Journal of Mining and Environment (JME), Vol. 12, No. 2, 2021, 299-311

Shahrood University of Technology
Iranian Society of Mining Engineering (IRSME)

Journal of Mining and Environment (JME)

journal homepage: www.jme.shahroodut.ac.ir

Monte Carlo Simulation-Based Uncertainty Integration into Rock Particle Shape Descriptor Distributions

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Article Info

Received 16 January 2021

Received in Revised form 8 March 2021

Accepted 24 March 2021

Published online 24 March 2021

DOI:10.22044/jme.2021.10472.1997

Keywords

Sandstone

Sensitivity analysis

Tabletop microscope

ImageJ

Abstract

The particles within the rock samples are present in extensive ranges of shapes and sizes, and their characterization and analysis exist with a considerable diversity. The prior research works have appraised the significance of the particle shape types and their effects on the geotechnical structures and deficiencies by evaluating the uncertainty-related rock particle shape descriptors (PSDs). In this work, the Monte Carlo simulation (MCS) is used in order to present a framework to integrate the inherent uncertainty associated with PSDs. A tabletop microscope is used to measure the primary particle shape distribution for the sandstone samples. An open-source processing tool, ImageJ, is used in order to analyze PSDs. The probabilistic distribution of PSDs is acquired using MCS according to the relative frequency histogram of the input parameters. Additionally, a probabilistic sensitivity analysis is performed in order to evaluate the importance of the input parameters in PSDs. The sensitivity analysis results demonstrate that the major axis and area are the most influential parameters involved. The simulation results obtained have revealed that the proposed framework is capable of integrating the inherent uncertainties related to the particle shape.

1. Introduction

In the early 20th century, the effects of the micro-structures on the mechanical behavior of soil have been suggested after the development of the techniques to represent the form and roundness of the particles [1]. In the geotechnical field, various researchers have studied the influence of particle shape and size on the stability of the geotechnical structures such as slopes, dams, and buildings, concluding that these micro-structures affect the soil properties such as the cohesion, friction angle, and shear strength [1-3]. Understanding the mechanical behavior of rock mass is the primary foci in the slope stability [4] since slope failures may lead to the loss of multiple lives and a more considerable property damage [5]. The slope failure of rocks typically happens as a result of the downslope movement of rock mass along the failure plane [6]. Understanding the triggering of a failure plane in rock mass must be understood [7]. Consequently, the effect of the rock micro-structure on the macroscopic mechanical behavior of the rock mass can be significant [8]. Most rocks in the nature are composed of irregular mineral particles that are strongly bonded together [9]. It is believed that the shapes and sizes of the mineral particles are crucial to the mechanical behavior of the failure surfaces under study. Description of the particles present or embedded in the failure surface and the asperities is required for a stability prediction [10]. Many researchers have tried to integrate the particle shape using the discrete element method (DEM) using various shape descriptors [11]. Nevertheless, naturally, rocks are very complex concerning the particle shape [7].

The literature indicates that the primary emphasis on the particle shape and size is in the area of geology compared to the geotechnical field [1]. The particle shapes can be categorized into quantitative and qualitative [1, 12, 13]; quantitative describes the measurement of the dimensions,

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while qualitative measures the shape of the particles such as spherical, elongated, and flaky [1, 13]. The qualitative description of the particle shape is based on the measured quantitative dimensions [1]. The particle shape has been described in three sub-quantities by various researchers. These terms describe the shape of the particles on a different scale. The terminology is the roundness, shape/morphology, and surface texture [1]. For classifying the particle shape based on morphology/form, the particle volume, parameter, axis-length, and surface area are taken into consideration [1, 14]. Furthermore, the particle corners can be angular or rounded (roundness); similarly, they can be rough or smooth (surface texture) [1, 14]. According to the historical viewpoint, various researchers have used different shape descriptors as terminologies such as roundness or angularity (sharpness or smoothness of the parameters) and sphericity or elongation (based on the circle diameter) [14-18]. For the particle shape descriptors (PSDs), a common terminology is required in order to ensure the comparability of the different descriptors but unfortunately, there is no common language for the researchers to consider and rely on. This significant problem can be tackled by using several types of shape descriptors simultaneously. It is not feasible since the particle size can be represented in numerous ways, which result in a number of shape descriptors. Consequently, the researchers are focusing on the development of new methods in order to measure the particle size and shape precisely.

Over the years, the researchers are focusing on the introduction of new methods for estimating the particle shape [1]. The first method to measure the particle form was the hand measurement technique, which was replaced by a chart due to being time-consuming [1, 19-21]. The sieving method has been introduced to find the particle elongation and flakiness index but this approach is limited to the small-size particles [22]. Nowadays, the computer-based image analysis method is mostly used in order to classify the particle shape because it is fast and automated [23-25]. Various techniques such as the Feret diameter method, Fourier technique, fractal dimension method, orthogonal image analysis, Laser scanning techniques, and Laser-aided tomography have been materialized to process the images [1]. The image analysis tools such as scanning electron microscopy (SEM) scans the surface of a rock sample and gives the results in 2D [24]. The image-based methods, specifically SEM, for particle shape and size, produce images having a limited sensing range to the depth of flow, which produces uncertainty [1]. The statistical analysis method has been suggested by various researchers in order to evaluate the uncertainty.

Nowadays, the researchers have presented the probabilistic methods in the geotechnical field using the concept of probabilistic modeling in order to deal with the inherent uncertainty. Generally, the rock profile is very complex; it often provides different results than those assumed in the analysis and design. These results may be attributed to the limited sampling and inherent uncertainty related to the particle shape and size distribution. There have been numerous investigations related to the particle size distribution using statistical modeling. Kutchko and Kim [26] have used an image analysis technique in order to determine the grain size, shape, and orientation of the sand and sandstone samples. Rahmat and Tajdari [27] has employed the digital image processing technique and the Kuz-Ram model in order to estimate the rock fragments size distribution. Schäfer and Teyssen [28] have used the image analysis and statistical methodology to find the minimum number of particles required for the particle size distribution analysis. The author used the Chi-square test in order to evaluate the particle shape and size of the guava juice powder. Mohamed et al. [29] have proposed an extraction algorithm based on the gray histogram peak values for the analysis of the sediment particle images that could provide technical support for the measurement of the particle size distribution.

However, no attempt has been made to evaluate the uncertainty-related particle shape distribution parameters. Additionally, a previous research work was also limited to the incorporation of the interdependencies between the uncertain PSD parameters and the effect of the distribution type on each shape descriptor. In this research work, the Monte Carlo simulation-based uncertainty analysis framework was developed to model the PSD distributions in order to assess the uncertainty in the shape descriptor parameters. The suggested framework was applied for illustrative purposes in a case study of Bukit Merah Laketown, Malaysia.

