



The Effect of Geopolymerization on the Unconfined Compressive Strength of Stabilized Fine-grained Soils

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ABSTRACT

This study focuses on evaluating the unconfined compressive strength (UCS) of improved fine-grained soils. A large database of unconfined compressive strength of clayey soil specimens stabilized with fly ash and blast furnace slag based geopolymer were collected and analyzed. Subsequently, using adaptive neuro fuzzy inference system (ANFIS), a model has been developed to assess the UCS of stabilized fine-grained soils. Types of additives and their compositions as well as soil characteristics were considered as the most important parameters affecting the resistance of stabilized soil. Subsequently, the accuracy of the proposed model was examined. Finally, a parametric study was conducted to investigate the performance of the proposed model and also the effect of each influential parameter on the unconfined compressive strength (UCS) of amended soil specimens. The results demonstrate that the ANFIS-based model, which was developed based on experimental results, can be successfully applied for assessment of unconfined compressive strength of stabilized fine-grained soils.

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1. INTRODUCTION

Weak soils are encountered in many regions, which lack adequate stiffness and strength to resist the loading due to construction projects. Soil improvement is a technique for amendment of these geomaterials [1-3]. Two common methods of soil improvement include mechanical [4, 5] and chemical [6-9] stabilization. Commonly mechanical procedures include compaction and earth reinforcement [10-13].

In recent years, treatment with geopolymer as a chemical stabilization technique has been widely investigated to earth improvement (e.g., [14-16]). Many experimental studies were conducted on the behavior of soils stabilized with geopolymers (e.g., [17-20]). Their results indicated that employing geopolymers improved the resistance behavior of stabilized soils.

Assessing strength of stabilized soils [21-24] is an essential subject in preliminary design of structures on improved deposits. Therefore, an accurate model is required to evaluate strength of stabilized soils.

Soft computing approach have been successfully utilized as a robust procedure to analyze and solve various geotechnical engineering problems such as dynamic properties of soils [25-28], soil liquefaction [29, 30], soil water content [31], modeling behavior of clayey soil [32], improved soils [33-35] ground motions due to earthquakes [36], nitrate concentration in groundwater [37]. Therefore, the soft computing methodology can be successfully employed in prediction of behavior of chemical stabilized soils.

In the present research, comprehensive experimental results of unconfined compressive strength (UCS) of geopolymer stabilized fine-grained soil specimens were gathered and analyzed.

Based on the most important parameters that affect unconfined compressive strength (UCS) of stabilized soils, a model was developed to predict UCS using adaptive neuro fuzzy inference system (ANFIS). The precision of developed ANFIS-based model was investigated. Finally, parametric study was performed to assess I) performance of the proposed UCS model, and II) the effect of each parameter on the USC of stabilized fine-grained soils.

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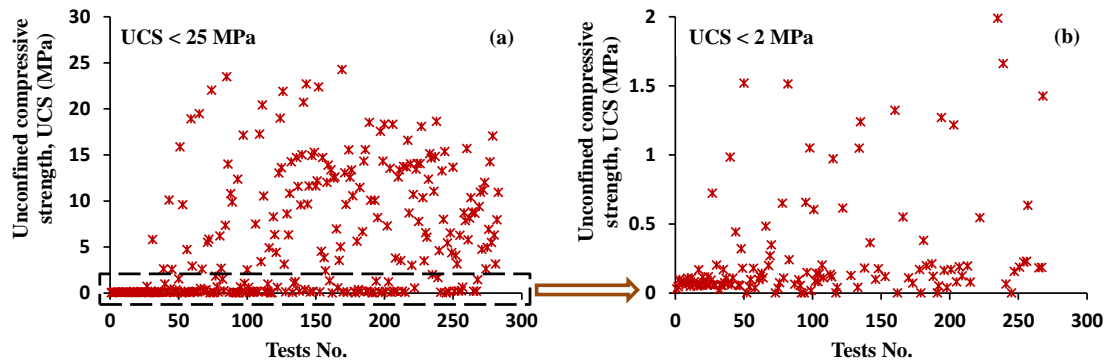


Figure 1. Compiled experimental data of fine-grained soils stabilized with geopolymer, a) all data, b) zoomed view for UCS<2MPa

2. LABORATORY DATA

A large experimental database was gathered from the comprehensive laboratory study conducted by Mozumder and Laskar [18]. They investigated the unconfined compressive strength of three cohesive soils stabilized by geopolymer. The 28 days UCS (unconfined compressive strength) of the amended soil samples was determined based on the IS: 2720.

