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Modelling of long-term permeability of compacted and consolidated clays permeated with leachate

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ABSTRACT

In this study, permeability variations of clay soil and removal rates of ions presented in the leachate are determined. Penalized linear regression (Lasso) and support vector regression methods are applied in order to model the relationship between the metal ions and the permeability. For this purpose, leachate is collected from Sanitary Landfill at Şile-Komurcuoda, Istanbul. Permeability of samples is determined via consolidated clays which are compacted via standard methods. The concentrations of Fe^{2+}, Mn^{2+}, Zn^{2+}, Cu^{2+} and Pb^{2+} ions in influent and effluent of reactor are anayzed and the removal rate of these ions are calculated in order to detect removal ability of clay soil. An overall evolution of Fe^{2+}, Mn^{2+}, Zn^{2+}, Cu^{2+} and Pb^{2+} parameters is that removal rate of clay soil which was compressed with standard methods and consolidated was found higher than that of clay soil compressed with standard compaction method. For prediction accuracy and interpretation purposes, two methods are considered for modelling the data. Both methods show good generalization capabilities.

Keywords: Leachate; Metal ions; Permeability; Standard compaction; Consolidation; Lasso regression; Support vector regression

1. Introduction

Groundwater and surface water are usually used for drinking water. However solid waste landfill areas produce leachate that may contain high concentration of organic and inorganic contaminants. Thus these contaminants pollute groundwater and surface waters. Compacted clay soils are used in solid waste landfill areas due to their low permeability and cost effectiveness, and they must have a low permeability to prevent the leakage of leachate from the solid waste into the groundwater [1].

Several studies have been carried out to investigate how soil and liquid properties control the permeability of clay soil liners [2–5]. In general, the permeability of soils decreases with increasing fine particle content [6]. The decrease in permeability can also be related to the exposure to domestic waste leachate due to bacterial clogging, layer expansion, some ions adsorption and changes in the arrangement of the soil particles due to the effect of ion charges [7]. It has been mentioned in various studies that leachate may also cause changes in the clay soils' chemical composition, mineral composition and

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physical properties of compacted clay soils. This is related to the increase of the permeability of compacted clay soil [8,9]. Some different studies reported that pure, reagent-grade organic chemicals may cause large increases in permeability of compacted clay soil [10–12]. Another study claims that certain chlorinated hydrocarbons of solvent type attack integrity of clay liners, causing them to be highly permeable [13]. Concentrated organic chemicals can increase permeability of compacted clay due to reduction in thickness of diffuse double layer that surrounds particles of clay soil. Various interdependent factors, which affect clay soil permeability, include density of soil, amount of water content used in compaction, void ratio, and composition of clay, structure of soil and characteristics of leachate used. Permeability of compacted soil with constant water content and density depends on grain size distribution [10,14]. Although, there are several studies in the literature, modelling of clay samples which used in landfill areas to prevent leachate leakage is not investigated.

Different statistical learning methods such as multiple linear regression and support vector regression (SVR) are successfully applied in various fields of environmental engineering. Aya et al. [15] investigated the fouling effects of Fe^{2+} and Mn^{2+} on membrane in a submerged membrane system for various concentrations of Fe^{2+}, Mn^{2+}, fulvic acid and iron hydroxide using SVR. The outcomes from the study of Ahmadi et al. [16] showed that the least squares support vector machine model can predict the SiO_2 solubility in the steam of boilers with high accuracy. For the classification and identification of pigmented soil bacteria Kumar et al. [17] used Raman spectroscopy. The minimally invasive nature of the technique coupled with a robust chemometric tool like radial kernel SVM makes the method ideally applicable for real-time taxonomic analysis of different cultivable and uncultivable bacteria from many environments.

