Int. J. Nonlinear Anal. Appl.
Volume 12, Special Issue, Winter and Spring 2021, 1025-1034
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/IJNAA.2021.5548

Application of machine learning for predicting ground surface settlement beneath road embankments

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(Communicated by Madjid Eshaghi Gordji)

Abstract

Predicting the maximum ground surface settlement (MGS) beneath road embankments is crucial for safe operation, particularly on soft foundation soils. Despite having been explored to some extent, this problem still has not been solved due to its inherent complexity and many effective factors. This study applied support vector machines (SVM) and artificial neural networks (ANN) to predict MGS. A total of four kernel functions are used to develop the SVM model, which is linear, polynomial, sigmoid, and Radial Basis Function (RBF). MGS was analysed using the finite element method (FEM) with three dimensionless variables: embankment height, applied surcharge, and side slope. In comparison to the other kernel functions, the Gaussian produced the most accurate results (MARE = 0.048, RMSE = 0.007). The SVM-RBF testing results are compared to those of the ANN presented in this study. As a result, SVM-RBF proved to be better than ANN when predicting MGS.

Keywords: Road embankment, Maximum ground surface settlement, Support vector machines, Kernel functions and artificial neural networks

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Received: June 2021 *Accepted:* September 2021

1. Introduction

Road embankments built on soft ground encourage lateral and vertical surface movement. The vertical surface movement, also known as ground surface settlement, is a major risk to surface and subsurface facilities and is particularly significant in soft soil [7]. As infrastructure development has expanded rapidly, many roads built on soft soil have been constructed worldwide. One of the main contributors to significant surface settlement is the poor quality of soft soil engineering properties. Thus, settlement control is a critical phase of any construction activity on soft ground, even if the surface ground is safe for facilities. The magnitude of ground surface movements prior to construction is a critical piece of essential information for settlement control. Several researchers have attempted to develop various methods for resolving the maximum ground surface settlement (MGS) caused by road embankments to address this critical issue. The wide range of parameters that influence surface settlement make it challenging to determine a closed-form mathematical solution [26]. As a result, many researchers attempted to use alternative methods, such as analytical [30], empirical [5], numerical [28], and artificial intelligence methods [15].

Empirical approaches have interpretations only relevant to the same conditions, which means they offer slight generalization [3]. Model development in numerical methods should be very sophisticated, incorporating many details and parameters [12]. As a result, building and running the model takes a long time. As an alternative, the application of artificial intelligence (AI), especially machine learning as a professional tool for modelling and analysing complex engineering systems, has recently been noted. Due to their high accuracy, machine learning techniques are extremely useful in various branches of civil engineering applications [4, 11, 16]. Ground settlement predictions are one of the most common applications of machine learning. Several different types of machine learning tools, including random forest (RF) [31], gene expression programming (GEP) [1], artificial neural networks (ANN) [23], smooth relevance vector machine (SRVM) [27], multivariate adaptive regression splines (MARS) [14], and the adaptive neuro-fuzzy inference system (ANFIS) [20] are often used to predict ground settlement beneath civil engineering structures.

Recently, researchers have made efforts to evaluate performance based on comparisons of results from several types of machine learning prediction tools. Liu et al. [13] predicted the load-settlement behaviour of raft-pile foundation installed in soft marine clay using ANFIS and ANN. The results established that ANN outperformed ANFIS. Moghaddasi et al. [19] developed more accurate models for predicting tunnelling-induced surface settlement through ANN and imperialist competition algorithms. They demonstrate that the presented method is more reliable than the multiple regression for arranging ground surface settlement. Zhang et al. [29] estimated tunnelling-induced settlement using two machine learning tools based on ANN and RF. Based on the comparative result, the ANN demonstrated superior prediction capability to the RF.

The support vector machine (SVM) is a relatively new machine learning technique that is highly effective in various fields, including regression [22], pattern recognition [21], classification [25] and project management [32]. SVM has three advantages. It can simulate nonlinear functional relationships and generalize in high dimensional space with only a few training samples [18]. Due to this advantage, SVM can be successfully applied in a wide variety of engineering fields.

The purpose of this paper is to develop an SVM based on four different kernel functions for MGS prediction beneath a road embankment stabilized with prefabricated vertical drains (PVDs). In order to estimate the MGS, a numerical analysis was conducted using the embankment design with various geometric features, followed by the application of different kernel functions to determine the best SVM model. Statistical indices are used to measure the performance of each kernel function. Furthermore, the performance of the more developed models in predicting MGS employing SVM is compared with ANN.