The UCS is the load per unit area at which an unconfined specimen of soil will fail in the axial compression test. The tested fine-grained soils classified as clay of high plasticity (CH) and clay of low plasticity (CL) based on the unified soil classification system (USCS) (ASTM D2487).

TABLE 1. Inputs and output parameters used in this study

Type	Parameter
Inputs	
Liquid limit	LL
Plasticity index	PI
Fly ash	FA
Blast furnace slag	S
Molar concentration of alkali solution	M
Alkali to binder ratio	A/B
Atomic ratio of Na to Al	Na/Al
Atomic ratio of Si to Al	Si/Al
Output	
Unconfined compressive strength	UCS

The mean values of liquid limit, plastic limit, plasticity index, grain size at 10% passing, and grain size at 50% passing of the tested soils were 78.7, 25.7, 53%, 0.020mm and 0.021mm, respectively.

The blast furnace slag (S) and fly ash (FA) based geopolymer were used for stabilization of fine-grained soils [18]. The S and FA additives had a specific surface area of 800 m²/kg and 300 m²/kg, respectively. The UCS experimental data points gathered for geopolymer stabilized fine-grained soils are shown in Figure 1.

The influential parameters on the unconfined compressive strength (UCS) are considered as inputs parameters. Inputs and output parameters utilized in the present study are presented in Table 1. Statistical index of all experimental results used to develop UCS model are introduced in Table 2. The gathered experimental data was separated into two sets namely training set and testing set including 75 and 25% of tests results, respectively. The datasets for the training and testing stages were chosen so that the statistical criteria (i.e., minimum, maximum, standard deviation, and average) of both sets remained close to each other.

3. ADAPTIVE NEURO FUZZY SESTEM

Adaptive neuro fuzzy inference system (ANFIS) is a robust method to analyze the complex issues and predict the behavior nonlinear problems [27]. This system is a feed-forward multi-layer network that each node conducts an operation on input information [31, 38, 39].

TABLE 2. Laboratory data of stabilized fine-grained soils used in the model development

Index	Inputs								Output
	LL	PI	S (%)	FA (%)	M	A/B	Na/Al	Si/Al	UCS (MPa)
Minimum	37.7	14.1	0	0	4	0.45	0.24	1.49	0
Maximum	116	88.5	50	20	15	0.85	1.98	2.49	24.3
Average	63.8	38.8	15.9	2.1	12.4	0.62	1.17	1.70	5.8
Standard deviation	32.3	30.7	12.9	4.7	2.7	0.14	0.44	0.35	6.5

The structure of ANFIS as a combination of artificial neural network [40] and fuzzy systems [41-43] can be presented in 5 layers as following (for example, for two inputs):

I) All nodes in the layer are adaptive nodes. In this layer, the values of membership functions are calculated for inputs. The outputs (O_i) of this layer are:

$$O_{A_i}^1 = \rho_{A_i}(\ln_1), i = 1, 2 \tag{1}$$

$$O_{B_i}^1 = \rho_{B_i}(\ln_2), i = 1, 2 \tag{2}$$

where, \ln_1 and \ln_2 are input parameter to nodes i and j , and ρ_{A_i} and ρ_{B_i} are membership functions related to inputs that, for example, can be calculated using bell-shaped membership function as Equations (3) and (4):

$$\rho_{A_i}(\ln_1) = \frac{1}{1 + \left| \frac{\ln_1 - a_i}{b_i} \right|^{2c_i}}, i = 1, 2 \tag{3}$$

$$\rho_{B_j}(\ln_2) = \frac{1}{1 + \left| \frac{\ln_2 - a_j}{b_j} \right|^{2c_j}}, j = 1, 2 \tag{4}$$

where, parameters a , b and c are the coefficients that can alter the shape of function.

