Geomechanics and Engineering, *Vol. 39, No. 1 (2024) 1-11*
https://doi.org/10.12989/gae.2024.39.1.001

The investigation of the applicability of Monte Carlo Simulation in analyzing TBM project requirements

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(*Received June 14, 2024, Revised August 13, 2024, Accepted August 14, 2024*)

Abstract. Geotechnical parameter estimation is critical to the design, performance, safety, and cost and schedule management in Tunnel Boring Machine projects. Since these parameters vary within a certain range, relying on mean values for evaluation introduces significant risks to the project. Due to the non-homogeneous characteristics of geological formation, data may not exhibit a normal distribution and the presence of outliers might be deceptive. Therefore, the use of reliable analyses and simulation models is inevitable in the course of the data evaluation process. Advanced modeling techniques enable comprehensive analysis of the project data and allowing to model the uncertainty in geotechnical parameters. This study involves using Monte Carlo Simulation method to predict probabilistic distributions of field data, and therefore, establish a basis for designs and in turn to minimize project risks. In the study, 166 sets of geotechnical data Obtained from 35 boreholes including Standard Penetration Test, Limit Pressure, Liquid Limit, and Plastic Limit values, which are mostly utilized parameters in estimating project requirements, were used to estimate the geotechnical data distribution of the study field. In this context, firstly, the data was subjected to multi-parameter linear regression and variance analysis. Then, the obtained equations were implemented into a Monte Carlo Simulation, and probabilistic distributions of the geotechnical data of the field were simulated and corresponding to the 90% probability range, along with the minimum and maximum values at the 5% probability levels presented. Accordingly, while the average SPT N30 value is 42.86, but the highest occurrence rate is 50.81. For Net Limit Pressure, the average field data is 17.07 kg/cm², with the maximum occurrence between 9.6 kg/cm² and 13.7 kg/cm². Similarly, the average Plastic Limit value is 22.32, while the most probable value is 20.6. The average Liquid Limit value is 56.73, with the highest probability at 54.48, as indicated in the statistical data distribution. Understanding the percentage distribution of data likely to be encountered in the project allows for accurate forecasting of both high and low probability scenarios, offering a significant advantage, particularly in ordering TBM requirements.

Keywords: atterberg limits; geotechnical data; Monte Carlo simulation; standard penetration test; TBM project requirements

1. Introduction

The investigation of geotechnical parameters and their variability is critical for the successful implementation of Tunnel Boring Machine (TBM) projects. Numerical simulations and advanced modeling techniques have been increasingly utilized to enhance the reliability of geotechnical assessments. Lü *et al*. (2024) introduced a numerical simulation-based Artificial Neural Network (ANN) method to determine the shear strength parameters of rock minerals, providing a nano-scale perspective that can improve understanding of material properties in geotechnical contexts.

Zhou *et al*. (2022) developed an open-source unconstrained stress updating algorithm for the modified Cam-clay model, which offers significant improvements in modeling the stress-strain behavior of soils under varying conditions

In the realm of strength theory, Lu *et al*. (2017) proposed a new nonlinear unified strength theory for geomaterials based on the characteristic stress concept, which can be instrumental in predicting the behavior of geomaterials under different stress conditions. Additionally, Jiao *et al*. (2021) introduced a novel pore-scale thermal-hydro-mechanical model for fracture propagation processes using Lattice Boltzmann Method (LBM) and Discrete Element Method (DEM). This model provides a detailed understanding of fracture mechanics and their interactions with geotechnical parameters.

Furthermore, Harichane *et al*. (2018) highlighted the benefits of probabilistic soil-foundation-structure interaction analysis, demonstrating the advantages of probabilistic methods in managing the inherent variability and uncertainties in geotechnical engineering. These studies collectively underscore the importance of advanced numerical methods and modeling techniques in enhancing the predictability and reliability of geotechnical assessments, which are crucial for TBM project planning and execution.

One of the key aspects of TBM operation planning is ground conditioning, which provides the excavated soil is remolded into a homogeneous paste to facilitate efficient excavation by applying appropriate pressure to the face and fully filling the excavation chamber. (Milliga 2000, Mair *et al.* 2003, Giulio *et al.* 2018), while also aiding in the

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http://www.techno-press.org/?journal=gae&subpage=7
ISSN: 2005-307X (Print), 2092-6219 (Online)

transport and disposal of the soil and prevent cutter blockages. In the literature, the risk of clogging primarily as a function of soil plasticity and consistency (Hollman and Thewes 2013, Alberto Hernandez *et al*. 2018). Additionally, the type of cutterhead and the selection of ground conditioning chemicals, such as soil conditioning foams, polymers, and anti-clogging agents, are determined largely by the plastic properties of the soil. The Limit Pressure and penetration tests are used for determine soil elasticity and bearing capacity. The determination of ground bearing capacity provides insights into the planning of injection quantities (Tang *et al*. 2024).

In this study, Monte Carlo Simulation (MCS) was used to conduct risk analysis. Monte Carlo is a simulation technique that works based on using random variables and adopting statistical methods. MCS is used to evaluate uncertainties and risks in engineering projects, designs, or production processes and helps conduct risk analysis by simulating how the system might react to different variables (Chen 2013, Amar 2006, Li *et al.* 2019). MCS is a powerful method and successfully implemented in the risk analysis of numerous engineering projects (Marek *et al.* 2002, Vargas *et al.* 2014, Peng *et al.* 2017, Zhang *et al.* 2012). In tunnel engineering, The Monte Carlo Simulation method has been widely applied across various geotechnical domains to effectively manage uncertainties. Tu *et al.* (2021) analyzed the probability of internal force and deformation in deep tunnels. Zhou *et al.* (2021) studied tunnel roof deflection under sequential excavation using ANN-based MCS. This study aims to fill a gap in the literature by investigating the applicability of Monte Carlo Simulation for evaluating key geotechnical parameters, such as SPT, limit pressure, and consistency limits, in tunnel projects for determining TBM requirements.