In this study, the permeability of clay soils and the removal rate of some metal ions which are present in leachate are investigated. Clay soil sample and leachate are taken from Şile-Komurcuoda Sanitary Landfill Sites. Clay soil is used in two formats; one is only compacted and the other one is both compacted and consolidated. Penalized linear regression and SVR methods are applied in order to model the relationship between these metal ions and the permeability. The Lasso method used as a variable selection method and the interpretation accuracy of the SVR model is improved.

2. Material and methods

2.1. Physico-chemical properties of the clay

Soil samples had brownish-gray color. The Şile-Komurcuoda landfill site soil samples contain kaolinite 68%–71%, free quartz 6%–9%, illite 15%–18% and others 2%–5%. The kaolinite and illite are considered to be true clay soil minerals. The soil samples have the permeability $k = 1 \times 10^{-8}$ cm/s and a discharge loss of 8.5%–9%, and water of 0.2%–0.4% [18–21]. Also, the experiments were made with dry unit weight which is 1.485 t/m^3.

2.2. Properties of the leachate

The properties of the leachate were determined. The results of the characterization studies conducted on the leachate from the Şile-Komurcuoda Landfill Site are presented in Table 1. Leachate has dark brown color and very small granules. It also contains large amounts of organic, inorganic contaminants and a high concentration of metals.

2.3. Standard proctor compaction, consolidation test and effluent analysis

Compaction is performed using clay from Komurcuoda taken with the method ASTM D698 [22]. Consolidation test is performed in the lab according to ASTM D2435-04 [22]. In order to determine the removal rate of the compacted clay, compacted and consolidated clay soils, some metal ions have been measured according to Standard APHA Methods [23].

2.4. Experimental setup

Constant head permeability test was carried in this study [18]. Reactors which are made of plexiglass materials (Fig. 1) were prepared and filled with compacted clay soil sample, and compacted and consolidated clay soil sample, respectively. Real image and schema of experimental setup were given in Fig. 1, and all experiments were conducted at room temperature (24°C).

2.5. Lasso and SVR analysis

For prediction accuracy and interpretation purposes, two methods are considered for modelling the data. First method is the least absolute shrinkage and selection operator (Lasso). This method combines the least-squares loss with an L_1-constraint. The Lasso is governed by a tuning parameter, lambda that controls how much we are favoring sparsity of our solutions relative to the fit on our training data. Relative to the least-squares solution, this constraint has the effect of shrinking the coefficients, and even setting some to zero. In this way it provides an automatic way for applying model selection in linear regression. Moreover, unlike some other criteria for model selection, the resulting optimization problem is convex, and can be solved efficiently for large problems. Next, a second method for regression analysis, SVR is presented. Hyper-parameter selection is discussed.

3. Results and discussion of modelling analysis

"Compacted clay contaminated sample" and "Compacted-consolidated clay contaminated sample" are high-dimensional datasets with many collinear regressors. Therefore, to generalize as accurately as possible, a penalized

Table 1
Properties of leachate

Parameter/averages	2014
pH	7.7
Fe^{2+} (mg/L)	65.3
Mn^{2+} (mg/L)	1.33
Zn^{2+} (mg/L)	2.38
Cu^{2+} (mg/L)	1.5
Pb^{2+} (mg/L)	0.54

