Compressive Strength of Sandy Soils Stabilized with Alkali Activated Volcanic Ash and Slag

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Abstract

In recent years, compared to the traditional Portland cement, environmentally friendly geo-polymers have gained more attention as construction materials. In this paper, volcanic ash (VA) and ground granulated blast furnace slag (GGBFS) in different percentages (0%, 3%, 7%, and 10%) are considered as a replacement for the conventionally used Portland cement to stabilize sandy soils. NaOH and Na_2SiO_3 in different concentrations (4M, 8M, and 12M) and alkali to binder ratios (1, 1.5, 2, and 3) are used as alkali activator solutions to build new geo-polymers. Samples are cured in both ambient and oven temperatures and in 1-, 7- and 28-days curing condition. Unconfined compressive strength (UCS) of samples is then evaluated. Two predictive approaches, artificial neural network (ANN) modeling and evolutionary polynomial regression technique (EPR) are applied to model UCS of geo-polymerized sand samples. Regarding the high value of the coefficient of determination of the proposed ANN, 97%, and acceptable prediction errors, RMSE of 0.0439 and MAE of 0.0336, an 8-5-10-1 ANN is introduced as a more accurate tool for the prediction of UCS. Next, three-dimensional parametrical studies are conducted to investigate effects of simultaneous changes in alkali solution, binder and curing condition parameters on UCS values of geo-polymerized samples. Sensitivity analysis based on the Cosine amplitude method has also introduced Si/Al ratio as the most and VA content as the least affecting parameters on the compressive strength of samples. Results attained are further analyzed using pH and electrical conductivity tests and interpreted based on the microstructural investigations throughout scanning electron microscopy (SEM) images, and X-ray diffraction analysis.

Keywords: Unconfined compressive strength, Sand, Geopolymer, Volcanic ash, Ground granulated blast furnace slag, Sodium hydroxide, Sodium silicate, Artificial neural network, Evolutionary polynomial regression, Sensitivity analysis.

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1. Introduction

Soft soils are one of the most common problems in geotechnical engineering. To improve the strength of those soils, steps must be taken to stabilize the in-situ soil to reuse it in the new geotechnical structure of the soil. Therefore, different mechanical and chemical soil stabilization techniques are employed to prevent soft soil failures (Jahandari, Mojtahedi, Zivari, Jafari, Mahmoudi, Shokrgozar, Kharazmi, Vosough Hosseini, Rezvani and Jalalifar, 2020, Leong, Ong, Sanjayan and Nazari, 2018). Mechanical approaches are usually used to improve soil shear strength through reinforcement elements or water drainage systems (Jahandari, Saberian, Zivari, Li, Ghasemi and Vali, 2019). While the chemical techniques are adopted to prevent soil failures using chemical bonding between soil particles (Shariatmadari, Reza, Tasuji, Ghadir and Javadi, 2020). One of the chemical approaches to stabilize the soil is adding materials namely lime, cement, industrial and natural wastes, such as volcanic ash, rice husk ash, coal fly ash, bottom ash, blast furnace slag, foundry sand, foundry slag, ground granulated blast furnace slag, and cement kiln dust (Jahandari, Mojtahedi, Zivari, Jafari, Mahmoudi, Shokrgozar, Kharazmi, Vosough Hosseini, Rezvani and Jalalifar, 2020, Miller and Zaman, 2000, Consoli, Prietto, Carraro and Heineck, 2001, Lee, Yoon, Cho, Salgado, Lee and Kim, 2002, Consoli, Heineck, Coop, Da Fonseca and Ferreira, 2007, Amaya, Massey-Norton and Stark, 2009, Safavizadeh, Montoya and Gabr, 2018, Jahandari, Saberian, Tao, Mojtahedi, Li, Ghasemi, Rezvani and Li, 2019, Jahandari, Li, Saberian and Shahsavarigoughari, 2017). Most of soils are stabilized with Portland cement and lime (Jahandari, Saberian, Zivari, Li, Ghasemi and Vali, 2019). The process of producing these stabilizers requires a lot of energy and also produces a significant amount of carbon dioxide which leads to significant environmental consequences. Therefore, proposing methods and materials that provide more resistance and are environmentally-friendly is necessary (Kim, Prezzi and Salgado, 2005, Hataf, Ghadir and Ranjbar, 2018). Recently, use of environmentally-friendly chemicals have gained more attention (Falamaki, Shariatmadari and Noorzad, 2008, Moon, Grubb and Reilly, 2009, Shariatmadari, Falamaki and Noorzad, 2010, Ghadir and Ranjbar, 2018, Tigue, Dungca, Hinode, Kurniawan and Promentilla, 2018, Ghorbani, Hasanzadehshooiili, Mohammadi, Sianati, Salimi, Sadowski and Szymanowski, 2019, Fatehi, Abtahi, Hashemolhosseini and Hejazi, 2018, Fatehi, Bahmani and Noorzad, 2019). Using waste to stabilize soils, especially if it is from natural sources, is very useful and practical. This material can be used as stabilizers and can bind soil particles and increase soil resistance. In this paper, a new cement called geo-polymer is studied with advantages such as lower cost, ease of access, lower carbon dioxide emissions, and optimum mechanical properties. Geo-polymer is a product of alkaline activation of aluminosilicate materials in industrial and natural waste products such as fly ash and blast furnace slag (Rahman, 1986, Maitland, Buckley, O'connor, Butler and

Hart, 2011). Davidovits (2013) first used the term geo-polymer in 1978 to name materials with chain linkages or networks of mineral molecules (Davidovits, 2013). Geo-polymers or "inorganic polymers" formation uses active thermal materials (e.g. Kaolinite clay) or industrial products (e.g. fly ash or slag) as sources of silicon (Si) and aluminum (Al). The Si and Al dissolve in an alkaline activating solution, and then the atoms of silicon, aluminum, and oxygen create a chain of silicates and alumina tetrahedron that intermittently bind together with sharing oxygen atoms, which results in three-dimensional polymeric Si-O-Al-O which is produced at nano-size (Zuhua, Xiao, Huajun and Yue, 2009, Swain, 2015). From a terminological point of view, geo-polymer cement is a binding system that is hard at the room temperature, like ordinary Portland cement, but it would be cured faster than Portland cement. Geopolymer cement is an innovative material and a real alternative to ordinary Portland cement for use in transportation infrastructure, construction, and marine applications (Rios, Ramos, da Fonseca, Cruz and Rodrigues, 2016). Fig. 1 shows the general process of geo-polymerization. As depicted, the process involves leaching, diffusion, reorientation, polymerization and condensation phases (Komnitsas and Zaharaki, 2007). As explained in Rao and Liu (2015), at the first stage, aluminate and silicate tetrahedral monomers are generated by alkali dissolution of solid aluminosilicate precursors. At the second stage, the monomers form oligomers resulting in the dissolution of more precursor materials. As a result, the solution is then saturated with a complex mixture of silicate, aluminate and aluminosilicate species. The complex made is then polymerized into an amorphous gel, which is changed to geo-polymers, while condensed and hardened (Rao and Liu, 2015).