II) In this layer, the nodes represent the simple multiplication. The outputs of this layer are expressed as Equation (5):

$$O_{ij}^2 = w_{ij} = \rho_{A_i}(\ln_1) \times \rho_{B_j}(\ln_2), i, j = 1, 2 \tag{5}$$

where, w_{ij} are the weights for the next layer.

III) The outputs of this layer are expressed as normalized form:

$$O_{ij}^3 = \bar{w}_{ij} = \frac{w_{ij}}{\sum_{i=1}^2 \sum_{j=1}^2 w_{ij}}, i, j = 1, 2 \tag{6}$$

the \bar{w}_{ij} are the normalized weights.

IV) The nodes of these layers are adaptive nodes with output as Equation (7):

$$O_{ij}^4 = \bar{w}_{ij} g_{ij} = \bar{w}_{ij} (r_{ij} \ln_1 + s_{ij} \ln_2 + t_{ij}), i, j = 1, 2 \tag{7}$$

where, \bar{w}_{ij} are the normalized weights from the 3rd layer and r_{ij} , s_{ij} and t_{ij} are the node's parameters.

V) The single node of this layer calculates general output as summation of inputs information from the previous layers:

$$\begin{aligned} Output &= O_{ij}^5 = \sum_{i=1}^2 \sum_{j=1}^2 \bar{w}_{ij} g_{ij} \\ &= \sum_{i=1}^2 \sum_{j=1}^2 \bar{w}_{ij} (r_{ij} \ln_1 + s_{ij} \ln_2 + t_{ij}) \end{aligned} \tag{8}$$

The learning algorithm for ANFIS is a combination of the least squares method and gradient descent. In the learning process of this hybrid algorithm, node outputs go forward until layer 4 and the consequent parameters are identified by the least squares method [27, 40, 42]. In the next step, the errors propagate backwards and the premise parameters are adjusted by gradient descent. The main advantage of the hybrid method is that it converges much faster since it reduces the search space dimensions of the back propagation method used in neural networks.

In this study, two Gaussian membership functions were defined for each input. The parameters of these functions were determined using the neural networks. The total numbers of applied fuzzy rules are 3. The model development was done using MATLAB program.

4. EVALUATING MODEL PERFORMANCE

Correlation coefficient (R), mean absolute percentage of error (MAPE), root mean square error (RMSE), Bias, and scatter index (SI) were employed to assess precision of developed models according to Equations (9) to (13):

$$R = \frac{\sum_{i=1}^N [Y_{i(m)} - \bar{Y}(m)] [Y_{i(p)} - \bar{Y}(p)]}{\sqrt{\sum_{i=1}^N [Y_{i(m)} - \bar{Y}(m)]^2 \cdot \sum_{i=1}^N [Y_{i(p)} - \bar{Y}(p)]^2}} \tag{9}$$

$$MAPE = \frac{1}{N} \left[\frac{\sum_{i=1}^N |Y_{i(p)} - Y_{i(m)}|}{\sum_{i=1}^N Y_{i(m)}} \times 100 \right] \tag{10}$$

$$RMSE = \left\{ \frac{\sum_{i=1}^N [Y_{i(p)} - Y_{i(m)}]^2}{N} \right\}^{1/2} \tag{11}$$

$$Bias = \frac{\sum_{i=1}^N [Y_{i(p)} - Y_{i(m)}]}{N} \tag{12}$$

$$SI = \frac{RMSE}{(1/N) \sum_{i=1}^N Y_{i(m)}} \tag{13}$$

where, $Y_{i(m)}$ is the measured value (laboratory result), $Y_{i(p)}$ is the predicted value (model output), $\bar{Y}(m)$ is the average of measured values, $\bar{Y}(p)$ is the average of predicted values, and N is the number of data.

5. RESULTS AND DISCUSSIONS

In the current research, several runs with different initial factors were carried out and the performance of the

developed models was assessed. Eventually, the most precise model was chosen on the basis of statistical parameters such as R, RMSE, MAPE, Bias and SI.

Precision of the developed ANFIS-based model is evaluated by comparison of the measured unconfined compressive strength (UCS) and predicted values of UCS for training and testing sets as depicted in Figures 2 and 3, respectively. It is noteworthy that the UCS results were sorted from small to large amounts to better describe the precision of developed model in various ranges of UCS. As shown in Figures 2 and 3, the ANFIS-based model's accuracy decreases with increasing unconfined compressive strength of stabilized fine-grained soils.

