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USE OF RELEVANCE VECTOR MACHINE (RVM) FOR PREDICTION OF OVERCONSOLIDATION RATIO (OCR)

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ABSTRACT: This article employs the Relevance Vector Machine (RVM) for the prediction of the Over Conslodation Ratio (OCR) of fine-grained soils based on the Piezocone Penetration Test (PCPT) data. RVM provides an empirical Bayes method of function approximation by kernel basis expansion. It uses the corrected cone resistance (q_t), vertical total stress (σ_v), hydrostatic pore pressure (u_0), pore pressure at the cone tip (u_1), and the pore pressure just above the cone base (u_2) as input parameters. An equation has also been developed for the determination of OCR. The developed RVM model gives the variance of the predicted data. Sensitivity analysis has been conducted for determining the influence of each input parameter. The results are also compared with some of the existing interpretation methods. Comparisons indicate that the developed RVM model performs better than the existing interpretation methods for predicting OCR.

KEYWORDS: Over Consolidation Ratio; Piezocone; Relevance Vector Machine; Variance; Prediction; Sensitivity Analysis.

INTRODUCTION

The Over Consolidation Ratio (OCR) of fine-grained soils is one of the most important in situ parameters that impact the mechanical behaviour of clay deposits. Therefore, the determination of the OCR is an essential task in geotechnical engineering. The standard one dimensional consolidation test (oedometer test) is routinely used for the determination of OCR. However, it is a time consuming and expensive test (Kurup and

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Dudani, 2002). Geotechnical engineers use several Piezocone Penetration Test (PCPT) based methods for the determination of OCR such as the empirical methods based on the pore pressure parameters (Baligh et al. 1980; Campanella and Robertson 1981; Tumay et al. 1982; Smits 1982; Senneset et al. 1982; Sully et al. 1988), cavity expansion theories and critical-state soil mechanics (Mayne 1987; Mayne and Holtz 1988; Mayne and Bachus 1988; Mayne 1991; Kurup 1993; Tumay et al. 1995), and yield stress and bearing capacity approaches (Konrad and Law 1987; Senneset et al. 1982; Sandven et al. 1988). Artificial Neural Network (ANN) has been successfully adopted for the determination of the OCR based on PCPT data (Kurup and Dudani, 2002). ANN has been successfully used to solve many problems in geotechnical engineering (Mayoraz and Vulliet, 2002; Akin and Karpuz, 2008; Samui and Sitharam, 2010; Zaman et al., 2010; Zhang et al., 2011; Miranda et al.,2011). However, ANN has certain limitations such as arriving at local minima, low convergence speed, black box nature of the approach, less generalization performance and absence of probabilistic output (Park and Rilett, 1999; Kecman, 2001). Recently, Samui et al (2008) have successfully developed the Support Vector Machine (SVM) to overcome some of the problems of ANN for predicting OCR based on PCPT data. However, the developed SVM model has certain limitations that are listed below (Tipping 2000):

- SVM makes unnecessarily liberal use of basis functions since the number of support vectors required typically grows linearly with the size of the training set.
- Predictions are not probabilistic.
- The determination of the design value of capacity factor (C) and error insensitive zone (ε) is a complicated task.

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- The kernel function must satisfy Mercer's condition.

This paper employs the Relevance Vector Machine (RVM) for the prediction of the OCR based on PCPT data. This study uses the same PCPT database analyzed by Kurup and Dudani (2002).

RVM is based on a Bayesian formulation of a linear model with an appropriate prior that results in a sparse representation (Tipping 2000). It can be seen as a probabilistic version of the Support Vector Machine (SVM) (Scholkopf and Smola 2002; Pal 2006; Goh and Goh 2007; Samui et al.2008; Samui 2008). It is exactly equivalent to a Gaussian Process (GP), where the RVM hyperparameters are the parameters of the GP covariance function. However, the covariance function of the RVM seen as a GP is degenerate; its rank is at most equal to the number of relevance vectors of the RVM. The paper has the following aims:

1. To investigate the feasibility of RVM for predicting the OCR based on PCPT data.
2. To determine the variance of the predicted OCR.
3. To develop an equation for the prediction of the OCR based on the developed RVM model.
4. To make a comparative study between the developed RVM and other interpretation methods for predicting the OCR.
5. To do sensitivity analysis for determination of the effect of each input parameter.