To simulate the obtained data probabilistically, firstly, multi-parameter linear regression equations were derived to estimate the Standard Penetration Test (SPT), Net Limit Pressure (LP'), Liquid Limit (Wl), Plastic Limit (Wp) data. To evaluate the predictive capability of the generated models, the coefficient of determination (R^2) was calculated, and hypothesis test (f-test) was applied. After statistically significant and high-predictive-capacity equations were obtained, probability distribution functions (PDF's) were created. Then, field distributions of geotechnical parameters were generated using the MCS method to reveal probabilistic distributions with a percentage range of the parameters that will be encountered in the project revealed within the 95% confidence interval. Thus, the range and frequency of geotechnical values that possibly experienced during the project have been determined, and a methodology that practitioners can use in the decision-making phase is presented.

In this study, rather than relying on the average of hundreds of data points, it is advised to determine the probabilistic frequency of encountering various values in the course of the evaluation of geotechnical data. The probabilistic calculation of these parameters plays a crucial role not only in directly influencing design decisions but also in indirectly determining the actual duration and cost of the project. This method assists in estimating support and excavation system, consumable requirements, and project completion time in advance. By understanding the probability of encountering specific conditions, TBM costs and management strategies can be pre-determined with more accuracy.

2. Study field

In the study, geotechnical data of the Istanbul terminal metro line, located in the residential area of Istanbul, Turkiye, was evaluated. Because of the geological location, geotechnical parameters vary in a wide range and densely populated areas increase the importance of the risk analysis. The location map of the study area with a geological section is given in Fig. 1 (Imm 2021). All geotechnical data from the 35 boreholes detailed in Yavas (2008), specifically focusing on the geotechnical challenges encountered during the construction of the Otogar- Kirazlı Metro Tunnel Project using tunnel boring machines, were employed as the primary dataset in this study.

The study area is located within the Gürpınar Member (Tdg) of the Danismen Formation (Td) and the Bakırköy Member (Tçb) of the Çekmece Formation (Tç) (Fig. 1). Gurpinar Member is characterized by greenish-dark gray to purplish shale, siltstone, sandstone, and thinly interbedded fine lignite. The Bakirkoy Member is dominated by white, beige, finely to moderately layered limestone, with intercalations of clayey limestone, shale, and marl (Imm 2021).

According to Yavas (2008), the study was conducted on the geotechnical evaluation of a tunnel project, and the engineering properties of the tunnel route determined through drilling activities, including Standard Penetration Test (SPT) and pressuremeter tests were used to determine the engineering properties of the tunnel route Yavas (2008). Accordingly, commonly encountered units in the field include clay, claystone, and sand units.

2.1 Description of the data set

The engineering properties of the tunnel route were determined through 35 drillings conducted in the study area. In addition to the Standard Penetration Test (SPT) and pressuremeter tests, laboratory experiments were carried out using samples obtained from these drillings to reveal the engineering characteristics of the route. The description of the data set is given in Table 1. A representative subset of the data used in this research is presented in Table 2.

The geotechnical data (SPT, Atterberg Limits and Limit Pressure) in the study was used as presented in the Yavaş (2008) study. Accordingly, SPT was conducted at 1.5-meter intervals in soil-defined regions. The SPT results were corrected for factors such as geological stress, groundwater, energy, rod length, borehole diameter, sample receiver, blow count efficiency, and anvil cushion. These corrections led to the determination of adjusted SPT N60 and N1,60 values, reflecting the energy and effective geological stress conditions. Additionally, pressuremeter tests were performed using 76 mm probes in boreholes along the

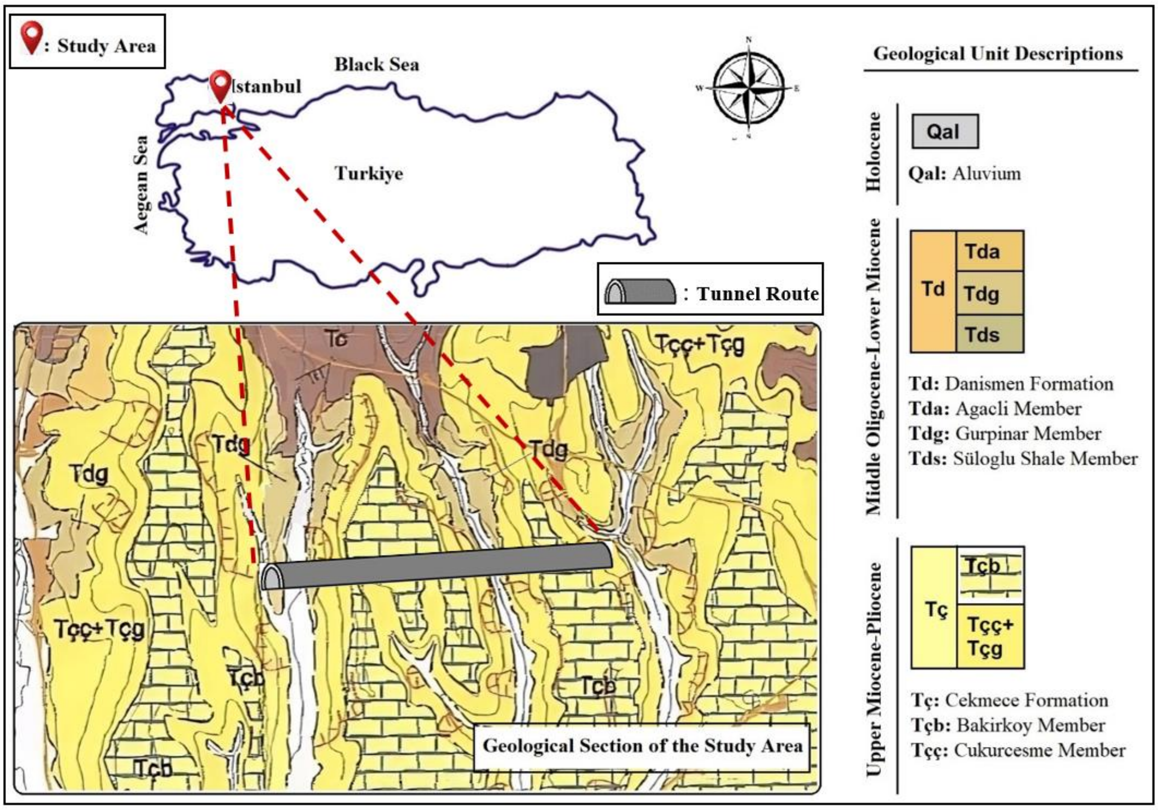

Fig. 1 Location and geological map of the study field (Modified from Imm, 2021)