2. Materials and methods

This key section provides an insight into the lithologic description of the sample, sample preparation, instrument theory, image processing, manual particle analysis, and data analysis method.

2.1. Sample preparation

The samples for this analysis were obtained in bulk from Bukit Merah Laketown in Malaysia. The primary samples were sliced into samples up to 95 mm in size. In addition, the samples for the trim saw were sliced using a Petro cut Geological cutter. Following that, using a Petro trim, trim saw, the samples were further cut to match the sample stand of the tabletop microscope (TTM). The samples were coated with a nano-thin coating of conductive material to get better images.

2.2. Instrument factors, image acquisition

A TTM was used for image acquisition (see Figure 1). TTM provides a highly flexible platform for the particle analysis. The automated nature of the TTM enables it to collect data over multiple fields of view.

For the analysis, the particles were manually tracked and saved. Only the particles having distinguishable boundaries were traced. The operators chose images with a suitable distinction between the particles and the background, and there was an issue found during the automated thresholding and with brightness and contrast.

2.2.1. Manual analysis

The particle shape and size were analyzed from the sample using a manual particle primary method. The particle images with clear and visible borders were reported. ImageJ, an open architecture software, was used to analyze and process the photos that had been reported. In the initial step of using ImageJ, the image file was upload into a new window using the File>Open, File>Import, and Drag & Drop options, followed by the spatial calibrations that involved calibrating a single image dimension in pixel against the known values. The line "selection tool" was used in order to draw a line over a scale bar of a known length followed by a "set scale" from the "analyze" menu. In our case, in the "set scale" dialog box, the "known distance" was entered as 200 μm, 500 μm, and 1 mm, and the "Global" checkbox was examined to apply the spatial calibration to all the open image windows. For the image processing algorithms, a binary image (black and white) was produced using the "Image>Adjust>Threshold" tool in the dialogue box. In the binary images, the objects were considered as black, while the background was white. In the proper thresholding, the images were converted into 8-bit, possessing 8^2 gray levels. Proceeding with a proper thresholding requires binary images that are produced, and the individual particles with distinguishable boundaries are manually traced. The particle size and shape descriptor measurement is accomplished using the "set measurement" dialog box command in ImageJ.

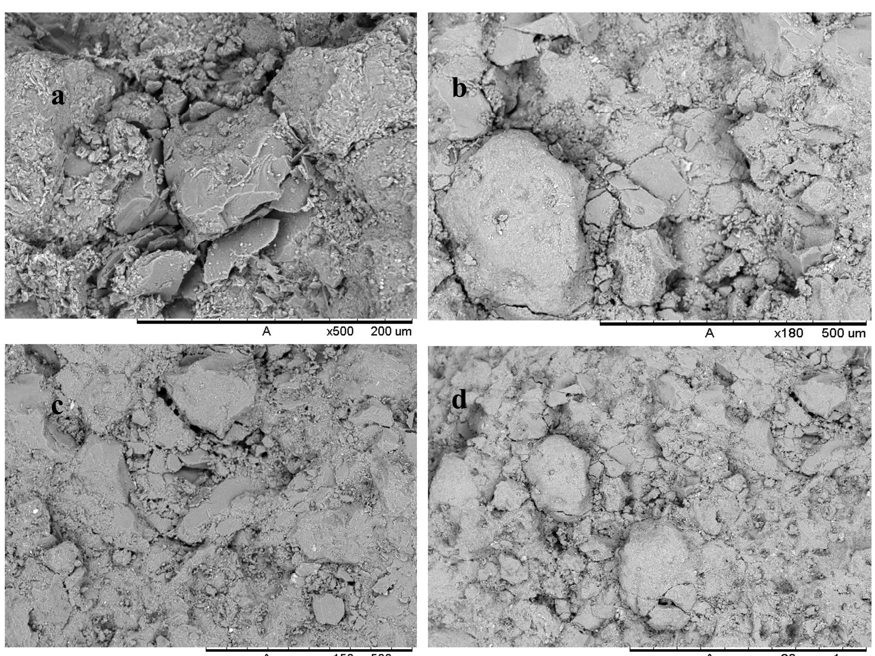

Figure 1. TTM micrographs of the sandstone samples with different magnifications (a) the image showing weathering; (b, c, and d) show the aggregate scale.

2.3. Shape descriptors

There are several shape and size descriptors in the literature; however, this work is mainly focused on the roundness, circularity, and aspect ratio. The size descriptors are used to calculate the shape descriptors. The size descriptors reported are area (mm^2), perimeter (mm), major and minor axes (mm), and minimum and maximum Feret diameters (mm). The three shape descriptors roundness, circularity, and aspect ratio are calculated using Equations 1, 2, and 3.

$$\text{Roundness} = 4 \times \frac{[\text{Area}]}{\pi \times [\text{Major axis}]^2} \tag{1}$$

$$\text{Aspect ratio} = \frac{[\text{Major Axis}]}{[\text{Minor Axis}]} \tag{2}$$

$$\text{Circularity} = 4\pi \times \frac{[\text{Area}]}{[\text{Perimeter}]^2} \tag{3}$$

The particle analysis is based on the physical size of the square units or the sum of the pixels, whether the pixel units are considered in the image. The thresholding procedure estimates the numbers of pixels and set into the minimum and maximum area sizes in order to specify the area of interest. The image thresholding is employed to calculate the particle size and shape automatically.

2.4. Data analysis

Using the Microsoft Excel, the SimulAr App, and the Kolmogorov-Smirnov, the Chi-square and maximum likelihood approach were adopted for fitting the distribution of the sampling data. The descriptor data could be analyzed using the conventional P-value statistics. The Cumulative Distribution Function (CDF) was configured for each descriptor in order to specify the probability of the individual value in the sample parameters. The best fit distribution process was employed in order to analyze the best-fit reference models (normal, long normal, beta, Weibull, etc.) for the sample parameters. The Monte Carlo simulation (MCS) was used for the random experimentation of the sampling data based on the previous fit distributions. In this work, the Monte Carlo method was intended to model the sampling data.

2.4.1. Probabilistic evaluation of rock PSDs

MCS is a stochastic simulation technique used to generate the models of possible outcomes based on the previous fit distribution of the input parameters (see Figure 2). The specific probability distributions are used as the input parameters in order to generate thousands of random values to model the possible outcomes. Microsoft Excel is a comprehensive set of analysis tools that implements MCS by characterizing the uncertainty to generate the possible outcomes. It evaluates the various types of probability distributions for the input values and chooses the most appropriate distribution and generates the statistics. For the shape descriptors, all the input parameters exhibit randomness. The relative frequency histogram can be used in order to depict the inherent uncertainty-related input parameters that can be acquired through micrograph using the ImageJ software. When the distributions are acquired for the four parameters, the distributions of roundness, aspect ratio, and circularity can be calculated according to Equations 1, 2, and 3; after that, MCS is used to model the probability of the output parameters. The input values for PSDs are obtained from a random sampling of the followed distributions, and the probability distributions of the shape descriptors are obtained from MCS.

