Correlation Between Capillary Flow and Dry Sieving Test Results of Woven and Nonwoven Geotextiles

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ABSTRACT

Dry Sieving and Capillary Flow tests are the two commonly used methods in North America to determine the largest pore opening and opening size distribution of geotextiles. Due to several disadvantages of Dry Sieving test and limited capabilities of measuring smaller pore sizes of geotextiles, researchers have been trying to correlate Dry Sieving and Capillary Flow test results. A study has been carried out at Syracuse University in which Capillary Flow tests were conducted on 51 different woven, non-woven and composites geotextiles with proper calibration. The goal of this study is to use statistical analysis, specifically machine-learning applications: Linear Regression, Random Forest and Support Vector Machine models to correlate Bubble Point and AOS results. Student’s t-test was performed with 99% confidence level, for testing the adequacy of predicted AOS results with each model. Additionally, the accuracy of the models was verified by determining the Root Mean Square Error.

INTRODUCTION

Recently, the production of geotextiles using different fiber types, manufacturing processes, and formulations has flourished extensively in the market of geotextiles. The most common types of geotextiles widely used, are woven slit film, monofilaments or multifilament, nonwoven needle-punched, and heat bonded. In terms of the performance of these geotextiles as a filter, pore size distribution is an important property of these geotextiles. In addition to the difference in fiber types, the pore size distribution and filtration properties are influenced by the variety in manufacturing process.

In the North America, Dry Sieving test (ASTM D 4751) has been used as an approved and commonly used method to determine the Apparent Opening Size (AOS, O95) of a geotextile. Several standard specifications such as AASHTO M288 and GRI-GT13 use this method as a reference for geotextile filter design. The other commonly used techniques to evaluate the largest pore openings and pore size distribution of geotextiles are: Hydrodynamic Sieving (CGSB 148.1 n°10), Wet Sieving (SW-640550-83), and Capillary Flow test (ASTM D 6767). Only Capillary Flow test provides the largest pore opening along with a complete pore size distribution of a geotextile. The detailed information and accuracy obtained by this test makes it more attractive to the geosynthetics testing laboratories to perform this test as compared to other tests. In addition, performing Capillary Flow test can potentially save valuable personnel and time resources of the laboratories.
Since 1996, very few Capillary Flow test studies (Vermeersch, et al. (1996), Bhatia et al. (1996), Lydon, et al. (2004), Aydilek, et al. (2006), Elton, et al. (2007), Przybylo (2007), Blond et al. (2015) and Lacina, et al. (2015)) have been carried out. However, in these studies different versions of the Capillary Flow devices have been used. Some of the devices were made by the researchers themselves and others were made of by the commercial companies like Coulter Corporation and Porous Materials, Inc (PMI). Two versions of Porometer manufactured by Coulter, Coulter Porometer I and Coulter Porometer II, were used by Vermeersch, et al. (1996) and Lydon, et al. (2004). Different versions of PMI devices have been used to perform Capillary Flow test. In addition, researchers have used different types of wetting liquids for the Capillary Flow tests. Due to the variation in the liquid, standard methods and lack of calibration, no conclusive results have been found from the previous studies.

Due to several disadvantages of Dry Sieving test including electrostatic effects and clogging of glass beads within the geotextiles, this method does not provide the accurate AOS (O95) values. In addition, Dry Sieving test is not designed to measure O50 or smaller pore openings of a geotextile. On the other hand, Capillary Flow test can measure the largest pore size (Bubble Point, O98) and as well as a complete pore size distribution of a geotextile. Several studies have been conducted to correlate Capillary Flow and Dry Sieving test results, however, none of them were adopted due to the use of different devices and wetting liquids, limited number of geotextiles and lack of calibration in the Capillary Flow test.

Hence, a study has been carried out in Syracuse University to perform the Capillary Flow Test using ASTM D6767 with 51 geotextiles from all over the world. The Dry Sieving test results were obtained from the manufacturers for some geotextiles and for other geotextiles Dry Sieving tests were performed in Syracuse University. Three different machine learning models have been used to develop correlations between Capillary Flow and Dry Sieving test results. Student’s t-test was performed to provide an acceptable range of predicted AOS values at 99% confidence level. Root Mean Square Error (RMSE) was calculated to determine the accuracy of the models as well.