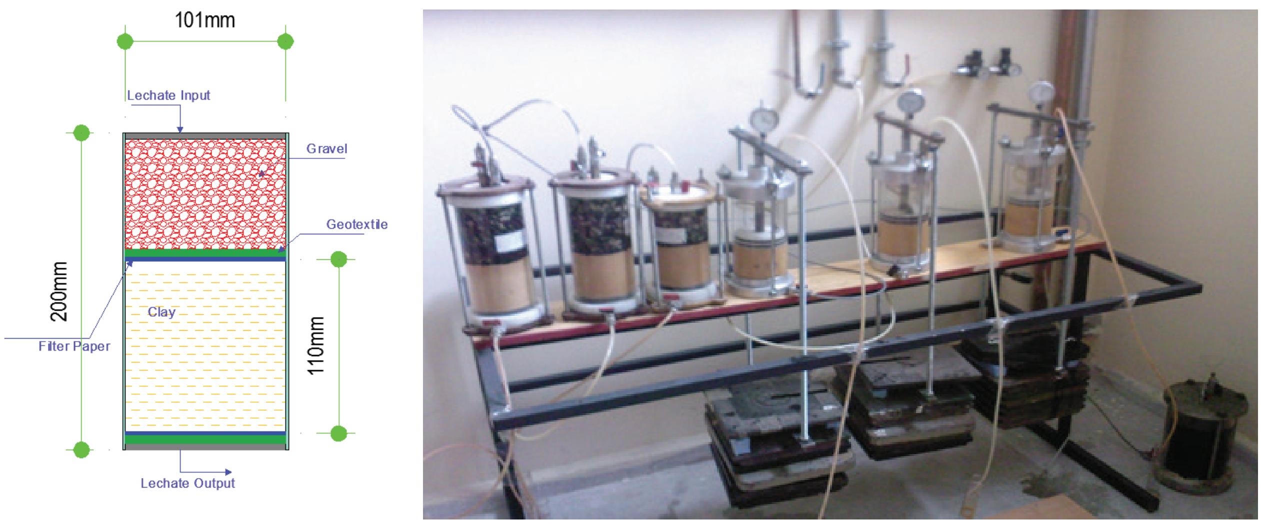

Fig. 1. Schema and real image of experimental setup.

linear regression method is preferred which is the Lasso [24]. This method penalizes the coefficients by adding their L1 norm to the cost function, as follows:

$$\mathrm{RSS}_{\mathrm{Lasso}} = \sum_{i=1}^{n}(y_i - x_i^{\tau}\beta)^2 + \lambda\sum_{j=1}^{p}\beta_j \quad (1)$$

In Eq. (1) $\mathrm{RSS}_{\mathrm{Lasso}}$ is the cost function (residual sum of squares) that needs to be minimized, y_i are the actual values, $x_i^{\tau}\beta$ are the predicted values. The model is parameterized by the vector of regression weights $\beta = (\beta_1,\ldots,\beta_p) \in R^p$. λ is the tuning parameter that balances the fit of the model and sparsity. The Lasso produces sparse parameters; most of the coefficients will become zero, and the model will depend on a small subset of the features. When explanatory variables are correlated, the Lasso will shrink the coefficients of one variable toward zero. The λ parameter controls the degree of sparsity of the coefficients estimated. The features are standardized by removing the mean and scaling to unit variance. Then the datasets are split into train and test sets, and the test set has the ratio of 0.3 of all data. Next, the Lasso λ parameter is selected using cross-validation on train set [25]. The coefficients for the model are listed in Tables 2 and 3.

In Tables 2 and 3, the coefficients are the regression weights in Eq. (1). We have a sparse set of features in our model. The ones that are equal to zero have dropped from the model. The nonzero coefficients are used in SVR method to improve the overall accuracy. These coefficients can have negative or positive values which mean negative effect and positive effect to the model, respectively. The procedure is discussed in the next section.

Models are plotted in Figs. 2(A) and 3(A). Regression validation is determined using the coefficient of determination (R^2) for test set (out-of-sample) and for all data (Table 4).

The Lasso results are fairly well, and the method is fast. However, a nonlinear method would have been performed well. Thus, another method is implemented in the modelling process. This time, a nonlinear method, support vector machine regression (SVR) is performed. The formulations of SVR generally results in a function estimation equation analogous to the following form:

Table 2
Lasso model coefficients for compacted contaminated clay sample

Time	0.27
Fe^{2+}	–0.08
Mn^{2+}	1.76
Zn^{2+}	0
Cu^{2+}	1.71
Pb^{2+}	–3.26

Table 3
Lasso model feature coefficients for compacted–consolidated contaminated clay sample