2.5. Uncertainty analysis in PSDs

2.5.1. Probabilistic sensitivity analysis in PSDs

Various sensitivity analysis methods were applied in order to determine the relationship between the input and output parameters within the model including the factorial design, correlation method, differential sensitivity analysis, one-at-a-time (OAT/OFAT), scatter plot, regression analysis, and variance-based method [30]. The PSD sensitivity analysis could be performed in Microsoft Excel. The sensitivity analysis was carried out using the correlation method, and the outcomes were presented through the tornado plots that compared the relative importance of the existing distributions and their influence on the modeled distribution. The horizontal bar depicts the impact of the input distribution on the modeled distribution with the highest-valued input at the top of the graph.

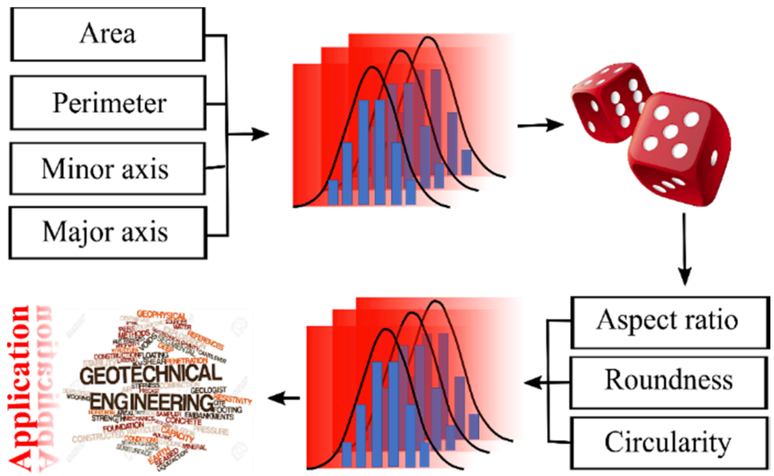

Figure 2. Schematic diagram of the proposed MCS-based uncertainty integration framework.

3. Results and analysis

The primary objective of this work was to measures the particle shape distribution for the sandstone samples. The principal elements of this analysis were the particle shape and size measurement using ImageJ, the statistical modeling of the shape descriptors of the sampling data, the MCS of the size parameters using the reference probability distribution and fitting the distribution to the simulated data. Five sandstone samples were tested for the particle shape distributions. The Chi-square test was used in order to determine the distribution of the particle shape before and after MCS.

4. Fitting distribution types to input parameters for PSDs

Figure 3, 4, and 5 show the histograms with a model, frequency, and the probability distribution of the input perimeters along with their Q-Q plot. All the four input parameters including the major axis, minor axis, perimeter, and area were best fitted with the inverse Gaussian reference model. The shape descriptor's values were first calculated by the deterministic method. After that, the shape descriptor's best-fitted distribution was evaluated. The aspect ratio was best fitted with the largest extreme value reference model (see Figure 6) and its P-value; the most possible and alternative most likely distribution are given in Table 1. The roundness distribution (see Figure 6) was typical of the three shape descriptors best fitted to the Weibull distribution, whereas circularity was best fitted to the smallest extreme value reference model (see Figure 6). The relationship of the particle size (Feret diameter) with the aspect ratio, roundness, and circularity is given in Figure 6. Most particles were between 0 µm and 100 µm in size. The statistics of the input parameters and deterministic shape descriptors are given in Table 1.

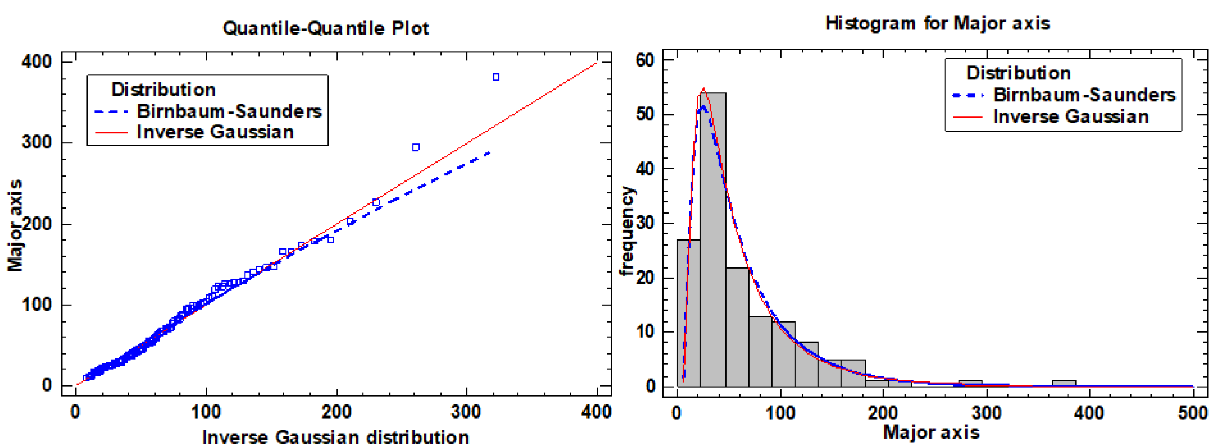

Figure 3. Left-hand-side: Q-Q plot showing the quantile come from the inverse Gaussian distribution; right-hand-side: frequency distribution, red color; best-fit distribution.