Geopolymers are divided into three main categories: slag based geo-polymers, rock based geo-polymers, and fly ash based geo-polymers (Ranjbar, Kashefi and Maheri, 2018). The geopolymer mechanical properties are influenced by various factors, including properties of the source material (types, amount, particle size distribution. and amorphous content), curing conditions (temperature, humidity, pressure, and curing time), concentration and chemical composition of the alkali activator, and alkali activator ratios (Si/Al and Na/Al ratios) (Ranjbar, Mehrali, Alengaram, Metselaar and Jumaat, 2014). Therefore, by adjusting the above parameters during the synthesis of geopolymer, soil can be stabilized using geo-polymers in order to obtain high compressive strength and high stiffness. The geo-polymerization mechanism can be described into three stages: destruction-coagulation, coagulation-condensation, and condensation-crystallization (Ghadir and Ranjbar, 2018). Geo-polymer can be used effectively as a stabilizer material for expensive, dispersive, and problematic soils (Rahman, 1986). So far, many studies have been done to evaluate effects of geo-polymers with different percentages and various tests on different types of soil (Ghadir and Ranjbar, 2018, Rios, Ramos, da Fonseca, Cruz and Rodrigues, 2016, Ranjbar, Mehrali, Alengaram, Metselaar and Jumaat, 2014, R. D. Babu, 2013, Cristelo, Glendinning, Fernandes and Pinto,

2013, Pourakbar, Huat, Asadi and Fasihnikoutalab, 2016, Mozumder and Laskar, 2015). The main focus of some of them have been the strength properties of geo-polymerized soils. Among all the conducted studies, Mozumder and Laskar (2015) and Leong et al. (2018) are the only ones focusing on the presentation of predictive models for the compressive strength of the geo-polymerized soils based on an experimental data bank (Mozumder and Laskar, 2015, Leong, Ong, Sanjayan, Nazari and Kueh, 2018). However, the studied host soils in their studies are, respectively, clay and residual soils. Investigations made by Mozumder and Laskar (2015) are restricted to proposing artificial neural networks for prediction of unconfined compressive strength of such materials (Mozumder and Laskar, 2015). Also, Leong et al. (2018) used neural networks and genetic programming for the prediction of compressive strength of the residual soil-fly ash geo-polymer (Leong, Ong, Sanjayan, Nazari and Kueh, 2018). Nevertheless, there is need for a comprehensive model for prediction of the geo-polymerized sand (with respect to different binder types and alkali solutions). Also, as their model does not consider effects of curing conditions (temperatures and days), proposing a comprehensive model followed by a multi-variable parametric analysis can make the effects of all the affecting parameters more obvious.

Although alkali activated materials offer great potential for many geotechnical applications, some limitations are existed in order to introduce these materials as environmentally-friendly binders in practical applications, which have not been studied before. The objective of the present study was to investigate the possibility of utilizing volcanic ash (VA) and ground granulated blast furnace slag (GGBFS) as the raw materials for geopolymer cement cured at ambient and elevated temperatures. Hence, the present research is carried out to investigate the effects of VA and GGBFS based geo-polymers on the geotechnical properties and stabilization of sandy soil. To have a comprehensive approach to the problem, all the binder's and solution's situations along with curing conditions should be considered in the development of experimental program. In addition, to make results of the conducted study more practical for future applications, a comprehensive and accurate model should, also, be presented. In this regard, different alkali activator solutions (NaOH and Na_2SiO_3) are considered in the formation of geo-polymers. To cover a wide range of possible situations, different molar concentrations (4M, 8M and 12M) and NaOH to Na_2SiO_3 ratios for alkali solutions are studied. As curing condition parameters, effects of curing days and temperatures are, also, taken into the consideration. To assess the geotechnical performance of stabilized samples, unconfined compressive strengths (UCS) of all samples are obtained. Next, as the modeling phase, two powerful and accurate soft computing techniques (artificial neural network modeling, ANN, and evolutionary polynomial regression, EPR) are adopted to present predictive equations for UCS (Naderpour, Rafiean and Fakharian, 2018, Naderpour, Nagai, Fakharian and Haji, 2019, Naderpour, Eidgahee, Fakharian, Rafiean and

125 Kalantari, 2020). Developed EPR model is then used as a basis for the three-dimensional parametric studies. It
126 worth to note that the developed relationship can be used by practitioners and design engineers in the early stage
127 of soil stabilization projects to determine the required binder and alkali materials, also, the alkali concentration.
128 A graphical optimization technique can be employed to obtain optimized values with respect to other available
129 parameters and field conditions. It can, also, be used as a basis for different purposes (validating the UCS of field
130 and laboratory samples, determination of the required raw material, etc.) in the quality control/assurance phases
131 of real soil stabilization projects. The most and the least influential parameters on the UCS are then introduced
132 adopting a proper sensitivity analysis. It should be described that mechanisms behind reactions and experimental
133 results are further discussed using pH, electrical conductivity, X-ray diffraction and scanning electron microscopy
134 analyses.

135 ## 2. Materials and Methodology

136 ### 2.1. Materials

137 #### *2.1.1. Sand*

138 The soil used in this study is Firouzkouh sand (No.161), which is available in the Firouzkouh mine north-east of
139 Tehran. Fig. 2 shows the grain size distribution curve of the sand determined based on ASTM D422 (2007).
140 According to the Unified Soil Classification System (USCS) (2017), the studied number 161 Firouzkouh sand is
141 classified as poorly graded sand (SP). The standard Proctor compaction tests were performed on the soil (2012)
142 to determine the maximum dry density (γ_{max}). The minimum and maximum unit weights are 1.397 gr/cm^3 and
143 1.635 gr/cm^3, respectively. Tables 1-2, respectively show physical properties and the result of the X-ray
144 fluorescence (XRF) analysis of the studied sand.

145

146 #### *2.1.2. Volcanic Ash (VA) and Ground Granulated Blast Furnace Slag (GGBFS)*

147 Volcanic ash (VA) is a natural pozzolanic substance that consists silicon oxides, aluminum, iron and calcium, and
148 it is found abundantly in volcanic areas. Recently, the use of volcanic ash has gained more attention. It is widely
149 found throughout the world and has many natural features that make it easy to become cementitious. Volcanic ash
150 is formed under high pressure and high temperatures in a completely natural process. In other words, nature has
151 made an important part of all chemical interactions that they need to produce cement. VA used in this study was
152 obtained from the Taftan Mountain located in south-eastern Iran in Sistan and Baluchestan province. According
153 to ASTM C618 (2019), as the total amount of (SiO_2, Al_2O_3 and Fe_2O_3) available in the VA used in this study is

94.40% while the CaO content is 1.68%, it is classified as a class F ash. Ground granulated blast furnace slag (GGBFS) used in this paper was collected from the blast furnace of Esfahan steel company, Iran. The X-ray fluorescence (XRF) tests were performed on the adopted VA and GGBFS to determine their chemical compounds as shown in Table 3.

