
Peer reviewed version

Link to publication record in Explore Bristol Research
PDF-document

This is the author accepted manuscript (AAM). The final published version (version of record) is available via Taylor & Francis. Please refer to any applicable terms of use of the publisher.

University of Bristol - Explore Bristol Research
General rights

This document is made available in accordance with publisher policies. Please cite only the published version using the reference above. Full terms of use are available: http://www.bristol.ac.uk/pure/about/ebr-terms
Some recent research on the hydraulic conductivity of road materials

P. J. Vardanega, S. Feng and C. J. Shepheard
University of Bristol, Bristol, United Kingdom

ABSTRACT: Hydraulic conductivity is an important material parameter for pavement engineers. The ability to make a priori estimates of the coefficient of permeability of road pavement materials is very useful when studying issues of pavement durability and predicting pavement performance. This paper presents two laboratory databases assembled from data sourced from the literature. Using a database of permeability tests on fine-grained soils, the ability of the Kozeny-Carman void ratio function to interpret the data is examined alongside a simple power-law relationship. A second database of permeability measurements on asphalt concrete specimens is used to re-examine the ‘representative pore size’ concept as a method of predicting the coefficient of permeability. The influence of nominal maximum aggregate size (NMAS) on the coefficient of permeability is also studied.

1 INTRODUCTION
1.1 Literature review
The hydraulic conductivity of road building materials is a useful engineering parameter and should be considered when asphalt concrete (AC) mixtures are designed and specified (e.g. McLaughlin and Goetz 1955, Liebenberg et al. 2004) to avoid moisture damage (e.g. Chen et al. 2004) which is detrimental to pavement performance (e.g. Abdullah et al. 1998, Mohammed et al. 2003). A recent review on the permeability of asphalt concrete (focussing on empirical prediction models) has been published (Vardanega 2014). The hydraulic conductivity of fine-grained materials has been reviewed in many publications (e.g. Olsen 1960, Olson & Daniel 1981). Fine-grained materials may constitute the natural materials that are used as road subgrades.

Comparisons of laboratory and field permeability measurements on AC have been made (e.g. Gogula et al. 2003). Methods for measuring permeability in field conditions have been developed by various researchers using water as a permeant (e.g. Zube 1962, Gerke 1982, Cooley 1999, Fwa et al. 2001) and air as a permeant (e.g. Kari & Santucci 1963). Construction issues such as lift thickness and time for compaction have also been investigated (e.g. Hainin et al. 2013). Neural network approaches for interpreting databases of AC permeability have been published (Tarefder et al. 2005).

1.2 Influence of porosity
A key predictor of asphalt concrete permeability is percentage air voids in the mixture (e.g. Zube 1962, Mullen 1967, Vivar & Haddock 2007, Vardanega 2014). Strictly speaking, the percentage of connected (accessible) voids should be evaluated during testing (cf. Bear 1972). This is not always done in practice but can be done using the ‘hand-pumping’ method (see Smith & Gotolski 1969, p.24 - the method was also used by Kumar & Goetz 1977).

1.3 Study aims
This paper presents the analysis of two databases. Database I (soil) contains over 100 measurements of the hydraulic conductivity of fine-grained soils. Database II (AC) contains over 1300 measurements of the hydraulic conductivity of asphalt concrete. Statistical analysis is performed with both databases using power-law functions. The results are compared to a previously published empirical model for the prediction of asphalt concrete permeability (Vardanega & Waters 2011, 2015).

The nominal maximum aggregate size (NMAS) has been suggested as a key influence on the hydraulic conductivity of asphalt concrete (e.g. Cooley et al. 2002, Yan et al. 2016). Therefore, the effect of NMAS will also be studied using Database II (AC).
2 DATABASE I (SOIL)

2.1 Permeability models

Permeability testing usually employs falling head or constant head approaches (e.g. Bear 1972). Dolžyč and Chmielewska (2014) recently reviewed various empirical and semi-empirical approaches to describe permeability data, emphasizing amongst other factors the importance of the temperature of the permeant – which is not always reported in the literature.