The values of R, MAPE, RMSE, Bias, and SI are equal to 0.931, 2.518, 1.012, 0.144, and 0.191, respectively, for training datasets (Figure 2) and 0.914, 2.836, 1.103, 0.153, and 0.205 respectively, for testing datasets (Figure 3). In reality, the developed UCS model has enough precision for both testing set and testing set. The values of statistical parameters for developed unconfined compressive strength model for training, testing, and all data are presented in Table 3.

For more evaluation of the model's accuracy in estimating UCS, the residuals (i.e., the differences between measured values and predicted ones) were calculated.

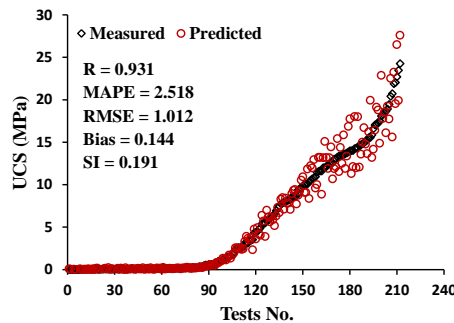


Figure 2. Measured amounts of unconfined compressive strength against those predicted by developed UCS model for training datasets

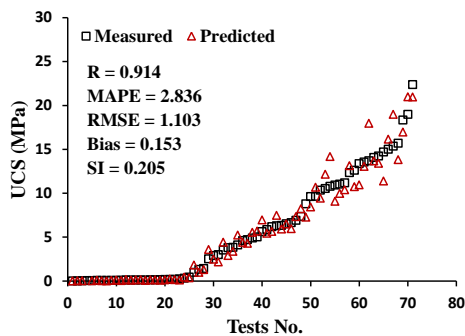


Figure 3. Measured amounts of unconfined compressive strength against those predicted by developed UCS model for testing datasets

TABLE 3. Results of evaluation of model performance in various stages

Group	Model Performance				
	R	MAPE	RMSE	Bias	SI
Training stage	0.931	2.518	1.012	0.144	0.191
Testing stage	0.914	2.836	1.103	0.153	0.205
All experimental tests data	0.927	2.607	1.049	0.147	0.196

Figure 4 shows the values of the residuals for all data sets. As depicted in this figure, the developed ANFIS-based model can predict the UCS of stabilized soils with reasonable precision because the residuals are distributed between two lines illustrating ± 3 MPa. Approximately 99% of residual values of predicted UCS results are less than 1.5 MPa (Figure 4) which confirms that the predictions are unbiased.

6. PARAMETRIC STUDY

The parametric study was carried out to assess 1) the effect of each input parameter on the unconfined compressive strength (UCS) of stabilized fine-grained soils and 2) the behavior of ANFIS-based model and compliance of variation the unconfined compressive strength (UCS) values from the developed model with the measured experimental results.

For this purposes, the influence of changes in each input factors on the amount of UCS was investigated while other effective factors were fixed at their average values in the experimental database (Table 2).

The variation of ANFIS-based predicted UCS with plasticity index (PI), liquid limit (LL), Fly ash (FA), blast furnace slag (S), molar concentration of alkali solution (M), alkali to binder ratio (A/B), atomic ratio of Na to Al (Na/Al), and atomic ratio of Si to Al (Si/Al) are depicted in Figures 5a-h.

All experimental data used in model development along with the best fitted curve was also superimposed on these figures for comparison purposes.

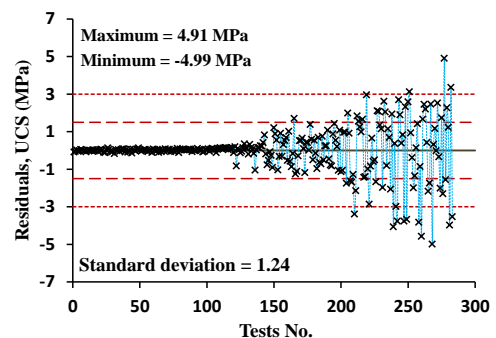


Figure 4. The histogram of the residuals

As depicted in Figure 5, the unconfined compressive strength (UCS) decreases with increasing LL (Figure 5a), PI (Figure 5b), FA (Figure 5d) and Si/Al (Figure 5h). With increase in S and M, unconfined compressive strength (UCS) of stabilized soils increases (Figures 5c and 5e). An increase in A/B and Na/Al first increased and then decreased UCS (Figures 5f and 5g).