2.1.3. Alkali Activator Solution

The base alkali activator used to activate the geo-polymerization reactions was sodium hydroxide (NaOH) due to its high capacity in liberating silicate and aluminate monomers (Zhang, 2003). In addition, it is believed that existence of sodium silicate in sodium hydroxide improves the kinetics of geo-polymerization reactions (Hardjito, 2005). It was, also, added to some of the mixtures to investigate its effects on the stabilized samples' compressive behavior. Different sodium hydroxide (SH) to sodium silicate (SS) ratios were chosen to make a comprehensive investigation. 1:0, 2:1, 1:1 and 1:2 ratios were adopted as SH:SS fractions applied in the experiments. Described ratios made the total alkali to binder ratios (A/B) of 1, 1.5, 2 and 3, respectively. Also, the molar concentrations of used alkali activators were 4M, 8M and 12M. The quality of water also has a significant influence on the geotechnical characteristics of stabilized soils and cementitious materials (Afshar, Jahandari, Rasekh, Shariati, Afshar and Shokrgozar, 2020, Sadeghian, Haddad, Jahandari, Rasekh and Ozbakkaloglu, 2020). Therefore, distilled water was used for preparation of alkali activator solutions (Saberian, Jahandari, Li and Zivari, 2017, Rasekh, Joshaghani, Jahandari, Aslani and Ghodrat, 2020).

2.2. Sample Preparation

As the first sample preparation phase, the geopolymer paste was produced. During the synthesis of the geopolymer paste, regarding the small size of binders' particles and to activate the particles, VA/GGBFS and alkaline activator solution of 8M sodium hydroxide were initially mixed together. Then, the paste was added to the soil and mixed for about 20 minutes to obtain a homogeneous mixture. The amount of soil used for each sample was calculated based on the relative density, which was assumed to be 30% (Dr =30%). In this state, sand was very loose, and the effect of the binder was less than that of the compacted sample. A constant activator content of 10 wt.% of the dried soil was used for all the specimens. After mixing the materials, the uniform mixture was placed into the mold (D 38 mm × H 76 mm), and was then compacted in three layers. Three samples were made for each test. Three samples were made for each test. All the cylindrical samples were cured in two conditions: the first group of samples were wrapped by nylon bags to prevent significant changes in their moisture content and cured at room temperature (20 ºC ± 2) at a relative humidity of 95 ± 2% for 1, 7 and 28 days. The second group were wrapped

and placed in oven at the temperature of 60 ºC and the relative humidity of 15 ± 2% for 1, 7 and 28 days. This process was similarly conducted for different binder and alkali percentages, also, alkali concentrations.

2.3. Calculation of Na/Al and Si/Al ratios

Regarding the prepared mixtures, used binders, amounts of different used Alkalis, types and molarities of adopted Alkalis, ratios of Na to Al, also, Si to Al vary. Amount of Na depends on the type and the value of the adopted Alkali. Hence, alkali to binder ratio, molarity and type of the activator controls Na to Al ratio in the mixtures. On the other hand, amount of Si in the prepared samples is controlled by both binder and alkali. SiO_2 content available in binder is a rich source of Silisium, while addition of a new alkali (e.g. addition of Na_2SiO_3 to the available NaOH) may, also, introduced new resource of Si to the samples. Al content in the mixture is only controlled by the type and the amount of the used binder and it is independent of the type and the amount of the alkali activator. Mozumder and Laskar (2015) proposed the general framework for the calculation of numbers of Na, Al and Si atoms in the geopolymers. Following the presented method, Eqs. 1-4 can be used for the calculation of Na to Al and Si to Al ratios in different conditions applied in this paper (Mozumder and Laskar, 2015). Required calculations are further elaborated in the Appendix section.

Eq. 1 is used for the calculation of Na/Al ratio in the non-GGBFS binder case (different VA percentages):

$$\frac{Na}{Al} = \frac{51 \times (\frac{A'}{B}) \times M}{0.2(1000 + 40M)} \quad (1)$$

As VA stabilized sand samples are only activated using NaOH alkali solution (Na_2SiO_3 alkali solutions are not introduced to the samples stabilized with VA alkali binders), Eq. 1 can be used for all samples containing VA binders. In this equation, A'/B is the ratio of NaOH alkali to the binder. For the samples containing GGBFS (non-VA samples), Na/Al ratios are obtained using Eqs. 2-3. Eq. 2 is for the case of using NaOH as the activator (without addition of Na_2SiO_3), and Eq. 3 is used for the cases that Na_2SiO_3 is added to the samples (in addition of previously used NaOH activator).

$$\frac{Na}{Al} = \frac{51 \times (\frac{A'}{B}) \times M}{0.08(1000 + 40M)} \quad (2)$$

$$\frac{Na}{Al} = \frac{51 \times M}{0.08} \times \frac{\left[\left(\frac{A'}{B}\right) \times (1000 + 122M)\right] + [2 \times (\frac{A''}{B}) \times (1000 + 40M)]}{(1000 + 40M) \times (1000 + 122M)} \quad (3)$$

where A'/B represents the ratio of NaOH alkali to the binder, M is the molarity of NaOH and Na_2SiO_3 activators and $A^{"}/B$ stands for the Na_2SiO_3 alkali to the binder ratio.

On the other hand, Si to Al atomic ratio equals to 2.3 for the case of samples polymerized using VA binder (non-GGBFS cases, and activated only with NaOH alkali activator). Si to Al ratio of samples stabilized with GGBFS binders equals to 3.29 for the samples activated using NaOH (without Na_2SiO_3 alkali solution) and Eq. 4 is used to gain Si/Al ratio of samples containing GGBFS binder (non-VA cases) and activated with the combination of NaOH and Na_2SiO_3 alkali solutions.

$$\frac{Si}{Al} = 3.29 + \frac{51 \times (\frac{A^{"}}{B}) \times M}{0.08(1000 + 122M)} \quad (4)$$

2.4. Program of Experiments

In this paper two different binders, VA and GGBFS with four different percentages, two different alkali solutions (NaOH and Na_2SiO_3) in variable concentrations were used to stabilize #161 Firouzkouh sand. Effects of curing conditions, time and temperature, were, also, taken into the consideration. In this regard, samples were cured in three curing periods, also, in two curing temperatures. Table 4 represents the program of unconfined compressive strength experiments with regards to the studied parameters and their corresponding values. It should be noted that all A/B and M variables provided in Table 4 are not used for the whole range of binder percentages and the selected ones (in view of binder percentages) are further studied using the complete mentioned range of A/B and M in order to get a comprehensive investigation. For example, samples containing VA, are only activated using NaOH solutions and addition of Na_2SiO_3 to the available NaOH alkali solution is carried out for GGBFS containing soil samples. Hence, a total number of 126 independent UCS tests were conducted on different described samples (repeating each test for three times).

In Table 4, A/B is the total ratio of the alkali to binder (the ratio of the total used alkali solution - total weight of the summation of NaOH and Na_2SiO_3 - to the weight percentage of the binder), M (M) represents concentration of the alkali solution in Molarity, CD is the curing days and T stands for the curing temperatures in ◦C. It should be noted that A/B parameter described here is different from A'/B and A"/B parameters (respectively, ratios of weight percentages of NaOH and Na_2SiO_3 alkalis to the binder) presented in section 2.3.