Carrier (2003) recommended that formulations based on the work of Hazen (Hazen 1892, 1911) for modelling permeability should not be used in geotechnical practice (the formulation is shown as equation 1 using the notation of Carrier 2003):

\[ k = (C_H)(D_{10})^2 \]  

(1)

where \( k \) is the coefficient of permeability (expressed in units of length per unit time); \( C_H \) is an empirical coefficient and \( D_{10} \) is the sieve aperture through which exactly ten percent of the material would pass. Carrier (2003) recommended that the Kozeny-Carman formulation (Kozeny 1927, Carman 1938, 1956) should be preferred for use in practice (the formulation is shown as equation 2 using the notation of Carrier 2003):

\[ k = \left( \frac{\gamma}{\mu} \right) \left( C_{k.c} \right) \left( \frac{1}{S_0} \right) \left( \frac{\epsilon^3}{(1+\epsilon)} \right) \]  

(2)

where \( \gamma \) is the unit weight of the permeant (usually water), \( \mu \) is the dynamic viscosity of the permeating fluid, \( C_{k.c} \) is an empirical coefficient, \( S_0 \) the specific surface area of the soil per unit volume of particles, and \( \epsilon \) is the void ratio, hereafter denoted as \( \epsilon_{soil} \).

Equation 2 relies on the principles of viscous fluid flow from the Navier-Stokes equation to treat the assembly of soil particles as creating a series of capillary tubes through which a fluid travels (Chapuis & Aubertin 2003). Through this method, it can be shown that the coefficient of permeability \( k \) strongly varies with the void ratio \( \epsilon_{soil} \). Chapuis & Aubertin (2003) showed that for plastic soils that are “hydrated, saturated, and consolidated before permeability testing”, the Kozeny-Carman formula may be used. Masad et al. (2004, 2006) presented semi-empirical approaches based in part on the Kozeny-Carman formulation to predict the permeability of asphalt concrete using databases.

2.2 Statistical Analysis

Table 1 summarises the sources of the data in Database I (soil). Permeability test data from six publications (ten soils) was collated and statistically analysed. The Matagami Clay and the Louisville Clay were reported as being tested using the constant head approach whereas for the other clays falling head testing was reported. The relationship between the coefficient of permeability \( k \) and the Kozeny-Carman void ratio function \( \epsilon_{soil} \) is plotted in Figure 1. The coefficient of determination \( R^2 \) of the regression function is 0.564, based on 119 data points (i.e. \( n = 119 \)). The scatter could probably be further reduced if the other parameters in equation (2) were known (cf. Chapuis & Aubertin 2003). The standard error (SE) of the regression is 0.940. The p-value of the regression is < 0.0001. The RD value for the regression shown in Figure 1 is 66.0%. The relative deviation (RD) is defined in Waters & Vardanega (2009) as:

\[ RD = 100 \left( 1 - R^2 \right)^{0.5} \]  

(3)

Figure 2 shows the data re-plotted with \( \ln(k) \) predicted using \( \ln(\epsilon_{soil}) \). The resulting trend-lines (re-arranged into power functions) are shown in the figure. The exponent on \( \epsilon_{soil} \) varies from 1.53 to 5.32 for each of the ten test series analysed. The RD values for the analysis of the individual test series varies from 4.5% \( (R^2 = 0.998) \) to 55.5% \( (R^2 = 0.692) \). The exponent on \( \epsilon_{soil} \) for the whole dataset is 3.29. For the regression of the entire dataset, \( R^2 = 0.573, RD = 65.4\% \) and \( n = 119 \). If the possible outlier test series (No. 3) is excluded from the main regression the \( R^2 \) increases to 0.624 \( (RD = 61.3\%, n = 113) \).

<table>
<thead>
<tr>
<th>No.</th>
<th>Source</th>
<th>Symbol</th>
<th>Soil Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Al-Tabbaa &amp; Wood (1987)</td>
<td>□</td>
<td>Kaolin</td>
</tr>
<tr>
<td>2</td>
<td>Chung et al. (2002)</td>
<td>◇</td>
<td>Pusan Clay</td>
</tr>
<tr>
<td>3</td>
<td>Lehka et al. (2003)</td>
<td>▲</td>
<td>IIT Clay</td>
</tr>
<tr>
<td>4</td>
<td>Lehka et al. (2003)</td>
<td>◆</td>
<td>Calcium Bentonite</td>
</tr>
<tr>
<td>5</td>
<td>Leroueil et al. (1990)*</td>
<td>▼</td>
<td>Backebol Clay</td>
</tr>
<tr>
<td>6</td>
<td>Leroueil et al. (1990)*</td>
<td>▼</td>
<td>Matagami Clay</td>
</tr>
<tr>
<td>7</td>
<td>Leroueil et al. (1990)*</td>
<td>▼</td>
<td>St. Esprit Clay</td>
</tr>
<tr>
<td>8</td>
<td>Leroueil et al. (1990)*</td>
<td>▲</td>
<td>Louisville Clay</td>
</tr>
<tr>
<td>9</td>
<td>Pane et al. (1983)</td>
<td>■</td>
<td>Kaolin</td>
</tr>
<tr>
<td>10</td>
<td>Walker &amp; Raymond (1968)</td>
<td>✔</td>
<td>Leda Clay</td>
</tr>
</tbody>
</table>