Table 1 Description of the data set used in the study

Parameters	Units	Symbol	Number of Data
Average Depth	m	d	166
Type of the formation		Tp	127
SPT N1,60		SPT N1.6	127
SPT N30		SPT N30	118
Elastic Modulus	(kg/cm^2)	Ep	113
Limit Pressure	(kg/cm^2)	Lp	84
Net Limit Pressure	(kg/cm^2)	Lp’	84
Liquid Limit		Wl	43
Plastic Limit		Wp	43
Water Content		Ws	64

tunnel route. Atterberg limits tests, including liquid limit (Wl) and plastic limit (Wp) measurements, were also conducted on samples taken from the exploratory boreholes.

3. Statistical evaluation of the project data

Multi-parameter linear regression is a statistical modeling technique used to analyze the effect of the values of independent variables on a dependent variable. The only difference between multiple linear regression and simple linear regression is that the former introduces two or more predictor variables into the prediction model, whereas the latter introduces only one. This technique typically mathematically formulates the effect of multiple independent variables (predictors) on a dependent variable (Chernick and Friis 2003).

In the study multi-parameter linear regression models were generated with SPSS software to create deterministic models for estimating geotechnical parameters. In this context, the variables are Standard penetration test results (SPT N30), Corrected Standard penetration test results (SPT N1.6), Depth (d), Sampled Ground Type (Tp), Limit Pressure (LP), Net Limit Pressure (Lp'), Liquid Limit (Wl), Plastic Limit (Wp), Elastic Module (Ep), and Water Content (Ws) data. In the analyses, the average values were used for the depth intervals. The used numerical values in the formation definition were 1.1 for Clay and 1.2 for Sand. In the subsections of this section, prediction models created for SPT N30, Lp, and consistency limits, including prediction equations, variance analyses, and significance tests are presented consequently. Afterward, the created deterministic models were implemented into the Monte Carlo stochastic model, and the data was simulated. One of the most crucial stages in statistical models used in geotechnical research is validation (Sari Ahmed *et al.* 2018). To evaluate the accuracy of the created models, the R^2 indicator (coefficient of determination) was used to assess predictive capability, variance analysis was conducted, and a p-value hypothesis test (f-test) was applied. The results of these hypothesis tests, as indicated in the "Significance (Sig.)" column, show statistical significance across all analyses. Performed evaluations and

Table 2 A representative set of Kirazlı-Otogar (Istanbul terminal metro line) geotechnical data (Yavas 2008)

Depth	Type of the formation	SPT N 1.60	SPT N 30	Elastic Modulus	Limit Pressure	Net Limit Pressure	Liquid Limit	Plastic Limit	Water Content
2.50 - 6.50	Clay	16.0	22.0	22.00	1.00	0.75	54.5	15.0	28.8
9.00 - 14.50	Sand	31.0	54.7	64.00	5.80	5.00	41.0	12.0	30.2
14.50 - 19.50	Clay	43.0	43.25	59.00	8.30	7.30	60.0	27.5	39.6
1.00 - 7.00	Clay	24.0	19.0	23.00	2.00	1.70	49.0	19.5	30.7
30.00 - 33.00	Sand	30.0	38.0	194.00	10.2	5.20	68.0	30.0	26.3
47.00 - 54.25	Clay	50.0	50.0	326.0	14.00	12.50	58.0	22.0	20.97
13.00 - 20.50	Clay	46.0	49.0	232.5	14.0	10.9	64.0	30.0	29.07
28.00 - 46.50	Clay	50.0	58.0	143.0	11.4	9.2	56.0	29.0	28.2
22.50 - 33.00	Clay	46.0	46.33	48.00	7.40	6.40	64.0	29.0	31.73
33.00 - 47.50	Clay	50.0	61.0	96.5	11.0	9.1	57.0	30.0	30.46
52.00 - 62 00	Clay	50.0	83.0	162.0	15.2	13.1	48.0	21.0	20.91
38.00 - 56.00	Clay	50.0	56.2	149.0	12.1	10.1	49.0	24.0	12.51
25.00 - 59.50	Clay	50.0	60.15	108.2	13.3	12.0	56.5	23.5	23.8
14.50 - 32.00	Clay	36.0	35.33	58.3	7.6	6.6	68.0	32.3	34.4

obtained results are presented in detail in the following sections.

3.1 SPT N30 estimation

This test method describes the procedure, generally known as the Standard Penetration Test (SPT), for driving a split-barrel sampler with a 140 lb (63.5 kg) hammer dropped 30 in. (750 mm) to obtain a soil sample for identification purposes and measure the resistance of the soil to penetration of the standard 2 in. (50 mm) diameter sampler (ASTM D1586, Kim *et al.* 2023). This value provides information about the shear-bearing behaviour of the formations. In the scope of the study, statistical analyses were conducted to predict SPT N30 data with input values described in Table 1. The equations derived through the multi-parameter linear regression method are provided in Eqs. (1)-(3), respectively. Accordingly, SPT N30 data is estimated using Ep, d, Tp, and Lp’ for Eq. (1), and d and Lp’ for Eq. (2). In Eq. (3), SPT N30 estimated using Lp’, SPT N1.6, Lp, Tp, d, Ep data. Additionally, a powerful equation for transition between SPT N1.6 and SPT N30 is also given as Model 3 and Eq. (3). The variance analysis of the data set (ANOVA) is given in Table 3 for Eqs. (1)-(3), respectively.

