Site Assessment using Seismic and Electrical Resistivity Tomography at Alamein Area, Egypt.

Mohamed M. Gadalhaq[1,2], Abdel-Khalek El-Werr[2], Ahmed Helaly[2], and Ahmed El-Gendy[3]

[1]Technical Development Solutions, Riyadh, Kingdom of Saudi Arabia. [2]Geophysics Department, Faculty of Science, Ain Shams University, Cairo, Egypt. [3]Geotechnical Engineering, Faculty of Engineering, Giza Engineering Institute, Giza, Egypt.

Abstract: Site assessment studies using geophysical methods have been carried out in the Alamein area, Egypt to distinguish the different soil/rock type materials (rock, sand, gravel, or clay). Seismic methods as well as electrical resistivity tomography (ERT) provide valuable results. An empirical approach created from shear wave velocity and electrical resistivity cross-plots was used to identify these soil types. Distinguishing soil types is required in site assessment studies for the evaluation of the subsurface heterogeneity. These heterogeneities are very important in engineering analysis to identify possibilities of finding cavities, clay pockets, and other geological problems that will be needed to consider in designing of possible structures. This research study starts with an introduction of the study area along with previous works on the statistical estimation technique, then briefly discusses the geophysical methods used for data acquisition, followed by the method of handling the data set. Afterward, it describes different methods for estimation of the statistical value of soil briefly discussed, and finally a conclusion for summarizing the results.

Keywords: Statistical Estimation, Regression, Surface Wave, ERT, Classification, Ideas, Geotechnical.

1. Introduction

Traditional site assessment uses boring methods that are expensive and have limitations such as not providing continuous data along the site profile in heterogeneous environments. Non-invasive, rapid, and continuous investigations are needed to support conventional investigation techniques including geophysical methods. The need for geophysical methods in site assessment studies is increasing day by day. Seismic methods and electric resistivity methods are used and have proven that they provide valuable results in site assessment studies. Combining shear wave velocity and resistivity in an integrated geophysical approach provides a more accurate description of soil type than the individual properties alone (Hayashi et al., 2013).

Providing such information as soil mechanics properties, engineering properties, and information on possible fluid content is highly needed. To evaluate sites quantitatively integrated geophysical methods were proposed by Hayashi et al. (2009) and Inazaki et al., (2009). An empirical approach that was introduced by Hayashi et al. (2013) to determine soil type from shear wave velocity and electrical resistivity cross-plots has shown predictive capabilities in Japan and the state of Washington. Hayashi et al. (2013) developed the second-order multivariable polynomial equation from a least square regression to fit the cross-plotted data from Japan. Their model considered clays, sands, and gravels.

Distinguishing soil types (Clay, Sand, or Rock) is required in site assessment studies for the evaluation of heterogeneity of the subsurface from the engineering viewpoint. The heterogeneity in many engineering analyses is important to identify possibilities of finding cavities, clay pockets, and geological problems that will be needed to consider in designing of possible structures. Physical properties obtained through geophysical methods have ambiguities in identifying soil type.

In this paper, we are going to try to reduce the ambiguity by estimating soil type by adapting the empirical approach (Hayashi et al., 2013) for use in our study to identify possible locations of clay concentrated zones using regression techniques on geophysical and geotechnical data collected from Alamein, Egypt as shown in Figure1.

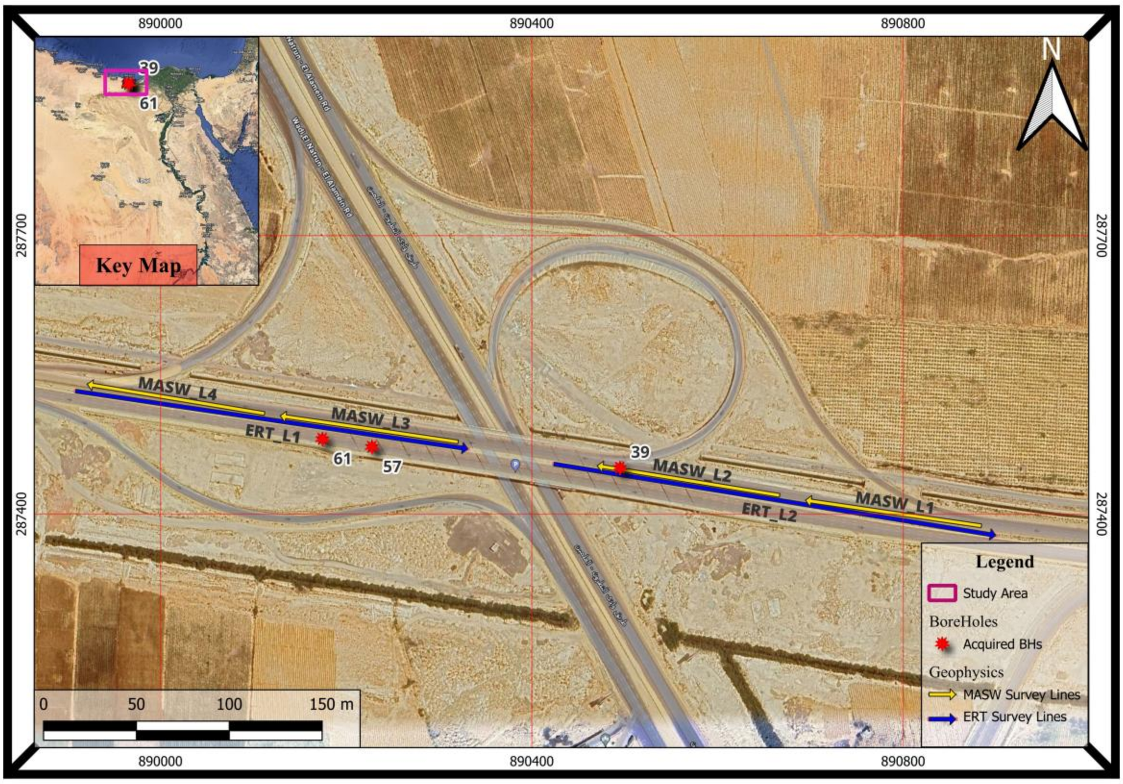

Figure 1: Location map of the acquired boreholes and geophysical survey lines in the study area. Coordinate System [EPSG:22993]

2. Background and Related Work

2.1. Multichannel Analysis of Surface Waves (MASW) Method

In-situ field testing using geophysical methods provides continuous information along the surveying line and without the need to retrieve samples to the laboratory. In seismic methods the propagation of acoustic waves to identify the mechanical properties of the investigated soil. When seismic waves are produced-acoustic waves- at/or near the ground surface, both body (compressional “P” and shear “S”) waves and surface (e.g., Ground Roll “Rayleigh”, “Love”, … etc.) waves are generated. Surface waves have dispersion properties that the body waves lack. This property is that every wavelength has a different penetration depth resulting in different velocities. Using this piece of information, analyzing the dispersion of the surface waves can provide data describing the near-surface velocity profile. MASW is a non-invasive method of estimating the shear-wave velocity “Vs” from the surface wave energy. It uses the dispersion curve that is produced from the dispersive properties of Rayleigh waves for visualizing the subsurface layers.