Time	1.26
Fe^{2+}	0.94
Mn^{2+}	–0.04
Zn^{2+}	0
Cu^{2+}	–5.31
Pb^{2+}	4.69

$$f(x) = \langle w, x \rangle + b \quad (2)$$

where $w \subset R^n$ and $b \subset R$ denote the n-dimensional weight vector and the offset of the linear regression function, respectively. Solving regression function in Eq. (2) can be expressed as a constrained optimization problem (3):

$$\mathrm{minimize}R(w) = C\sum_{i=1}^{l}\left(\xi_i + \xi_i^*\right) + \frac{1}{2}\|w^2\|$$

$$\text{subject to}\begin{cases} f(x_i) - y_i \le \xi_i^* + \varepsilon \\ y_i - f(x_i) \le \xi_i^* + \varepsilon \\ \xi_i, \xi_i^* \ge 0 \;\; (i = 1, 2, \ldots, l) \end{cases} \tag{3}$$

where f is a real value function on the field x. Loss function $|y - f(x)|_\varepsilon$ describes ε as the fitting precision and if the difference between predicted value and the actual value is less than ε, the loss is equal to 0. The constant $c > 0$ represents a regularization parameter that allows tuning the trade-off between the smoothness of the function f and the value of that allowed error is larger than ε. The cost parameter is the main tool for adjusting the complexity of the model. In the modelling process, the dataset is split into train and test sets; and the test set has the ratio of 0.3 for all data. Next, the hyper-parameters for SVR, the cost (C), the kernel and scale parameters y and ε are selected using grid-search method on train set [23]. The results showed that the polynomial kernel fitted well to both datasets. Models are plotted in Figs. 2(B) and 3(B). Regression validation is determined using the coefficient of determination (R^2) for test set (out of sample) and for all data (Table 5).

After running Lasso, it is observed that Zn has a coefficient of zero. Hence, unlike other metal ions, it is possible to state that Zn does not affect the permeability of the clay so it does not affect the structure of the clay. As it is clear that Zn is an amphoteric metal, it does not precipitate and adsorb easily. Thus, in the second SVR run, Zn is excluded and therefore the results are slightly improved (Table 6).

As a result of the permeability experiments conducted with leachate, various changes in the permeability were observed in the samples to which standard compaction applied and in the samples to which standard compaction and consolidation applied together.

It is observed that the spaces among particles in the compacted and consolidated soil samples were less than those in the compacted soil samples due to the effect of compaction and, therefore, the permeability of compacted and consolidated clay soil was found lower (Fig. 4). As it is known, leachate have solid particles and microorganisms which cause