* Vertical permeability data included in the database

Figure 1. The relationship between \( k \) and the Kozeny-Carman void ratio function.
3 DATABASE II (AC)

3.1 Original database

Waters (1998) used the $D_{50}$ i.e. the sieve aperture through which 50% of the granular material in the mix would pass in conjunction with the percentage air voids, to define the normalised voids ($NV$) as $NV = [AV(\%)][D_{50}(mm)]/4.75$. Vardanega & Waters (2011, 2015) assembled a laboratory database and after performing regression analysis proposed equation (4):

$$k = 0.46(R_p)^{3.70} \quad [R^2 = 0.74; \ n = 467]$$ (4)

where $k$ has units of mm/s and $R_p$ has units of mm and where $R_p$ is the representative pore size (RPS), where, $R_p = (2/3)[AV(\%)/100][D_{75}(mm)]$.

Vardanega & Waters (2011, 2015) selected the effective particle size statistically and determined that the $D_{75}$ (i.e. the sieve aperture through which 75% of the granular material in the mix would pass) was the best fit to the entire dataset (although any effective particle size upwards of $D_{50}$ i.e. the 'coarse fraction', was shown to yield a good fit to the data). Both the normalized voids and the representative pore size concept are based on channel theory work detailed in Taylor’s classic textbook (e.g. Taylor 1965, p.109-110). A more extensive discussion of the derivation of these parameters is given in Waters (1998) and Vardanega & Waters (2011, 2015).

Goode & Lufsey (1965) observed that “Air permeability is a function of aggregate gradation as well as air voids. The effect of gradation was found to be much more pronounced at high air voids than at low air voids”. Zhang et al. (2014) used the representative pore size to study pavement permeability and skid resistance; reporting that permeability increases with increasing representative pore size (based on numerical simulations). Waters (1998) compared the normalised voids parameter ($NV$) with asphalt concrete texture depth and showed that a positive correlation existed (i.e. as $NV$ increased so did the texture depth).