DETAILS OF RVM

The RVM, introduced by Tipping (2000), is a sparse linear model.

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Let $D = \{(x_i, t_i), i = 1,\ldots, N\}$ be a dataset of observed values, where x_i=input, t_i=output, $x_i \in R^N$ and $t_i \in r$. In this study, input parameters are the corrected cone resistance (q_t), vertical total stress (σ_v), hydrostatic pore pressure (u_0), pore pressure at the cone tip (u_1), and pore pressure just above the cone base (u_2). So, $x = [q_t, \sigma_v, u_0, u_1, u_2]$. The output of the RVM model is the OCR. So, $t = [OCR]$. One can express the output as the sum of an approximation vector, $y = (y(x_1),\ldots, y(x_N))^T$, and zero mean random error (noise) vector $\varepsilon = (\varepsilon_1,\ldots,\varepsilon_N)^T$ where $\varepsilon_n \sim \mathbf{N}(0, \sigma^2)$ and $\mathbf{N}(0,\sigma^2)$ is the normal distribution with a mean value of 0 and variance σ^2. So, the output can be written as

$$t_n = y(x_n, w) + \varepsilon_n \tag{1}$$

where w is the weight parameter vector. Let us assume

$$p(t_n \mid x) \sim \mathbf{N}(y(x_n), \sigma^2) \tag{2}$$

where $\mathbf{N}(y(x_n), \sigma^2)$ is the normal distribution with mean $y(x_n)$ and variance σ^2. The Mean, y(x), can be expressed as a linearly weighted sum of M nonlinear fixed basis functions.

$\{\Phi_j(x) \mid j = 1,\ldots, M\}$:

$$y(x; w) = \sum_{i=1}^{M} w_i \Phi_i(x) = \mathbf{\Phi} w \tag{3}$$

The likelihood of the complete data set can be written as

$$p(t \mid w, \sigma^2) = (2\pi\sigma^2)^{-N/2} \exp\left\{-\frac{1}{2\sigma^2}\|t - \Phi w\|^2\right\} \tag{4}$$

Where $t = (t_1 \ldots, t_N)^T$, $\omega = (\omega_0, \ldots, \omega_N)$ and

$$\Phi^T = \begin{bmatrix} 1 & K(x_1, x_1) & K(x_1, x_2) & \cdots & K(x_1, x_n) \\ 1 & K(x_1, x_2) & K(x_2, x_2) & \cdots & K(x_2, x_n) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & K(x_n, x_1) & K(x_n, x_2) & \cdots & K(x_n, x_n) \end{bmatrix}$$ Where $k(x_i, x_n)$ is a kernel function.

To prevent over-fitting, automatic relevance detection (ARD) has already been set over the weights.

$$p(w \mid \alpha) = \prod_{i=0}^{N} N(\omega_i \mid 0, \alpha_i^{-1}) \tag{5}$$

where α is a hyperparameter vector that controls how far from zero each weight is allowed to deviate (Scholkopf and Smola 2002). Consequently, using Bayes' rule, the posterior over all unknowns could be computed given the defined noninformative prior distribution:

$$p\left(w, \alpha, \sigma^2 / t\right) = \frac{p\left(y / w, \alpha, \sigma^2\right) p(w, \alpha, \sigma)}{\int p\left(t / w, \alpha, \sigma^2\right) p\left(w, \alpha, \sigma^2\right) dw\, d\alpha\, d\sigma^2} \tag{6}$$

Full analytical solution of this integral (6) is obdurate. Thus, decomposition of the posterior according to $p\left(w, \alpha, \sigma^2 / t\right) = p\left(w / t, \alpha, \sigma^2\right) p\left(\alpha, \sigma^2 / t\right)$ is used to facilitate the solution (Tipping 2001). The posterior distribution over the weights is then given by:

$$p\left(w / t, \alpha, \sigma^2\right) = \frac{p\left(t / w, \sigma^2\right) p(w / \alpha)}{p\left(t / \alpha, \sigma^2\right)} \tag{7}$$

The resulting posterior distribution over the weights is the multi-variable Gaussian distribution

$$p\left(w / t, \alpha, \sigma^2\right) = \mathbf{N}(\mu, \Sigma) \tag{8}$$

where the mean and the covariance are respectively given by:

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$$\Sigma = \left(\sigma^{-2}\Phi^{T}\Phi + A\right)^{-1} \tag{9}$$

$$\mu = \sigma^{-2}\,\Sigma\Phi^{T}t \tag{10}$$

With diagonal $A = \mathrm{diag}(\alpha_0,...,\alpha_N)$.