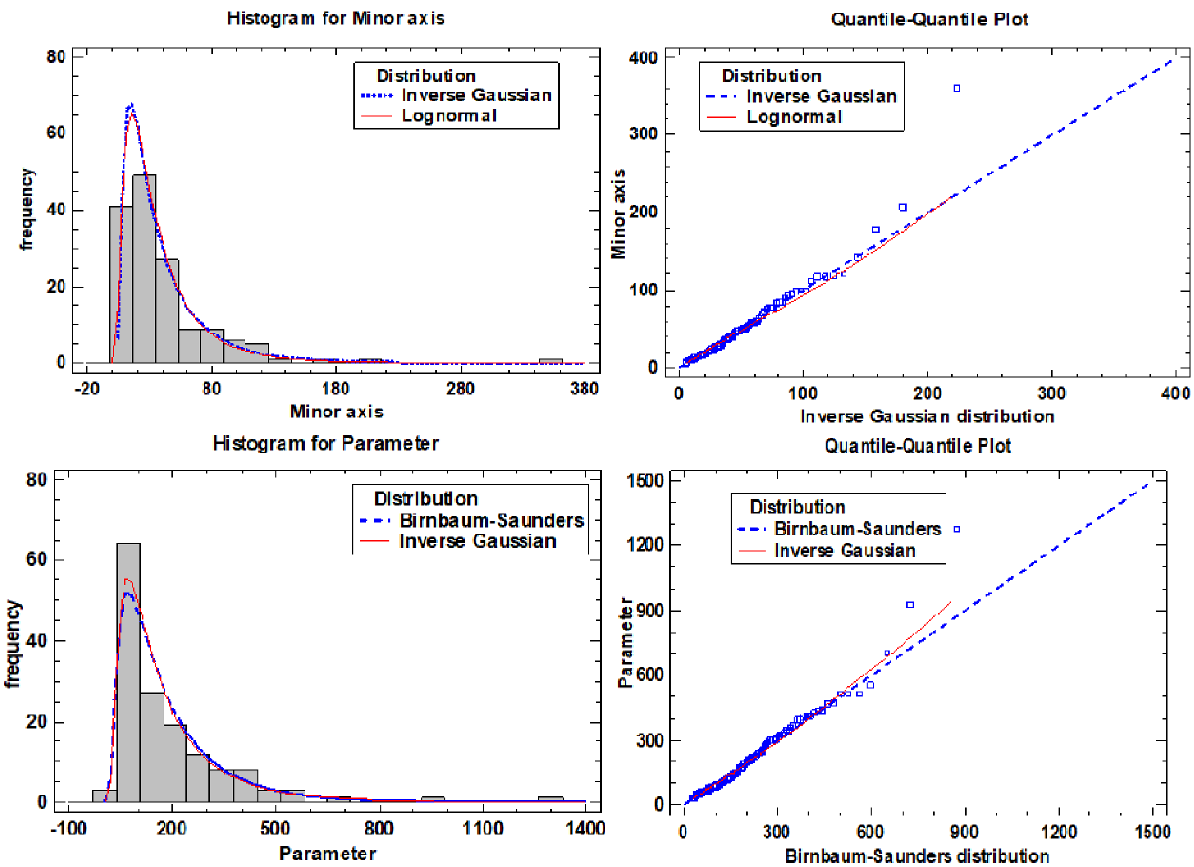

Figure 4. Left-hand-side: frequency distribution, blue color; best-fit distribution; right-hand-side: Q-Q plot showing quantile came from inverse Gaussian distribution.

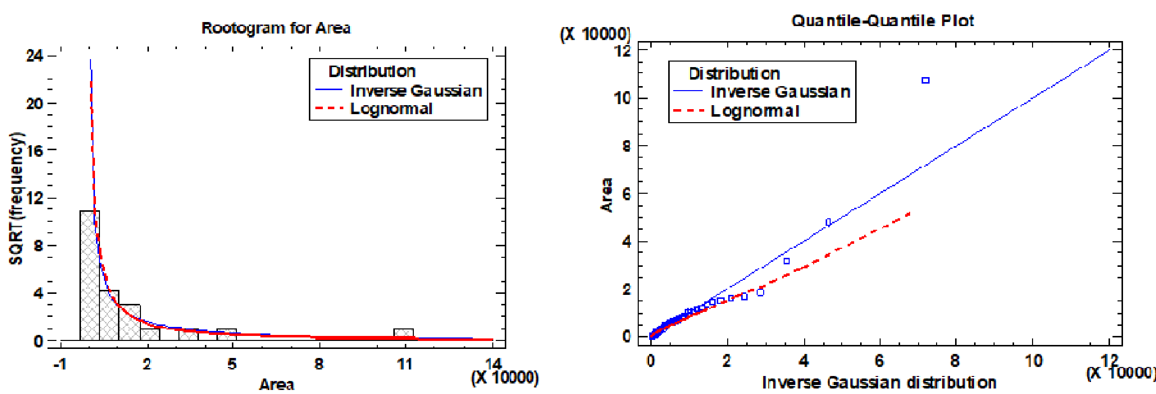

Figure 5. Right-hand-side: Q-Q plot showing quantile come from inverse Gaussian distribution; left-hand-side: frequency distribution, red color; best-fit distribution.

Table 1. Summary of distribution types fitted for input parameters.

Parameter	Fitted distribution	P-value	Log-likelihood	Alternative nearest likely distribution	Log-likelihood
Area	Inverse Gaussian	0.6564	-1313.53	Lognormal	-1318.47
Perimeter	Inverse Gaussian	0.28	-904.594	Birnbaum-Saunders	-906.141
Minor axis	Inverse Gaussian	0.43	-678.659	Lognormal	-680.97
Major axis	Inverse Gaussian	0.44	-772.773	Birnbaum-Saunders	-743.935
Aspect ratio	Largest extreme value	0.51	-74.6628	Inverse Gaussian	-79.4359
Roundness	Weibull	0.95	69.0804	Normal	67.506
Circularity	Smallest extreme value	0.989	118.623	Weibull	117.652

