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Prediction of Soil-Water Characteristic Curves of Four Subgrade Materials using a Modified Perera Model

Rokhaya Gueye [1]*, Makhaly Ba [1], Ibrahima Mbaye [2], Ida Bibalo Josiane Ki [1]

[1] *UFR Sciences de l'Ingénieur, Université Iba Der Thiam, Thiès, Sénégal.*

[2] *UFR Sciences et Technologie, Université Iba Der Thiam, Thiès, Sénégal.*

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Abstract

One of the main hydraulic properties of unsaturated soils is the Soil-Water Characteristic Curve (SWCC). It is essential to understand, predict soil water storage and determine the hydraulic and mechanical behaviour of soils. These curves can be obtained by direct and indirect measurements. The measurements to obtain these curves are expensive, delicate to perform and can be really slow for fine soils, so predictive models become necessary. In order to make a numerical model, a couple of identification tests were carried out to obtain the physical properties of each sample among the four subgrade materials collected in the regions of Dakar and Thies (Senegal). The measurement tests of the matric suction were then conducted depending on the nature of the material (fine-grained soil or coarse-grained soil) and allowed to draw the SWCC of each soil. Among numerous predictive models developed for SWCC in the last decades; this study used the Perera model to fit the SWCC of four (04) subgrade materials, which did not give a satisfactory coefficient of correlation (R^2 = 58% and a relatively low sum of the squared residuals (SSR)). This leads to modifying the Perera model to better fit the SWCC on the basis of an understanding of the effect of each parameter on the shape of the SWCC. The proposed modified model was validated by checking the adjusted R^2, minimizing the SSR in order to approach at most the experimental air entry value. The modified model works pretty well on coarse-grained and fine-grained soils. This modified model of Perera provided a very good correlation R^2 equal to 99.98, 98.74, 99.64, and 99.73 for the sandy soils (Sebikotane and Keur Mory) and the Marley and Clayey soils of Diamniadio, with a minimal SSR obtained compared to Perera's and Hernandez model.

Keywords: Soil-Water Characteristic Curve (SWCC); Suction; Degree of Saturation; Predictive Model; Grain Size Distribution.

1. Introduction

Several research studies have been done over the last decades to better understand the mechanics of unsaturated soils. In the previous studies [1–5], the soil–water characteristic curve (SWCC) was defined as the most useful concept of unsaturated soil mechanics. It can serve to estimate the water storage and also intervene in slope stability, bearing capacity, and agriculture fields [6]. The SWCC is a non-linear relationship between the volumetric water content, θ or degree of saturation, S_r and matrix suction, ψ. The latter is defined as that suction component that relates to the height to which water can be drawn or sucked up into unsaturated soil. These retention curves can be obtained either directly or indirectly by measurement. A SWCC describes the amount of water retained in soil under equilibrium at a given matric suction. This most important hydraulic property of unsaturated soils is related to the size and connectedness of pore spaces and is strongly affected by the soil texture and structure. However, the shape of the SWCC is hysteretic, with wetting and drying curves. In this study, only the drying process (Figure 1) is determined due to the experimental difficulties associated with the measurement of the wetting curve [7, 8].

* Corresponding author: rokhaya.gueye@univ-thies.sn

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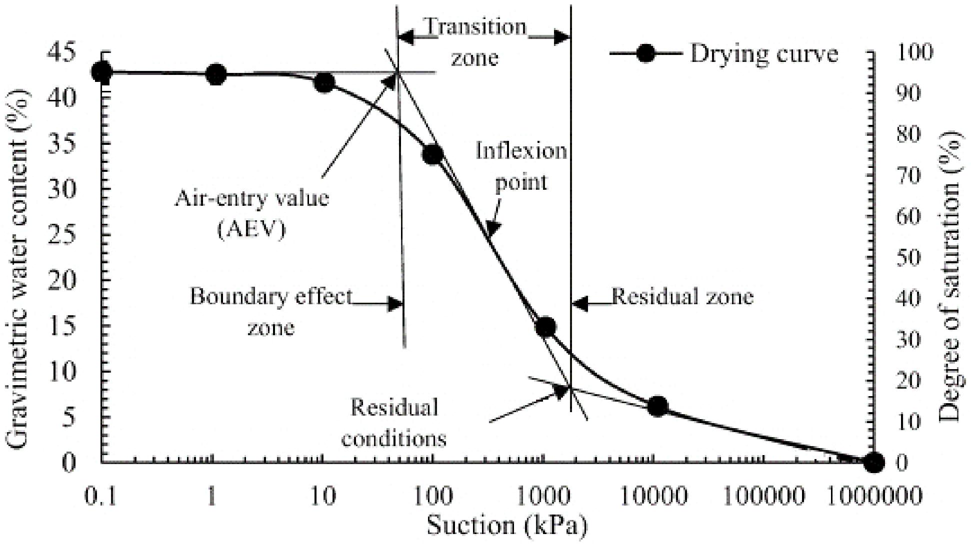

Figure 1. Typical features of the Soil-Water Characteristic Curves (SWCC) [9])

Figure 1 describes a typical sigmoidal shape, which can be divided into three parts commonly named boundary effect zone, transition zone, and residual conditions. There are three main features that necessarily define the shape of the SWCC. The first is the air entry value (AEV) corresponding to the suction required to drain freely the water from the largest pores; the second feature represents the slope of the SWCC obtained in the transition zone or the rate of water loss [10], and the third feature represents the volumetric water content below which an increase in suction has no effect on the water content [11].

These tests are expensive, really delicate to handle, and can be influenced by several factors [12]. To overcome the lack of devices, expensive cost, and delicacy of these tests, an estimation of the SWCC became necessary in this field. Several models have already been developed for the prediction of the SWCC and can be classified into three groups. The first approach and the most popular are classified as empirical models [13–16]. In this approach, having data (measured suction and water content) is necessary to make predictions in order to find the corresponding suction for a given water content. The second approach was based on the soil properties [17–19]. This approach is really interesting as it uses the physical properties of the materials (Atterberg limits, grain size distribution) to predict the suction value. It is an alternative, given that suction measurement tests are expensive, delicate to handle, and very difficult to perform. And finally, the third approach was based on machine learning using programming software. Artificial Neural Networks is used to estimate the soil-water characteristic curves. This method is considered an aid to determining the suction value [20–25]. This system is built similarly to the human brain, with a neural network to connect the input data to the output data. The advantage of this method is the unnecessity to know the link between the input and output data. However, the main inconvenience of this approach is the need for a very large database. Given the required time, the complexity of these tests, the lack of a device to measure the SWCC in Senegal, and the ease of obtaining physical parameters in practically all laboratories, the second approach was used to predict the SWCC in this paper.

Fredlund & Xing (1994) model is a popular empirical model used to estimate the SWCC because it can describe a much wider range of suction than other models up to 10^6 kPa at zero water content [14]. Each parameter of the model has an impact on the shape of the SWCC. Indeed, the parameter "a_f" is related to air entry value, "b_f" to the pore size distribution (PSD); while "c_f" is related to the residual zone, specifically the water content and the residual soil suction. Fredlund et al. (2002) also used a database of 6000 soils implemented in SoilVision to found a predictive model using the particle size distribution to predict the fitting parameters a_f, b_f and c_f in the Fredlund model [26].