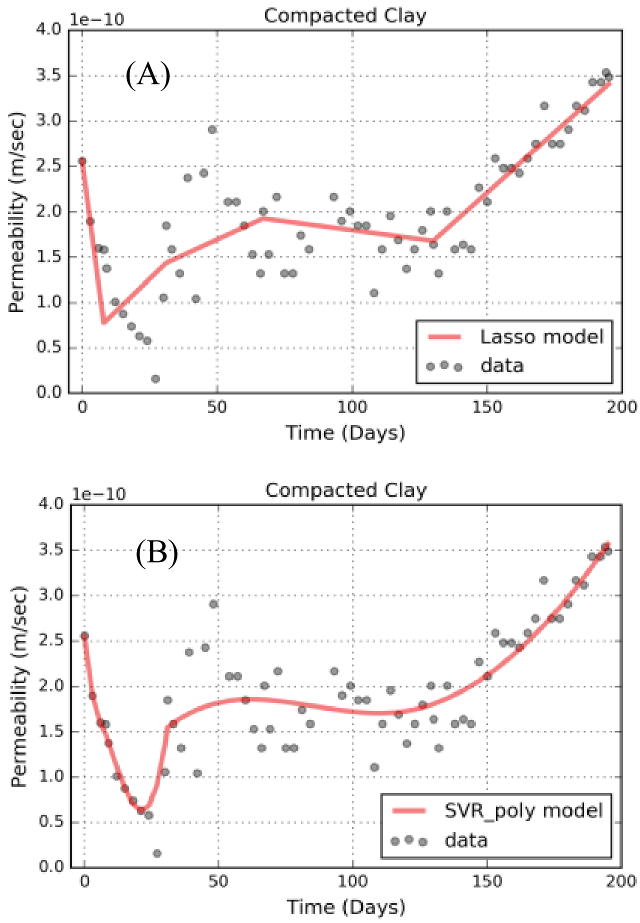

Fig. 2. Lasso regression model (A) and SVR model (B) for compacted contaminated clay sample.

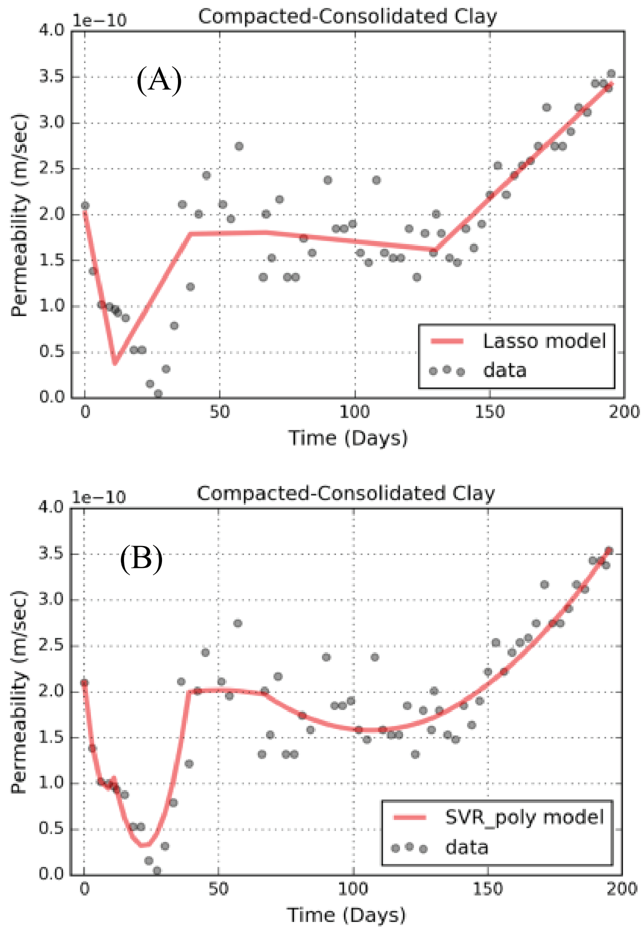

Fig. 3. Lasso regression model (A) and SVR model (B) for compacted–consolidated clay sample.

Table 4
Regression validation for Lasso model

Lasso model	Out-of-sample R^2	All-data R^2
Compacted contaminated clay sample	0.70	0.71
Compacted–consolidated contaminated clay sample	0.72	0.77

decrease of permeability at the beginning of experiment. However, it has been observed that permeability started to increase on account of deformations that the leachate causes on the clay soil [26].

At the beginning, the permeability decreases, since the voids in the clay soil were filled by the suspended solids, some metal ions and microorganisms within the leachate. The pore clogging caused by the growth of the microorganisms inside the soil pores, suspended solids and precipitated metal ions fill the voids of the clay soil. Then, the permeability increases due to deformations in the structure of the clay soil. The deformations are caused by the presence of very high concentration and variety of pollutants in leachate. After filtration of leachate though compacted clay and compacted–consolidated clay soils, the removal efficiencies of Fe^{2+}, Mn^{2+}, Zn^{2+}, Cu^{2+} and Pb^{2+} are obtained and the results are given in Table 7. As can be seen from Table 7, compacted–consolidated clay soils are found more effective than only compacted clay soil to remove metal ions [26].