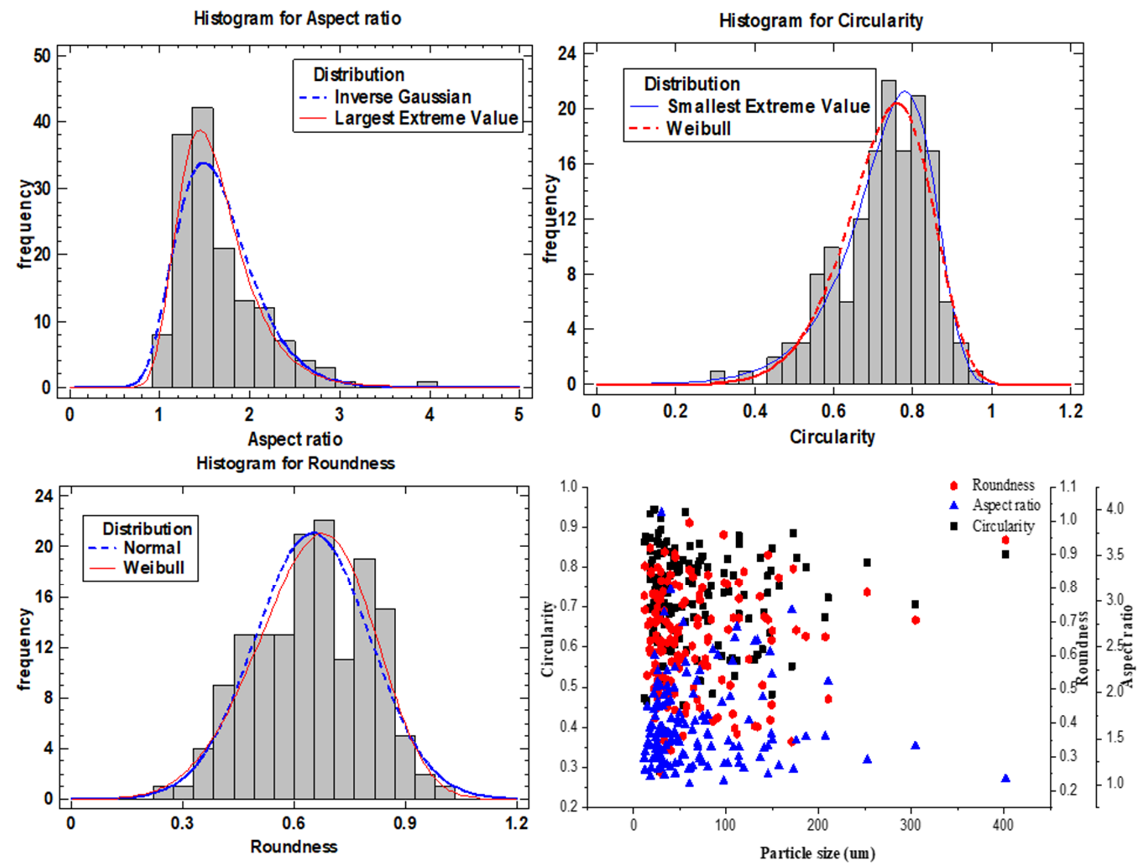

Figure 6. Fitted distribution for PSDs using the deterministic method; scatter graph-correlation between particle size and descriptors.

Table 2. Summary of statistics of input parameters.

Descriptors		Average (um)	Median (um)	S.D.	Coeff. of variation	Stand. skewness	Stand. kurtosis
Parameters	Area	3724.73	870	10319.5	277.1%	38.4	179.1
	Perimeter	184.127	123.213	170.795	92.76%	14.2044	31.3
	Minor axis	40.7	26.3	42.8	105.35%	18.8	54.2
	Major axis	62.2	41.8	55.4	89.120%	12.1	21.5
Deterministic shape descriptors	Aspect ratio	1.646	1.53	0.48	29.013%	7.82	8.78
	Roundness	0.65	0.6535	0.1548	23.82%	-0.905	-1.52
	Circularity	0.73	0.74	0.12	16.031%	-4.0613	1.999

4.1. Probabilistic analysis of PSDs

The PSD histogram details were acquired using the ImageJ software, and a frequency chart of the PSD values is shown in Figure 7. Understandably, the PSD input values are demonstrated as the continuous random variables in terms of the probability mass functions (PMF). The roundness is nearly approaching the normal distribution, and the aspect ratio is roughly negatively skewed about leftwards with lower values, while angularity is approximately positively skewed towards the right. The statistical distributions of the PSD parameters were acquired using Microsoft Excel and SimulAr employing Equations 1, 2, and 3. The input parameters were simulated up to 1000 iterations. The Kolmogorov-Smirnov Goodness-of-Fit test was used in order to evaluate the best fit distribution. The frequency distributions of the MCS-based PSD values are given in Figure 7.

The statistics of the simulated PSD values are given in Table 3. Traditionally, comparing the statistics of the PSD simulated and deterministic values show small variations. The average and median values are 0.63 and 0.66 from the simulated roundness distribution, which is close to 0.65 and 0.65; the results were obtained using the deterministic procedure. The other statistics results also show small significant differences such as standard deviation reducing from 0.155 to 0.153, coefficient of variation from 23.82% to 23.52%, standard skewness from -0.905 to -203.55, and standard kurtosis from -1.52 to -10.35. The quotient obtained by dividing the standard deviation (S.D.) by the mean is called the coefficient of variance (COV) and depicts the uncertainty. Similarly, the average simulated aspect ratio is decreased from 1.65 to 1.62, while the median is increased from 1.53 to 1.56. The S.D. and COV show small changes from 0.48 to 0.411 and from 29.013% to 25.3%. Comparably, the S.D. and COV values for both the simulated and deterministic procedure for circularity provide no significant difference between the values. Nevertheless, the average decreases from 0.73 to 0.70, and the median increases from 0.74 to 0.75; however, no significant difference were found from the statistical data for both the deterministic and simulated PSD values.

Table 3. Summary of statistics of the output parameters.

PSD	Average	Median	S.D.	COV (%)	Std. skewness	Std. kurtosis
Roundness	0.63	0.66	0.153	23.5	-203.55	-10.35
Aspect ratio	1.62	1.56	0.411	25.3	1052.8	160.5
Circularity	0.701	0.75	0.121	16.7	-1050.62	158.7

MCS for the PSD models gives results with best-fitted distribution, and their parameters are given in Table 4. The simulated PSD parameters show a significant resemblance to the deterministic PSD. Traditionally, the P-value uses an alternative to rejection of the distribution type, and its small value means a stronger evidence in favor of the alternative distribution. The P-value estimated for the simulated PSD models shows a significant increase, and the nearest alternate fit distribution is also estimated. The result revealed that the MCS-based PSD distribution was identical to the distribution followed by the deterministic method.

Table 4. Summary of the distribution types fitted for the output parameters.

PSD	Fit distribution	Parameters		P-value	Log-likelihood	Alternative nearest distribution
Aspect ratio	Largest extreme value	Mode Scale	1.44 0.32	0.99	-43782.4	Lognormal
Roundness	Weibull	Shape Scale	4.85 0.71	0.99	46398.4	Normal
Circularity	Smallest extreme value	Mode Scale	0.78 0.094	1.0	78134.3	Logistic

The simulation results unearth that MCS is a powerful tool for the deterministic procedure for evaluating the PSD statistics. The simulation also allows the users to get a comprehensive probability distribution and an exceedingly capacious range of the PSD values against the deterministic technique. MCS can also provide more informative statements and detailed analysis. By contrast, the deterministic method only provides little analysis information along with a huge amount of uncertainty, which makes the decisions subjective. Moreover, the statistics of the PSD values calculated using MCS are more reliable compared to the deterministic procedure. The statistics (average, median, maximum, minimum, standard deviation, coefficient of variation, Std. skewness, and Std. kurtosis) of the MCS particle shape descriptors were acquired from a large number (1000 in this case) of the simulated samples using MCS. Contrary to the deterministic analysis, the average and median of the PSD values are directly obtained from the statistics of the input parameters. The most critical aspect of MCS is its inclusion; the influence of the PSD standard deviations was taken into account. Unfortunately, the deterministic analysis ignores this consequence, which may relate to a certain discrepancy.