Zapata et al. (2000) developed a model based on 190 soils depending on the nature of the sample (granular or plastic soils) [19]. The parameter D_{60} was used for the granular soils, while the parameter ωPI was used for the plastic soils. The coefficient of determination R^2 was not high; but at the time it was a real advance in the field. Moreover, numerous authors have used that work to find new correlations.

Perera et al. (2005) selected the 134 best soil-water characteristic curves from a database collected by Zapata and added another dataset of 83 from the NCRHP 9–23 project [18]. After identification tests, this database was divided into 154 non-plastic soils and 63 plastic soils. The particle size distribution of each soil was used to obtain the diameters from D_{10} through D_{90} as well as the Atterberg limits (LL, PL, and PI) for the statistical analysis used to find the fitting parameters. The results of this study, compared with Zapata results, showed a decrease in the algebraic and absolute errors from 88.5% to 8.6% and 14.8%, respectively, associated with an increase in adjusted R^2 values from 2% to 58% for the non-plastic soils. However, the algebraic errors decreased from 20.4% to 0.1% for the plastic soils, while they decreased from 23.9% to 9.2% with a R^2 of 51. It can therefore be observed that these results are not satisfactory enough, even if they were a notable advance in the field because they managed to minimize the errors of Zapata's model.

Torres Hernandez (2011) collected the largest database at the time to predict the SWCC and also used the Fredlund & Xing equation and a non-linear regression analysis to predict the fitting parameters of the model [17]. In this model, hysteresis is not taken into account; only the dry path is presented. 36394 samples were obtained from the NRCS "National Resources Conservation Service," including 31876 plastic soils, 4518 granular soils and 68 soils not usable for lack of insufficient information. Two series of equations were proposed according to whether the soil was granular or plastic. For plastic soils, the P_{200}, plasticity index, and liquidity limit constituting the "Group Index" were used to estimate the fitting parameters. For granular soils, the model of prediction depends only on a single parameter named D_{10} (diameter of sieve corresponding to 10% of passing). The results showed an adjusted R^2 of 81% for fine soils and 89% for the granular materials.

In the present study, the Perera model was used to fit the SWCC based on the experimental data. The study was also interested in understanding the effect of each parameter on the shape of the curve in order to propose a modified Perera mode. A statistical analysis to minimize errors was also carried out to test the reliability of the modified model.

2. Materials and Methods

2.1. Sample Locations and their Physical Properties

The marl and clay were sampled at Diamniadio in the city of Rufisque, around 25 km southeast of Dakar. The marl and clay lie between 14° 73' 50" North, 17° 19' 64" West in the context of the Senegalese-Mauritanian sedimentary basin. The geology of Diamniadio is part of the geology of the Cap Verde peninsula, which is located at the western end of the Senegal-Mauritania basin. The various outcrops encountered in the Rufisque-Bargny zone are formed by a volcanic group and a sedimentary group of Tertiary or Quaternary. Diamniadio is marked by the appearance of faults delimiting ascending blocks such as the Ndiass and Dakar horsts, and collapsed blocks such as the Rufisque garden. Two other sandy soils have also been collected, one at Sebikotane (14° 78' 74" North, 17° 13' 03" West) and the other at Keur Mory (14° 77' 80" North, 16° 75' 47" West). These are characterized by a Quaternary dune system composed of three elements that were established between the Ogolian and Holocene periods in Senegal. These are:

- Rubbed sands of the Ogolian ergs of Sangalkam, Pikine, Keur Massar, Bambilor and Tivaouane;
- Semi-fixed dune sand known as yellow dune;
- Sand of living dune of the north coast called white dune.

The Sebikotane sample belongs to the Ogolian ruby sand and the Keur Mory sand would belong to the white dune dated to the Holocene.

All four samples were subjected to a series of identification tests. These included grain size analysis, Atterberg limits, specific gravity test, to identify and classify them. The physical properties are given in Table 1 while the sample location map is shown in Figure 2. A summary of the methodology used in this study in Figure 3.

Table 1. Summary of the physical properties of the subgrade materials

Materials	$\gamma\left(\frac{kN}{m^3}\right)$	G_s	C_u	PI	P_{200} (%)	D_{10} (mm)	D_{20} (mm)	D_{30} (mm)	D_{60} (mm)	D_{90} (mm)
Sebikotane Sand	1.817	2.666	1.26	-	0.78	0.17	0.19	0.20	0.21	0.248
Keur Mory Sand	1.78	2.668	3.41	-	4.61	0.082	0.099	0.19	0.28	0.39
Diamniadio Clay	1.63	2.741	-	26	77.13	-	-	-	-	-
Diamniadio Marl	1.92	2.609	-	14.38	51	-	-	-	-	-