$$SPT\ N30 = -20{,}034 + 0{,}831xLp' + 0{,}524xd + 39{,}397xTp - 0{,}007xEp \quad (1)$$

$$SPT\ N30 = 23{,}867 + 0{,}893xLp' + 0{,}502xd \quad (2)$$

$$SPT\ N30 = -137{,}616 + 0{,}804xSPT\ N1.6 - 0{,}022xEp + 0{,}012xPL + 126{,}74xTp + 0{,}248xd + 0{,}803xLp' \quad (3)$$

When Eqs. (1)-(3) are subjected to a p-value hypothesis test, they are found significant according to a 99% significance level. Data pairs are able to represent the presented relation meaningfully according to lower Sig. values than 0,001. Which means the chance of being wrong is less than one in a thousand. As a result of the conducted analyses, statistically significant and highly correlated equations were obtained for both SPT N30 estimation and use in simulation models.

Table 3 Analysis of variance (ANOVA) for SPT N30 estimation

	Model	Sum of Squares	df	Mean Square	Sig.
1	Regression	8203,4	4	2050,8	<,001
	Residual	4873,2	33	147,7	
	Total	13076,6	37		
2	Regression	8094,7	2	4047,3	<,001
	Residual	4981,9	35	142,3	
	Total	13076,6	37		
3	Regression	9946,544	6	1657,8	<,001
	Residual	3130,061	31	101	
	Total	13076,605	37		

Eqs. (1)-(3). Dependent Variable: SPT N30
Eq. (1). Predictors: (Constant), Ep, d, Tp, Lp’
Eq. (2). Predictors: (Constant), d, Lp’
Eq. (3). Predictors: (Constant), Lp’, SPT N16, Lp, Tp, d, Ep

3.2 Net limit pressure estimation

Limit pressure is the effective pressure at the point where the ground undergoes plastic deformation or begins to flow. Net limit pressure is the net effective pressure obtained by subtracting water pressures from the limit pressure. Limit pressure (Lp) and deformation modulus (E) values obtained from the pressuremeter experiment are important parameters in terms of deformation and revealing the properties of the ground in engineering applications (Likitlersuang *et al*. 2013, Gultekin and Dogan 2022). In the scope of the study, Net Limit Pressure (Lp’) was estimated using SPT N1.6 and SPT N30, Elastic module (Ep), type of the unit (Tp), and the mean depth (d) data. According to the given parameters, constituted multi-parameter linear

Table 4 Analysis of variance (ANOVA) for Net Limit Pressure estimation

Model		Sum of Squares	df	Mean Square	Sig.
Eq. (4)	Regression	2240,783	5	448,157	<,001[b]
	Residual	882,130	32	27,567	
	Total	3122,913	37		

Eq. (4). Dependent Variable: Lp

Eq. (4). Predictors: (Constant), SPT N1.6, Ep, type, d, SPT N30

statistical model (Model 4) can be expressed as Eq. (4).

$$Lp' = -4{,}29 + 0{,}58xd + 4{,}862xTp + 0{,}248xSPTN30 + 0{,}035xEp - 0{,}242xSPT\,N1.6 \quad (1)$$

When Eq. (4) is subjected to a hypothesis test, it was found significant according to a 95% significance level. Data pairs are able to represent the presented relation meaningfully according to lower Sig. values than 0,001. The variance analysis of the data set (ANOVA) is given in Table 4 for Eq. (4).

3.3 Consistency limits (atterberg limits) estimation

The liquid limit represents the water content at which a soil sample transitions to a liquid state or becomes fluid, serving as a measure of shear resistance. On the other hand, the plastic limit is a crucial parameter in geotechnical engineering for understanding soil behavior and making accurate predictions in the design process (ASTM D4318; Kwon *et al.* 2019). The plastic limit characterizes the point at which a soil sample becomes plastic and can undergo changes in shape. Consistency limits are utilized in understanding the ground behavior under different drainage conditions, contributing to determining shear strength, bearing capacity, and durability properties. Additionally, determining the water content with clay influence aids in assessing soil carrying capacity, displacement, and other essential parameters.

Statistical models (Model 5 and Model 6) are generated for Plastic Limit and Liquid Limit estimation, respectively. For Plastic Limit estimation, the constituted model utilizes SPT N1.6, SPT N30, elastic modulus (Ep), unit type (Tp), and mean depth (d) data. The variance analyses, including significance levels, are provided in Table 5 for Eqs. (5) and (6).

$$Wp = 63{,}101 + 0{,}111xd - 52{,}655xTp - 0{,}026xEp + 0{,}32xWs + 4{,}009xPL + 0{,}517xSPT\,N1.6 - 4{,}472xLp' - 0{,}259xSPT\,N30 \quad (5)$$

$$Wl = 104{,}597x0{,}366xd - 71{,}311xTp + 0{,}018xEp + 1{,}003xWs + 3{,}449xPL + 0{,}314xSPT\,N1{,}6 - 4{,}673\mathrm{xLp}' - 0{,}354\mathrm{xSPT\ N30} \quad (6)$$

According to variance analysis, Eqs. (5) and (6) was found significant and data pairs able to represent the dependent data in %99 significance level for Wp and Wl data pairs.