TESTING PROGRAM

Capillary Flow and Dry Sieving tests were conducted to determine the largest pore opening of geotextiles. This study included seven monofilament woven, eleven slit-film woven, two multifilament, eight heat-bonded non-woven, twenty-one needle-punched non-woven and two composite (a combination of woven and non-woven geotextiles) geotextiles. Figure 1 shows Scanning Electron Microscope (SEM) images of some of the tested geotextiles. The geotextiles were selected based on the difference in manufacturing process from four US, one Canadian and one UK geotextile manufacturers. These manufacturers produce diverse kinds of geotextiles to fulfill the multi-purpose requirements of industries and research institutions.
Capillary Flow Test

Capillary Flow test is a standardized test which is used to determine pore size distribution of woven, non-woven and composite geotextiles with pore sizes ranging from 1 to 1000 microns. This test is delineated in ASTM D 6767, “Standardized Test Method for Pore Size Characteristics of Geotextiles by Capillary Flow Test”. The Capillary Flow test is based on the principle that the continuous pores in a geotextile hold a wetting liquid by capillary attraction and surface tension, and they will only allow the liquid to pass when the pressure applied exceeds the capillary attraction of the liquid in the largest pore. Consequently, smaller pores demand higher pressure to discharge liquid, since they have larger solid-liquid attraction. In order to originate the air flow through a saturated sample, it needs a gateway pressure or minimum pressure, which is related to the largest pore size, or Bubble Point, and the type of wetting liquid. A state of the art Capillary Flow porometer (2015), Geo Pore Pro (GPP 1001A) was used at Syracuse University for the Capillary Flow tests. This device is fully automated and manufactured by the Porous Materials Inc. (Ithaca, NY). To assess the accuracy of the Capillary Flow test results, the latest version of PMI equipment, Geo Pore Pro (GPP-1001A) was calibrated using six different materials, including thin metallic plates and membranes. Mineral oil was used as a wetting liquid in the Capillary Flow test. Surface tension of the mineral oil was measured by KRUSS USA (1020 Crews Road, Suite K Matthews, NC 28105, USA). The dynamic contact angle between mineral oil and thin metallic plate was tested as well by KRUSS USA. In the current study, the shape factor (0.82) proposed by TRI Environmental, Inc. (Lacey, 2018) was used for both calibration materials and the geotextiles. The calibration metal plates were cleaned with Methanol (from PHARMCO-AAPER, Batch no: 12214-03) prior to testing. The details on Capillary Flow test is described in Fatema (2017).

Dry Sieving Test

In this study, for many geotextiles, the manufacturers provided the AOS results. However, Dry Sieving tests were conducted at Syracuse University for all heat-bonded geotextiles, and some woven geotextiles and needle-punched non-woven geotextiles. ASTM D4751 “The Standard Test Method for Determining the Apparent Opening Size (AOS)” was followed to perform the tests. The Dry Sieving test is based on the concept that glass beads of a specific diameter are sieved in a shaker to determine the percentage of beads that may pass through a geotextile, whether it is 5% or less. The repetition of the process with glass beads of different diameters provides the Apparent Opening Size (AOS, O95) of a geotextile. In this test, a #4 sieve frame, a pan, a cover, and a hoop
to secure the geotextile inside the frame were used. A mechanical sieve shaker was used in the test to sieve the glass beads through the geotextile. The test details are described in Fatema (2017).

**Machine Learning Applications**

Machine learning is categorized as a subset of an artificial intelligence in the vast field of modelling, which applies statistical approaches to assist computers with the ability to learn successively with the data provided and without being programmed excessively. With the principles of pattern recognition and computational learning theory in artificial intelligence, machine learning investigates the establishment of algorithms, which can predict an outcome from the given data. Machine learning is correlated to computational statistics, which is also designed to make predictions on data with the use of a computer. The models developed by the machine learning allow the researchers to develop reproducible results and disclose the hidden parameters through learning from orientation in the data. The models developed by the machine learning applications can be used for further analysis of same datasets with new variables. Machine learning includes several methods to produce a model with associated learning algorithms to analyze the data set. In this study, three learning models were used to analyze the dataset of Capillary Flow test and Dry Sieving test results (Machine Learning, Wikipedia, the free encyclopedia).