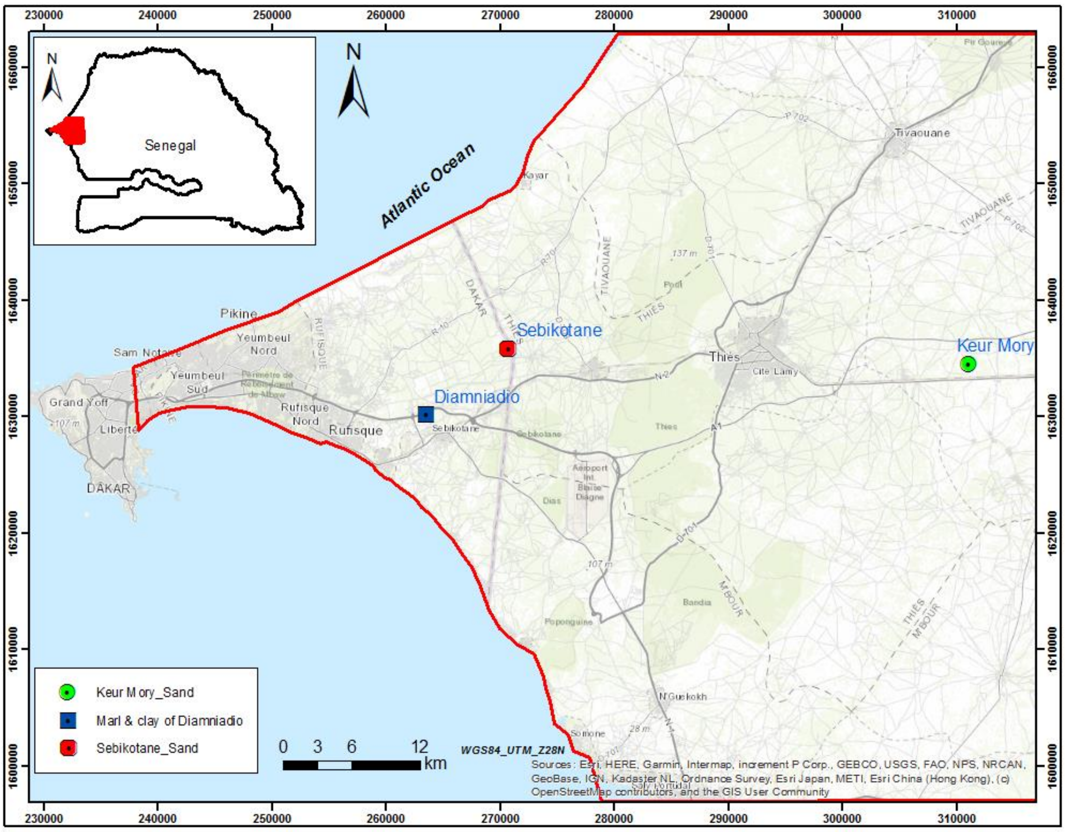

Figure 2. Sample location

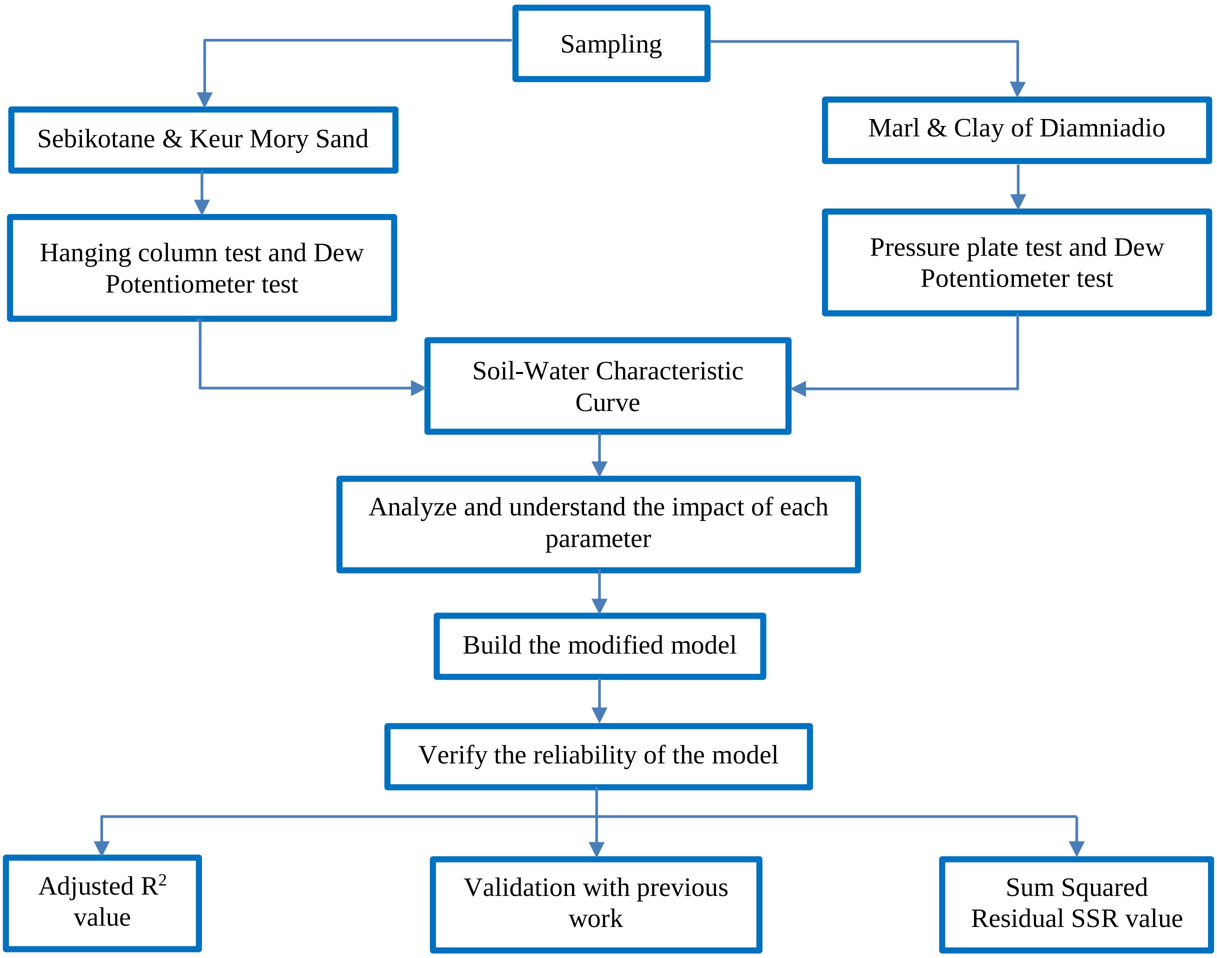

Figure 3. Flowchart describing the methodology of this work

2.2. Experimental Methods

The selected materials were subjected to suction measurement tests, mainly depending on the nature of the material. The pressure chamber test was conducted on the Marl and Clay soils to determine the equilibrium water content retained in the soil. The testing procedure described in ASTM standard D6836-16 method B or C was followed [27]. After saturation and setting the sample in the chamber, the suction is applied until equilibrium is reached, i.e., when the level of water does not change. Another step of suction is then applied until the curve is complete or the maximum suction that the device can apply is reached. On the other two samples (Sebikotane and Keur Mory sand), the hanging column test adapted for granular soils was carried out following procedure method A in ASTM D6836-16 [27]. And to complete the SWCC at low water content, a chilled hygrometer test (Method D of the ASTM standard D6836-16) was used to measure the activity water of the soils within 0.001.

When the tests were done, the Perera model described in the Equations 2 to 16 was used to plot the retention curves. Let's recall that Perera model is based on Fredlund's equation (Equation 1) to predict the fitting parameters.

$$\theta = (\theta_s - \theta_r)\left[1 - \frac{\ln\left(1+\frac{\psi}{h_r}\right)}{\ln\left(1+\frac{10^6}{h_r}\right)}\right]\left[\frac{1}{\ln\left(e+\left(\frac{\psi}{a_f}\right)^{b_f}\right)^{c_f}}\right] + \theta_r \quad (1)$$

where θ is Volumetric water content, θ_r is Residual volumetric water content, θ_s is Saturated water content, ψ is Matric suction, h_r is Residual suction, and a_f, b_f et c_f is Fitting parameters of Fredlund's model.

Equations 2 to 16 described below the two sets of equations used by Perera to find the fitting parameters of Fredlund's model.

- For non-plastic soils

$$a_f = 1.14a - 0.5 \quad (2)$$

$$D_{100} = 10^{\left[\frac{40}{m_1}+log(D_{60})\right]} \quad (3)$$

$$a = -2.79 - 14.1log(D_{20}) - 1.9 * 10^{-6}P_{200}^{4.34} + 7log(D_{30}) + 0.055D_{100} \quad (4)$$

$$m_1 = \frac{30}{[log(D_{90}) - log(D_{60})]} \quad (5)$$

$$b_f = \left\{5.39 - 0.29ln\left[P_{200}\left(\frac{D_{90}}{D_{10}}\right)\right] + 3D_0^{0.57} + 0.021P_{200}^{1.19}\right\}m_1^{0.1} \quad (6)$$

$$D_0 = 10^{\left[\frac{-30}{m_2}+log(D_{30})\right]} \quad (7)$$

$$m_2 = \frac{20}{[log(D_{30}) - log(D_{10})]} \quad (8)$$

$$c_f = 0.26e^{0.758c} + 1.4D_{10} \quad (9)$$

$$c = log\ m_2^{1.15} - \left(1 - \frac{1}{b_f}\right) \quad (10)$$

$$h_r = 100 \quad (11)$$

with D_{10} is Grain diameter corresponding to 10 % passing by weight, D_{20} is Grain diameter corresponding to 20 % passing by weight, D_{30} is Grain diameter corresponding to 30 % passing by weight, D_{60} is Grain diameter corresponding to 60 % passing by weight, and D_{90} is Grain diameter corresponding to 90 % passing by weight.