2. Materials and methods

2.1. Numerical analysis

In order to estimate MGS, a total of 100 embankment designs were modelled with different geometric features were performed using FEM. The range of values for the FEM modelling design parameters is presented in Table 1. The numerical modelling for this study is performed using two-dimensional Plaxis, a finite element software commercially available, which includes geotechnical engineering deformation analysis. The present study developed a numerical model for a PVDs-stabilized embankment located on soft clay, as illustrated in Figure 1. The width of the embankment is set at 11m to facilitate the design of FEM modelling. The groundwater level (GWL) is on the surface of soft clay with a thickness of 20 m. The PVD is 100 mm x 4 mm, 16 m long, and the spacing was 1.3 m centre to centre in a triangular layout. The geotextiles are installed on the foundation soil surface to increase the shear strength with a tensile stiffness value of 19 kN/m.

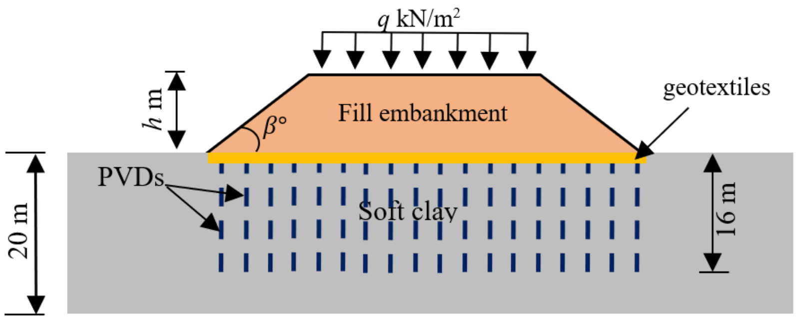

Figure 1: The profile model of embankment construction

The embankment construction stage is a crucial input parameter in FEM final settlement calculations. In this study, FEM analysis was performed after the embankment was constructed for 180 days. An adapted Cam-clay model is used to model the soft clay, while the Mohr-Coulomb model is used for modelling the embankment fill. In modelling PVDs in foundation soils, the smear effect was considered with a permeability ratio of 1.2. The model of PVDs includes a rectangular drains element with zero thickness, which is then converted to an equivalent cylindrical shape using the Hansbo [10] solution. Table 2 presents the material parameters used in FEM modelling. The R_{inter} values of 1 have been utilized to represent a geotextile with a non-slip mechanism regarding the surrounding soil elements.

Table 1: The range parameters value of embankment design

Height of embankment, h (m)	Applied surcharge, q (kN/m^2)	Side slope, $\beta(\circ)$
1-3	0-15	25-45

The simulation contains a FEM model where the standard fixity was applied. In order to prevent the domain from warping, the lower edge was made stiff, with vertical and horizontal fixities used for the vertical and horizontal edges, respectively. Due to the apparent lack of rigid elements, the slope face has free movement. In this study, MGS was evaluated at the centre of the embankment, at the soil surface of the foundation. The geometry has been divided into a finite number of finite elements for the finite element simulation. The 15-node triangular elements were selected over the six-node triangular elements, as they have more nodes and Gauss points. This study was performed with a fine mesh, and local refinements were used wherever large stress concentrations were expected.

Table 2: Material parameters for FEM analysis

Materials	$\gamma(kN/m^3)$	$k(m/day)$	$c(kPa)$	$\varphi(o)$	$E(kPa)$	ν	M	λ	κ
Embankment	19	0.045	5	20	10,000	0.3	-	-	-
Soft clay	16	1.6×10^{-3}	30	1	-	0.3	1.5	0.2	0.03

2.2. *SVM model development*

The SVM is a statistical learning theory-based method that uses the structural risk minimization principle [6]. This approach is a compelling computational method for classifying and predicting outcomes. The SVM regression method, also known as support vector regression (SVR), is used for regression problems. The SVR purpose is to construct a model that predicts the data set used in experiments and measured outcomes. The features of SVM can be studied in the many available books and literature [9, 2, 24]. Figure 2 shows the flowchart for the methodology used to develop SVM model creation in this study.

Regression models use a small amount of noisy training data to estimate an unknown continuous-valued function. An overview of SVR may be useful when thinking about a regression function $y(x)$ that is calculated from given training data, where $\{(xn, yn)|n = 1, 2, ..., N\}$ are the training datasets. The input data with an input vector of d-dimension is $x \in R^d$ and the output space with a dimension of $y \in R$. The following equation describes the linear regression model, which relates input and output variables.

$$y(x) = w^T \phi(x) + b \qquad (1)$$

where input space $\phi(x)$ is non-linearly mapped to high-dimensional feature space (x). Also, the model's weights and biases are w and b, respectively. The loss function (L_f) is used in the SVR procedure to penalize the model. It is characterized as:

$$L_f(t_n, y_n) = \begin{cases} 0 & |t_n - y_n| \leq \epsilon \\ \xi & |t_n - y_n| > \epsilon \end{cases} \qquad (2)$$

where the non-negative slag variable, ξ_n, is concerned. Equation (1) penalizes the model when the target-output vector difference exceeds a constant, ϵ.