**Linear Regression**

Linear Regression develops a correlation between a dependent variable and one or more independent variables. The regression model evolved from an independent variable is called simple Linear Regression. The simple Linear Regression method forms a relationship between the response, Y and the independent variable, X using the following equation,

\[ Y = \beta_0 + \beta_1 * X \]  

(1)

Where, \( \beta_0 \) is the intercept and \( \beta_1 \) is the slope. The parameters in the equation (1) are described in the results section.

The relationships between two or more variables are modeled using linear predictor functions, which facilitate in estimating the unknown parameters from the data. In the field of statistical analysis, Linear Regression is widely used as a common method to develop a predictive model with an observed dataset of response and independent variables. This model can be used to further analyze the same dataset with additional values of independent variables without an association with response values (Linear Regression, Wikipedia, the free encyclopedia).

**Random Forest**

Random Forest is a machine learning algorithm, which develops a large number of decision trees in a training dataset and the training set is used to produce the mode of classification or mean prediction in a regression method of individual tree. An extension was later developed, which combines the bootstrap aggregating or bagging method. Bagging is designed to enhance the stability and accuracy of machine learning algorithms, such as Random Forest, by decreasing the variances and over prediction. Random Forest is extensively used in the analysis of large datasets, because of its simplicity and flexibility to use both in classification and regression. In the Random Forest method, the training algorithm follows the general technique of bagging. The decision trees developed at training time are utilized to obtain a more rigorous and reliable prediction on the
dataset. Sometime bagging makes a prediction based on the strong predictors in a dataset, which may create a little biased model. Random Forest uses a process called “feature bagging”, a modified tree learning algorithm, which selects random samples of features at each part in the learning process (Random Forest, Wikipedia, the free encyclopedia).

**Support Vector Machine**

Support Vector Machines (SVMs) are associated with algorithms to analyze the large datasets for both classification and regression. SVM develops a model where the algorithm is trained on the initial set of data of specific categories and then the algorithm is used to predict the outcome of the new dataset with similar categories. The algorithms used in SVM model develop a hyperplane to divide the entire dataset with the maximum fit margin between the hyperplane and any data within the training dataset, which allows the new data to be classified accurately. A mapping algorithm is used to develop the hyperplane by transforming the dataset using linear algebra. This algorithm is called Kernel (Support Vector Machine, Wikipedia, the free encyclopedia).

The three models described above have been widely used in the field of statistics, engineering, biology and other sciences. In the current study, these three models were used to correlate the results of Capillary Flow and Dry Sieving tests of 51 woven, non-woven and composite geotextiles. For three models, Bubble Point values were used as independent variables and AOS values were predicted using the model specific algorithms. Student’s t-test was performed with 99% confidence interval for testing the hypothesis of predicted AOS values corresponding to their Bubble Point values.

**Student’s t-test**

Student’s t-test is a statistical hypothesis test that uses Student’s t-distribution table. The table is based on a faction (t) whose numerator is drawn from a normal distribution with a mean of zero and denominator is the root mean square of k terms (k = degrees of freedom) which is also drawn from the same normal distribution. In the statistical analysis, if the value of scaling term in the test statistic were known, the test follows a normal distribution. Whereas, the test follows a Student’s t-distribution when the scaling term is uncertain, and two sets of data are significantly different from each other. Student’s t-test is used to analyze a dataset when the sample size is small, and the data is assumed to follow a normal distribution (Student’s t-test, Wikipedia, the free encyclopedia).