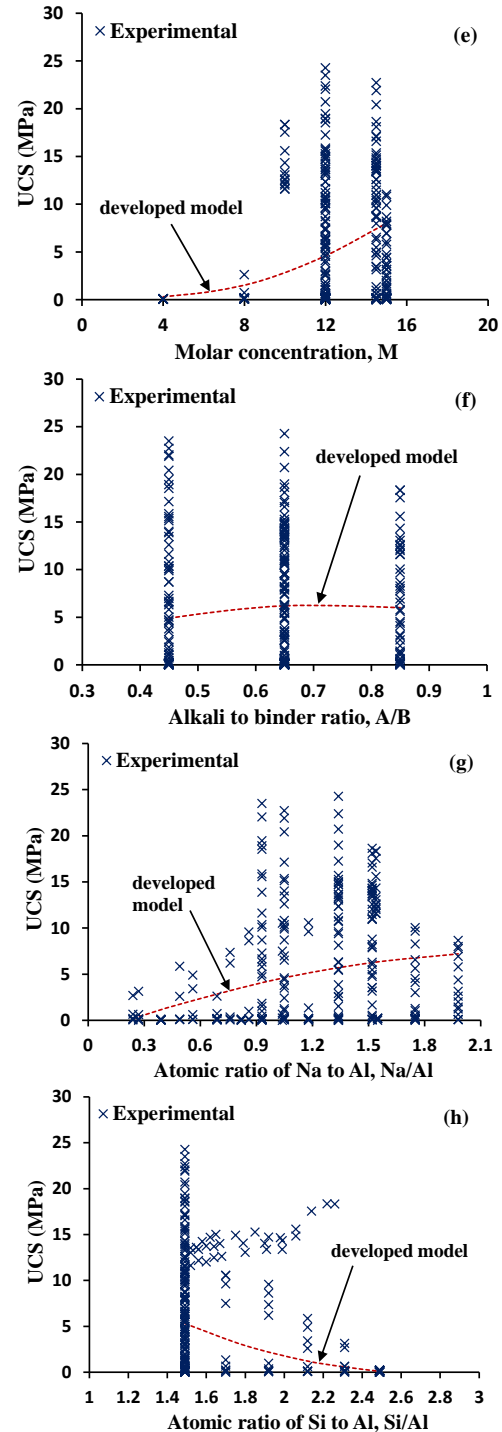
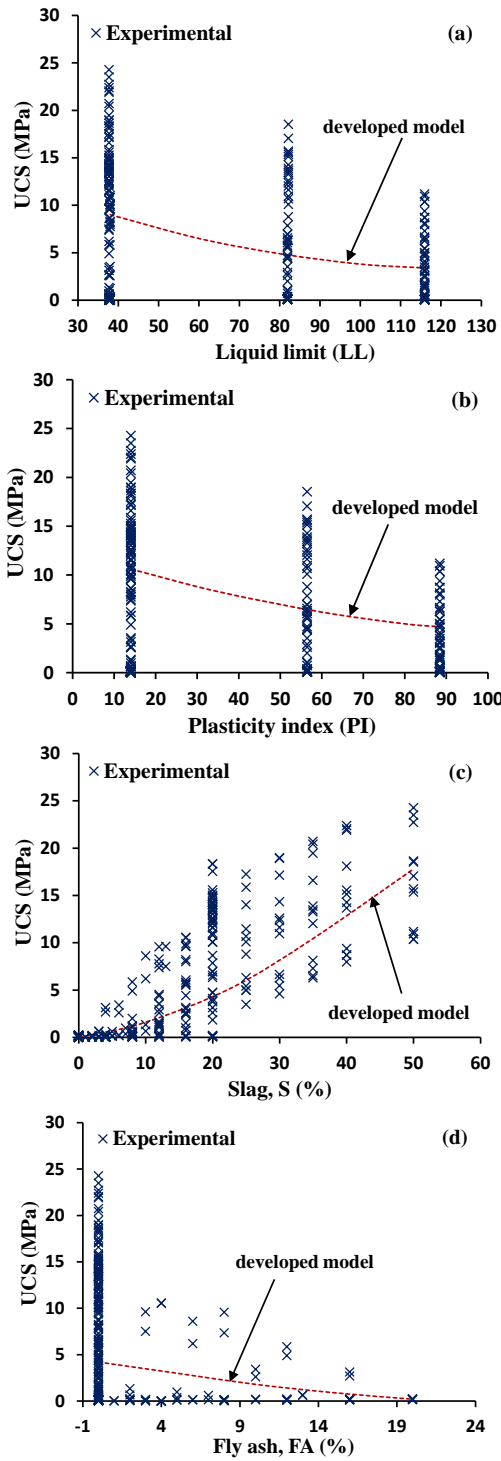