The Multianalysis of Surface Wave (MSW) method was proposed before 50 years ago in Japan and then called the microtremor survey method (MSM). In the 1990s, electronic equipment was developed for the MASW by the Kansas Geological Survey called multi-channel analysis of surface wave, MASW (Park et al., 1999). This technique has been developed, and used for applications in civil engineering, for example, for site characterization (Long and Donohue, 2007) and for compaction controlling by measuring the decay of soil vibrations (Adam et al., 2007) also for the quality of stone column (Madun et al., 2012). The approach of the MASW offers considerable advantages over based upon a single transmitter-receiver pair.

The method of carrying out measurements using a multiple-receiver strategy reduces acquisition time and indicates lateral resolution (Park et al., 1999), while the sub-surface characterization in both the vertical and lateral axes provides a useful 2D representation (Socco and Strobbia, 2004). MASW introduced by Park et al. (1999) used similar equipment to seismic refraction, which can result in identifying and removing noise from scattered and reflected waves during the data analysis. As a result, a best-fit line can be drawn through the phase angle-distance plot, minimizing the influence of variations in data, and allowing enhanced robustness in data processing.

The entire procedure for MASW consists of the following steps:

1. Acquiring multichannel field records (or shot gathers).
2. Processing the data to extract the dispersion curve for each shot gathered.
3. Inverting the extracted dispersion curves to obtain 1D (depth) Vs profiles by selecting the surface wave zonation and filtering the data from the other wave types.
4. Producing a new dispersion curve without the other wave type frequencies.
5. Preparing the vertical sections of the shear wave velocities (Vs) by placing each 1D Vs profile at a surface location corresponding to the middle of the receiver line, a 2D (surface and depth) Vs model can be created through an appropriate interpolation scheme.

The MASW method has improved production in the field and improved the characterization of dispersion relationships by sampling the spatial wave field with multiple receivers.

Rayleigh waves are generated in all shallow seismic surveys as shown in Figure 2 and have the strongest energy, so they appear as dominant events all over the seismic records. Their propagation in the vertical direction through a vertically heterogeneous layered is displayed as a dispersive behavior. Dispersion means that different frequencies have different phase velocities. There occurs an exponential decrease in their amplitude with depth and most of the energy is dispersed in a shallow zone. In a layered medium, the surface wave does not have a constant velocity but a phase velocity that is a function of the frequency. The dispersion curve represents the relation between the frequency and the phase velocity as shown in Figure 3. That means, at higher frequency values, the phase velocity signified the Rayleigh velocity of the shallower layer (uppermost layer) and vice versa the lower values of frequency mean the Rayleigh velocity of the deepest layer. Figure 4 describes the construction of 2D Vs seismic section interpolation of several 1D models.

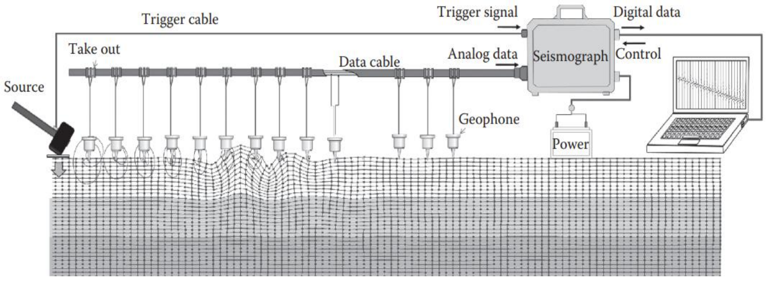

Figure 2: Schematic View of the field equipment (after Foti et al. 2014).

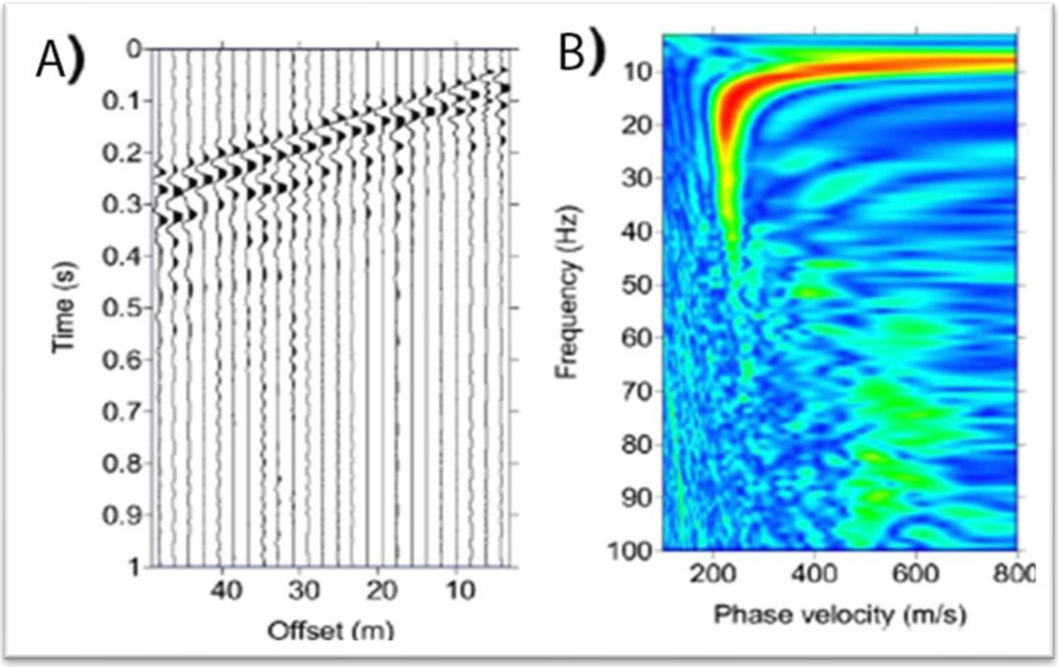

Figure 3: Shot gather of surface wave (a), dispersion curve showing its frequency-phase velocity relation (b).