In the current study, for each geotextile eight to eleven Capillary Flow tests were performed. Hence, for a small size of dataset, n = 8 to 11, Student’s t-test was used. This test follows an equation which is related to the population mean, sample mean, sample standard deviation and sample size of the dataset (Walpole, et al. (1993)).

\[
\bar{X} - t \times \frac{S}{\sqrt{n}} < \mu < \bar{X} + t \times \frac{S}{\sqrt{n}}
\]  

(2)

Where, \(\bar{X}\) = sample mean, \(\mu\) = population mean, \(S\) = sample standard deviation, \(n\) = sample size. The value of t is obtained from Student’s t-distribution table, which depends on the degrees of freedom and confidence limit. If for a monofilament woven geotextile, \(\bar{X}\) (average Bubble Point) = 705.31 microns, \(S\) = 180 microns, \(n\) = 9 (number of tests), \(k\) = degrees of freedom = 9-1 = 8, the value of t at 99% confidence limit = 5.041 (Student’s t-distribution table), the upper and lower range of Bubble Point values for that geotextile = 402.84 microns < \(\mu\) < 1007.79 microns.
TEST RESULTS AND CORRELATIONS

Capillary Flow tests and Dry Sieving tests were performed to find out the largest pore opening of geotextiles. In Syracuse University laboratories, eight to eleven Capillary Flow tests were performed for each geotextile to obtain the Bubble Point ($O_{98}$). Based on the pore structure and manufacturing process of geotextiles, the range of pore opening, $O_{98}$ varied from geotextile to geotextile. In addition, the testing samples were selected randomly from a large sheet of geotextile, which resulted in some differences in the pore sizes, and as a result, in the Bubble Point results. Therefore, box plot and whisker diagrams were used to calculate the minimum and maximum outliers of pore sizes for each geotextile. The outliers were removed from the analysis to establish a correlation between Capillary Flow test and Dry Sieving test results. The details on the test results and outlier removing process are described in Fatema (2017).

Figure 2a shows the correlation between Bubble Point and actual AOS values (average results) with a best fitted line using a Linear Regression method. A positive linear relationship is found with an increasing trend of AOS corresponding to a Bubble Point for each geotextile irrespective to its manufacturing process. For the tested geotextiles, 26 out of 51 geotextiles provided larger AOS results as compared to the equivalent Bubble Point results. A value of 0.77 of $R^2$ indicates that 77% AOS results can be justified precisely corresponding to the Bubble Point results. The equation presented with the best-fitted line is $y = 1.01x - 36.3$, where, $y =$ Predicted AOS (microns), $\beta_1 =$ slope $= 1.01$, $\beta_0 =$ intercept $= -36.3$ and $x =$ Bubble Point (microns). As example, when, $x =$ Bubble Point $= 300$ microns, $y =$ Predicted AOS $= 266.7$ microns. Hence, using the equation of best fitted line, the predicted AOS values were obtained smaller as compared to their respective Bubble Point values.

Figure 2b and 2c show results of predicted AOS values corresponding to the Bubble Point values (average results), obtained from Random Forest and SVM models respectively. To execute the algorithms in both Random Forest and SVM models, some properties of geotextiles were used, such as physical properties: mass per unit area and weave type, and hydraulic properties: Bubble Point values of geotextiles. Similar to Linear Regression model, Figure 2b and 2c show that both Random Forest and SVM provided smaller predicted AOS values as compared to Bubble Point values for most of the geotextiles. As example, if Bubble Point of a needle-punched non-woven geotextile is 300 microns, the predicted AOS values of same geotextile are 204 microns (Random Forest) and 138 microns (SVM).
The 99% confidence interval using Student’s t-test was plotted as a range with the results for three models. The results in Figure 2a, 2b and 2c show that most of the results for needle-punched non-woven and the results of both composite geotextiles were out of the range of 99% confidence interval. For Linear Regression and SVM models, the outliers in the lower range of 99% confidence interval were clustered altogether with two heat-bonded non-woven and two woven geotextiles. Whereas, for Random Forest model, the outliers in the lower range were very close to the boundary. In the comparison of three models, Linear Regression showed the most scattered results in Figure 2a and Random Forest showed the least scattered results of predicted AOS in Figure 2b. Based on the 99% confidence level, one can say that Random Forest provides the best predicted AOS values. However, it should be kept in mind that these models were designed to analyze thousands of data, whereas, in the current study, 400-560 data were used to develop correlations using these models.