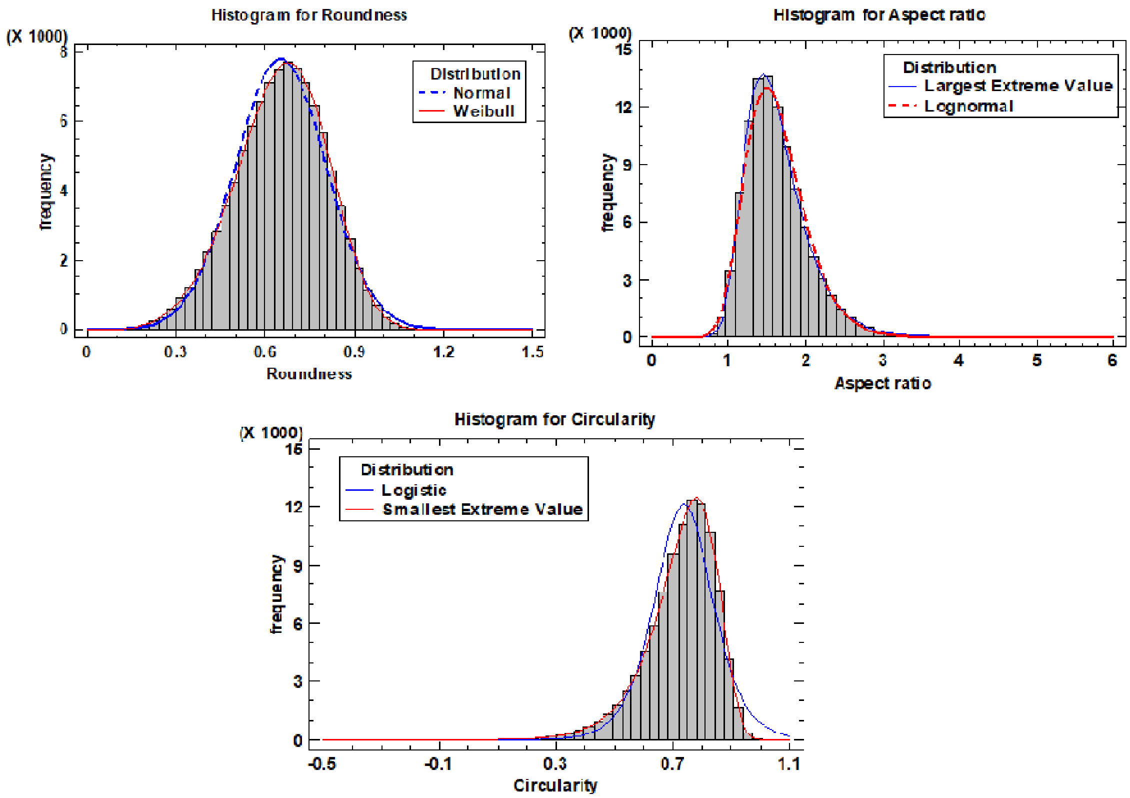

Figure 7. Fitted model of MCS-based PSD values and their optimal frequency distribution.

4.2. Probabilistic sensitivity analysis

In order to investigate the influence of the input variables, a sensitivity analysis was performed using MCS of the shape descriptors in the Microsoft Excel software. Figure 8 illustrates the sensitivity tornado plot for the shape descriptor parameters. The findings reveal that the area and major axis parameters exhibit the greatest influence on the PSD values, whereas the minor axis and perimeter have a minor impact. In Microsoft excel, the sensitivity analysis for MCS is performed simultaneously with varying the input parameters in order to evaluate the influence of the input variables on the output. However, the rock particle shape descriptor's input parameters sensitivity analysis was not performed. Instead, most researchers think that all the input parameters are similarly significant, which makes it difficult to identify determining parameters that affect the output.

Consequently, performing the sensitivity tests on the ground parameters during the site analysis stage is important. The model form and likelihood function for each input parameter as well as their effect on the measurement are missing from the one-way sensitivity analysis (Si-based). Contrastingly, the MCS-based sensitivity analysis in Microsoft Excel can simultaneously execute a multi-factor sensitivity analysis in order to evaluate the influence of the multiple input parameters on the output parameters.

5. Discussion

The material's property response is a function of the interaction between the particles. Therefore, appraising the influence of the particle shape on the mechanical behavior is crucial in terms of the damage response, strength properties, cohesion, and angle of internal friction. The discrete element method (DEM) and clump particle model are the two widely used methods to evaluate the mechanical behavior of rock mass. Unfortunately, these methods comprise a scarcity of matching the simulated particle size and shape distribution to the rock particles. In order to simulate a rock in DEM and particle flow code (PFC), it is necessary to investigate the particle shape distribution in a real-time. The diversity of the outcomes of the geotechnical studies indicates the uncertainty associated with the particle shape distribution to rock mechanical behavior. In order to address this problem, in this research work, we propose an approach focused on the use of image processing techniques in conjunction with MCS. The conceptual framework is based on studies into the morphology of the particles in various materials.

Many researchers have used the image processing techniques to examine the shape and size of the particles from various sources including the wood dust particles [31], fly ash [32], guava juice powder [33], titania powder [26], chlorite–amphibolite rocks [30], 3D-printed sandstone, and tight gas sandstone [34]. MCS is also often used in order to produce particles during simulations of different materials such as granular materials [35] and Brownian motion of the particles [36]. In order to obtain the suitable and accurate results, a sufficient number of particles must be analyzed statistically. During the particle analysis, uncertainties related to the particle shape are present due to the heterogeneous nature of the rocks. The deterministic approach, on the other hand, is incapable of dealing with these intrinsic inconsistencies. Abreu et al. [37] have used MCS in order to incorporate the uncertainty-related Q-system in a tunnel, while Pearson et al. [38] have used it to estimate the Hoek-Brown strength parameters for Ankara andesite. As a result, an MCS-based framework is the ideal way to address the inherent uncertainties.

In this research work, we mainly focused on the three types of shape descriptors including the roundness, circularity, and aspect ratio because it was infeasible to use a number of shape descriptors simultaneously. This is due to the fact that the particle shape can be described in a variety of ways. The proposed framework is validated through the Bukit Merah slope, and the consistency of the results obtained from the MCS-based method is supported by the same distributions accompanied by the simulation results relative to the deterministic results.