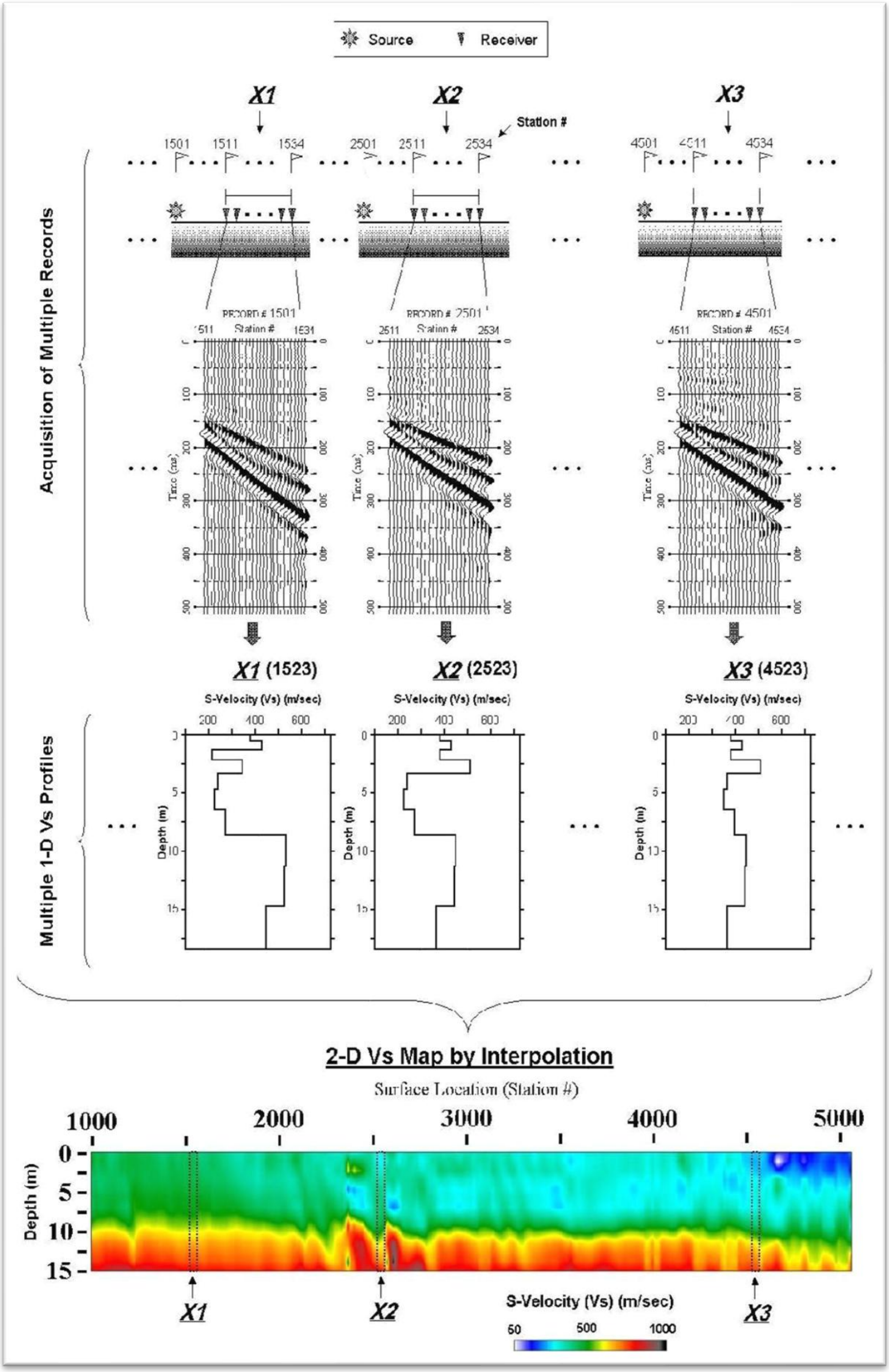

Figure 4: Describing the construction of 2D section interpolation of several 1D Models.

2.2. MASW Data Acquisition

Four seismic refraction profiles were acquired using an active seismic source (Sledgehammer). The length of each seismic profile was 187.5 m with a geophone interval of 7.5 m collected along the site on two sides separated by Wadi El Natrun-Alamein Road the eastern and the western sides. When a wave is generated by the seismic source with several impacts to enhance the data quality and the pulse amplitudes along the shot gather. This process is repeated with different source offsets (normal-middle-reverse) to sample the desired frequency range. Both seismic and resistivity profiles were measured on the same alignment as close as possible to the geotechnical borehole previously made. The profile is parallel to the underdeveloped new Alamein Road at that time. As a limitation the collected data appeared to have noisy results due to the presence of the road and constructions processing steps were needed to enhance the results.

The seismic data was acquired using a multi-channel seismograph (OYO McSeis 1500-24-Channels Seismograph). This device is usually used for recording, filtering, and stacking seismic data. A sledgehammer (18 kg) was used as a source of energy in this survey generating seismic waves by repeating several vertical impacts (stacks) on a metal striker plate. Twenty-four vertical electromagnetic geophones with a natural frequency of 14 Hz were used as detectors and they were well-planted (good coupling) into the ground. The data is then saved in SEG 2 format for later use by software to process and model. After the model was created, it was exported to an XML format to be contoured for further usage.

2.3. Electric Resistivity Tomography (ERT) Method

Geoelectrical resistivity imaging has played an important role in addressing a wide variety of hydrogeological, environmental, and geotechnical issues. Resistivity is a physical property of materials. It is the ability to resist a flow of charges; it is the measurement of how strongly a material resists the flow of electric current (Denchik and Chapellier, 2005). The purpose of electrical surveys is to determine the subsurface electrical resistivity distribution by making measurements on the ground surface. The 2D resistivity measurements are normally made by injecting current into the ground through two current electrodes and measuring the resulting voltage difference at two potential electrodes (Nordiana et al., 2012).

Resistivity imaging technique depends on Ohm’s law, which states that the electric current in a material is proportional to the potential difference across it (Abdelwahab, 2013). From these measurements, the true resistivity of the subsurface can be estimated (Loke, 2012). Electrical resistivity is known to be highly variable among other physical properties of rock (Adli et al., 2010). The resistivity of the 2D model is assumed to vary both vertically and laterally along the survey line but is constant in the direction perpendicular to the survey line (Aizebeokhai et al., 2010). The resistivity of a soil or rock is dependent on several factors that include the amount of interconnected pore water, porosity, amount of total dissolved solids such as salts and mineral composition (clays) (Nordiana et al., 2012), and degree of water saturation in the rock (Srinivasamoorthy et al., 2009).

The work on introducing current into the ground for prospecting purposes started around a century ago. Early work was done qualitatively by locating conductive anomalies by moving a potential electrode pair while keeping the current electrodes fixed, i.e. a gradient technique. Such work was carried out in Sweden in 1906 and onwards, initially using Daft and William’s method and equipment (Petersson, 1907), and later by equipment made locally (Bergström, 1913). Conrad Schlumberger started his pioneering work on electrical prospecting in 1912, and approximately at the same time, Wenner developed the same idea in the USA (Schlumberger, 1920; Kunetz, 1966). The resistivity method is based on measuring the potential between one electrode pair while transmitting DC between another electrode pair (Figure 5).

The depth of penetration is proportional to the separation between the electrodes, in homogeneous ground, and varying the electrode separation provides information about the stratification of the ground. The measured quantity is called apparent resistivity. Interpreting the resistivity data consists of two steps: a physical interpretation of the measured data, resulting in a physical model, and a geological interpretation of the resulting physical parameters. Figure 6 shows the roll-along configuration setup for the ERT survey.

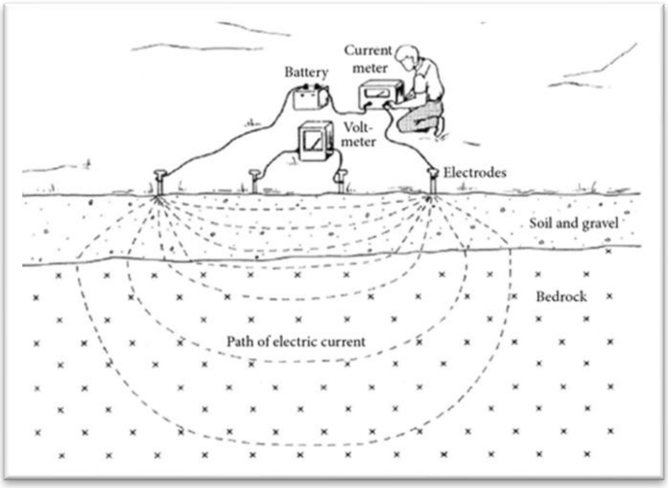

Figure 5: The configuration of modern electrical resistivity, the configuration usually is of four electrode system. One set of 2 electrodes is connected to a battery for current injection and the other two is connected to a voltmeter to measure potential difference. This figure also shows the paths of electric current.

