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Estimation of physical, mechanical and hydrological properties of permeable concrete using computational intelligence approach

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ABSTRACT

Permeable concrete (PC) has gained a wide range of applications as a result of its unique properties which result into highly connected macro-porosity and large pore sizes. However, experimental determination of these properties is intensive and time consuming which necessitates the need for modeling technique that has a capability to estimate the properties of PC with high degree of accuracy. This present work estimates the physical, mechanical and hydrological properties of PC using computational intelligent technique on the platform of support vector regression (SVR) due to excellent generalization and predictive ability of SVR in the presences of few descriptive features. Four different models were built using twenty-four data-points characterized with four descriptive features. The estimated properties of PC agree well with experimental values. Excellent generalization and predictive ability recorded in the developed models indicate their high potentials for enhancing the performance of PC through quick and accurate estimation of its properties which are experimentally demanding and time consuming.

1. Introduction

Permeable concrete (PC) is a special type of concrete that has high permeability rate due to their highly connected macro-porosity and large pore sizes. It has gained a wide range of applications as sustainable construction materials which can be used for parking lots, walkways, sidewalks, construction of secondary roads, in-situ aerobic bioreactor, and plants purification. It has great advantages because of its physical (such as density), mechanical (such as tensile and compressive strength) and hydrological properties (such as porosity) which give rise to high water infiltration capacity, storm water retention ability, ground water recharge capacity, hydrocarbon pollution control and suspended solid removal [1,2]. The desired properties of PC are majorly obtained by controlling the amount of nominal coarse aggregate size of the concrete, cement, water to cement ratio and coarse aggregate. This present work utilizes these descriptive features to develop models which allow accurate estimates of the properties of PC without the use of intensive conventional methods.

The compressive strength and tensile strength of PC are key parameters that determine its suitability as a pavement structural material. These mechanical properties are affected by pore connectivity, diameter of the pore, surface roughness of the pore and the volume fraction of the pore. However, porosity has been identified to be the primary determinant of the magnitude of the compressive strength and hydraulic conductivity [2]. Porosity also affects water permeability, the higher the porosity ratio, the higher the water permeability, but an inverse relationship exists between the porosity and compressive strength [3]. The proper usage of PC is attributed to accurate determination of its physical, mechanical and hydrological properties which will guarantee its effectiveness when use to reduce the noise generated on the road, to remove the suspended solid in the water, to prevent stagnation of water on the road and thereby ensuring the safety of the road users [4]. The laboratory determination of the PC properties according to the ASTM standard is time consuming and expensive. Given the importance of this material and the research interest it has generated over the years, it is a worthwhile endeavor to develop models that can accurately estimate the properties of PC.

Quite a lot of experimental and theoretical work has been conducted on PC [5]. Most of these works have focused more on the experimental design of PC with a view to derive a comprehensive understanding of its properties and at the same time seek means to enhance the properties of the material [6,7]. A typical example

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is the work of Cheng [8] on the design of a pervious concrete from recycled aggregate. The objective of the work is to study the mechanical properties and performance of pervious concrete. It is a fact that the research in PC design and construction is a laborious endeavor, most times, consuming time and limited resources. As such, it is extremely important to perform a theoretical estimation of the fundamental properties of PC in order to minimize wastage of materials during fabrication and testing of samples. To this regards, several approaches have been deployed to estimate these properties. For instance, Atici's [9] estimated compressive strength of concrete that contains various amount of blast furnace slag and fly ash using a combination of multiple regression analysis and artificial neural network. In a similar effort, Ahmet [10] utilized neural network to predict the compressive strength and slump of high strength concrete. Marai [11] also employed neural network for predicting compressive strength of structural light weight concrete. Although, ANN has performed well in all cases mentioned above. However, it has been demonstrated that SVR gives a better performance than ANN in many instances due to its unique properties such as non-convergence to local minimal and superior ability to generalize well in the presence of small dataset [12–16]. Among the uniqueness of this present work is that its develops models for estimating properties of special type of concrete (PC) as a result of the important roles play by these properties on the application of PC.

SVR is a robust machine learning algorithms based on statistical learning theory [17]. It has been successfully applied to regression problems in wide range of science and engineering applications. The algorithm was developed by Vapnik in 1995 and it has been attracting much attention in recent time due to its many attractive features and improved performance [18]. Unlike the traditional neural network which generalizes as a result of the optimization algorithms utilized in the selection of the parameters and the statistical approach used in selecting the best model, SVR employs structural risk minimization principle that minimizes the upper bound on the expected risk thereby increasing SVR ability to generalize well in the presence of few data-point and descriptive features. The choice SVR in this work is due to the limited data-points that characterized the experimental results in determining the properties of PC. SVR stands a good chance in modeling properties of PC using few experimental data because of its sound mathematical foundation and non-convergence to local minimal [19,20].