2.5. Unconfined Compressive Strength (UCS) Test

Unconfined Compressive Strength (UCS) tests were performed according to the ASTM D1633 standard on molded samples with an inner mold diameter of 38mm and a height to diameter ratio of 2.0 using a strain-controlled method at a rate of 1 mm/min (2017). Tests were conducted using a universal testing machine (Digital Tritest 50/ELE). It should be described that special considerations were paid to the loading axis to be perpendicular to the sample and to the proper treatment with the capping effect. All the tests were repeated for three times and the average obtained UCS value was reported as the final output.

2.6. pH and Electrical Conductivity (EC) of Samples

pH and the electrical conductivity (EC) of samples stabilized with geo-polymers were measured using pH- and EC- meters according to ASTM D4972 (ASTM D4972-19 2019). To measure pH and EC, samples were prepared by crushing and sieving of 10g of soil specimens through a 2.0 mm (No. 10) sieve and mixing with 10 mL of water for 5 min. Samples were settled in a curing room for 1 hour until the solution was deposited, and then pH and EC values were, respectively, displayed on the pH meter screen and on the digital EC-meter. Fig. 3 shows that the geo-polymerization process increased pH of the studied VA-based mixtures. It shows that addition of alkali solution prepared the required situation (alkaline state) for the initiation of geo-polymerization reactions.

Dissolution and precipitation reactions of silicates, aluminates and calcium sources and hence the stable equilibrium phase assemblages of the oxide compositions are mainly depending on the pH of the medium and oxide concentration. Based on the obtained results, the pH of the geopolymer treated soil was shown to be in the range of 10.3 to 12.8 depending on the activator concentration and binder content. Such measurements were carried out to qualitatively assess the relationship between the pH value of samples and their mechanical strength and it was observed that a higher mechanical strength was obtained at higher pH where alkali activator concentration is higher. This behavior is believed to be attributed to the predominance of smaller chain oligomers and monomeric silicate available to react with soluble aluminum in the presence of higher concentration of hydrogen ions during dissolution and hydrolysis stages. This mechanism can be incorporated by calcium precursors available in VA. Therefore, higher binder gel is produced. pH assessment methodology/range (where applicable) adopted in this paper is in agreement with other studies available in the literature aiming on the short-term pH measurements of geo-polymerized/stabilized samples (Miller and Azad, 2000, Chew, Kamruzzaman and Lee, 2004, Jiang, Du, Liu, Wei, Horpibulsuk and Arulrajah, 2015, Sol-Sánchez, Castro, Ureña and Azañón, 2016, Lin, Ou and Chien, 2018, Paudel, Yang and Gao, 2020, Du, Yu, Liu, Jiang and Liu, 2017).

However, in the case of the long-term pH assessment (e.g. 365 days) of the effect of high alkaline concentration in pore solutions of geo-polymerized samples, special attention should be paid to the pH of pore solution instead, where the remaining NaOH in soil may lead to the overestimated pH value. Such effects are studied in the study conducted by (Paudel, Yang and Gao, 2020), where neglecting the remained alkaline in the samples can be conducive to overestimation in the calculation of proper pH value. In (Paudel, Yang and Gao, 2020), it was shown that for all the studied fly ash stabilized samples, differences between pH of 1-day to 28-day cured samples are significantly lower than those for samples cured in long periods.

Nevertheless, in this paper, finding a conceptual relationship between the overall pH of the geo-polymerized samples and their respected UCS was the main purpose of pH investigations.

Next, it was observed that with the initiation of geo-polymerization reaction, also, with increasing VA content, EC of samples were increased (Fig. 4). This is due to the increased concentration of ions due to the dissolution of additives.

Similarly, Fig. 5 and Fig. 6, respectively, show the variation of pH and EC of geo-polymerized, GGBFS- based samples. As shown, there is not a simple relationship between the temperature, molarity and alkali to binder ratio. This emphasized the need for a comprehensive investigation to consider effects of simultaneous changes in concerning parameters affecting on the geo-polymerization process.

For the samples cured in the room temperature, and for a constant A:B ratio, with increasing the alkali solution molarity from 4M to 8M, pH value increased and then with increasing the molarity to 12M, pH decreased, while for the samples cured in the elevated temperature, the general pH trend was increasing for all molarities. It can be associated to the later initiation of geo-polymerization reactions in the room temperature, also, the amount of alkali solution needed to activate all the contributing binder percentage available in the reactions. Indeed, with increasing the alkali solution in term of molarity, geo-polymerization process enhances. On the other hand, there is some binders have not participated in the reactions since they are not still activated. With an increased alkali ratio, the required situation for the geo-polymerization is better provided in the elevated temperature and this is why there will be higher binder particles activated with extra added alkali solution. However, in the room temperature, extra alkali solution (in term of the increased molarity for a constant A/B, or in term of the increased A/B for a constant molarity) surrounds binder's particle and due to the inappropriate reaction situation, cannot take part in the geo-polymerization process.

3. Data Analysis on the Results of Experimental Tests

In this section, results obtained from unconfined compressive strength tests on different VA- /GGBFS- based and NaOH- /Na_2SiO_3- activated, geo-polymerized sand are used to develop predictive models for UCS. Two well-developed and broadly adopted soft computing based- techniques are used to develop new, accurate models. Evolutionary polynomial regression (EPR) as a gray box technique, also, artificial neural network (ANN) as a black box model are employed for this purpose.

3.1. Evolutionary Polynomial Regression Modeling

As a hybrid regression method, EPR can be introduced as a combination of the best features of the conventional numerical regression and the genetic programming. In this evolutionary computing technology, a parameter estimation is employed to get the constants for different sentences based on the least square method (Giustolisi and Savic, 2006). Eq. 5 is used to express the general form used in this technique.

$$y = \sum_{j=1}^{m} F(X, f(X), a_j) + a_0 \tag{5}$$

where y is the estimated output vector, a_j represents a constant, F is a function constructed by the process, X is the matrix of inputs, f is a user defined function and m represents the maximum term numbers of the target. The general algorithm implemented to develop Eq. 5 can be found in Ahangar-Asr et al. (2011) (Ahangar-Asr, Faramarzi, Mottaghifard and Javadi, 2011).

To develop an EPR model, general form of the model, type of the adopted function, number of the used terms, range of exponents, and the generations' numbers are parameters to control the output model (Rezania, Javadi and Giustolisi, 2008). Described terms affect the accuracy of the output function. During the evolutions, the level of accuracy of the target function is, first, evaluated using the coefficient of determination. If the model fitness is not satisfactory or other termination criteria are not acceptable, the current evolution proceeds to the next step to get a higher model accuracy using new contributing terms.

In this paper, based on the described affecting parameters in the determination of unconfined compressive strength of the geo-polymerized sand, eight parameters are used for the prediction of *UCS* values. Used parameters along with their statistical analysis (their minimum, maximum, average and the standard deviation values of all input

and output parameters) are presented in Table 5.