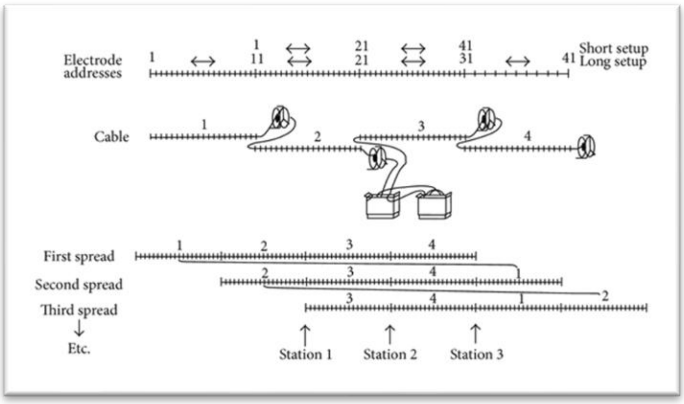

Figure 6: Roll-along configuration setup for ERT survey, the system is connected to a large number of electrode that switches between them to simultaneously take readings of several resistivity measurements. For the lateral extension for the readings a segment on the measuring electrodes is laterally move to the end of the section.

2.4. ERT Data Acquisition

ERT data was collected using SYSCAL Pro Switch 72 using the Dipole-Dipole method to create a pseudo section on a roll-along sequence. The resulting data is presented after the processing and interpretation as a 2D section for the measured line and exported to XML format to be contoured. Figure 6 shows the ERT sample displayed using ZONDRES2D software of the observed apparent resistivity, the calculated apparent resistivity, and the contoured interpreted resistivity.

After overlapping the two sections of ERT and MASW the ERT section is shown to be wider and deeper than the MASW section. Therefore, the ERT section is cropped to match the width and depth of the MASW section.

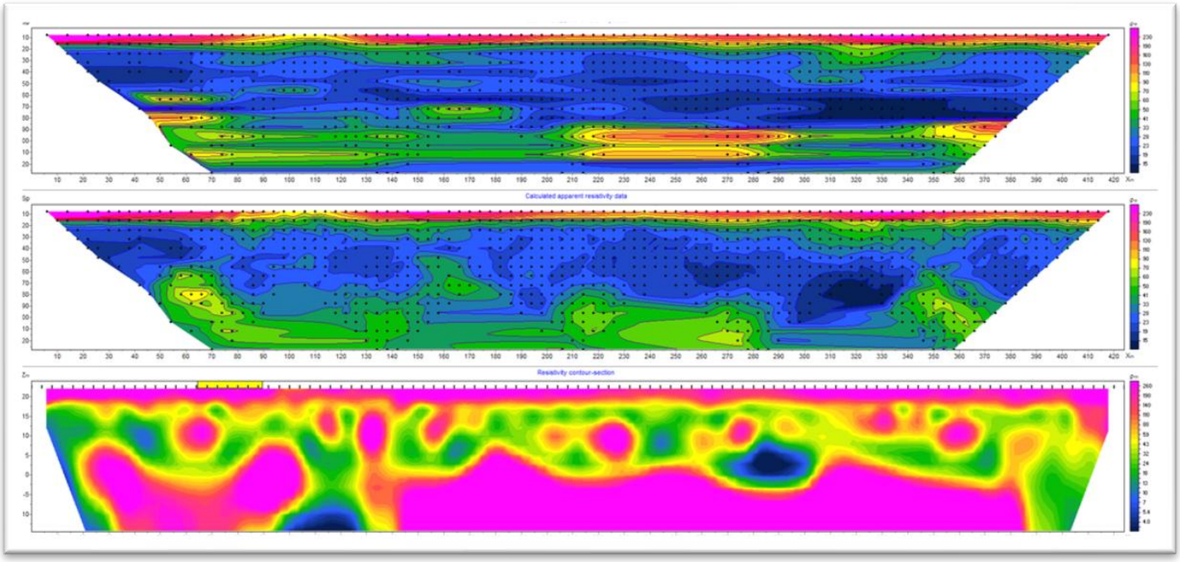

Figure 7: ERT sample displayed using ZONDRES2D software where the top image is the observed apparent resistivity, the middle is the calculated apparent resistivity, and the bottom is the contoured interpreted resistivity. The software takes the measured observed resistivity data and preform interpretation processes to result a section of apparent resistivity which is close to the actual lethology.

2.5. Processing and Interpretation of the Geophysical Data

Dispersion curve was created using the MASW processing technique pioneered by Park et al. (1999). After recording the data, ZONDST2D can be used to manually pick the ground roll surface waves, then to create and pick the dispersion curve with its L-shaped along the maximum amplitudes, and finally to invert it to 1D shear wave velocity Vs profile.

By picking the dispersion curve for each shot gathered along the seismic profile, the 1D shear wave velocity profiles are interpolated together using a kriging method to create an inverted 2D shear wave velocity model.

For ERT data the most important step of data processing is removing bad data points. In ZONDRES2D after opening the window of the “Quality control module” the apparent resistivity is viewed concerning the data level. Bad data points appear as very high or very low values with respect to the neighboring values which sharp localized changes in the subsurface are clearly wrong. The cause of these abnormal data is usually of an outsource noise such as bad ground conductivity with certain electrodes, faulty relays at one electrode, shorting in cables to very wet ground conditions, …etc. Dropping/Deleting those data is the best way to handle them if not deleted it may influence the model with higher or lower values. After interpretation the interpreted values is exported to SURFER to be contoured using the kriging method and the dataset is cropped to match the size of the 2D shear wave profile.

Figures 8 and 9 show the interpolated sections of both MASW and ERT profiles of the eastern and western sides of the Wadi El-Natrun-Alamein Road study area, respectively.

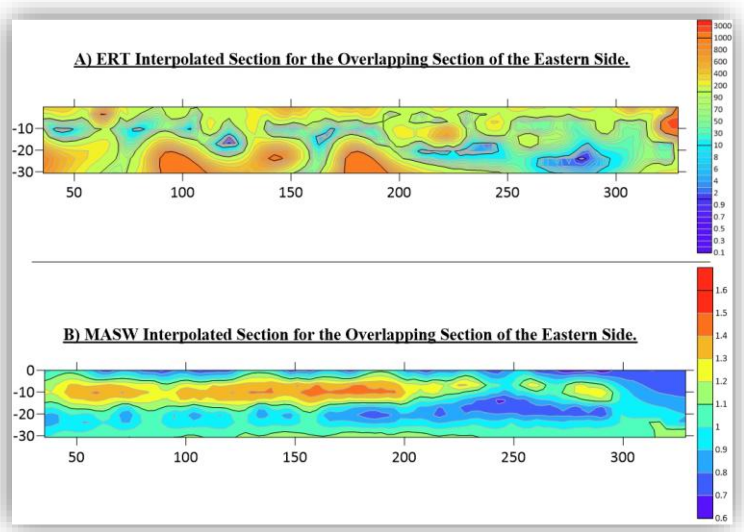

Figure 8: Interpolated sections at the eastern side of the road; the MASW_L1, MASW_L2 lines a), and the resistivity values of the ERT_2 b).