For uniform hyperpriors over α and σ^2, one needs only maximize the term $p\left(t/\alpha,\sigma^2\right)$:

$$p\left(t/\alpha,\sigma^2\right) = \int p\left(t/w,\sigma^2\right)p(w/\alpha)dw$$

$$= \left((2\pi)^{\frac{-N}{2}} \Big/ \sqrt{\left|\sigma^2 + \Phi A^{-1}\Phi^{T}\right|} \right) \times \exp\left\{-\frac{1}{2}y^{T}\left(\sigma^2 + \Phi A^{-1}\Phi^{T}\right)^{-1}y\right\} \tag{11}$$

Maximization of this quantity is known as the type II maximum likelihood method (Berger 1985; Wahba 1985), or the "evidence for hyper parameter"(MacKay 1992). Hyper parameter estimation is carried out in iterative formulae, e.g., gradient descent on the objective function (Tipping 2001). The outcome of this optimization is that many elements of α go to infinity such that w will have only a few nonzero weights that will be considered as relevant vectors.

This study adopts the above methodology for the prediction of the OCR based on PCPT data. The dataset consists of the magnitude of q_t,σ_v,u_0,u_1,u_2 and the OCR. The database is comprised of 202 cases of intact, fissured, and Leda (sensitive intact) clays. The compiled data consists of piezocone measurements, pertinent soil information, OCR as determined from laboratory oedometer or one dimensional consolidation tests. OCR values fall between 1.0 and 15.5 for the (typical) intact clays, 1.6 and 80.0 for the fissured clays, and 1.0 and 3.0 for the Leda clays. Table 1 shows the different statistical parameters of the dataset. The data has been further divided into two sub-sets; a training dataset, to construct the model, and a testing dataset to estimate the model performance. The same

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training data, testing data, and normalization technique has been used in this study as used by Samui et al (2008). In this study, 137 out of a total of 202 data sets are considered for training. The remaining 65 out of 202 are used as the testing data set. The data are normalized between 0 to one. The following formula has been adopted for normalization.

$$d_{normalized} = \frac{(d - d_{\min})}{(d_{\max} - d_{\min})} \tag{12}$$

Where d=any data (input or output), d_{min}= minimum value of the entire dataset, d_{max}= maximum value of the entire dataset, and $d_{normalized}$=normalized value of the data. Radial basis function ($\exp\left\{-\frac{(x_i - x)(x_i - x)^T}{2\sigma^2}\right\}$), polynomial and spline have been used as a kernel function.

In this study, a sensitivity analysis has been done to extract the cause and effect relationship between the inputs and outputs of the RVM model. The basic idea is that each input of the model is offset slightly and the corresponding change in the output is reported. This procedure has been taken from the work of Liong et al (2000). According to Liong et al (2000), the sensitivity (S) of each input parameter has been calculated by the following formula

$$\mathrm{S}(\%) = \frac{1}{\mathrm{N}} \sum_{j=1}^{\mathrm{N}} \left(\frac{\%\ \text{change in ouput}}{\%\ \text{change in input}} \right)_{j} \times 100 \tag{13}$$

where N is the number of data points. In this study, N=137 was used. The analysis has been carried out on the trained model by varying each of input parameters one at a time at a constant rate of 20%. In the present study, training, testing, and sensitivity analysis of RVM has been carried out using MATLAB.