Generalization performance evaluation conducted on our developed models shows excellent results as deduced from high coefficient of correlations, low root mean square error, low mean absolute error, low mean absolute percentage error and low value of scatter index.

2. Proposed computational intelligent method

The main underlying principle in SVR is the mapping of input data into a high-dimensional feature space by nonlinear transformation mapping function that is defined by inner product function which allows a linear regression to be performed in the high dimensional space.

SVR algorithm selects a function that estimates the actual value of target as close as possible to the reference value with a precision ϵ defined as the insensitive loss function which measures the flatness of generalized pattern and the maximum permitted deviations of the targets from the estimated values for all the given training dataset [21,22]. Consider a decision function represented by Eq. (1), in order to ensure the flatness of the equation, it is required that w is made small through minimization of the Euclidean norm $\|w\|^2$.

$$f(x, \alpha) = \langle w, x\rangle + b \tag{1}$$

where $w \in R'$ and $b \in R$ for a set of training samples

Minimization of the Euclidean norm results in Eq. (2).

$$\text{minimize} \quad \frac{1}{2}\|w\|^2$$
$$\text{subject to} \quad \begin{Bmatrix} y_i - \langle w, x_i\rangle - b \le \varepsilon \\ \langle w, x_i\rangle + b - y_i \le \varepsilon \end{Bmatrix} \tag{2}$$

Eq. (2) holds on the assumption that there exists a function that is capable of providing error which is less than ε for all training pairs of the dataset. The slack variables (ξ_i and ξ_i^*) are introduced in order to create room for another kind of error that may arise while dealing with real life problems. Therefore, Eq. (3) is modified and presented as Eq. (4).

$$\text{minimise} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{k}(\xi_i + \xi_i^*)$$
$$\text{subject to} \quad \begin{Bmatrix} y_i - \langle w, x_i\rangle - b \le \varepsilon + \xi_i \\ \langle w, x_i\rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \quad \text{for all} \quad i = 1, 2, \ldots, k \end{Bmatrix} \tag{3}$$

The optimization problem in Eq. (3) can be solved using Lagrangian multipliers (η_i, η_i^*, λ_i and λ_i^*) to transform the problem into dual space representation. Hence, the Lagrangian for the Eq. (3) result in the Eq. (4).

$$L = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{k}(\xi_i + \xi_i^*) - \sum_{i=1}^{k}\lambda_i(\varepsilon + \xi_i - y_i + \langle w, x_i\rangle + b)$$
$$- \sum_{i=1}^{k}\lambda_i^*(\varepsilon + \xi_i^* + y_i - \langle w, x_i\rangle - b) - \sum_{i=1}^{k}(\eta_i\xi_i + \eta_i^*\xi_i^*) \tag{4}$$

By equating the partial derivatives of the Lagrangian (with respect to w, b, ξ_i and ξ_i^*) to zero, the saddle point of the Langrangian can be found.

Hence, this results in the following equations:

$$w = \sum_{i=1}^{k}(\lambda_i^* - \lambda_i)\cdot x_i \tag{5}$$

$$\eta_i = C - \lambda_i \tag{6}$$

$$\eta_i^* = C - \lambda_i^* \tag{7}$$

By substituting Eq. (5)–(7) in (4), the optimization equation is maximized and gives rise Eq. (8).

$$\frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k}(\lambda_i^* - \lambda_i)(\lambda_j^* - \lambda_j)(x_j\cdot x_i) - \varepsilon\sum_{i=1}^{k}(\lambda_i^* + \lambda_i)$$
$$+ \sum_{i=1}^{k}y_i(\lambda_i^* - \lambda_i) = 0 \tag{8}$$
$$\text{subject to} \quad \sum_{i=1}^{k}(\lambda_i^* - \lambda_i) = 0, \quad 0 \le \lambda_i^* \quad \text{and} \quad \lambda_i \le C$$

By solving Eq. (8), the solution of λ_i^* and λ_i obtained are substituted in Eq. (1) to give Eq. (9)

$$f(x, \alpha) = \sum_{i=1}^{k}(\lambda_i^* - \lambda_i)K\langle x_i, x\rangle + b \tag{9}$$