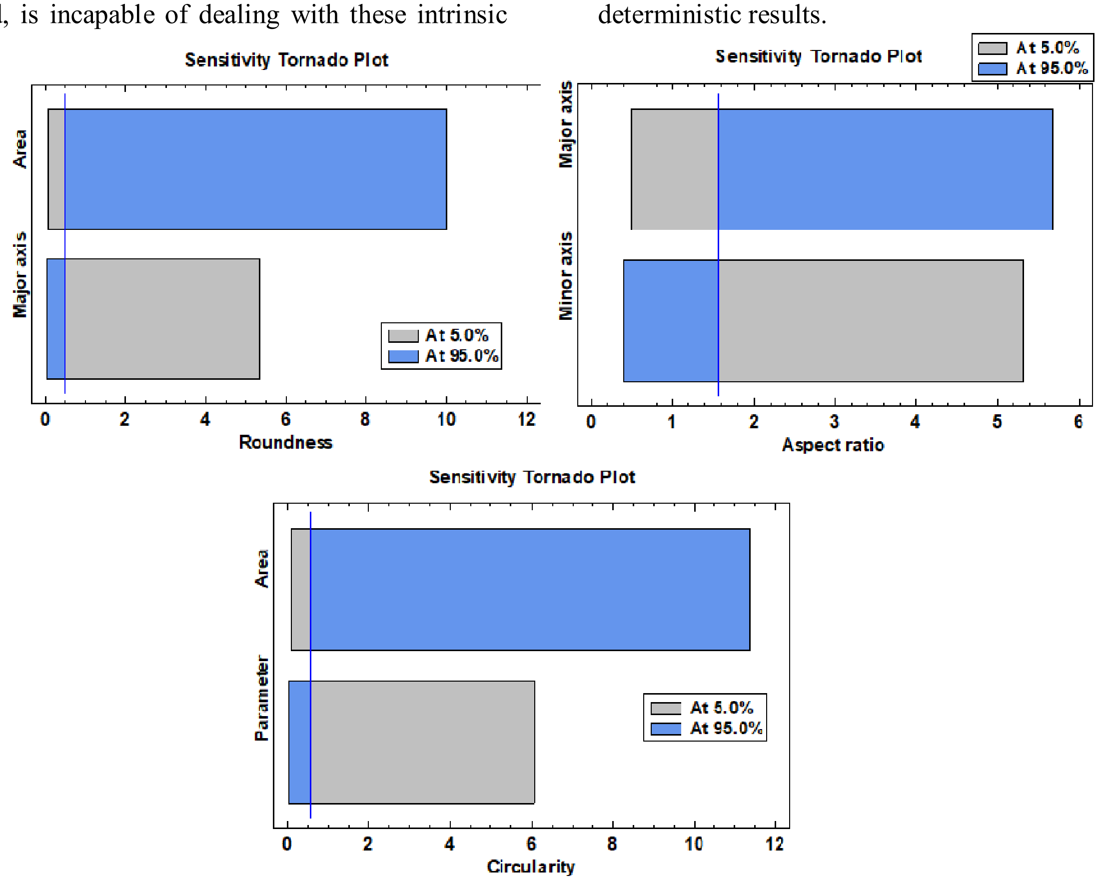

Figure 8. Sensitivity tornado plot showing the significance of each parameter.

6. Conclusions

In this work, the Monte Carlo simulation (MCS)-based uncertainty analysis framework was developed in order to model the particle shape. The available sample was analyzed for particle shape and size using a tabletop microscope (TTM). Furthermore, the statistical protocol was used to estimate the uncertainty-related input parameters and their influence on the output parameters. The case study of Bukit Merah Laketown (Malaysia) was selected to execute the proposed framework. From the results obtained, it was revealed that the MCS-based probabilistic analysis enabled us to characterize the variability and uncertainty-related input parameters. MCS was used in order to obtain the probabilistic distribution of the particle shape descriptors (PSDs) on the basis of the relative frequency histogram of the input parameters.

Furthermore, the uncertainty analysis of the probabilistic PSD values evinces that the probabilistic sensitivity analysis imparts the influence of the input reference model on the PSD distribution. The outstanding feature of the probabilistic sensitivity analysis is the simultaneous multi-factor analysis (MFA) using the input distribution variation. The results obtained demonstrated two things. First, the sensitivity analysis revealed that the major axis and area had a significant impact on the PSD values. Secondly, the presented framework of the image analysis using SEM together with the MCS-based uncertainty analysis provided an approach for assessing the inherent uncertainty in PSDs.

Acknowledgment: (Kausar Sultan Shah) is extremely thankful to the Higher Education Commission (HEC) of Pakistan for the HRDI-UESTPs scholarship.

Conflicts of Interest: The authors declare no conflicts of interest.

References

[1]. Rodriguez, J., Edeskär, T. and Knutsson, S. (2013). Particle shape quantities and measurement techniques: a review. The Electronic journal of geotechnical engineering. 18: 169-198.

[2]. Shah, K. S., bin Mohd Hashim, M. H., Emad, M. Z., bin Ariffin, K. S., Junaid, M., & Khan, N. M. (2020). Effect of particle morphology on mechanical behavior of rock mass. Arabian Journal of Geosciences. 13 (15): 1-17.

[3]. Aminzadeh, A. and Hosseininia, E.S. (2013, June). A study on the effect of particle shape and fragmentation on the mechanical behavior of granular materials using discrete element method. In AIP Conference Proceedings (Vol. 1542, No. 1, pp. 915-918). American Institute of Physics.

[4]. Norazirah, A., Fuad, S.H.S. and Hazizan, M.H.M. (2016). The effect of size and shape on breakage characteristic of mineral. Procedia Chemistry. 19: 702-708.

[5]. Shah, K.S., Mohd Hashim, M.H., Ariffin, K.S. and Nordin, N.F. (2020). A Preliminary Assessment of Rock Slope Stability in Tropical Climates: A Case Study at Lafarge Quarry, Perak, Malaysia. Journal of Mining and Environment. 11 (3): 661-673.

[6]. Shen, J. and Karakus, M. (2014). Three-dimensional numerical analysis for rock slope stability using shear strength reduction method. Canadian geotechnical journal. 51(2): 164-172.

[7]. Wyllie, D.C. (2014). Rock fall engineering. CRC Press.

[8]. Stead, D. and Wolter, A. (2015). A critical review of rock slope failure mechanisms: the importance of structural geology. Journal of Structural Geology. 74: 1-23.

[9]. Chen, T., Deng, J., Sitar, N., Zheng, J., Liu, T., Liu, A. and Zheng, L. (2017). Stability investigation and stabilization of a heavily fractured and loosened rock slope during construction of a strategic hydropower station in China. Engineering Geology. 221: 70-81.

[10]. Liu, H.Y., Kou, S.Q., Lindqvist, P.A. and Tang, C.A. (2002). Numerical simulation of the rock fragmentation process induced by indenters. International Journal of Rock Mechanics and Mining Sciences. 39 (4): 491-505.

[11]. Rong, G., Liu, G., Hou, D. and Zhou, C.B. (2013). Effect of particle shape on mechanical behaviors of rocks: a numerical study using clumped particle model. The Scientific World Journal, 2013.

[12]. Potyondy, D.O. and Cundall, P.A. (2004). A bonded-particle model for rock. International journal of rock mechanics and mining sciences. 41 (8): 1329-1364.

[13]. Pourghahramani, P. and Forssberg, E. (2005). Review of applied particle shape descriptors and produced particle shapes in grinding environments. Part I: Particle shape descriptors. Mineral Processing & Extractive Metall. Rev. 26 (2): 145-166.

[14]. Mitchell, J. K. and Soga, K. (2005). Fundamentals of soil behavior (Vol. 3). New York: John Wiley & Sons.