Based on different developed equation types and adopted functions (exponential, logarithmic, secant and tangent hyperbolic functions), number of terms, range of powers, and number of generations, Eq. 6 with the best coefficient of the determination and least errors in the predictions was selected as the best, proposed EPR model.

$$UCS = -\left[14604696.0493e^{-2\left(\frac{Na}{Al}\right)}\right] + \left[11378257.3803e^{0.25\left(\frac{A}{B}\right)-2\left(\frac{Na}{Al}\right)}\right] + \left[2.0023\left(\frac{Na}{Al}\right)^{0.5}\left(\frac{Si}{Al}\right)^{-0.25}(T)^{1.5}\right] + \left[1281565.0299(GGBFS)^{0.25}(M)^{3}\left(\frac{A}{B}\right)^{2.5}\left(\frac{Na}{Al}\right)^{0.5}\left(\frac{Si}{Al}\right)^{-0.5}(CD)^{0.25}(T)^{-3}e^{-\left(0.5M+\frac{A}{B}\right)}\right] - 450.4299. \quad (6)$$

where *Na/Al, A/B, Si/Al, T, GGBFS, M* and *CD,* respectively, represent sodium to aluminum, total alkali to binder, and silisium to aluminum ratios, curing temperature, ground granulated blast furnace slag percent, molarity of activator, and curing days. Also, *e* is the Neperian number.

Prediction errors shown in Fig. 7, also, the coefficient of the determination of 84% shown in Fig. 8 declares an acceptable fitness between measured and predicted *UCS* values and implies that the proposed relationship is useful in UCS predictions. Also, it can be efficient for practitioners in the preliminary design step of engineering construction projects.

The developed relationship can be used as a basis for the parametric studies (discussed in next sections). Nevertheless, there is still a need for a more accurate predictive tool.

3.2. Artificial Neural Network Modeling

Artificial neural network (ANN) is a branch of artificial intelligence. It has been widely adopted for lots of pattern recognition problems and for prediction of various engineering complicated target functions (Samui and Sitharam, 2010, Zaman, Solanki, Ebrahimi and White, 2010, Kulatilake, Qiong, Hudaverdi and Kuzu, 2010, Ghorbani and Hasanzadehshooiili, 2018, Hasanzadehshooiili, Lakirouhani and Medzvieckas, 2012, Hasanzadehshooiili, Mahinroosta, Lakirouhani and Oshtaghi, 2014).

As a general basis of ANN, the data is first divided to training, cross validation and testing data series. Training datasets are used to train the network and then, based on the training rules and relationships, testing *UCS* values are predicted. Multi-layer perceptron (MLP) networks are believed to be the best type of neural networks, which

331 can be widely used to predict each continuous function (Ghorbani and Hasanzadehshooiili, 2018). Such a network
332 type is composed of three kinds of layers (input, hidden and output layers). Type of the problem, which is to be
333 solved also its complexity define the required number of layers. As another modeling requirement for an MLP
334 network, one need to define transfer functions between different layers, introduce a proper learning law to the
335 network, and to adopt an efficient network topology. These factors have a direct impact on the network's
336 performance and should be gained using a trials and errors method for different rules, functions and architectures
337 (Jong and Lee, 2004).

338 ***3.2.1. Network Training***

339 Feed forward back propagation (FFBP) algorithm is generally used for learning purposes (Hasanzadehshooiili,
340 Mahinroosta, Lakirouhani and Oshtaghi, 2014). It is made of two phases of forward pass and back propagating
341 phase to minimize the prediction errors. During the first phase, a preliminary value is assigned for connecting
342 neurons. Based on the pre-assigned neuron values, output values are predicted. Next, the second phase is started
343 comparing the measured output with the predicted ones and the calculated summation of the squared error is then
344 calculated and back-propagated using the gradient descent rule to update the available weights and minimize the
345 obtained summation of the squared error (Hasanzadehshooiili, Lakirouhani and Medzvieckas, 2012). Performance
346 of well-trained networks should then be assessed to get the network with the highest possible accuracy for the
347 prediction of the output parameter, when a new set of data is available.

348 It should be described that before the analysis, the developed datasets should be normalized and dimensionless to
349 an [0-1] using Eq. 7.

$$\text{Scaled Value} = (\text{unscaled value} - \text{min. value}) / (\text{max. value} - \text{min. value}) \quad (7)$$

350 In the present paper, datasets were divided into 75 % training, 15% cross validation and 10% testing ones. As
351 described and based on trials and errors, Tangent Sigmoid (TANSIG) nonlinear transfer function shown in Eq. 8
352 had a better performance in view of the prediction errors and hence, was selected as the transfer function in the
353 prediction of UCS of sand samples geo-polymerized with VA/GGBFS binder and activated using $NaOH/Na_2SiO_3$
354 alkali solutions.

$$TANSIG = \frac{2}{1 + e^{-2e_x}} - 1 \quad (8)$$

where e_x is the weighted sum of the inputs for a neuron (Demuth et al. 1996).

3.2.2. Network Architecture and Performance

To obtain the best model topology, lots of 1-layer and 2-layer, MLP networks were built to predict UCS values. As the performance criteria, values of root mean squared error, RMSE, mean absolute errors, MAE, and coefficients of determination, R^2, were calculated and compared for all the developed models. Also, slopes of fitting lines are presented to better interpret the fitness of the forecasted versus measured UCS values with y=x line. Formulas used for the calculation of *RMSE*, *MAE* and R^2 are presented in Eqs. 9-11 (Lehmann, 1998).

$$RMSE = \sqrt{\frac{\sum\left(O_i - T_i\right)^2}{n}} \tag{9}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|O_i - T_i\right|}{n} \tag{10}$$

$$R^2 = 1 - \frac{\sum_i (T_i - O_i)^2}{\sum_i (T_i - \frac{1}{n}\sum_{i=1}^{n} T_i)^2} \tag{11}$$

T_i and O_i in Eqs. 9-11, respectively, represent the measured and predicted *UCS* values. Also, n is the number of data sets. Table 6 presents values of RMSE, MAE, R^2 and slopes of fitting lines for some of built neural networks. In addition, based on the performance criteria available in Table 6, Fig. 9 shows the architecture of the best developed network (8-5-10-1) for the prediction of UCS.

Figs. 10 and 11, respectively, show the predicted and measured UCS for different data series and their fitness with y=x line.

As shown in Table 6 and Fig. 11, network with the architecture of 8-5-10-1 is the best FFBP-ANN for the prediction of UCS of sandy soils stabilized with VA/GGBFS binders and activated using $NaOH/Na_2SiO_3$ alkali solutions. Based on the values obtained for the 8-5-10-1 network (RMSE=0.0439, MAE=0.0336, and R^2=97%), it can be concluded that back propagation neural networks are capable, efficient and timely tools for the prediction of UCS of sandy soils stabilized with geopolymers.