**Figure 2. Correlation between Bubble Point and AOS values. (a) Linear Regression model, (b) Random Forest model and (c) Support Vector Machine (SVM) model**

The accuracy and certainty of a model can be calculated observing the cross-validation or out of bag error. In the Random Forest model using bagging method, if one or few features are very strong predictors for the response variable, these features would be selected in many of the
trees to develop a correlation, which causes the training set developed by the bagging method may get little biased. Therefore, it is necessary to determine the accuracy of the models. In this study, Root Mean Square Error (RMSE) was calculated for all three models. RMSE was used as a measure of the differences between actual values and predicted values obtained from the models.

![Figure 3: RMSE values obtained from Random Forest, Linear Regression and SVM models](image)

Figure 3 shows the RMSE results of six types of geotextiles obtained from three models. It was found that SVM provided the least RMSE for monofilament woven, multifilament woven, heat-bonded non-woven and composite geotextiles. For needle-punched non-woven geotextiles, RMSE obtained from SVM model was almost similar to the RMSE obtained from both Random Forest and Linear Regression models. For slit-film geotextiles, SVM provided a little bit larger RMSE as compared to Random Forest and Linear Regression models. However, only eleven slit-film woven geotextiles were used in this study. In addition, the testing specimens were collected randomly from a large sheet of geotextile, which may result in the differences in AOS results obtained by the industries. The overall results of RMSE showed that SVM model provided the least RMSE values. The least RMSE indicates that the predicted AOS values in SVM model are closer to the actual AOS values, as compared to Linear Regression and Random Forest models.

Table 1 shows the actual and predicted AOS values of a sample from each type of geotextiles.

<table>
<thead>
<tr>
<th>Geotextiles</th>
<th>Predicted AOS, microns (Linear Regression)</th>
<th>Predicted AOS, microns (Random Forest)</th>
<th>Predicted AOS, microns (SVM)</th>
<th>Actual AOS, microns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monofilament woven</td>
<td>673.66</td>
<td>524.83</td>
<td>622.08</td>
<td>637.5</td>
</tr>
<tr>
<td>Slit-film woven</td>
<td>338.88</td>
<td>434.40</td>
<td>421.53</td>
<td>406</td>
</tr>
<tr>
<td>Multifilament woven</td>
<td>269.62</td>
<td>220.06</td>
<td>165.44</td>
<td>150</td>
</tr>
<tr>
<td>Heat-bonded non-woven</td>
<td>200.93</td>
<td>260.90</td>
<td>298.94</td>
<td>283.5</td>
</tr>
<tr>
<td>Needle-punched non-woven</td>
<td>444.22</td>
<td>300.87</td>
<td>347.05</td>
<td>362.5</td>
</tr>
<tr>
<td>Geo-composite</td>
<td>119.72</td>
<td>95.92</td>
<td>96.89</td>
<td>81.5</td>
</tr>
</tbody>
</table>

Table 1 shows that the predicted AOS values of each type of geotextile are almost similar to actual AOS results in SVM model. Whereas, Random Forest and SVM models provided distinct differences between actual and predicted AOS results. Therefore, SVM model provided the best prediction on AOS results, as compared to Random Forest and SVM models.
CONCLUSION

In this study, correlations between the Bubble Point (O₉₈) and Apparent Opening Size (AOS, O₉₅) have been investigated. Linear Regression, Random Forest and Support Vector Machine (SVM) were used to develop correlations. Student’s t-test was performed in three models to provide a feasible range at 99% confidence limit, of actual and predicted AOS results. In the North America, despite several disadvantages of Dry Sieving test, many soil retention criteria currently used are still based on AOS values of geotextiles. Hence, it is necessary to correlate Bubble Point and AOS results of geotextiles. Using the correlations explored in the current study, it is possible to obtain AOS results of new geotextiles without being Dry Sieving test performed.

The current study showed that, among three models, SVM provided the least Root Mean Square Error (RMSE). RMSE is used to validate the accuracy of the predictions established on the given data. The least RMSE in SVM model indicates that the predicted AOS results are mostly close to the measured AOS results. Whereas, Random Forest and Linear Regression resulted in noticeable difference between actual and predicted AOS results. Therefore, it appears that the SVM model provided the most accurate predicted AOS results of geotextiles and this model can be used further for new geotextiles with unknown AOS values.

REFERENCES