Instead of optimizing agreement with a given training set, SVMs seek to balance model complexity and the ability to reproduce empirical data. The kernel function and its parameters define the distribution of the training set of samples in the high-dimensional feature space. SVR can use a variety of kernel functions. Therefore, it is essential to select an appropriate kernel function. The performance of four SVR models with different kernel functions is compared in this study. Table 3 lists the considered kernel functions. Good optimization of the SVR parameters determines how well the model performs. Thus, the SVR model must be trained using predefined C and constant, . These constants have a significant impact on SVR prediction performance. Table 3 also requires that each kernel function predefine the kernel constant. Parameters of the model were optimized by trial and error, resulting in more accurate predictions [8]. Therefore, three parameters C, ϵ, and the kernel constant are found by trial and error. So, to find the best trial and error constants, the main SVR program was extended with new loops and nearly 1000 runs. Using STATISTICA software, 10-fold cross-validation was used to find the constant parameters of SVR for this study.

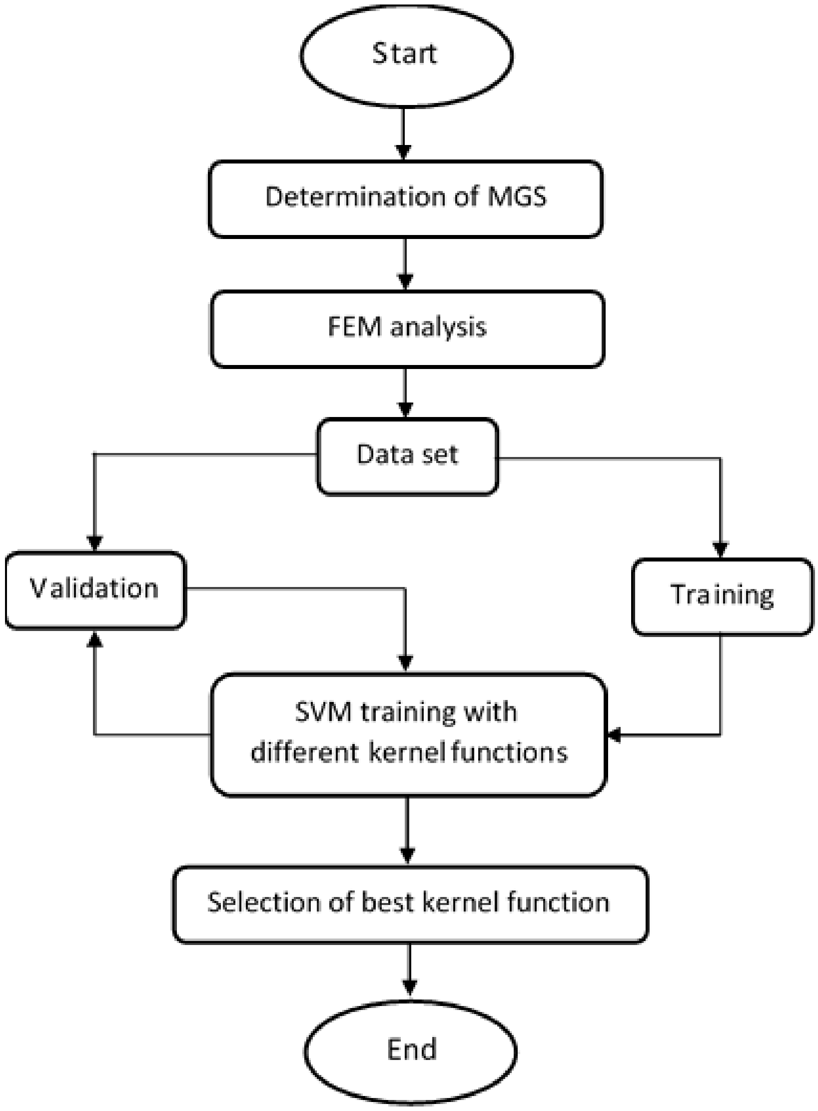

Figure 2: SVM Model Development Flowchart

Table 3: Types of kernel functions in SVR

Kernel	Equation	Constant
Linear	$k(x_n, x_i) = x_n, x_i$	-
Polynomial	$k(x_n, x_i) = \gamma((x_n, x_i) + r)^d$	γ, r, d
Sigmoid	$k(x_n, x_i) = tanh(\gamma(x_n, x_i) + r)$	γ, r
Radial Basis Function (RBF)	$k(x_n, x_i) = exp(-\gamma\|\|x_n, x_i\|\|^2 + C)$	γ