As described, the proposed neural network model is superior to the EPR model in view of the prediction accuracy. On the other hand, regarding the black box nature of the artificial neural networks, they do not propose explicit

relationships for further parametric studies. In this regard, to attain a comprehensive, three-dimensional parametric study, which considers the effect of simultaneous variations in some of the affecting parameters on the UCS, EPR relationship can be used as a basis. Depicting the developed relationship in the general three-dimensional space for different cases, one can study variations of UCS with simultaneous changes in the binder percentage, curing days and temperatures or activator molarity, alkali to binder, Na to Al and Si to Al ratios.

3.3. Parametric Studies

To get a proper and comprehensive investigation about the role of different affecting parameters on the variation of UCS of geo-polymerized samples, it is believed that effects of different parameters are better to be simultaneously evaluated. In this regard, Eq. 6 is used as a basis for multi-variable, and three-dimensional parametric studies. Hence, two different cases are considered in the following sub-sections.

3.3.1. Effects of Binder, Curing Day and Temperature for Different Alkali Solution Molarities

As the first case for the parametric studies, it has been assumed that NaOH is the only alkali solution used to activate the geo-polymers and hence, A/B ratio is kept constant and equals to 1 (Na_2SiO_3=0). In this case, VA%=0, Na/Al=3.86, and Si/Al=3.29. Figs. 12-13 show the variation of UCS with GGBFS (%) and CD (day) for different curing temperatures and for the case of M=8. As seen and as a general trend, increasing CD (day) and GGBFS (%) will lead to increasing UCS values. The effect of binder percentage in increasing the strength is more meaningful in higher curing days. Also, the rate of UCS enhancement with an increased curing day is greater for samples containing higher binder percentages. With regards to Fig. 12, there is a transition zone in which, the behavior of samples cured in the ambient and elevated temperatures varies, which is better clarified in Fig. 13. Indeed, the curing temperature emphasized in these figures declares that at lower curing days (1-7 day), samples cured at higher temperature reveal greater UCS, while with increasing the curing days, samples' behavior will change and geo-polymerized samples cured at the ambient temperature will have higher UCS values. It should be noted as shown in Fig. 13, in (1-7 day) curing period, which is introduced as the transition zone, a 1-day curing period corresponds to high GGBFS contents and a 7-day curing period is related to low GGBFS contents.

Similarly, Figs. 14-15 depict values of UCS versus CD and GGBFS, respectively, for the cases of M=4 and 12. According to Fig. 14, the behavior of samples activated with 4M alkali solution is still in agreement with that of samples containing an 8M, NaOH solution.

On the other hand, with increasing the molar concentration of alkali solution to 12M (Fig. 15), the compressive strength of samples cured at the elevated temperature is more than UCS of samples cured at the room temperature. It should be noted that in this case, there is not a transition zone and this behavior governs in the whole range of curing days and the binder percentage.

3.3.2. Effects of Na/Al and Si/Al for Different Values of Alkali to Binder Ratios

This section assesses the role of Na/Al and Si/Al ratios for the cases that Na_2SiO_3 is added to the available NaOH alkali solution in variable ratios (A/B=1, 1.5, 2 and 3) to initiate the geo-polymerization process. To conduct a comparative study, other affective parameters are kept constant (M=8 M, VA=0 %, T=60 °C and CD=7 day). As shown in Fig. 16, increasing each of Na/Al, Si/Al and A/B ratios will results in an enhanced UCS for samples. It is useful to note that the observed trends are the same for other curing temperatures/days. As another interesting result, it can be seen from Fig. 16 that the rate of increasing UCS with Na/Al is greater for lower Si/Al ratios.

3.4. Sensitivity Analysis

Sensitivity analysis based on the Cosine Amplitude Method (CAM) is employed to evaluate the strength of relationship between input parameters and UCS of geo-polymerized samples. The express similarity relation between the target function and the input parameters is generally obtained using CAM. In this regard, all of data pairs are expressed in the common X-space. They would form a data array X defined as Eq. 12 (Ghorbani, Hasanzadehshooiili, Ghamari and Medzvieckas, 2014, Shariatmadari, Karimpour-Fard, Hasanzadehshooiili, Hoseinzadeh and Karimzadeh, 2020):

$$X = \{x_1, x_2, x_3, x_4, ..., x_i, ... x_n\}. \tag{12}$$

where each vector element, x_i, has the length of *m* as shown in Eq. 13.

$$x_i = \{x_{i1}, x_{i2}, x_{3i}, ..., x_{im}\}. \tag{13}$$

Each dataset is then considered as a point in the m-dimensional space with m-coordinates. Eq. 14 presents the strength of the relationship between x_i and x_j (Ghorbani and Hasanzadehshooiili, 2018, Ghorbani and Hasanzadehshooiili, 2017).

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2}}. \quad (14)$$

The strength of relationships between UCS, and concerning input parameters are computed based on Eq. 14 and shown in Fig. 17.

As shown in Fig. 17, Si/Al ratio is the most important factor determining the samples' UCS. Na/Al, GGBFS (%) and M (M) are respectively other parameters with high impact on the UCS. On the other hand, VA (%) and the curing temperature are, respectively, the parameters with the least effects on the compressive strength of geo-polymerized sands.

4. Discussion on the Experimental Results

4.1. Interpretations of Mechanisms Behind the Reactions Using Scanning Electron Microscopy (SEM)

A scanning electron microscopy (SEM) imaging test was used to indicate the growth of the geo-polymerization products (Pourakbar, Huat, Asadi and Fasihnikoutalab, 2016) and ensure the mixing of materials with the soil and the synthesis of these materials. In this regard, images of soil samples stabilized with geopolymers containing 7% and 10% volcanic ash cured in 28 days of treatment in the oven (60°C) were prepared. As shown in Fig. 18, after adding 10% alkali activator to the 7% VA sample, a cementitious (aluminosilicate) geo-polymer gel was formed, which filled the voids and caused in an enhanced compressive strength. Evolution of this gel is believed to be responsible for the mechanical improvement of the geo-polymerized sample. Gels and crystals made from the geo-polymerization process surround the soil particles and cause the particles to interconnect with each other.

This result indicates leaching of silica and alumina oxides from VA by alkaline dissolution with time. Contrary to Fig. 18, Fig. 19 representing the SEM image of 10% VA geo-polymer, shows that there are some not activated VA particles. Points marked using rectangles in the left-side Fig. 19 declare non-activated VA grains. It declares that a 10% alkali activator solution is capable to fully activate 7% VA samples with a maximum effect on increasing the UCS, while samples geo-polymerized with higher VA content and still activated using 10% NaOH have lower UCS values. Hence, the amount of the used alkali solution to activate the adopted binder value was not sufficient.

448 In a similar manner, Fig. 20 shows the geo-polymerization process made in samples containing GGBFS binder.
449 In this figure, points defined using circles show the formation of the cementitious gel between grains, while points
450 marked using rectangles in the right-side figure declare non-activated and flocculated GGBFS grains.

