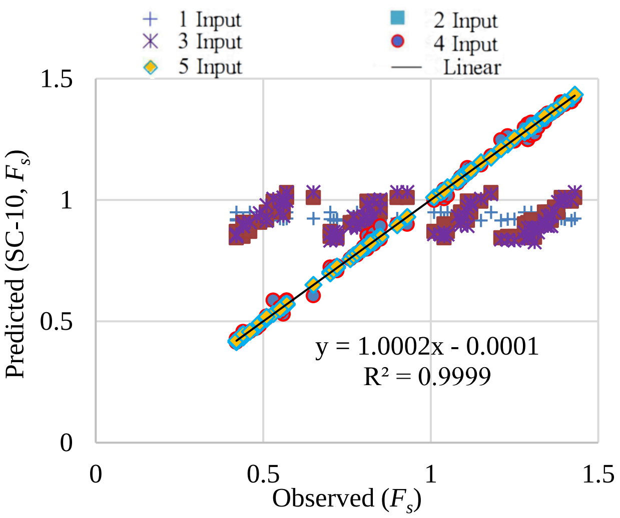

Fig. 9. Scatter plot for 10 iterations of SC method.

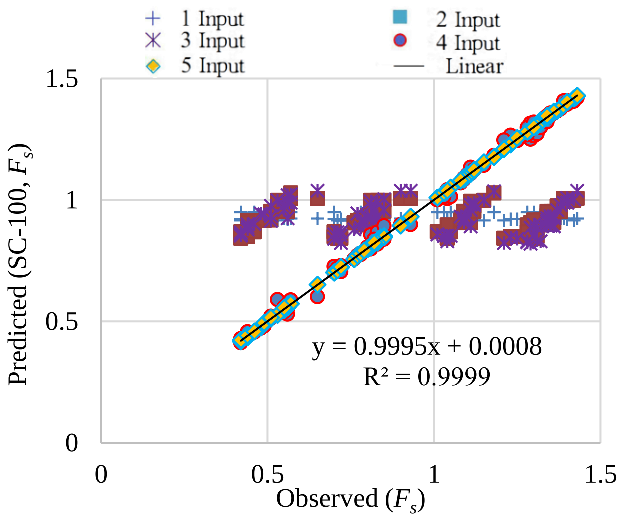

Fig. 10. Scatter plot of SC method for 100 iterations.

4. Conclusions

In this study, the prediction of retaining wall stability control was investigated using an adaptive network-based fuzzy inference system including ANFIS-GP and ANFIS-SC. In the study; A data set containing 1024 (4^5) different wall designs was created by considering four wall dimensions including stem thickness (X_1), toe extension (X_2), bottom stem thickness (X_3), heel extension (X_4), base thickness (X_5). Randomly selected 90% of these data were used in the training phase and the remaining 10% were used in the testing phase. In addition, two models were created by changing the number of iterations to 10 and 100. Models were compared using three different error criteria (*RMSE*, *MAE*, and R^2). When the results are examined;

- Since the best result is for ANFIS-SC with *MAE*= 0.002 *RMSE*=0.001, R^2= 0.999 for 10 iterations and 5 inputs, the ANFIS-SC method is more prosperous than the ANFIS-GP method in predicting safety factors.
- It has been determined that the errors are further reduced by including the 4th and 5th inputs in the models.
- It has been observed that the performance values obtained in the 1st, 2nd, and 3rd input sets of both methods are quite low (errors are high and the coefficient of determination is close to zero) and the predictions do not represent the observed values.
- The relationship between the input parameters employed in the models and the predicted sliding safety factors is consistent with the modeling performance. In other words, it was determined that the errors were less in the inputs with a high correlation coefficient.

- It has been inferred that the model with 100 iterations takes longer in different iteration applications and gives predictions with fewer errors.
- As a result, in this study, the sliding safety factors predicted by considering 1024 different wall designs were used and the success of the fuzzy logic methods in prediction was compared.
- When the evaluation criteria obtained are examined, it has been shown that fuzzy logic-based prediction methods can be used robustly and effectively in complex engineering design problems.

Author Contributions

All of the authors made substantial contributions to conception and design, or acquisition of data, or analysis and interpretation of data; were involved in drafting the manuscript or revising it critically for important intellectual content; and gave final approval of the version to be published.

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Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this manuscript.

Data Availability

The datasets created and/or analyzed during the current study are not publicly available, but are available from the corresponding author upon reasonable request.

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