Table 5 Analysis of variance (ANOVA) for Plastic Limit estimation

Model		Sum of Squares	df	Mean Square	Sig.
Eq. (5)	Regression	626,993	8	78,374	<,001[b]
	Residual	70,136	9	7,793	
	Total	697,129	17		
Eq. (6)	Regression	3964,098	6	660,683	<,001[b]
	Residual	2521,231	26	100,849	
	Total	6485,329	31		

Eq. (5). Dependent Variable: Wp

Eq. (5). Predictors: (Constant), SPT N30, Tp, Ws, Ep, Lp, d, SPT N1.6, Lp'

Eq. (6). Dependent Variable: Wl

Eq. (6). Predictors: (Constant), Ws, SPT N1.6, Tp, Ep, d, SPT N30

4. Probabilistic distribution and Monte Carlo Simulation of geotechnical data

The Monte Carlo Simulation Method is used to predict the probability of a variety of outcomes. The simulation process involves three fundamental steps: 1. Input specification as probability distributions, wherein key inputs are defined using probability distributions derived from project-specific site data, data classifications, or subjective judgments to encompass a range of probable values. 2. Utilization of predictive models, which establish the relationship between the dependent variable to be predicted and the independent input variables. 3. Iterative simulations, where simulations are run repeatedly to generate random values for the independent variables. The number of iterations varies depending on the nature of the formulae being used (Look 2022).

Probabilistic Distribution Functions (PDFs) are employed in statistical analyses, risk assessments, engineering designs, and many other applications to model uncertainties. A probabilistic distribution function is a mathematical function that defines the probabilities of possible values of a random set of variables (Xiang *et al.* 2017). In this study, to generate random variables, meaningful and highly correlated equations identified through statistical models were implemented into the Monte Carlo Simulation models. Probability distribution functions were created for SPTN30 using Model 1, Net Limit Pressure using Model 4, Plastic Limit using Model 5, and Liquid Limit using Model 6. These generated functions, along with their distribution parameters are presented sequentially in the following sections.

The Monte Carlo Simulation provides probabilistically distributed probability density. In this study, the probabilistic distributions of fundamental geotechnical parameters were analyzed to determine the percentage of data intervals encountered in the project.

4.1 Probabilistic distributions for SPT N30 estimation

Probability functions generate probabilities based on various distributions. In this section, to obtain the probabilistic distribution function for SPT N30, firstly the

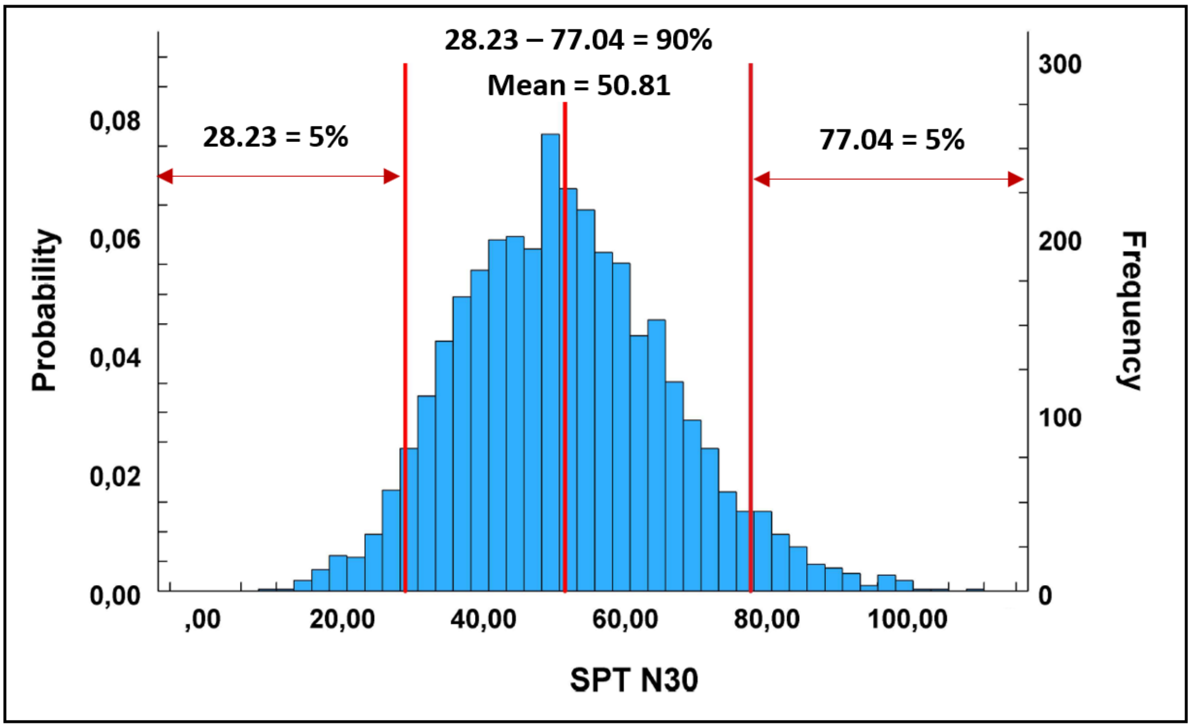

Fig. 2 Probability distribution of SPT N30 resulting from Monte Carlo Simulation

Table 6 Probabilistic distribution of input and output parameters for SPT N30 estimation

Input	Distribution	Parameters
Ep	Triangular	max. : 500 min. : 11 mode : 17.74
Lp	Weibul	a : 15.43 b : 1.53
d	Normal	mean : 28.82 stdev. : 18.55
Tp	Triangular	max. : 1.2 min. : 1.1 mode : 1.16
Output	**Distribution**	**Parameters**
SPT N30	Normal	mean : 50.811 stdev. : 15.0

distribution functions for Ep, Lp, d, and Tp were generated and then utilized as input parameters using the interrelationship given in Eq. (1). In the developed model, the probabilistic distributions of input and output parameters for SPT N30 estimation are given in Table 6.

In Table 6, the input parameters Ep, Lp, d, and Tp are characterized by Triangular, Weibull, and Normal distributions, respectively, whereas the resulting SPT output exhibits a Normal distribution. The distribution graph and associated frequencies for SPT N30 is illustrated in Fig. 2.

Probabilistic SPT N30 distribution was simulated using Eq. (1) with a maximum of 100,000 cases. Accordingly, the most frequent SPT 30 value of 50.811 is expected, and the field distribution is anticipated within the range of 28.23 to 77.04, considering a 90% confidence interval. The likelihood of encountering values lower than 28.23 or higher than 77.04 for each group is to be 5% in the project.