2.3. ANN model development

Recent studies suggest that neural networks are a universal approximation for any nonlinear continuous function with arbitrary precision. The architecture of their brains is based on the human brain's neural network, which consists of many linked components called neurons. The system performs nonlinear feature extraction on input data to locate an indirect relationship between input vectors and the system's target parameters. Also, weights connect different neurons in different networks, and network performance is highly dependent on weights.

The most widely used neural network is a backpropagation MLP. An MLP typically has an input layer, one or more hidden layers, and an output layer of nodes. The number of input and output variables can vary depending on the problem. As hidden layers provided acceptable results in this field study [17], hidden layers were incorporated into the neural networks in this study.

This study employed neural networks that were constructed with the Simulink in MATLAB 6.5 toolbox neural network components. Due to the data contain both positive and negative values, the input data were scaled to the interval [1, 1] using a simple linear transformation. In this study, a sigmoid transfer function was selected for the hidden nodes and the output node. Furthermore, Levenberg-Marquardt (MLP) is regarded as the most efficient gradient algorithm in various studies for training an MLP network.

2.4. Statistical indices

Various model performance appraisal measures can be considered using statistical parameters. The two indices used in this study to evaluate the performance of the presented models and compare them with existing methods are the root mean square error (RMSE) and the mean absolute relative error (MARE). The RMSE index is the square difference between the observed and predicted values, and this index's best value is zero. It is worth noting that MARE, an unbiased, non-negative index with a zero-lower limit, is used to measure the relative error in error functions, not correlation. In other words, less variation between the predicted and actual values is found as the MARE draws closer to zero.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_{prd.i} - y_{obs.i})^2}{N}} \tag{3}$$

$$MARE = (\frac{1}{N})\sum_{i=1}^{N}\left(\frac{|y_{obs.i} - y_{prd.i}|}{y_{obs.i}}\right) \tag{4}$$

where N is the number of data, $y_{obs.i}$ is the ith observed value and $y_{prd.i}$ is the ith predicted value.

3. Results and discussion

The scatter plot of four different kernel functions used in developing the SVM model for MGS prediction beneath a road embankment is shown in Figure 3. The sigmoid and polynomial kernel functions exhibited overestimation when the MGS values were less than 0.3m than the RBF, and linear kernel functions approaching the line is $y = x$. However, the polynomial, linear, and RBF kernel functions show good agreement when the MGS values are in the range of 0.4–0.6 m. Thus, the RBF kernel outperforms other kernel functions, as it provides superior performance compared to other models for all of the MGS ranges. On the other hand, a quantitative model study is required to determine the model's superiority over other models.

The results of the SVM can be seen in Figure 4, which uses different kernel functions. The MARE index that showed the lowest relative error was RBF which was around 0.048, followed by linear (0.073), polynomial (0.124), and sigmoid (0.89). Surprisingly, the difference in MARE values between RBF and sigmoid is seen to be quite significantly around 0.842. In contrast, the difference in values for the other two kernel functions with RBF was smaller than 0.08. Therefore, RMSE indices were developed to measure the root mean square and absolute error (RMSE = 0.007) and use the RBF kernel function, the best-performing method of all kernel functions. As expected, sigmoid is seen to produce the highest RMSE values of 0.37. Thus, the best MGS lead predictions can be made using the RBF kernel function in SVM design.