451 4.2. Discussion on Experimental Results Using XRD Analysis

452 The XRD analysis was, also, performed to verify the microstructure and amorphous and crystalline phase of the
453 materials and final products with the XRD machine. For VA-geo-polymerized samples, XRD patterns of the un-
454 stabilized soil along with the sample containing 10% VA and cured in 28 days in the elevated temperature are
455 shown in Figs. 21-22. XRD scans were performed at 0-80◦. There were no significant changes in the patterns of
456 the stabilized samples, except that the intensity of the peaks associated with quartz varies. These changes indicate
457 that the desired synthesis was done in the soil. The lack of changes in XRD patterns of the stabilized soil indicates
458 that no new minerals were created by adding geo-polymers to the soil (i.e., no direct chemical reaction between
459 the geopolymer precursor and the soil minerals). Therefore, the increase of mechanical properties is mainly due
460 to the effects of the binding of geopolymer gels.

461 In addition of what observed in the XRD analysis of VA-polymerized samples, Figs. 23-24 (XRD analysis of 10%
462 GGBFS stabilized samples in different A/B ratios), also, prove that there was not any new mineral created by
463 adding GGBFS and activated by using NaOH/Na_2SiO_3 to the host soil. Fig. 23 represents the availability of quartz
464 and anorthite minerals as two main minerals in samples activated with the combination of NaOH and Na_2SiO_3
465 alkali solutions. As described, quartz minerals detected are those available from the hosting sandy soil and the
466 observed anorthite minerals are from the GGBFS binder as previous studies have also emphasized on this fact
467 (Kumar and Kumar, 2011, Kuo and Hou, 2014, Nikolov, Rostovsky and Nugteren, 2017). Calcite minerals shown
468 in Fig. 24 (10% GGBFS, geo-polymerized sample activated by NaOH alkali solution at the room temperature)
469 refer to the availability of 35% CaO in the studied GGBFS. Such an observation re-states that minerals available
470 in the hosting soil skeleton do not directly take part in new relationships with added binders to form new minerals
471 and the enhanced compressive strength obtained from the stabilized samples are due to the geo-polymerization
472 and the formation of new bonding around the soil skeleton.

473 5. Conclusions

474 Based on the results obtained from UCS, pH and EC tests, also considering the proposed EPR relationship and
475 corresponding parametric studies, the GGBFS-based geopolymer cured at the ambient temperature could

476 generally satisfy the mechanical performance as a cementitious binder for soil stabilization projects, while the VA
477 -based geopolymer showed better performance at the elevated temperature. In other words, GGBFS-based
478 geopolymer could be introduced as an alternative binder for traditional cements in tropical regions, while VA-
479 based geopolymer showed great potential as a green binder for the soil stabilization in torrid zones. This finding
480 is directly related to the chemical composition of the precursors. However, in order to realize such an application,
481 its viability in sustainability should be investigated in further studies. Therefore, developing cost effective
482 activators with less environmental impacts than conventional activators (sodium silicate or sodium hydroxide) as
483 well as optimizing mix designs based on the broader range of raw materials may be a solution to decrease the
484 geopolymer production cost. In this line, the environmental issues caused by cement production could be
485 diminished by using alternative green binders with relatively similar performance to Portland cement for serving
486 engineering requirements in soil stabilization projects.

487 In addition, two soft computing models were proposed for the prediction of UCS of the geo-polymerized sand.
488 EPR model was further studied to provide a framework for multi-variable parametric studies, also, a mixture
489 design/optimization approach useful in QC/QA phase of real soil stabilization projects. On the other hand, FFBP-
490 MLP neural network with the architecture of 8-5-10-1 was obtained to be accurate (RMSE=0.0439 kPa,
491 MAE=0.0336 kPa, and CoD=97 %) in the prediction of UCS of samples with superiority to the best EPR model.
492 Based on the parametric studies, It was obtained that for the molarity concentration of up to 8M, there was a
493 transition zone with regards to CD (day) and GGBFS (%), in which the effects of curing temperature on UCS
494 changes, while there was not such a threshold for the samples activated using 12M alkali solutions. In addition, it
495 was observed that Si/Al, Na/Al, and A/B ratios had a direct influence on the compressive strength of samples. The
496 rate of increasing UCS with Na/Al was, also, attained to be higher for lower Si/Al ratios. Sensitivity analysis
497 based on CAM was then considered to introduce the most and the least affecting parameters on UCS and Si/Al
498 ratio was shown that to be the most influential parameter. On the other hand, the curing temperature and the
499 percentage of volcanic ash had the least effects on UCS. Experimental results obtained and mechanisms behind
500 reactions were then further discussed based on microstructural investigations using SEM images and XRD
501 analysis. It was shown that during the stabilization process no new minerals were created and the enhanced
502 strengths were results of the geo-polymerization and the formation of new bonding around the soil skeleton.

503 **Data Availability Statements**

504 Some or all data, models, or codes that support the findings of this study are available from the corresponding
505 author upon reasonable request.

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Appendix: Calculation of Na/Al and Si/Al ratios for different cases:

In a certain mixture, we have assumed that the total amount of the dry soil taken is x gr. Binder percentage is s gr. Also, molarity and total alkali to binder ratio will be represented by M and A/B, respectively. A'/B represents the ratio of $NaOH$ alkali to the binder, and A''/B stands for the Na_2SiO_3 alkali to the binder ratio.

Then, we will have:

Amount of the binder presented in the mixture in gr: $(\frac{s}{100}) \times x$.

Amount of the alkali solution (in the case of using *NaOH* as the sole solution) presented in the mixture in gr: $(\frac{s}{100}) \times x \times (\frac{A'}{B})$.

1 molar *NaOH* solution contains = 40 gr NaOH in 1 l solution (40 gr NaOH+1000 gr water).

M molar *NaOH* solution contains = $40 \times M$ gr NaOH in 1 l solution (40M gr NaOH+1000 gr water) solution.

Therefore $(1000 + 40 \times M)$ gr alkali solution contains = $40 \times M$ gr of NaOH.

Hence, $(\frac{s}{100}) \times x \times (\frac{A'}{B})$ gr alkali solution contains = $\frac{40 \times M}{(1000+40 \times M)} \times (\frac{s}{100}) \times x \times (\frac{A'}{B})$ gr of NaOH.

40 gr NaOH contains 23 gr of *Na.*

$\frac{40 \times M}{(1000+40 \times M)} \times (\frac{s}{100}) \times x \times (\frac{A'}{B})$ gr of *NaOH* = $\frac{23}{40} \times \frac{40 \times M}{(1000+40 \times M)} \times (\frac{s}{100}) \times x \times (\frac{A'}{B})$ gr of *Na.*

Using the Avogadro's number: 23 gr *Na* contains = 6.023×10^{23} number of *Na* atoms.

$\frac{23}{40} \times \frac{40 \times M}{(1000+40 \times M)} \times (\frac{s}{100}) \times x \times (\frac{A'}{B})$ gr of Na contains = $\frac{(\frac{s}{100}) \times x \times (\frac{A'}{B}) \times M}{(1000+40 \times M)} \times 6.023 \times 10^{23}$ number of Na atoms.