Table 7 Probabilistic distribution of input and output parameters for Net Limit Pressure estimation

Input	Distribution	Parameters
Ep	Triangular	max. : 500 min. : 11 mode : 11
d	Weibull	a : 29.02 b : 1,39 c : 0
SPT N1.6	Triangular	max. : 50 min. : 5 mode : 45.03
SPT N30	Normal	mean : 48.54 stdev. :18.55
Tp	Triangular	max. : 1.2 min. : 1.1 mode : 1.15
Output	**Distribution**	**Parameters**
Lp’	Normal	mean : 12.81 stdev: 7.253

While the average of the SPT N30 field data is 42.86, the statistical data distribution (Fig. 2) indicates that the maximum occurrence is expected to be 50.811 with an 80% probability.

4.2 Probability distribution of SPT N30 resulting from Monte Carlo Simulation

Probabilistic distributions for Net Limit Pressure were created using the multi-parameter linear regression equation given in Model 4 (Eq. (4), and distribution functions were created. The probability density function (PDF) for LP’ was generated using the developed probabilistic models. The

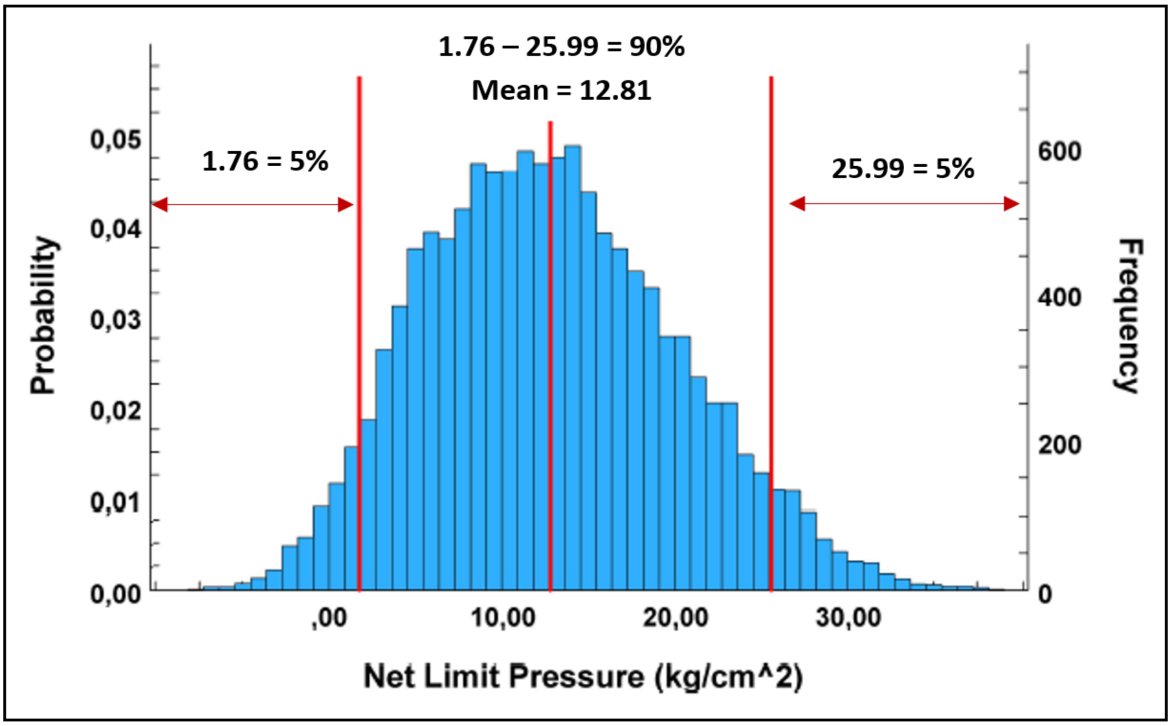

Fig. 3 Probability distribution of for Net Limit Pressure resulting from Monte Carlo Simulation

input parameter distributions for LP' are presented in Table 7.

According to Table 7, generated functions for Lp' estimation shows Triangular, Weibull, and Normal distributions for input parameters of Ep, d, SPT N1.6, SPT N30, and Tp. Utilizing the formulation in Model 4 (Eq. (4)), the input distributions have been modeled with respect to their probabilities relative to the LP' values based on a maximum of 100,000 iterations. The probabilistic distribution graph and associated Lp' frequencies are illustrated in Fig. 3.

When Fig. 3 is examined, the most frequently expected Lp' value is 12.8 kg/cm^2 however, values of 9.6 kg/cm^2 and 13.2 kg/cm^2 are also deemed highly probable. Besides, the average of the Net Limit Pressure field data is 17,07 kg/cm^2. The anticipated field distribution is confined to the interval of 1.76 kg/cm^2 to 25.59 kg/cm^2, with a confidence level of 90%. The probability of encountering values lower than 1.76 or exceeding 25.59 kg/cm^2 in the project is expected to be less than 5% of probability.

4.3 Probabilistic distributions for plastic limit estimation

Probabilistic distributions related to the Plastic Limit estimation were established through the utilization of the multi-parameter linear regression equation as outlined in Model 5 are shown in Table 8.

According to the information given in Table 8, Derived distribution functions for the estimation of Plastic Limit (Wp) show Triangular, Uniform, and Weibull distributions for input parameters of Ep, Lp, Lp', Ws, d, SPT N1.6, and SPT N30. The stochastic Monte Carlo model for Wp were

Table 8 Probabilistic distribution of input and output parameters for Plastic Limit estimation

Input	Distribution	Parameters
Ep	Triangular	max. : 326 min. : 11 mode : 11
Lp	Uniform	max. : 15.2 min. : 1
Lp'	Uniform	max. : 13.1 min. : 0.75
Ws	Triangular	max. : 39.6 min. : 12.51 mode : 30.32
d	Weibull	a : 27.02 b : 1.06 c : 0
SPT N1.6	Triangular	max. : 50 min. : 5 mode : 50
SPT N30	Triangular	max. : 83 min. : 10.5 mode : 35.02
Output	**Distribution**	**Parameters**
Wp	Normal	mean: 20.61 stdev.: 5,07

generated based on the probabilistic distributions of input parameters. Utilizing the formulation in Model 5 (Eq. (5)), the input distributions have been modeled with respect to their probabilities relative to the Wp values based on a maximum of 100,000 iterations. The probabilistic distribution graph and associated Wp frequencies are illustrated in Fig. 4.