3.2 Expanded database

In this paper, the database of Vardanega & Waters (2011, 2015) has been expanded with data from an additional ten publications. This has increased the number of permeability measurements available for regression analysis to over 1300. The first ten entries in Table 2 are the newly added data sources in this paper.
<table>
<thead>
<tr>
<th>Reference</th>
<th>NMAS (mm) (*)</th>
<th>(n) **</th>
<th>Stated (AV) measurement method</th>
<th>Stated (k) measurement method</th>
<th>(R^2) of regression (ln(k)) vs. (ln(Rp, D_{eff}=D_s})***</th>
<th>(n) = 1318</th>
</tr>
</thead>
<tbody>
<tr>
<td>Choubane et al. (1997, 1998)</td>
<td>9.5(1), 12.5(85), 19(65)</td>
<td>151</td>
<td>FM I-T 166(4) &amp; FM1-T 209(5)</td>
<td>Falling head</td>
<td>0.508 - 0.432 0.536 0.499 0.494</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Al-Omari et al. (2002)</td>
<td>12.5(8), 19(2), 25(3)</td>
<td>13</td>
<td>ASSHTO T-166 &amp; Core-lōk</td>
<td>Karol-Warner permeameter</td>
<td>0.916 - 0.382 0.588 0.457 0.455</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Bhattacharjee &amp; Mallick (2002)</td>
<td>9.5(23), 12.5(45), 19(18)</td>
<td>88</td>
<td>Vacuum seal &amp; Saturated Surface Dry</td>
<td>Falling head</td>
<td>0.632 - 0.751 0.728 0.678 0.706 0.693</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Brown et al. (2004 a,b,c,d)</td>
<td>9.5(131), 12.5(209), 19(64)</td>
<td>404</td>
<td>Vacuum seal &amp; ASSHTO T-166</td>
<td>ASTM PS 129-01; NCAT Field Permeameter</td>
<td>0.532 0.341 0.375 0.421 0.365 0.342</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Haddock &amp; Prather (2004)</td>
<td>9.5(5)</td>
<td>5</td>
<td>FDOT method</td>
<td></td>
<td>0.384</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Chen et al (2004)</td>
<td>19(42)</td>
<td>42</td>
<td>AASHTO T269</td>
<td>Falling head</td>
<td>0.786 0.385 0.963 0.940 0.917 0.893</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Noram-buenac-Contreras et al. (2013) &amp; Noram-buenac-Contreras (2014)</td>
<td>11.2(18), 16(54)</td>
<td>72</td>
<td>geometric</td>
<td>BS 1377-6</td>
<td>0.845 0.812 0.831 0.846 0.846 0.832</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Schmitt et al. (2007)</td>
<td>12.5(19)</td>
<td>19</td>
<td>Falling head test with NCAT device</td>
<td></td>
<td>0.072 0.001 0.018 0.021 0.003 0.027</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Pease et al (2010)</td>
<td>12.5(6)</td>
<td>6</td>
<td>ASTM D5084</td>
<td></td>
<td>0.379 0.736 0.518 0.424 0.650 0.487</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Yan et al. (2016)</td>
<td>9.5(12), 12.5(13), 19(7), 25(6), 37.5 (13)</td>
<td>51</td>
<td>FDOT permeameter</td>
<td></td>
<td>0.519 0.646 0.534 0.591 0.647 0.642</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Previous database (Vardanega &amp; Waters 2011, 2015)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hewitt (1991)</td>
<td>10(27)</td>
<td>27</td>
<td>Falling head</td>
<td></td>
<td>0.800 0.865 0.879 0.923 0.911 0.921</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Maupin (2000, 2009)</td>
<td>9.5(38), 12.5(151)</td>
<td>189</td>
<td>VDOT TM120</td>
<td></td>
<td>0.606 0.362 0.325 0.463 0.557 0.514</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Cooley Jr. et al. (2001)</td>
<td>9.5(30), 12.5(45), 19(20), 25(35)</td>
<td>130</td>
<td>Field permeameter</td>
<td></td>
<td>0.430 0.410 0.564 0.683 0.735 0.762</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Kanitpong et al. (2001)</td>
<td>12.5(19)</td>
<td>19</td>
<td>ASTM D5084</td>
<td></td>
<td>0.913 0.724 0.679 0.678 0.791 0.877</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Mallick et al. (2003)</td>
<td>9.5(20), 12.5(10), 19(9), 25(10)</td>
<td>49</td>
<td>FDOT permeameter</td>
<td></td>
<td>0.413 0.620 0.606 0.789 0.807 0.875</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
<tr>
<td>Vardanega et al. (2008)</td>
<td>14(53)</td>
<td>53</td>
<td>FDOT permeameter</td>
<td></td>
<td>0.380 0.702 0.687 0.722 0.682 0.630</td>
<td>9.516 - 0.444 0.554 0.548 0.517</td>
</tr>
</tbody>
</table>

* Number of samples at this NMAS;
** Number of measurements where both a \(k\) value and \(AV\) value are given (tests where \(k\) or \(AV\) reported as zero were excluded from the regression analyses);
*** Values in bold indicate the highest \(R^2\) for the data sub-set.
In those publications where percentage air voids \((AV)\) were measured using a ‘vacuum method’ in addition to other methods the ‘vacuum’ data was entered into the database. When the NMAS was not stated in the original reference, it was assigned based on the supplied gradation curve.

Table 2 shows the \(R^2\) of the regression of \(\ln(k)\) with \(\ln(AV)\) and \(\ln(R_p)\) with the \(D_{eff}\) being assigned as \(D_{10}, D_{25}, D_{50}, D_{75}\) and \(D_{90}\). For seven sub-datasets the \(D_{eff}\) is not required statistically or weakens the regression (this may be because the range of gradations in the sub-dataset is not significant) but for nine of the sub-datasets improvement is shown.

Analysis of the entire data-set \((n = 1318)\) shows that \(D_{50}\) is actually the preferred choice for the effective particle size. The \(D_{50}\) was used by Waters (1998) when developing the ‘normalised voids’ approach. Statistically, the \(D_{75}\) remains an acceptable choice for \(D_{eff}\) (the \(R^2\) is similar to that of \(D_{50}\) for the whole dataset). In order to compare the analysis of the updated database with the regression relationships reported in Vardanega & Waters (2011, 2015) the \(D_{75}\) will be used to compute the RPS in the analysis that follows in this paper.

Figure 3 shows that \(\ln(AV)\) is a key predictor of \(\ln(k)\) (as is void ratio for fine-grained soils, see Figure 2). Figure 4 shows that the inclusion of the effective particle size via the \(R_p\) parameter does slightly increase the \(R^2\) (and visually reduce some of the scatter) but the effect is not as marked as that reported in Vardanega & Waters (2011, 2015). The updated trend-line is given as equation (5):

\[
\ln(k) = 3.578 \ln(R_p) - 1.645 \tag{5}
\]

\([R^2 = 0.548; n = 1318; SE = 1.581; RD = 67.2\%]\]

where \(k\) has units of mm/s and \(R_p\) has units of mm. Equation (5) can be re-arranged to give:

\[
k = 0.193(R_p)^{3.58} \tag{5a}
\]

Figure 3. \(\ln(k)\) versus \(\ln(AV)\) for the expanded database (air voids expressed numerically not as a percentage).