Now, calculations of *Na/Al* and *Si/Al* ratios at different conditions:

a) *Na/Al* ratio:

a-1) In VA-stabilized samples:

As described, VA-stabilized samples are activated using *NaOH* activator. Hence, there will be just a single case, in which *A'/B* is the ratio of *NaOH* to the binder. Hence, the calculations will be as follows:

Percentage of Al_2O_3 in VA is 20%. So:

Amount of Al_2O_3 presented in the binder is = $(\frac{s}{100}) \times x \times 0.2$ gr.

Now, 102 gr Al_2O_3 contains = 54 gr of *Al*.

$(\frac{s}{100}) \times x \times 0.2$ gr Al_2O_3 contains = $\frac{54}{102} \times (\frac{s}{100}) \times x \times 0.2$ gr of *Al.*

Again, 27 gr of *Al* contains = 6.023×10^{23} No. of *Al* atoms.

So, $\frac{54}{102} \times (\frac{s}{100}) \times x \times 0.2$ gr of Al contains = $\frac{1}{51} \times (\frac{s}{100}) \times x \times 0.2 \times 6.023 \times 10^{23}$ number of *Al* atoms.

Hence, the ratio of *Na/Al* in VA-stabilized samples will be:

$$\frac{Na}{Al} = \frac{(\frac{s}{100}) \times x \times (\frac{A'}{B}) \times M}{1000 + 40M} \times 6.023 \times 10^{23} = \frac{(\frac{A'}{B}) \times M \times 51}{0.2(1000 + 40M)}$$

a-2) In GGBFS-stabilized samples:

For GGBFS-stabilized samples, there will be two cases:

a-2-1) those who are activated using *NaOH* as the sole activator (represented by *A'/B* ratio);

a-2-2) those who are activated using the combination of *NaOH* (represented by *A'/B* ratio) and Na_2SiO_3 (represented by *A''/B* ratio) solutions.

Following calculations similar to those explained in a-1 section,

a-2-1) Samples activated using NaOH as the sole activator:

$$\frac{Na}{Al} = \frac{(\frac{A'}{B}) \times M \times 51}{0.08(1000 + 40M)}$$

a-2-2) Samples activated using the combination of NaOH (A'/B) and Na_2SiO_3 (A''/B) solutions:

$$\frac{Na}{Al} = \frac{51M}{0.08} \times \frac{\left[\left(\frac{A'}{B}\right) \times (1000 + 122M)\right] + \left[2 \times \left(\frac{A''}{B}\right) \times (1000 + 40M)\right]}{(1000 + 40M)(1000 + 122M)}$$

733 **b) *Si/Al* ratio:**

734 *b-1) In VA-stabilized samples:*

735 As described, VA-stabilized samples are activated using *NaOH* activator. Hence, there will be just a single
736 case. Hence, the calculations will be as follows:

737 $$\frac{Si}{Al}=\frac{(\frac{1}{60})\times(\frac{s}{100})\times x\times 0.54\times 6.023\times 10^{23}}{(\frac{1}{51})\times(\frac{s}{100})\times x\times 0.2\times 6.023\times 10^{23}}=\frac{51\times 0.54}{60\times 0.2}=2.3$$

738 *b-2) In GGBFS-stabilized samples:*

739 For GGBFS-stabilized samples, there will be two cases:

740 *b-2-1) Samples activated using NaOH as the sole activator:*

741 $$\frac{Si}{Al}=\frac{[(\frac{1}{60})\times(\frac{s}{100})\times x\times 0.31\times 6.023\times 10^{23})]}{\frac{1}{51}\times(\frac{s}{100})\times x\times 0.08\times 6.023\times 10^{23}}=3.29$$

742 *b-2-2) Samples activated using the combination of NaOH and Na_2SiO_3 solutions:*

743 $$\frac{Si}{Al}=\frac{[(\frac{1}{60})\times(\frac{s}{100})\times x\times 0.31\times 6.023\times 10^{23})]+[\frac{(\frac{s}{100})\times x\times(\frac{A''}{B})\times M}{1000+122M}\times 6.023\times 10^{23}]}{\frac{1}{51}\times(\frac{s}{100})\times x\times 0.08\times 6.023\times 10^{23}}=3.29+\frac{(\frac{A''}{B})\times M\times 51}{0.08(1000+122M)}$$

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748 **Tables**

749 **Table 1** Physical properties of the studied Firouzkouh #161 sand

Parameter	Value
C_c	1.02
C_u	0.35
D_{50} (mm)	0.47
D_{60} (mm)	0.38
D_{30} (mm)	0.31
D_{10} (mm)	0.2
G_s	2.65
γ_{min} (gr/cm^3)	1.397

γ_{max} (gr/cm^3)	1.635

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Table 2 Chemical properties of the studied Firouzkouh #161 sand

Chemical name	Percentage
SiO_2	94.33
Fe_2O_3	0.9
Al_2O_3	2.03
CaO	1.05
Na_2O	0.49
K_2O	0.21

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758 **Table 3** Results of chemical analysis of VA and GGBFS

VA		GGBFS	
Chemical name	Percentage	Chemical name	Percentage
SiO_2	*53.9*	CaO	43
CaO	8.97	*SiO_2*	*30.5*
Al_2O_3	*20.31*	*Al_2O_3*	*8*
Fe_2O_3	3.45	Fe2O3	0.5
K_2O	1.92	MgO	9.5
Na_2O	5.15	Others	0.8
MgO	1.42		
TiO_2	0.51		

SrO	0.07
SO_3	0.26
P_2O_5	0.3
MnO	-
ZrO_2	0.02
LOI	3.8

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Table 4 Program of experiments

Studied parameters and ranges																		
VA (%)				GGBFS (%)				A/B				M (M)			CD (days)			T (°C)	
0	3	7	10	0	3	7	10	1	1.5	2	3	4	8	12	1	7	28	20	60

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766 **Table 5** Statistical analysis of input and output parameters

Statistical Parameter	GGBFS (%)	VA (%)	M (M)	A/B	Na/Al	Si/Al	CD (day)	T (°C)	UCS (kPa)
Maximum	10	10	12	3	17.588	9.5	28	60	6218.6
Minimum	0	0	4	1	1.55	2.3	1	20	0
Average	5.714	0.952	8	1.5	5.897	4.382	12	40	1129.683
STD.	3.548	2.583	3.036	0.71	4.253	1.946	11.622	20.08	1017.61

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768 **Table 6** Architectures and performances of developed artificial neural networks

Architecture	RMSE (kPa)	MAE (kPa)	R^2 (%)	Line slope

8-5-10-1	*0.0439*	*0.0336*	*97*	*0.84*
8-5-13-1	0.0965	0.0658	72	1.28
8-6-1	0.0556	0.0411	90	0.83
8-6-12-1	0.1046	0.0704	94	0.52
8-7-14-1	0.0875	0.0571	86	1.07
8-10-5-1	0.0803	0.0659	62	0.63
8-10-15-1	0.1276	0.0858	53	0.4
8-12-1	0.0596	0.0469	88	1.75

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