- For plastic soils

$$a_f = 32.835ln(wPI) + 32.438 \quad (12)$$

$$b_f = 1.421wPI^{-0.3185} \quad (13)$$

$$c_f = -0.2154ln(wPI) + 0.7145 \quad (14)$$

$$h_r = 500 \tag{15}$$

ωPI is Weighed Plasticity index

$$\omega PI = P_{200} * PI \tag{16}$$

P_{200} is Material passing the n°200 Standard Sieve expressed as a decimal, PI is Plasticity Index (%) = Liquid Limit – Plastic Limit

Figures 4 to 7 describe the SWCC with the Perera model used to fit the experimental data.

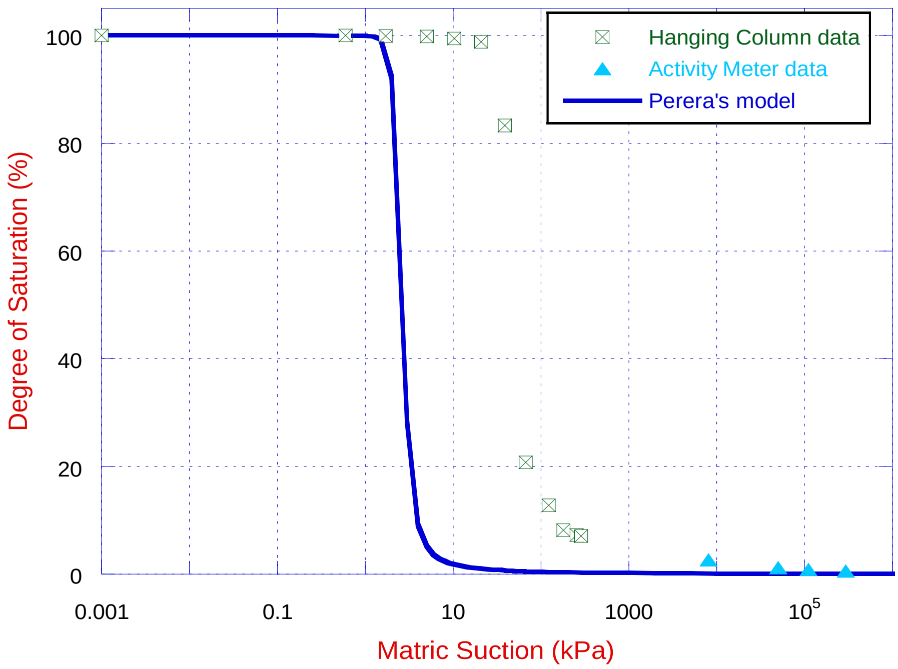

Figure 4. SWCC fit with Perera model on Sebikotane Sand

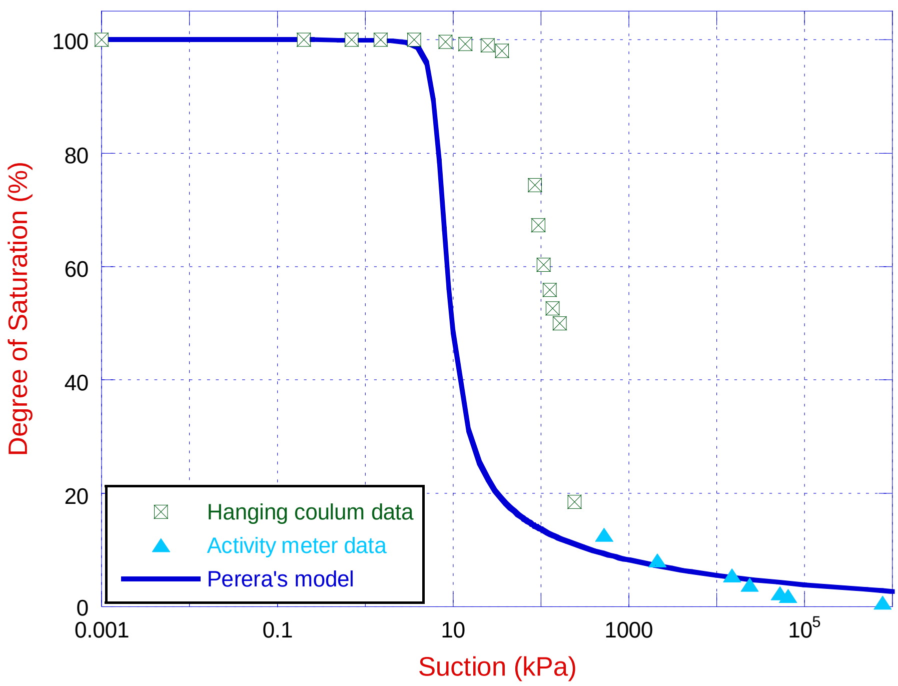

Figure 5. SWCC fit with Perera model on Keur Mory Sand

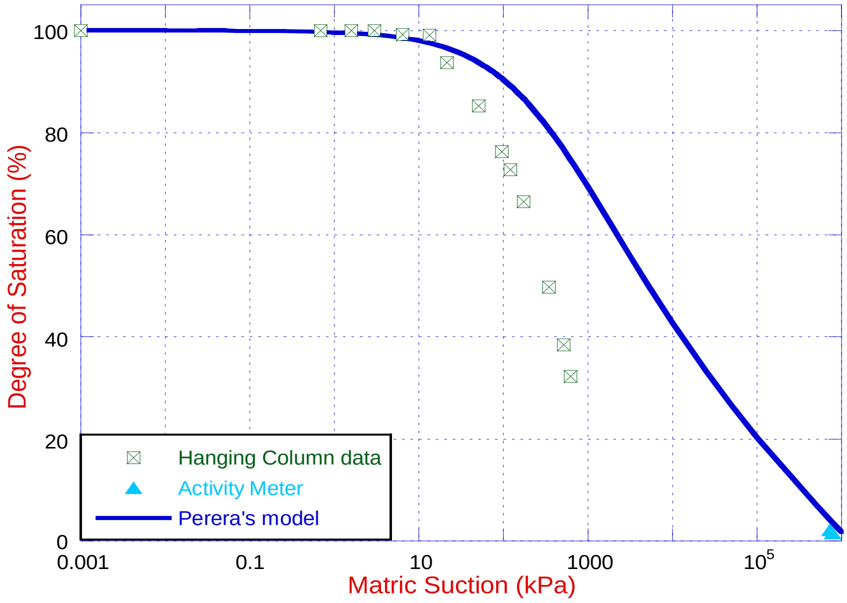

Figure 6. SWCC fit with Perera model on Diamniadio Marl

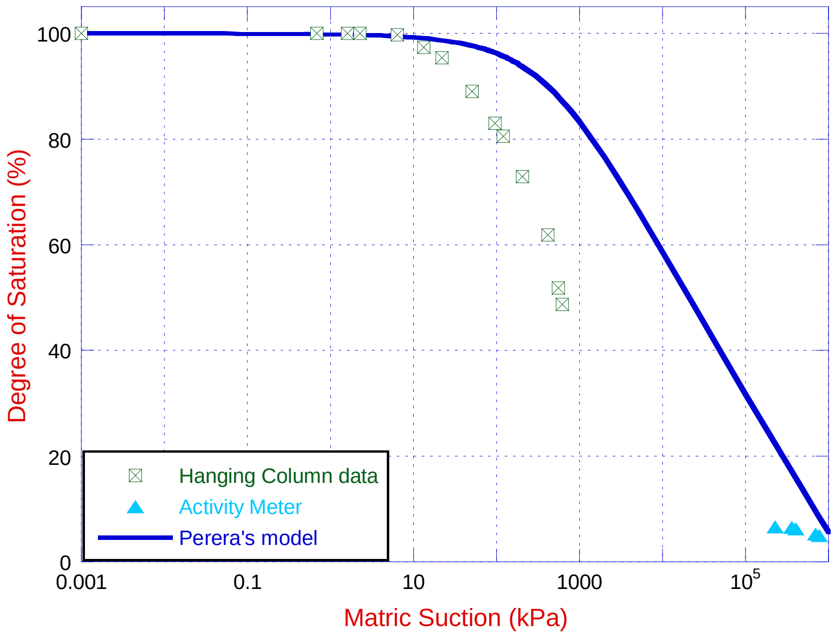

Figure 7. SWCC fit with Perera model on Diamniadio Clay

The prediction of the four (04) SWCC fitting with the Perera model does not give a good correlation. It can be observed that the air entry value pressure is underestimated for the sandy soils; while it is overestimated for marly and clayey soils of Diamniadio. This leads to thinking that it would be necessary to modify the values of a_f related to the air entry value; but also, for b_f and c_f related to the slope of the transition zone and the residuals suctions of the SWCC. As shown in Figure 6 and 7, the air entry value for the clayey and marly soils of Diamniadio is overestimated. So in order to fix it, it is necessary to understand how the fitting parameters of Perera's model behave on the SWCC.

2.3. Process of Analysis

For the plastic soils (clay and the marl of Diamniadio), Equations 12 to 16 show that the fitting parameters only depend on wPI which itself depends on $P_{200}$and PI. The wPI was varied from 1 to 30 to see how it affects the shape of the SWCC. Compared with the experimental data, Figure 8 shows that varying wPI influences the three zones (boundary effect, transition and residual zone) of the SWCC. This means that not only the a_f must change by decreasing it to get the right air entry value; but also, the b_f and c_f must be modified to better fit the experimental data. Some modifications have been made in the fitting parameters of Perera's model. Equations 17 to 21, describe the new fitting parameters for plastic soils.