Based on the applied simulation, the most frequent Wp is expected as 20.609 and %90 of data is expected within

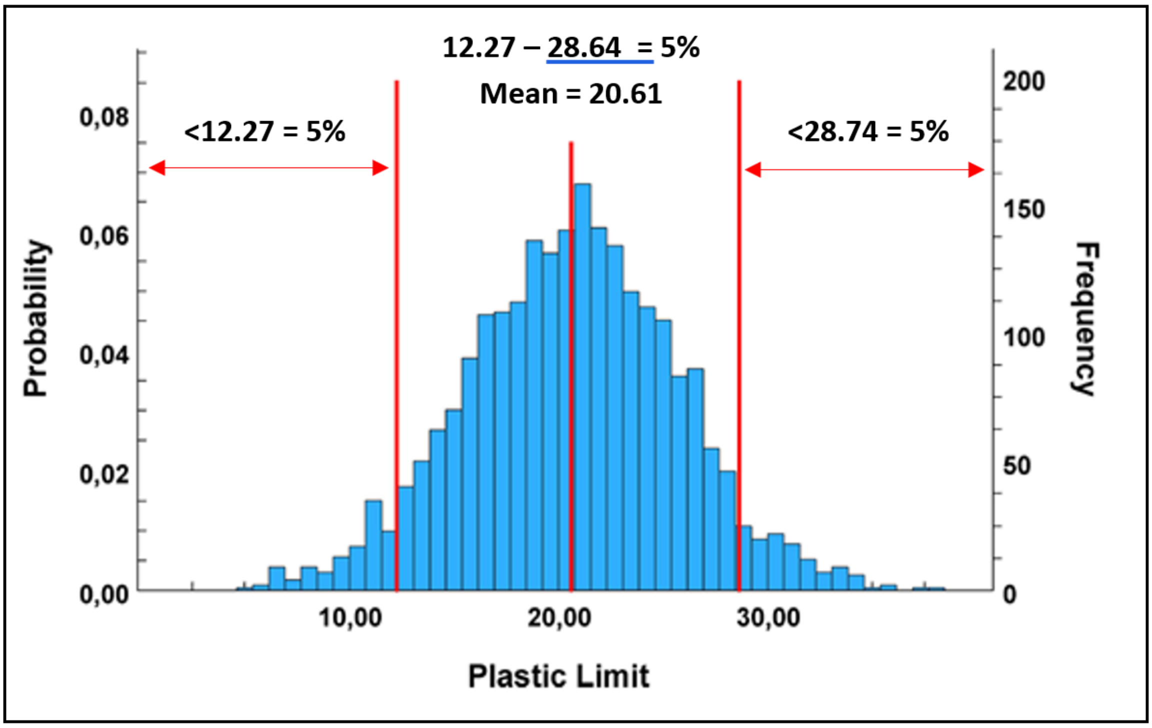

Fig. 4 Probability distribution of for Plastic Limit resulting from Monte Carlo Simulation

the range of 12.29 to 28.74 with a 70% probability. Moreover, the mean Plastic Limit value obtained from field data is 22.32. The likelihood of encountering a rate lower than 12.29 or higher than 28.74 for each group is anticipated to be 5% in the project.

4.4 Probabilistic distributions for Liquid Limit Estimation

Probabilistic distributions for Liquid Limit estimates were created through the utilization of the multi-parameter linear regression equation as outlined in Eq. (6) (Model 6) is given in Table 9.

When Table 9 is examined, the functions for Wl estimation exhibit Triangular and Weibull statistical distributions. According to descriptive statistics of the Scale Targets for the predictive model, the average Wl estimate is 54.03 and the range is estimated within a 95% confidence level is expected between 53.61 and 54.45. The related probabilistic distribution graph as the output of Monte Carlo Simulation and frequencies are shown in Fig. 5.

In line with the information obtained from Fig. 5, the most probable Wl value is 54.48 with 80% probability while the mean Wl value obtained from field data is 56.73, and the maximum probability of the possibility of values lower than 38.15 and higher than 72.71 is expected less than a 5% statistical chance.

Table 9 Probabilistic distribution of input and output parameters for Liquid Limit estimation

Input	Distribution	Parameters
Ep	Weibull	a : 101,14 b : 1.17 c : 0
Ws	Triangular	max. : 46.88 min. : 12.51 mode : 24.63
d	Weibull	a : 24.8 b : 1.5 c : 0
SPT N1.6	Triangular	max. : 50 min. : 5 mode : 50
SPT N30	Triangular	max. : 83 min. : 10.5 mode : 36.75
Tp	Triangular	max. : 1.2 min. : 1.1 mode : 1.1
Output	**Distribution**	**Parameters**
Wl	Normal	mean: 54.48 st.dev..: 10.35

5. Discussion

Geotechnical data, which forms the basis of geotechnical decision-making, is difficult to collect and evaluate. The importance of appropriately evaluating geotechnical data is emphasized in the literature (Zumrawi 2014, Haeri 2016, Albatal 2013, Ferson 1996). However, in geotechnical studies, especially in places with mixed ground conditions such as Istanbul, parameters can be distributed in a wide range. In such fields, methods are quite limited to determine the data that would be the basis of engineering designs. Relying on the arithmetic mean for the evaluation of geotechnical data can result in errors in geo-