[15]. Arasan, S., Hasiloglu, A.S. and Akbulut, S. (2010). Shape properties of natural and crushed aggregate using image analysis. International Journal of Civil and Structural Engineering. 1 (2): 221.

[16]. Barrett, P.J. (1980). The shape of rock particles, a critical review. Sedimentology. 27 (3): 291-303.

[17]. Hawkins, A.E. (1993). The shape of powder-particle outlines (p. 115). Taunton: Research Studies Press.

[18]. Teller, J.T. (1976). Equantcy versus sphericity. Sedimentology. 23 (3): 427-428.

[19]. Wentworth, C.K. (1933). The shapes of rock particles: a discussion. The Journal of Geology.41 (3): 306-309.

[20]. Aschenbrenner, B.C. (1956). A new method of expressing particle sphericity. Journal of Sedimentary Research. 26 (1): 15-31.

[21]. Krumbein, W.C. (1941). Measurement and geological significance of shape and roundness of

sedimentary particles. Journal of Sedimentary Research. 11 (2): 64-72.

[22]. Krumbein, W.C. and Sloss, L.L. (1951). Stratigraphy and sedimentation, vol. 71.

[23]. Pye, W.D. and Pye, M.H. (1943). Sphericity determinations of pebbles and sand grains. Journal of Sedimentary Research. 13 (1): 28-34.

[24]. Persson, A.L. (1998). Image analysis of shape and size of fine aggregates. Engineering Geology. 50 (1-2): 177-186.

[25]. Andersson, T. (2010). Estimating particle size distributions based on machine vision (Doctoral dissertation, Luleå tekniska universitet).

[26]. Kutchko, B.G. and Kim, A.G. (2006). Fly ash characterization by SEM–EDS. Fuel. 85 (17-18): 2537-2544.

[27]. Rahmat, M.F. and T. Tajdari. (2011). Particle size measurement techniques: A review of methods and applications. Jurnal Teknologi. 55 (1): p. 137-149.

[28]. Schäfer, A. and Teyssen, T. (1987). Size, shape and orientation of grains in sands and sandstones—image analysis applied to rock thin-sections. Sedimentary Geology. 52 (3-4): 251-271.

[29]. Mohamed, F., Riadh, B., Abderazzak, S., Radouane, N. and Ibsa, T. (2019). Distribution analysis of rock fragments size based on the digital image processing and the Kuz-Ram model Cas of Jebel Medjounes Quarry. Aspects in Mining & Mineral Science. 2 (4).

[30]. Mohamed, F., Riadh, B., Abderazzak, S., Radouane, N. and Ibsa, T. (2019). Distribution analysis of rock fragments size based on the digital image processing and the Kuz-Ram model Cas of Jebel Medjounes Quarry. Aspects in Mining & Mineral Science: 2 (4).

[31]. Hong, C., Tang, H. W., Yun, L., Hao, W. and Liu, G.P. (2013). Measurement of particle size based on digital imaging technique. Journal of Hydrodynamics, Ser. B. 25 (2): 242-248.

[32]. Hamby, D.M. (1994). A review of techniques for parameter sensitivity analysis of environmental models. Environmental monitoring and assessment. 32 (2): 135-154.

[33]. Mazzoli, A. and Favoni, O. (2012). Particle size, size distribution and morphological evaluation of airborne dust particles of diverse woods by scanning electron microscopy and image processing program. Powder Technology. 225: 65-71.

[34]. Grulke, E.A., Yamamoto, K., Kumagai, K., Häusler, I., Österle, W., Ortel, E. and Stromberg, A.J. (2017). Size and shape distributions of primary crystallites in titania aggregates. Advanced Powder Technology. 28 (7): 1647-1659.

[35]. Yang, X., Wang, J., Zhu, C., He, M. and Gao, Y. (2019). Effect of wetting and drying cycles on microstructure of rock based on SEM. Environmental Earth Sciences. 78 (6): 1-10.

[36]. Desbois, G., Urai, J.L., Kukla, P.A., Konstanty, J. and Baerle, C. (2011). High-resolution 3D fabric and porosity model in a tight gas sandstone reservoir: A new approach to investigate microstructures from mm-to nm-scale combining argon beam cross-sectioning and SEM imaging. Journal of Petroleum Science and Engineering. 78 (2): 243-257.

[37]. Abreu, C.R., Tavares, F.W. and Castier, M. (2003). Influence of particle shape on the packing and on the segregation of spherocylinders via Monte Carlo simulations. Powder Technology. 134 (1-2): 167-180.

[38]. Pearson, H.J., Valioulis, I.A. and List, E.J. (1984). Monte Carlo simulation of coagulation in discrete particle-size distributions. Part 1. Brownian motion and fluid shearing. Journal of Fluid Mechanics. 143: 367-385.

ادغام عدم قطعیت مبتنی بر شبیه سازی مونت کارلو در توزیع های توصیف کننده شکل ذرات سنگ

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ارسال ۲۰۲۱/۰۱/۱۶، پذیرش ۲۰۲۱/۰۳/۲۴

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چکیده:

ذرات موجود در نمونه‌های سنگ در طیف وسیعی از اشکال و اندازه‌ها وجود دارند و خصوصیات و تجزیه و تحلیل آنها با تنوع قابل توجهی مواجه است. تحقیقات پیشین با ارزیابی توصیف کننده‌های شکل ذرات سنگ مربوط به عدم قطعیت (PSD)، اهمیت انواع شکل ذرات و تأثیرات آنها بر ساختارهای ژئوتکنیکی و کمبودهای موجود را ارزیابی کرده‌اند. در این پژوهش، از شبیه سازی مونت کارلو (MCS) به منظور ارائه چارچوبی برای ادغام عدم قطعیت ذاتی مرتبط با PSD استفاده شده است. برای اندازه گیری توزیع اولیه شکل ذرات برای نمونه‌های ماسه سنگ از میکروسکوپ رومیزی استفاده شده است. به منظور بررسی PSD، از یک ابزار پردازش منبع باز، ImageJ استفاده شده است. توزیع احتمالی PSD با استفاده از MCS با توجه به هیستوگرام فرکانس نسبی پارامترهای ورودی بدست می‌آید. علاوه بر این، یک تحلیل حساسیت احتمالی به منظور ارزیابی اهمیت پارامترهای ورودی در PSD انجام می‌شود. نتایج تجزیه و تحلیل حساسیت نشان می‌دهد که محور و منطقه اصلی تأثیرگذارترین پارامترها هستند. نتایج شبیه سازی به دست آمده نشان داده است که چارچوب پیشنهادی توانایی ادغام عدم قطعیت‌های ذاتی مربوط به شکل ذرات را دارد.

کلمات کلیدی: ماسه سنگ، آنالیز حساسیت، میکروسکوپ رومیزی، ImageJ.