$$a_f = 32.835 ln(\omega PI) + 3.3781 \tag{17}$$

$$b_f = 3.2937 \omega PI^{-0.3185} \tag{18}$$

$$c_f = -0.1 ln(\omega PI) + 0.942 \tag{19}$$

$$h_r = 500 \tag{20}$$

where

$$\omega PI = P_{200} * PI \tag{21}$$

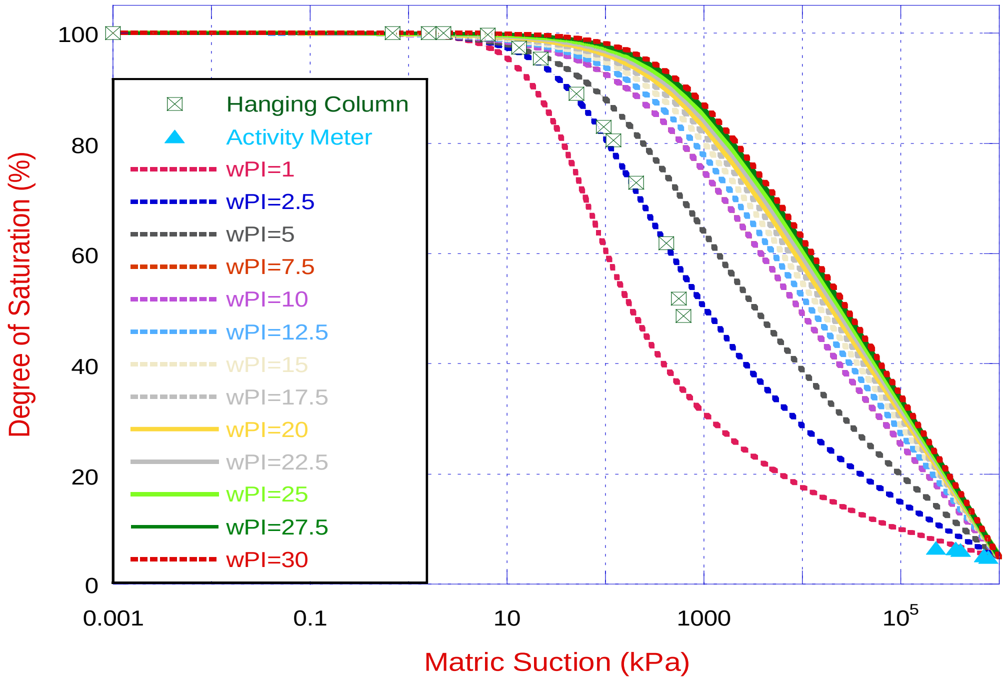

Figure 8. Impact of wPI on the shape of the SWCC of Diamniadio Marl

For non-plastic soils, three new parameters α , β and λ have also been introduced in the Perera's model to modify the fitting parameters. The modified model is presented below:

$$a_f = \alpha * (1.14\, a - 0.5)\ avec\ a_f \geq 1 \tag{22}$$

$$a = -2.79 - 14.11 log D_{20} - 1.9.10^{-6} P_{200}^{4.34} + 7 log D_{30} + 0.055 D_{100} \tag{23}$$

$$D_{100} = 10^{\left[\frac{40}{m_1} + log(D_{60})\right]} \tag{24}$$

$$m_1 = \frac{30}{[log(D_{90}) - log(D_{60})]} \tag{25}$$

$$b_f = \beta * (0.936 b - 3.8) \tag{26}$$

$$b = \left\{5.39 - 0.29\, ln\left[P_{200}\left(\frac{D_{90}}{D_{10}}\right)\right] + 3\, D_0^{0.57} + 0.021\, P_{200}^{1.19}\right\} m_1^{0.1} \tag{27}$$

$$D_0 = 10^{\left[\frac{-30}{m_2} + log(D_{30})\right]} \tag{28}$$

$$m_2 = \frac{20}{[log(D_{30}) - log(D_{10})]} \tag{29}$$

$$c_f = \lambda(0.26 e^{0.758c} + 1.4 D_{10})\ with \begin{cases} c_f \geq 0.5 \\ if\ not\ \lambda = 1 \end{cases} \tag{30}$$

$$c = \log\, m_2^{1.15} - \left(1 - \frac{1}{b_f}\right) \tag{31}$$

$$h_r = 100 \tag{32}$$

3. Results and Discussions

Firstly, the analyze is made on how separately each new parameter influences the shape of the SWCC in the non-plastic soils. Figure 9 shows that a variation of α from 0.5 to 20 does not have an effect on the shape of the SWCC; but on the other hand, it increases the air entry value suction. It is like a translation of axis. So, comparing with the experimental data, we can say that α is close to 20.