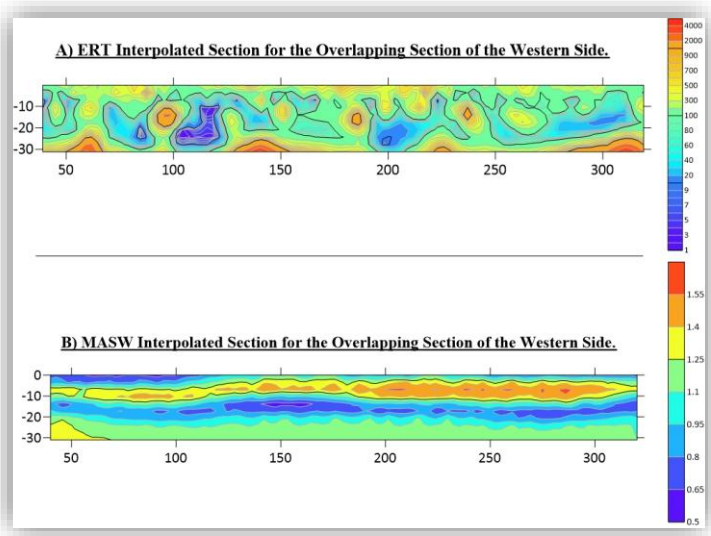

Figure 9: Interpolated sections at the western eastern side of the road; the MASW_L1, MASW_L2 lines a), and the resistivity values of the ERT_2 b).

2.6. Geophysical Data Interpretation

Interpretation of interpolated sections software showed that the subsurface of the study area consists of four major units. Looking at the provided boreholes the geophysical results are a good match with the borehole log from top to bottom as follows:

1. A unit with relatively high resistivity (150 Ω.m ~ 750 Ω.m) and low shear wave velocity layer (0.5 km/sec ~ 0.8 km/sec) with thickness varying from 1 to 5 meters. This can be interpreted as a topsoil layer.
2. A unit with relatively moderate to high resistivity (100 Ω.m ~ 500 Ω.m) and high shear wave velocity layer (1.25 km/sec ~ 1.55 km/sec) with thickness varying from 2 to 9 meters. This can be interpreted as hard rock.
3. A unit with relatively low to high resistivity (5 Ω.m ~ 900 Ω.m) and low to moderate shear wave velocity layer (0.65 km/sec ~ 1.1 km/sec) with thickness varying from 7 to 12 meters. This can be interpreted as a fractured rock with zones of clay pockets.
4. A unit with relatively very high resistivity (≥300 Ω.m) and moderate shear wave velocity layer (≥ 1.1 km/sec) with a thickness of around 10 meters completing the rest of the section. This can be interpreted as solid bedrock.

2.7. Data Handling and Geotechnical Soil Type Estimation

Data resulting from geophysical investigations are represented by numerical values for which is interpreted and labeled by a geophysicist to give a geological meaning based on geological and geophysical knowledge. Hayashi et al. (2013) introduces an empirical soil type estimation method using crossplots of shear wave velocity Vs , resistivity data ρ and borehole core samples as anchor points to identify a small segment of geophysical measured section and label it with the parameter needed to be classified depending on the measured geophysical methods to form a group of training data for our upcoming model which is used for estimation of the whole measured section. The result of this process is a contoured section with the parameters used in the classification which in our case is soil type (Clay, Sand and Rock).

In this paper, three supervised learning methods are used for the identification of the coefficients of Hayashi's empirical formula:

$$S = aV_s^2 + bV_s + c(\log_{10}(\rho))^2 + d\log_{10}(\rho) + eV_s^2\log_{10}(\rho) + fV_s(\log_{10}(\rho))^2 + gV_s\log_{10}(\rho) + h \qquad (1)$$

Equation 1: Hayashi's empirical formula.

where S is a representation of the classification parameter-geological feature in our case- treating the geological data gathered as numbers where there is a value given for each where Clay = 1, Sand = 2, and Rock = 3. For the coefficients {a, b, c, … h} supervised learning methods (Stochastic gradient decent, Bayesian regression, and support vector machine) are used to identify them using the sci-kit library from Python programming language after coefficients are identified an estimation is then calculated for the rest of the measured section resulting in a contoured section of soil type values.

2.8. Geotechnical Measurements

Available geotechnical data provided is for three geotechnical boreholes drilled with a diameter of 76 mm and depths up to 36 meters deep. Two of the boreholes fall on the western side, and one is in the eastern side. The data from the boreholes show different variations of soil and rock types but for simplification, the lithologies are categorized into Sand, Clay, and Rock. Using the collected data and with the intersection with the measured geophysical sections, a value of shear wave and resistivity was assigned for each depth point along its lithology with 1 m sampling. A cross-plot can now be created using shear wave velocity on the x-axis and the resistivity on the y-axis as shown in Figure 11.

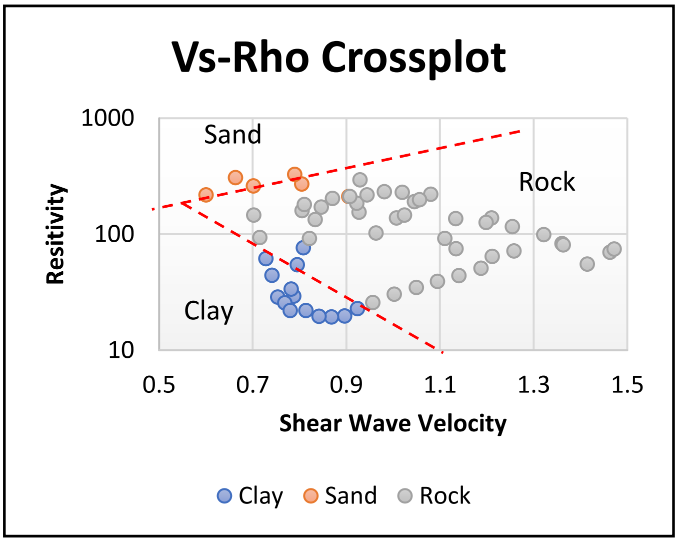

Figure 10: Cross-plot of the obtained borehole samples and their geophysical values.

3. Methodology

In Hayashi's approach a polynomial approximation is used for building a relation between soil type, shear wave velocity Vs and resistivity ρ. As previously mentioned in this paper a cross plot is established with the data collected from boring samples of known criteria and their values of resistivity and shear wave velocity from the geophysical exploration. The polynomial fitting for the data is done by several computing methods to determine the values of the constants in Hayashi's formula **Equation 1**.

In this paper the results of using three different regression methods used in machine learning for the computation of the constant values and compares them by their accuracy of estimation and their results are involved.

3.1. Gradient Decent Method

This method was first introduced by Kiefer and Wolfowitz (1985). Gradient decent is an optimization algorithm that is used to find the local minimum of a function to identify the values of that function's constants. The application of this method depends on the initial parameters that are identified from borehole and given to the algorithm that uses calculus to iteratively adjust the values to reduce the cost function as minimum as possible. This method depends on the learning rate and the number of iterations to reduce the cost function as minimum as possible.

$$x_{n+1} = x_n - \alpha \nabla f(x_n) \tag{2}$$

Equation 2: Cost function of Gradient Decent Method where Xn is the current guess, α is the learning rate, Xn+1 is the new guess and ∇f(x_n) is the partial derivative of the function.

3.2. Bayesian Ridge Method

This method was first introduced by Neal (1995). Bayesian regression is a linear regression that uses Bayesian statistics to estimate the constants of a function or any unknowns in a model. It uses Bayes' theorem to estimate the likelihood of a set of parameters given observed data. Bayes Theorem. gives the relationship between an event's prior probability and its posterior probability after evidence is considered. The goal of Bayesian regression is to find the best estimate of the parameters of a linear model that describes the relationship between the independent and the dependent variables.

$$P(A|B) = \frac{P(B|A).P(A)}{P(B)} \tag{3}$$

Equation 3: Present Bayesian Theorem, where P(A|B) is the probability of event A happening given that event B has already occurred, P(B|A) is the probability of event B occurring given that event A has already occurred, P(A) is the probability of event A

3.1. Supported Vector Machine (SVM) Method

This method was first introduced by Vapnik (1992). SVM is considered a nonparametric technique because it relies on kernel functions. The working methodology is that this method finds a hyperplane in a high-dimensional space that best separates the data into different categories. It aims to maximize the distance between the separator "hyperplane" and the nearest points of each category, where this distance is called the margin in addition to minimizing classification errors. SVM can handle classification problems of data in both linear and non-linear states.