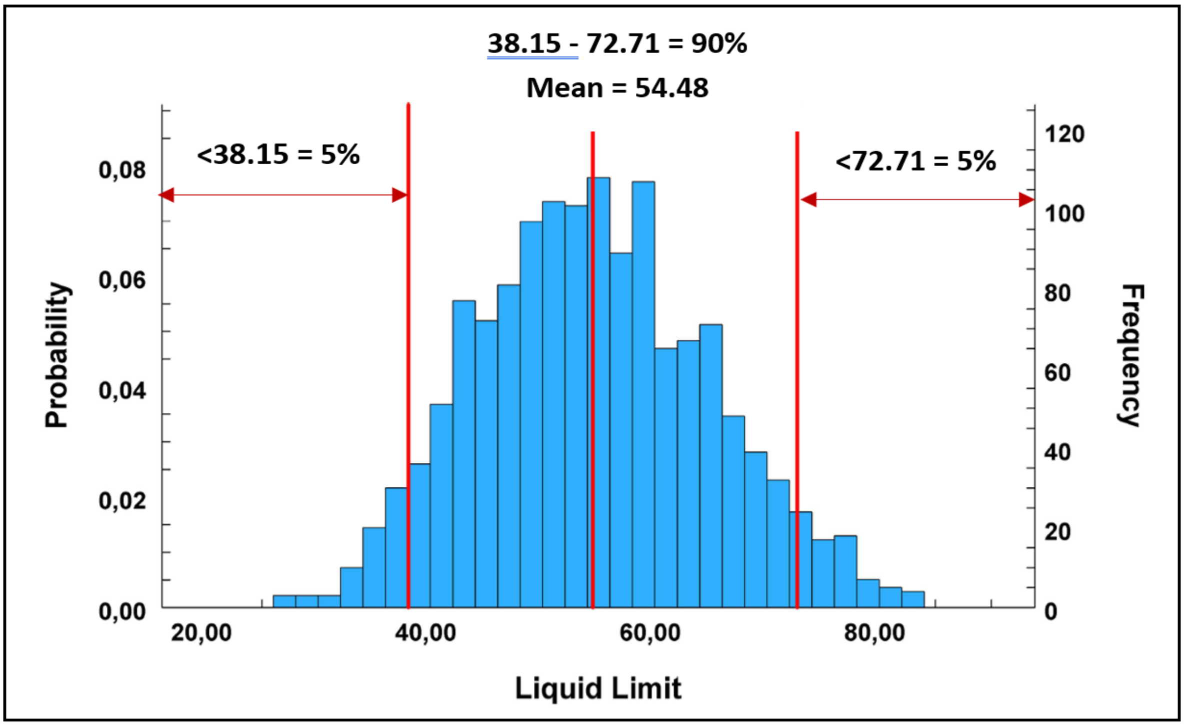

Fig. 5 Probability distribution of for Liquid Limit resulting from Monte Carlo Simulation

engineering projects. In the 4th section of the study, it was revealed that the highest encountering probabilities differed from the average.

When examining Monte Carlo Simulation studies conducted for tunneling research in the literature, emphasis is often placed on the probabilities of direct design parameters. However, this study underlines the indirect effects of determining probabilistic distributions on the time and cost of the project. Thus, this study also highlights the advantages of assessing the frequency of encountering geotechnical parameters in tunnel projects, as they influence both the cost and time of the project.

Although MCS has the potential to generate solutions for almost all geotechnical problems, it should be noted that geotechnical models often involve simplifications and idealizations of complex physical processes. Those simplifications may not be captured in the Monte Carlo analysis. Whereas Monte Carlo methods are flexible and useful for risk assessment, they have four key limitations in geotechnical analysis: they require a lot of data, cannot handle partial ignorance accurately, cannot determine specific exceedance risks, and cannot solve back-calculation problems (Ferson, 1996). However, in order to partially reduce uncertainties in the developed model, multi-parameter equations were employed. This study presents the analysis of probabilistic distributions of the evaluated data using appropriate methods as the next step.

Utilizing probabilistic approaches enable contributions to TBM planning and consumable requirements by calculating the quantity of consumables for each percentage range based on the overall project percentage (e.g., values below 5%, and value ranges encountered 90% of the project). MCS method has the potential to contribute to more accurate and effective planning. The findings from the geotechnical analysis provide essential data for the selection of the appropriate Tunnel Boring Machine (TBM) consumable requirements, which are directly and indirectly affect the design and planning of TBM projects, ensuring that the tunneling process is both technically feasible and economically viable.

6. Conclusions

In engineering designs, determining geotechnical data is crucial for both engineering planning and implementation phases. However, conducting geotechnical research can be costly and time-consuming, and intense field studies are challenging, especially in urban area projects. Making reliable estimates with valuable limited data in engineering projects has great importance.

In this study, the Monte Carlo method is used to simulate geotechnical data of an urban tunnel project site, uncovering probabilistic distributions that represent a range of geotechnical parameters along with their respective percentages. As a result, values such as Standard Penetration Test, Net Limit Pressure, Liquid Limit, and Plastic Limit with probable encountering rates were identified and compared with averages of the collected field data. Additionally, encountering range and associated probability were provided for each geotechnical parameter. Although, averages moderately and ultimately in close range, it is revealed that the possible data varies in a range, and should be considered in fundamental design analyses.

The use of advanced analyses allows to conduct of risk analysis and more reliable design. Since the study is specific to Tunnel Boring Machine (TBM) excavation, understanding geotechnical data ranges and maximum occurrences is essential and significantly influences machine and related support design selection. In cases where tunnel lengths are extensive but available data is limited, or where assessments need to be made over large areas, the averaging method may provide information about the type of operational requirements. However, using Monte Carlo simulations in addition offers percentage-based quantities, providing a more detailed analysis.

This study could serve as a guide for subsequent works, especially in planning the supply of tunnel boring machine (TBM) requirements (such as TBM chemicals, additional support systems, and predicting the probability of potential surface deformations frequency) and estimating the project completion time in TBM projects. Additionally, the equations and probabilistic simulations presented in the study can be applied to various geotechnical problems within the same geological formation, such as foundation excavation and bored pile design.

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