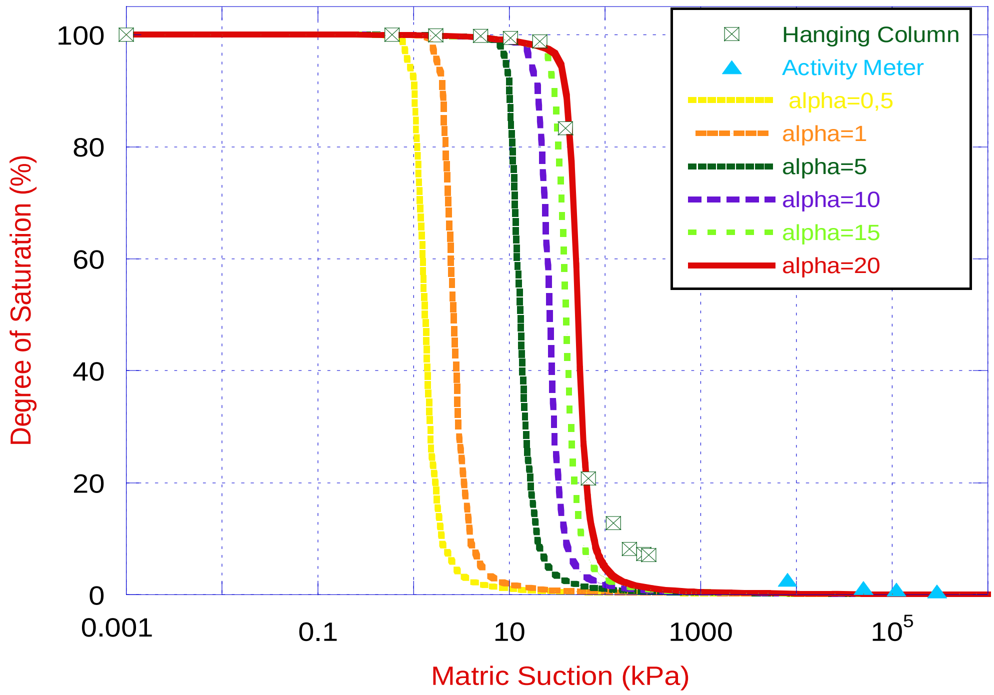

Figure 9. Impact of α on the shape of the SWCC of Sebikotane Sand

An increase of β from 0.05 to 0.25 influences the air entry value as well as the slope of the transition zone, while above 0.25 up to 1, a slight increase of the air entry value can be observed. For β higher than 1, the air entry value, the slope of the transition zone as well as the residual suction remain unchanged (Figure 10).

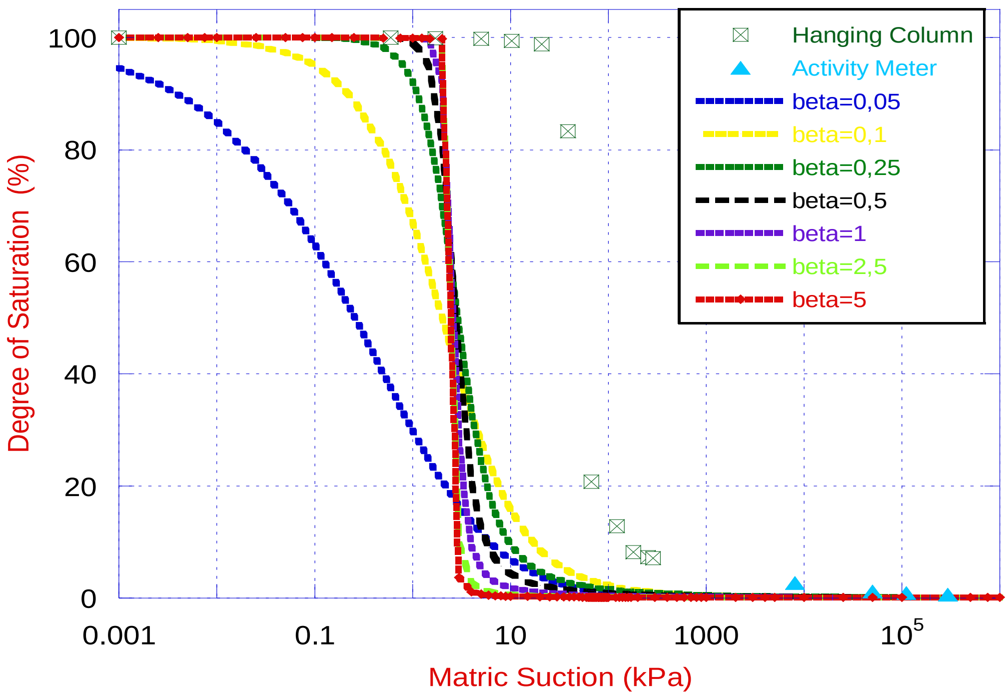

Figure 10. Impact of β on the shape of the SWCC of Sebikotane Sand

λ affects the residual suctions unlike β where the effect was more noticeable on the transition zone. Figure 11 shows that λ and the residual suctions act in opposite direction. Indeed, when the value of λ is low, the residual suctions are high; while they tend to zero when λ tends to 0.5.