Stochastic Gradient Descent (SGD) is a simple yet very efficient approach to fitting linear classifiers and regressors under convex loss functions such as (linear) Support Vector Machines and Logistic Regression. Using the scikit-learn library in python language the data sample of known Vs, ρ and soil type is fitted using the embedded function for Stochastic Gradient Descent, then the resulted model is used for predicting the unknown value of S for the rest of the geophysical section. After predicting S for the rest of the geophysical section, accuracy for S is plotted and values of S are contoured as mentioned in the previous methods. In Figure 11 shown how this method classifies the data showing the spread of the data along the classification zone and the decision boundaries estimated.

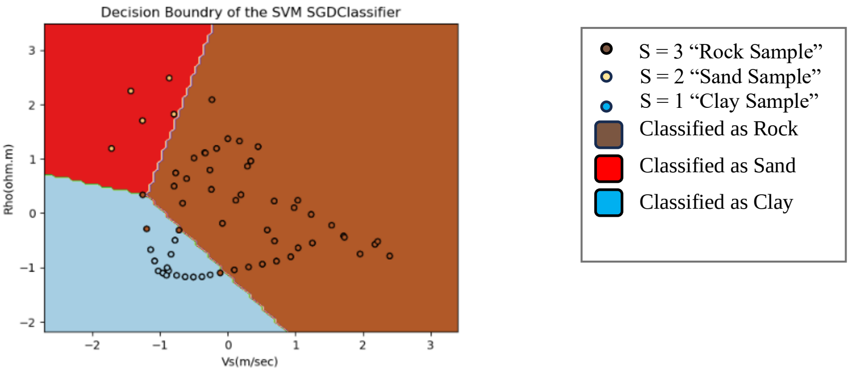

Figure 11. Decision boundary model created by the SVM.

4. Results and Discussions

4.1. Gradient Decent Method

In our case study, the initial values for the constants were randomly chosen and after a series of trial and error it was found that number of iterations of 20000 and learning rate of 0.01 gives best results for the regression. After reducing the cost function to as minimum as possible Figure 12 the constants are exported and used in the prediction of the S using the known data sample. The accuracy of S is calculated by comparing the values of the measured S with the actual data from the training sample. The data is grouped into 4 categories depending on the S values [1:1.5, 1.5:2, 2:2.5, and 2.5:3] and the comparison is demonstrated as in Figure 13.

Table 1: Constants values using stochastic gradient decent method

Category	**a**	**b**	**c**	**d**	**e**	**f**	**g**	**h**
Value	**0.91268**	**1.01301**	**0.18265**	**-0.26802**	**-0.80302**	**0.18507**	**0.93604**	**-0.56673**

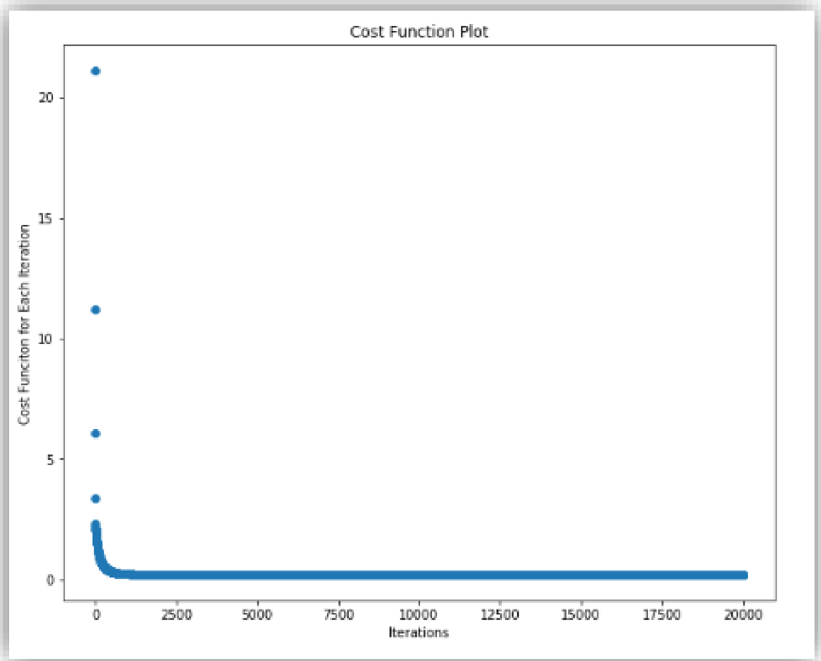

Figure 12: Plot showing the decrease the fitting error for every iteration by the decrease of the cost function as the number of iterations is increased until a certain limit and then the change of the cost function per iteration is negatable.

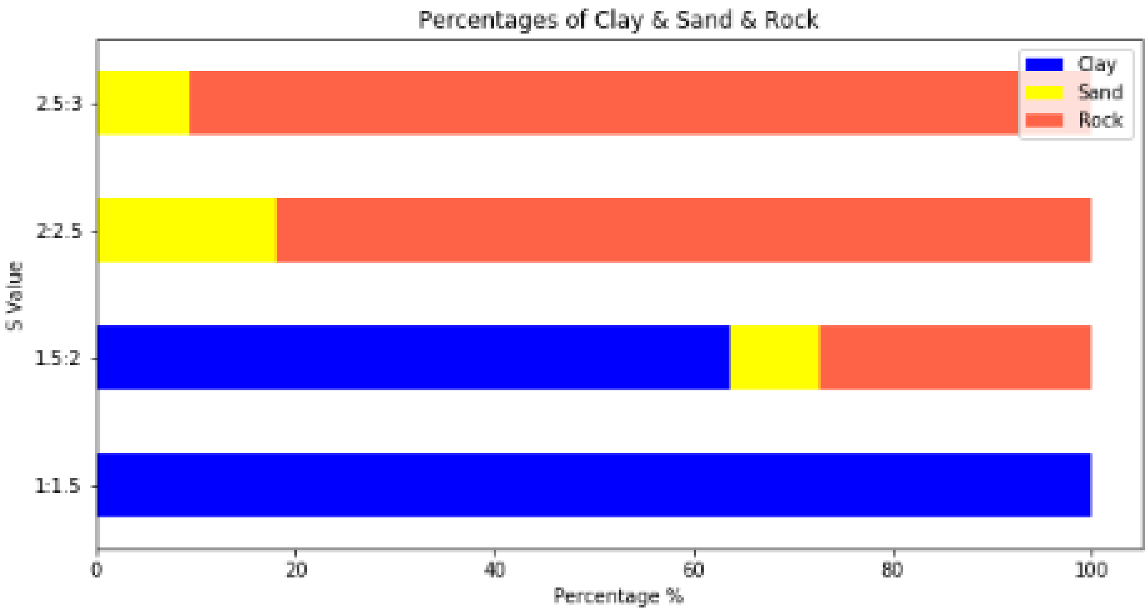

Figure 13: Plot Showing the Accuracy of The S Value Estimation by Using the Gradient Decent Method.