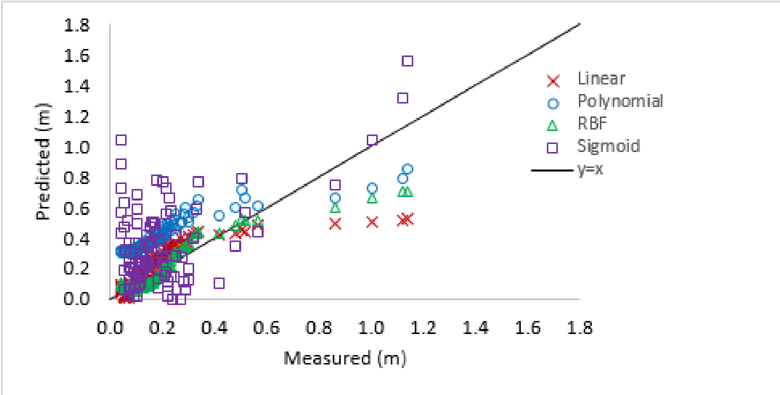

Figure 3: Correlation between predicted and measured

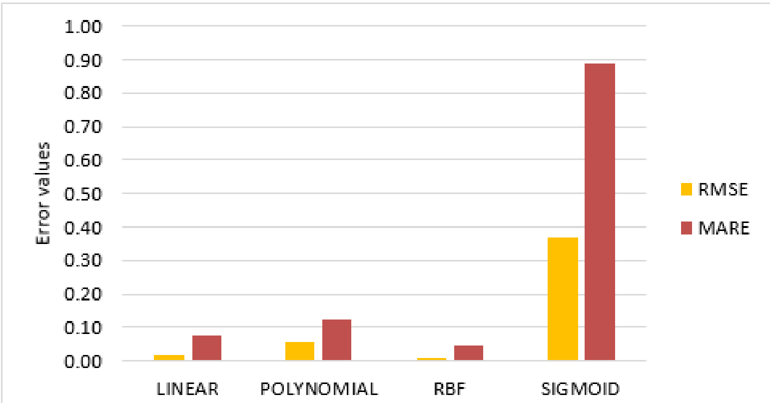

Figure 4: Statistical indexes for four kernel functions

The capabilities of SVM-RBF to estimate MGS in comparison with ANN is evaluated in Figure 5. The ANN model was seen to have the worst performance compared to the SVM-RBF for evaluating MGS whose values were less than 0.4 m. However, several of the MGS samples for which ANN predictions were made exhibited high error in their prediction results, with overestimations and underestimations occurring. Increasing MGS has a positive effect on the accuracy of ANN, but some samples show high relative error in ANN underestimations with a greater of MGS. The statistical indices in Table 4 are used to choose the best machine learning techniques. According to the data in this table, SVM-RBF is the most effective index, proving that it is the best performing predicting model. With regard to the values of MARE and RMSE found in this table, the SVM model is significantly different from the ANN model.

Table 4: Statistical indices of SVM-RBF and ANN

Kernel	Equation	Constant
Machine learning	MARE	RMSE
SVM-RBF	0.048	0.007
ANN	0.073	0.019

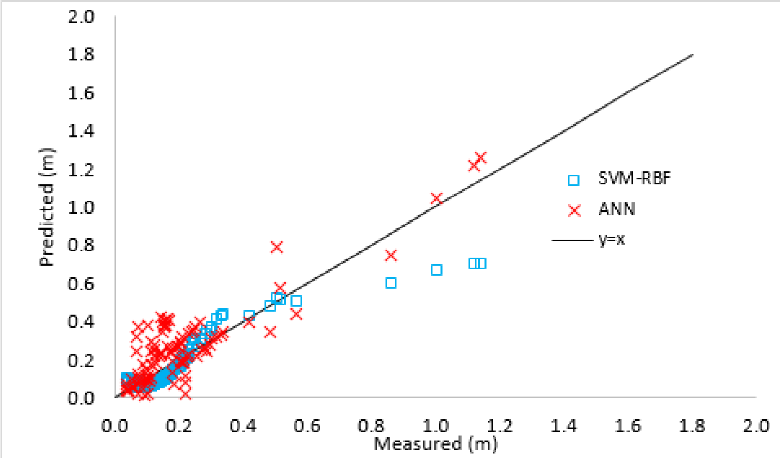

Figure 5: Comparison of SVM-RBF with ANN

4. Conclusion

This study predicted MGS beneath road embankment using SVM with three inputs: height of embankment, applied surcharge, and side slope. FEM was used to estimate MGS with 100 different geometric designs. The SVM model is best compared to ANN for performance evaluation. Thus, the study's findings are summarized as follows:

- Four kernel functions were used to design the SVM network. The RBF kernel function outperforms the SVM (MARE = 0.048, RMSE = 0.007).
- Comparing SVM-RBF to ANN showed that using SVM-RBF improves MGS prediction accuracy over neural networks.
- The proposed SVM-RBF for predicting MGS was compared to ANN. The results show that SVM-RBF outperforms ANN in MGS prediction and overcomes their high relative error.

Acknowledgement

The authors would like to acknowledge the Politeknik Ungku Omar and Malaysia Institute of Transport (MITRANS), Universiti Teknologi MARA Shah Alam, Selangor, Malaysia, for the cooperation and financial support of this project.

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