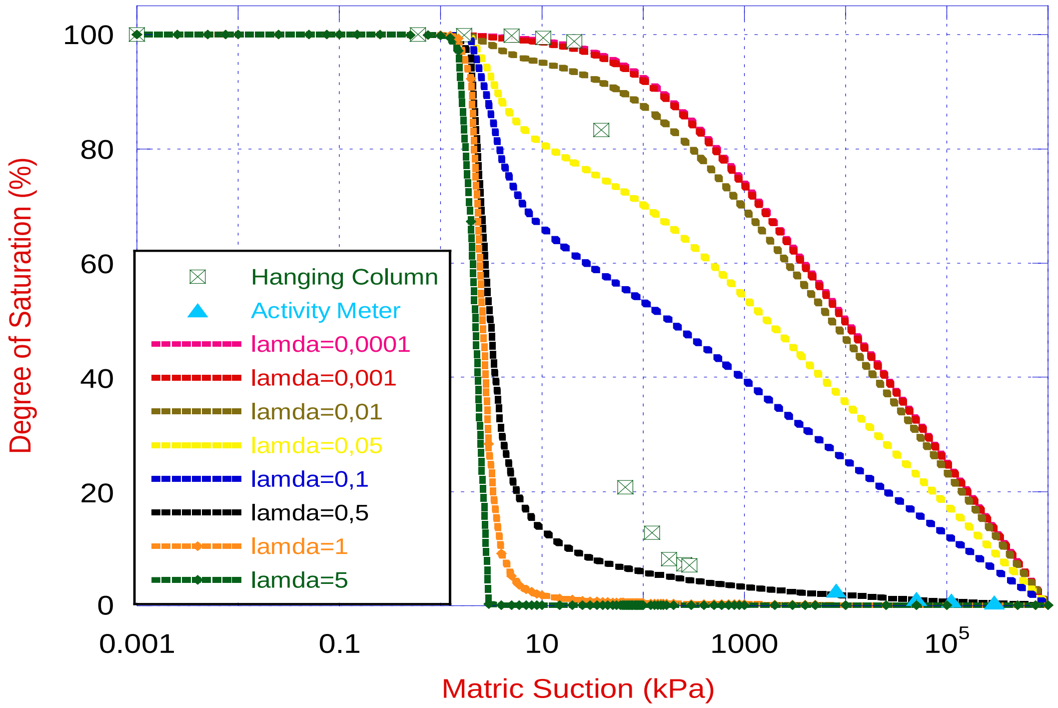

Figure 11. Impact of λ on the shape of the SWCC of Sebikotane Sand

The separate analysis of the impact of each parameter allows to have a rough overview of α, β, and λ that could predict the whole SWCC based on the experimental data. According to that analyze, α seems to be around 20, while $0.25 \leq \beta \leq 2.5$ and λ appears to be equal to 0.5. By varying α, β and λ, mentioned above taking into account the approximative values found earlier gives the best combinations.

3.1. Statistical Analysis

Equation 17 to 32 were used to fit the experimental data by finding the fitting parameters; while minimizing the errors. Indeed, a statistical analysis is associated with this study. In order to verify the reliability of the model, three parameters that can be considered as the most relevant were analyzed.

- The adjusted R^2 is widely used for a regression analysis because it allows to compare the experimental data with the predicted model. It is considered good when it is close to 100%.
- A statistical technique named Sum Squared Residuals (Equation 33) is used to find the best fit from the data. It measures the amount of error remaining between the regression function and the experimental data by altering the fitted parameters iteratively until the squared differences between the predicted and measured data were minimized. According to previous study [7, 28] a best fit should have a SSR less than 10^{-3}

$$SSR = \sum_{i=1}^{n} w_i \left(\theta_i - f(\omega_i)\right)^2 \tag{33}$$

where θ_i represents the value of the measured volumetric water content, $f(\psi_i)$ represents predicted value of the volumetric water content, and ω_i weighting factor set equal to 1.

- And finally, the results obtained with the modified model should be compared with those obtained with other authors (Hernandez and Perera).

In order to obtain the best SWCC while minimizing the errors, several simulations were carried out with α, β and λ. The values of these three parameters introduced in the modified Perera model for granular soils and used to predict the SWCC of the Sebikotane and Keur Mory sands (Figures 12 and 15) are presented in Table 2.