In the modelling process, a variable selection method in the linear model setting, Lasso, is used to improve the accuracy of support vector machine regression model. The tuning parameter λ controls the strength of the L1 penalty. The Lasso uses a penalty in the L1 norm of the coefficient vector, which causes the estimates of some coefficients to be exactly zero. The fact that it sets coefficients to zero is a big advantage for the sake of the interpretation as seen from the improved results of SVR.

Table 5
Regression validation for SVR model

SVR model	Out-of-sample R^2	All-data R^2
Compacted contaminated clay sample	0.79	0.80
Compacted–consolidated contaminated clay sample	0.79	0.84

Table 6
Regression validation for SVR model, second run excludes Zn

SVR model (Zn excluded)	Out-of-sample R^2	All-data R^2
Compacted contaminated clay sample	0.83	0.84
Compacted–consolidated contaminated clay sample	0.79	0.85

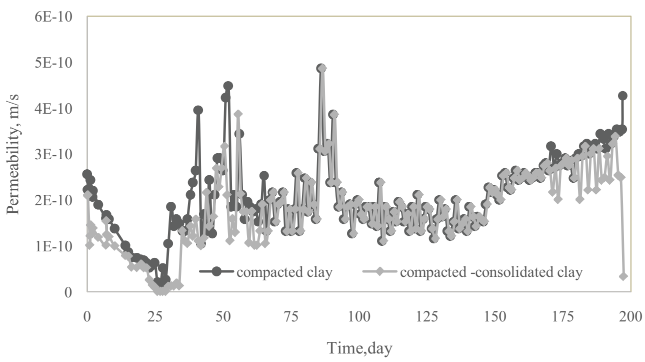

Fig. 4. Permeability changes in compacted clay and compacted–consolidated clay.

4. Conclusions

In this study, high removal efficiencies are obtained in the chemical parameters after leachate passes through compacted clay samples and it is observed that the clay has a natural purification capacity. In general, when experimental results of Fe^{2+}, Mn^{2+}, Zn^{2+}, Cu^{2+} and Pb^{2+} parameters are examined, removal rate of clay soil which are compressed with standard methods and consolidated is higher than that of clay soil compressed with standard compaction method. It has been observed that the suspended solids, some metal ions and microorganisms in the leachate filled the spaces between the clay particles and the growth of microorganisms inside the soil pores caused pore clogging that led the permeability to decrease. In the long term, it is observed that this variation takes place in the reverse direction, in other words the permeability increases. It is considered that this variation would be the result of the certain chemical and physical deteriorations produced by the contaminative components in the leachate.

The (regression) results showed that SVR has better accuracy, but slower than Lasso. Lasso method is also used for selecting important features. First, the Lasso regression is performed to get the appropriate number of features, and then these features are used in Lasso and SVR implementation. Thus, after running Lasso regression, results showed that Zn has a coefficient of zero in both clay data samples, meaning it has less importance compared with other materials. As Zn is an amphoteric metal, it does not precipitate and adsorb easily. Thus excluding Zn slightly improved the accuracy of Lasso and SVR methods and

Table 7
Removal efficiency of metal ions, %

Time, d	Compacted clay					Compacted–consolidated clay				
	Fe^{2+}	Mn^{2+}	Zn^{2+}	Cu^{2+}	Pb^{2+}	Fe^{2+}	Mn^{2+}	Zn^{2+}	Cu^{2+}	Pb^{2+}
0	0	0	0	0	0	0	0	0	0	0
31	68	21	3	29	14	71	24	49	54	53
59	90	43	16	41	38	93	53	58	77	72
87	98	59	38	70	53	99	90	81	81	81
150	96	68	36	59	51	98	86	76	68	78
214	94	31	32	56	48	98	83	75	67	74

sped up the procedure. Faster implementation is very important because the computation time might be a problem for larger datasets.

Mathematical models can be used to estimate long-term data, select features and accurate results. According to this study SVR and Lasso model found promising to model environmental issues. For next studies, researcher should make interdisciplinary studies to advance environmental issues.

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