3.3 Influence of NMAS

The NMAS may affect the co-efficient of permeability as recently reported by Yan et al. (2016). NMAS is not explicitly accounted for in equation 5. Figures 5 and 6 show the database subdivided into mixtures that have NMAS \(\leq 12.5mm\) (Figure 5) and those with NMAS \(> 12.5mm\) (Figure 6).

3.3.1 NMAS \(\leq 12.5mm\)

Figure 5 shows (as with Figure 4) that the fitted trend-line is similar to that proposed in Vardanega & Waters (2011, 2015). Therefore, for mixtures with NMAS \(\leq 12.5mm\) we can write:

\[
\ln(k) = 3.668 \ln(R_p) - 1.313 \tag{6}
\]

\([R^2 = 0.603; n = 917; SE = 1.351; RD = 63.0\%]\]

where \(k\) has units of mm/s and \(R_p\) has units of mm. Equation (6) can be re-arranged to give:

\[
k = 0.269(R_p)^{3.67} \tag{6a}\]

For this sub-dataset (NMAS \(\leq 12.5mm\)) the \(R^2\) value when \(\ln(k)\) is regressed against \(\ln(AV)\) is 0.555.

3.3.2 NMAS \(> 12.5mm\)

Figure 6 shows (as with Figure 4) that the fitted trend-line is similar to that proposed in Vardanega & Waters (2011, 2015). Therefore, for mixtures with NMAS \(> 12.5mm\) we can write:

\[
\ln(k) = 4.123 \ln(R_p) - 1.872 \tag{7}
\]

\([R^2 = 0.540; n = 401; SE = 1.875; RD = 67.8\%]\]

where \(k\) has units of mm/s and \(R_p\) has units of mm. Equation (7) can be re-arranged to give:

\[
k = 0.154(R_p)^{4.12} \tag{7a}\]

For this sub-dataset (NMAS \(> 12.5mm\)) the \(R^2\) value when \(\ln(k)\) is regressed against \(\ln(AV)\) is 0.470.
Figure 7 shows equations (4, 5a, 6a and 7a) compared. Bearing in mind the degree of scatter in the data shown in Figures 5 and 6 there is not a significant difference between the two sub-sets in the database (NMAS > 12.5 mm and NMAS ≤ 12.5 mm), however for smaller datasets with consistent testing methods the effect may be more visible (cf. Yan et al. 2016).

4 DISCUSSION

The results of the analysis of Database II (AC) reveal that while the representative pore size ($R_p$) remains a useful parameter to predict the coefficient of permeability, there are limitations - including:

(i) use of power laws means that coefficient of permeability values reported as ‘zero’ cannot be included (even if some air voids are reported) in the database;

(ii) some of the scatter on Figure 4 is probably due to the mixing and matching of various air void measurement methods being present in the database (connected voids are not always explicitly measured in practice).

Therefore, further work studying the influence of the ‘shape of the grading curve’ on asphalt concrete permeability is proposed. Some preliminary work using ‘grading entropy’ (e.g. Lörincz 2005) has recently been undertaken (James 2015) as part of this on-going study.

5 SUMMARY

This paper has presented the results of the analysis of two databases of hydraulic conductivity measurements on road building materials. The analysis of Database I (soil) revealed that the exponent on void ratio varies and on average is about 3.3. Database II (AC) was used to show that the original empirical equation presented in Vardanega & Waters (2011, 2015) is similar to that generated using the expanded database presented in this paper. The revised exponent on the $R_p$ parameter was computed to be around 3.6. However, the influence of the grading parameter on reducing the scatter about the regression line is not as marked as reported in Vardanega & Waters (2011, 2015). The effect of NMAS was statistically detectable but relatively minor compared to the influence of air voids.

6 ACKNOWLEDGMENTS

CJS undertook some of this work with the support of a University Research Committee Interdisciplinary Research Internship in 2015 at the University of Bristol. SF thanks Dr Erdin Ibraim for co-supervising her MSc project. PJV thanks Mr Max James for his helpful comments.

7 REFERENCES


James, M.A. 2015. *The Grading Entropy and Permeability of Road Surfaces*. Undergraduate research project report (unpublished), University of Bristol, Bristol, UK.