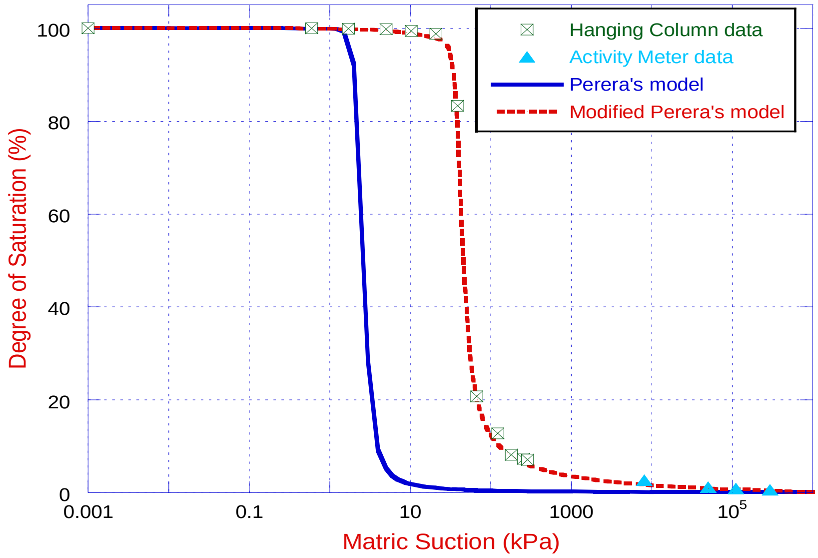

Figure 12. SWCC fit with modified Perera's model on Sebikotane Sand

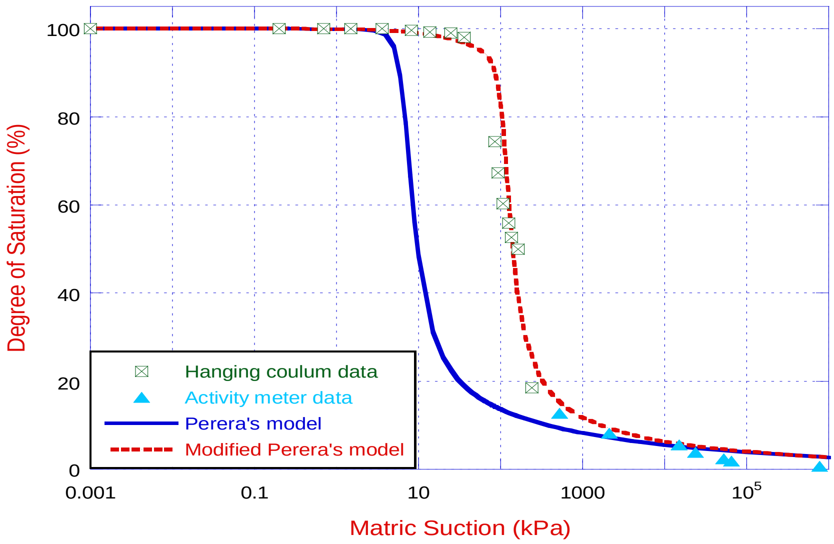

Figure 13. SWCC fit with modified Perera's model on Keur Mory Sand

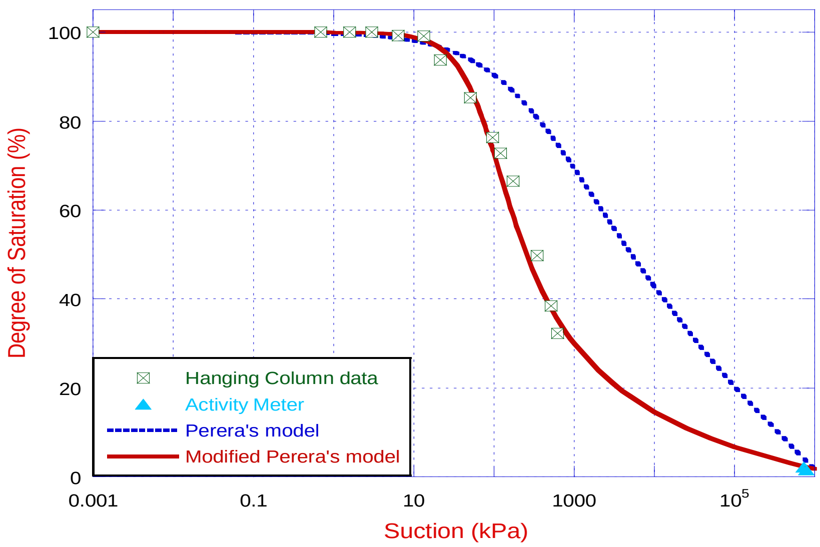

Figure 14. SWCC fit with modified Perera's model on Marl of Diamniadio

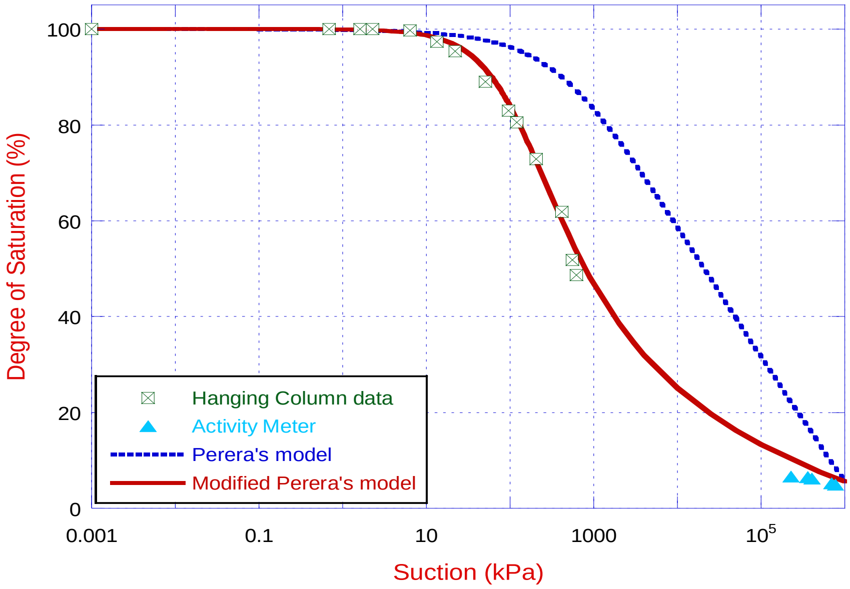

Figure 15. SWCC fit with modified Perera's model on Clay of Diamniadio

Table 2. values of parameter α, β et λ for the modified Perera's model

Parameter	Value
α	16.1
β	1.222
λ	0.6

The following Tables 3 to 6, show the results obtained with the Perera's model, Hernandez model and the modified Perera's. It can be observed a clear improvement of the coefficient of correlation R^2associated with the Sum Squared Residuals SSR in particular for the two coarse-grained soils. Indeed, as mentioned above, for the sandy soils (Sebikotane and Keur Mory respectively), the R^2 increased from 58% to 99.98% and 78.78 to 98.74% while the minimum sum squared residual is obtained with the modified model defining the error committed by the predictive model on the experimental data was obtained with the modified model (1.96 10^{-5} and 6.73 10^{-4}) in Tables 3 and 4.

Table 3. Soil Water Characteristic Curve fit parameters for Sebikotane Sand

Model	Parameters						R^2 (%)	SSR
	θ_s	θ_r	a_f	b_f	c_f	h_r		
Perera			2.45	9.494	1.55		58	2.8 10^{-2}
Hernandez	0.3550	0.004	5.894	3.964	0.693	100	85	8. 10^{-3}
Perera's modified			39.442	11.53	0.849		99.98	1.96 10^{-5}

Table 4. Soil Water Characteristic Curve fit parameters for Keur Mory Sand

Model	Parameters						R^2 (%)	SSR
	θ_s	θ_r	a_f	b_f	c_f	h_r		
Perera			6.735	6.415	0.739		78.78	1.47 10^{-2}
Hernandez	0.375	0.102	8.703	6.773	0.646	100	78	1.51 10^{-2}
Perera's modified			108.44	7.839	0.726		98.74	6.73 10^{-4}

Table 5. Soil Water Characteristic Curve fit parameters for Marl of Diamniadio

Model	Parameters						R^2 (%)	SSR
	θ_s	θ_r	a_f	b_f	c_f	h_r		
Perera			97.862	0.753	0.285		90.48	2.24 10^{-3}
Hernandez	0.2621	0.0047	519.955	4.013	1.005	500	92.6	2.7 10^{-3}
Perera's modified			68.8016	1.7461	0.7050		99.64	6.09 10^{-5}

Table 6. Soil Water Characteristic Curve fit parameters for Clay of Diamniadio

Model	Parameters						R^2 (%)	SSR
	θ_s	θ_r	a_f	b_f	c_f	h_r		
Perera	0.4048	0.0227	130.891	0.547	0.069	500	94.88	4.31 10^{-3}
Hernandez			809	1.06	1.104		91.8	9.4 10^{-3}
Perera's modified			101.8315	1.2675	0.6044		99.93	6.85 10^{-5}

The same can be said for the fine soils. As a matter of fact, the adjusted R^2 value is respectively equal to 99.64 and 99.93 for the Marley and Clayey soils of Diamniadio were going from 58% to 85% for Perera's and Hernandez model. It is also found that the minimal SSR respectively equal to 6.09 10^{-5} and 6.85 10^{-5} were obtained with the modified model (Tables 5 and 6). All the results obtained in this study, show that this modified model is good for fitting these four subgrade materials.

4. Conclusion

Determining the soil-water characteristic curves (SWCC) is delicate to perform, time-consuming, and the devices are expensive. To overcome all these parameters, prediction was and still is the way to go in this field. In this paper, Perera's model did not give a good fit. Therefore, the look at modelling, starting from understanding the effect of each parameter on the shape of the SWCC, finally allowed to modify the Perera's model. The results of this study show that the modified model works well for both fine- and coarse-grained soils. A statistical analysis was carried out to confirm these results. Indeed, the adjusted R^2 values for the sandy soils of Sebikotane and Keur Mory and the clayey and marly soils of Diamniadio are respectively 99.99, 98.74, 99.64, and 99.93, which are high compared to the other models (Perera's and Hernandez). This study also showed that the minimal SSR was all obtained with this modified model, respecting the values prescribed by Miller et al. and Leong et al. According to them, the lower the residual value SSR is, the closer the model is to the experimental data, which is the case here. The statistical analysis confirms the result, this modified model better fits the SWCC of these four subgrade materials. However, even if this work is a good start, it has only been tested on four soils, and the database should be expanded to test it on more samples. That will be useful for using Artificial Neural Network to play our part in this unsaturated field.

5. Declarations

5.1. Author Contributions

Conceptualization, R.G.; methodology, R.G.; formal analysis, R.G.; investigation, R.G., M.B., I.M., and I.B.J.K.; data curation, R.G.; writing—original draft preparation, R.G.; writing—review and editing, R.G., M.B., I.M., and I.B.J.K.; visualization, M.B. and I.M.; supervision, M.B. and I.M. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

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5.5. Conflicts of Interest

The authors declare no conflict of interest.

6. References

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