Using the Hayashi equation previously mentioned. the values of S was calculated using the shear wave velocity Vs, resistivity ρ and the constants obtained from regression. The calculated values are contoured using SURFER software to give a contoured section with values of S as shown in Figure 14.

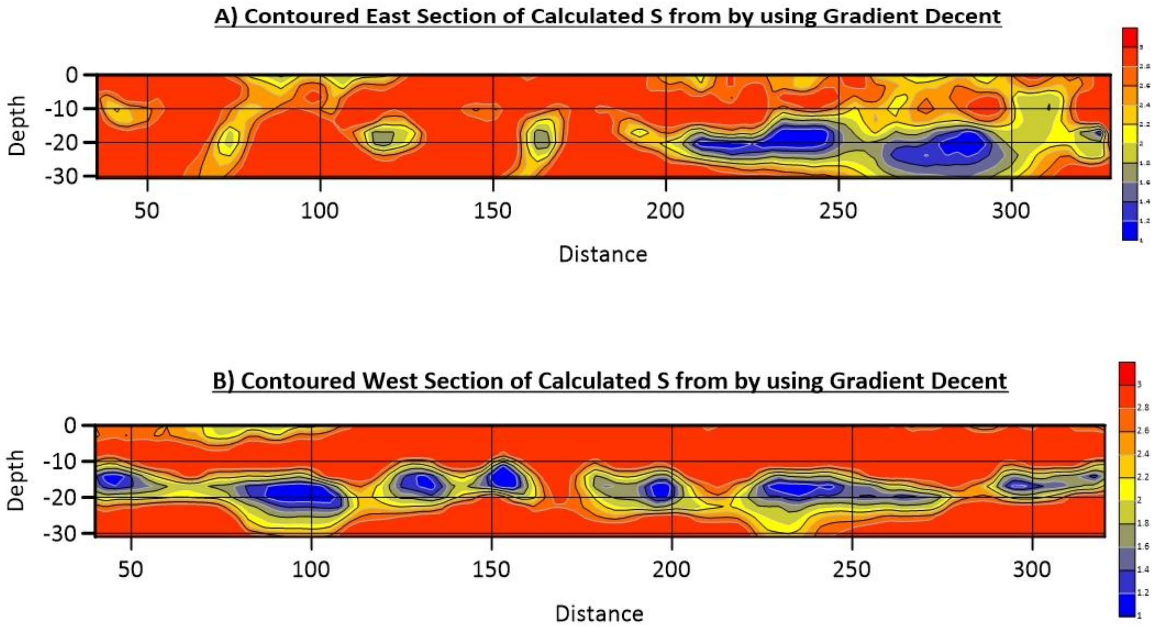

Figure 14: Contoured values of S for the eastern and western sections using stochastic gradient decent method.

4.2. Bayesian Ridge Method

This method was first introduced by Neal (1995). Bayesian regression is a linear regression that uses Bayesian statistics to estimate the constants of a function or any unknowns in a model. It uses Bayes' theorem to estimate the likelihood of a set of parameters given observed data. Bayes Theorem. gives the relationship between an event's prior probability and its posterior probability after evidence is considered. The goal of Bayesian regression is to find the best estimate of the parameters of a linear model that describes the relationship between the independent and the dependent variables.

Using the scikit-learn library in python language the data sample of known Vs, ρ and soil type is fitted using the embedded Bayesian Ridge function. Following the fitting the parameters of the function is exported and accuracy of S is calculated, and values of S is calculated and contoured for the rest of the section in the same method used in Gradient Decent.

Table 2: Values of Hayashi's equation constants using the Bayesian Ridge Regression.

Category	a	b	c	d	e	f	g	h
Value	**0.14744**	**0.12748**	**0.07312**	**0.08882**	**0.15260**	**0.17395**	**0.21832**	**0.0**

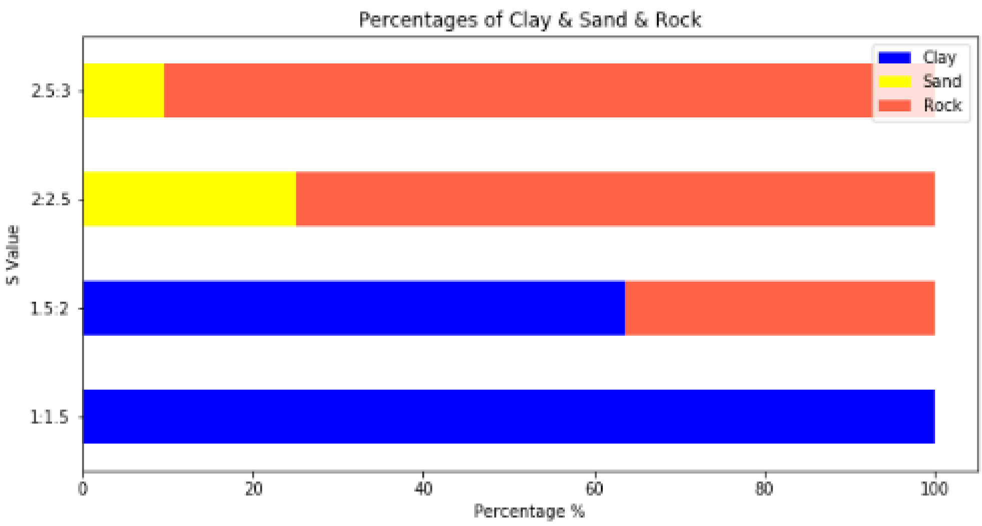

Figure 15: Plot showing the accuracy of the S value estimation using the Bayesian regression method.