Figure 5. Variation of ANFIS based predicted values of UCS versus influential parameters, a) LL, b) PI, c) S, d) FA; Experimental results are also superimposed on the charts for comparison purposes

Generally, comparison of the variation of predicted UCS of stabilized fine-grained soils with the experimental data indicated good accuracy of the ANFIS-based model in estimation of unconfined

compressive strength of geopolymer stabilized fine-grained soils.

7. SUMMARY AND CONCLUSIONS

Weak soils have always been considered a problem to geotechnical engineers due to their inability to resist loads. Soil stabilization is a technique for amendment of the behavior of these soils. Evaluating strength of stabilized soils is an essential step for construction on improved geomaterials. In this study, a predictive model was developed for evaluation of unconfined compressive strength (UCS) of stabilized soil samples applying adaptive neuro-fuzzy inference system (ANFIS). For this purpose, comprehensive experimental database of USC results of the stabilized fine-grained soils specimens were compiled. The characteristics of soils and additives were considered as inputs parameters. Soil stabilization was carried out by furnace slag and fly ash (as source substances for geopolymerization) and also their combinations. The proposed ANFIS-based model indicated an acceptable performance in assessment of unconfined compressive strength of geopolymer-stabilized fine-grained soil specimens ($R=0.927$, $MAPE=2.607$, $RMSE=1.049$, $Bias=0.147$, and $SI=0.196$). Investigation of the model's accuracy has also confirmed reasonable performance of the developed UCS model. The relative errors of predicted values of UCS were less than 1.5 MPa. It is noteworthy that the proposed model has a higher accuracy in prediction of the lower values of UCS. Parametric study was carried out to assess the behavior of the ANFIS-based model and also evaluate the influence of each input parameter on the predicted values of UCS of stabilized fine-grained soils. The model behavior was compared with measured experimental data. The results showed that the variation trends of the proposed UCS model are in reasonable agreement with the experimental results. Generally, the results of this study show the good performance of the ANFIS-based model in estimation of unconfined compressive strength of geopolymer-stabilized fine-grained soils.

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Soil Improvement

Unconfined Compressive Strength

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Adaptive Neuro Fuzzy Inference System

در این مطالعه به ارزیابی مقاومت فشاری محدود نشدهی (UCS) خاک‌های ریزدانه‌ی بهسازی شده پرداخته شده است. مجموعه‌ای از نتایج مقاومت فشاری محدود نشدهی خاک‌های رسی تثبیت شده با ژئوپلیمرها مورد تحلیل قرار گرفت. با استفاده از سیستم استنتاج فازی عصبی تطبیقی مدلی جهت برآورد UCS ارائه شد. مشخصات خاک و نوع مواد افزودنی شیمیایی به عنوان مهمترین پارامترهای مؤثر بر مقاومت خاک اصلاح شده در مدل UCS لحاظ گردید. دقت مدل پیشنهادی بررسی شد. به منظور بررسی اثر هر یک از پارامترهای مؤثر بر مقاومت فشاری محدود نشده و همچنین چگونگی عملکرد مدل پیشنهادی، مطالعه‌ی پارامتریک انجام شد. نتایج بیانگر دقت قابل قبول مدل مبتنی بر ANFIS در پیش‌بینی مقاومت فشاری محدود نشدهی خاک‌های ریزدانه‌ی تثبیت شده با ژئوپلیمر است.

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