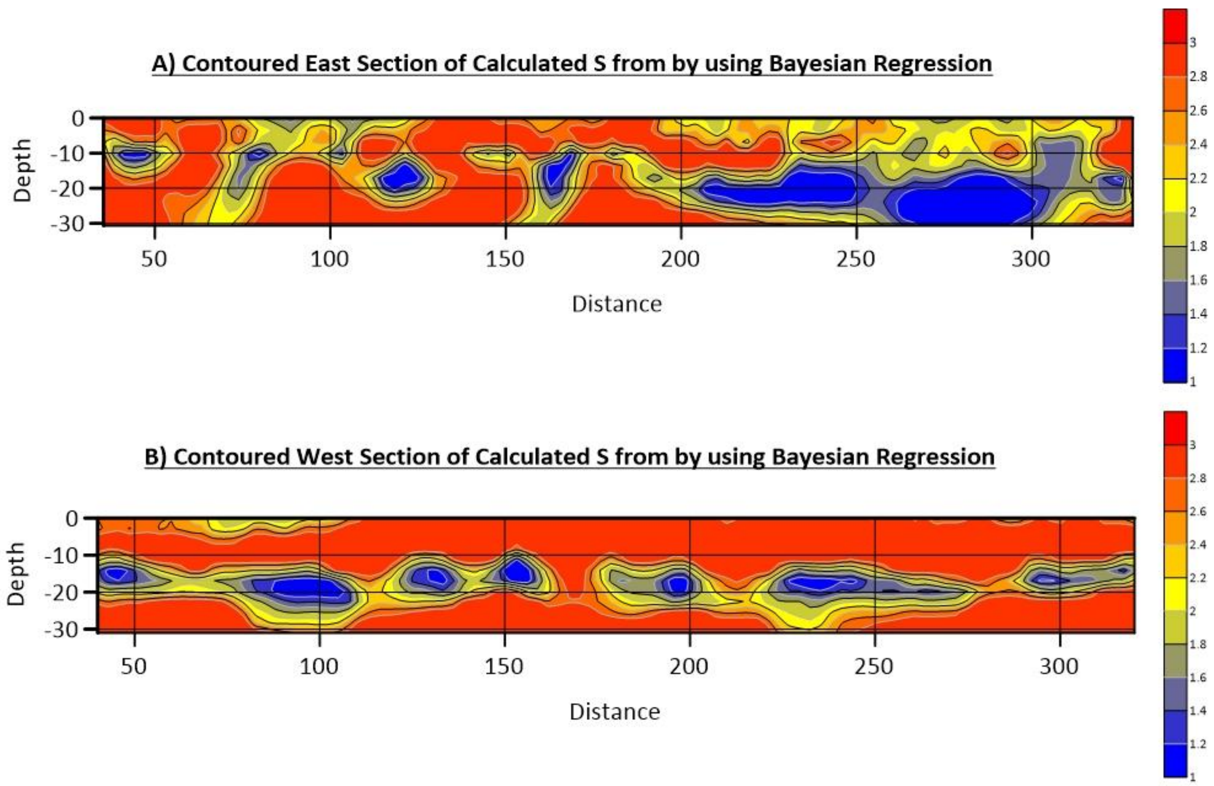

Figure 16: Contoured values of S for the eastern and western sections using Bayesian regression.

4.3. Supported Vector Machine (SVM) Method

This method was first introduced by Vapnik (1992). SVM is considered a nonparametric technique because it relies on kernel functions. The working methodology is that this method finds a hyperplane in a high-dimensional space that best separates the data into different categories. It aims to maximize the distance between the separator “hyperplane” and the nearest points of each category, where this distance is called the margin in addition to minimizing classification errors. SVM can handle classification problems of data in both linear and non-linear states.

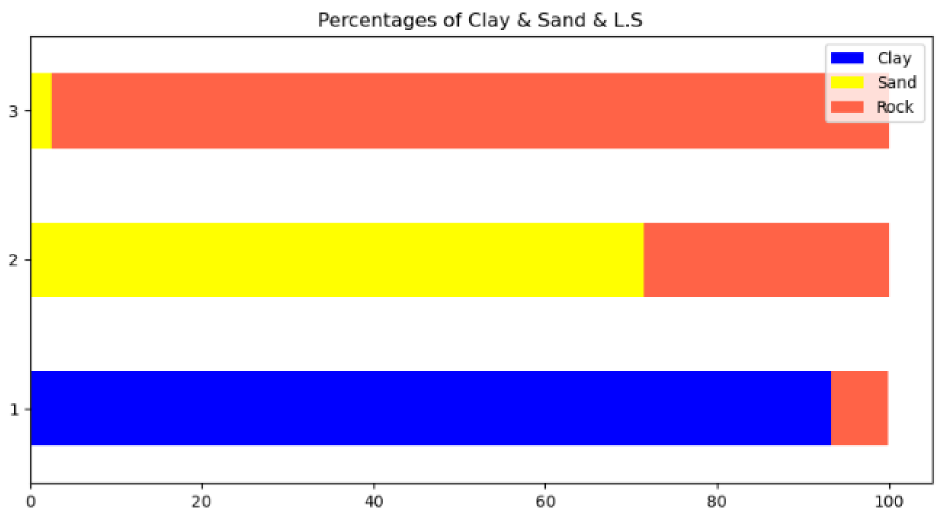

Figure 17: Plot showing the accuracy of the S value estimation by using the Stochastic

Gradient Decent Classifier.

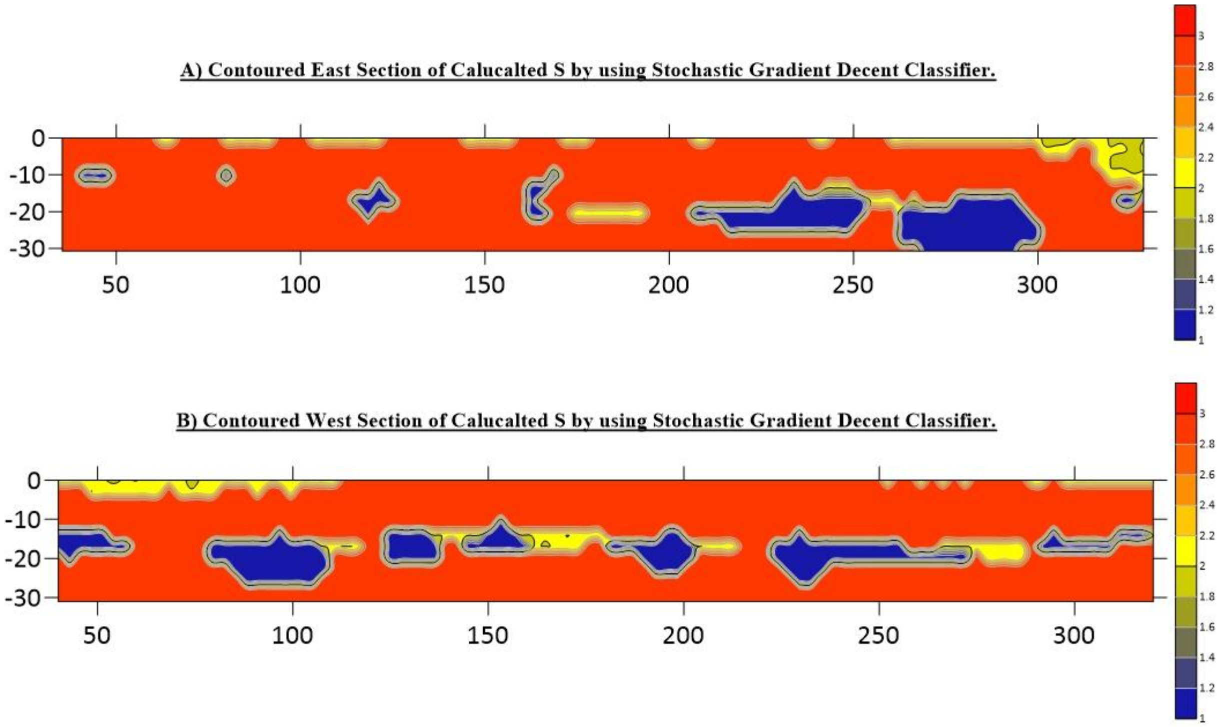

Figure 18: Contoured Values of S For the Eastern and Western Sections using Stochastic Gradient Decent Classifier.

4. Conclusions and Future Work

Statistical soil type estimation from shear wave velocity and resistivity data can be used as a tool for enhancing the interpretation of geological complex zones. For the polynomial approximation, various methods can be used which can lead to more accurate predictions and interpretation. Looking back to the results, the generated sections from regression methods show a higher level of ambiguity than the sections from the classification. Comparing figures (**Figure *13***, **Figure *15***, **Figure *17***) the values of S have a range of values, and both used methods proved to be hard to identify the sand with high statistical value leading to high ambiguity in the determination of the soil type. Otherwise, the classification method due to its nature of dividing the data into categories proved to give higher accuracy in the determination of the soil type. Further comparisons between different regressions and classification techniques, with larger data sets to perform more accurate evaluating methods such as (the test-split method) are needed to confirm the optimized method for statistical estimation for best soil type estimation methodology using regression methods.

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