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RESULTS AND DISCUSSION

Coefficient of correlation (R), which evaluates the linear correlation between the actual and predicted OCR, Coefficient of Efficiency (E) and Agreement Index(I_a) have been adopted for assessing the performance of RVM models. For good model, the value of R, E and I_a should equal one. The performance of the different kernels has been shown in Table 2. It is observed from table 2 that the performance of radial basis function is best. This study employs trial and error approach for determining the design value of width (σ) of the radial basis function. The trail and error approach has been adopted by different researchers (Goh and Goh, 2007; Pal and Deswal, 2010; Samui, 2008). The design value of σ is 0.07. The performance of the training dataset has been determined by using the design value of σ. Figure 1 illustrates the performance of the training dataset. The value of R = 0.972, E=0.946 and I_a=0.998 is close to one for the training dataset. In order to evaluate the performance of the developed RVM, the developed RVM has been used on the testing dataset. Figure 2 depicts the performance of the testing dataset. Based on these results, it has been concluded that the developed RVM has the capability for predicting the OCR based on PCPT data. The developed RVM model gives the following equation for prediction of OCR,

$$OCR = \sum_{i=1}^{137} w_i \exp\left\{-\frac{(x_i - x)(x_i - x)^T}{0.0098}\right\} \quad (14)$$

And Figure 3 shows the values of the weights, w.

The developed RVM model has been used for predicting the variance of the training and testing dataset. Figures 4 and 5, respectively show the variance of training

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and testing data. The predicted variance allows one to assign a confidence interval about the model prediction.

A comparative study has been carried out between the developed RVM and other interpretation methods (Sully et al.1988; Mayne 1991; Chen and Mayne 1994; Kurup 1993; Tumay et al.1995; Kurup and Dudani, 2002) for determination of OCR. According to Sully et al.(1988), OCR has been determined from the following relation:

$$OCR = 0.49 + 1.50(PPD) \tag{15}$$

where PPD stands for Pore Pressure Difference and it is computed according to the following equation:

$$PPD = \frac{(u_1 - u_2)}{u_0} \tag{16}$$

Mayne (1991) derived the following expressions for predicting the OCR:

$$OCR = 2\left[\frac{1}{1.95M + 1}\left(\frac{q_t - u_2}{\sigma_v'}\right)\right]^{1.33} \tag{17}$$

$$OCR = 2\left[\frac{1}{1.95M}\left(\frac{q_t - u_1}{\sigma_v'} + 1\right)\right]^{1.33} \tag{18}$$

where $M = \frac{(6\sin\phi')}{(3 - \sin\phi')}$ is the slope of the critical state line and ϕ' is the drained friction angle.

Chen and Mayne (1994) proposed the proposed the following equations to estimate the OCR based on spherical cavity expansion and critical-state theories.

$$OCR = \frac{0.81(q_t - u_1)}{\sigma_v'} \tag{19}$$

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$$OCR = \frac{0.81(q_t - u_2)}{\sigma'_v} \tag{20}$$

Tumay et al.(1995) proposed the following equation (21) for estimating the OCR

$$OCR = 2\left[\frac{3}{(1.95M + 1)}\left(\frac{q_t - u_2}{\sigma'_v(1 + 2a) + 2b(u_1 - u_2)}\right)\right]^{1.33} \tag{21}$$

where a and b are constants.

The bar chart of Root-Mean-Square-Error (RMSE) and Mean-Absolute-Error (MAE) of RVM and other models for the testing dataset have been shown in Figure 6 and 7, respectively. Figures 6 and 7 also confirm that the performance of the developed RVM is better than some of the existing interpretation methods. The developed RVM model employs 41 training datasets as relevance vectors. These relevance vectors are only used for final prediction. Therefore, there is real advantage gained in terms of sparsity. Sparseness means that a significant number of the weights are zero (or effectively zero), which has the consequence of producing compact, computationally efficient models, which in addition are simple and therefore produce smooth functions. RVM employs mainly one kernel parameter. In ANN, there are a larger number of controlling parameters, including the number of hidden layers, number of hidden nodes, learning rate, momentum term, number of training epochs, transfer functions, and weight initialization methods. Obtaining an optimal combination of these parameters is a difficult task as well. The result of sensitivity analysis has been presented in Figure 8, and it can be seen that q_t has the most significant effect on the predicted OCR. Figure 8 also shows that u_1 has the smallest impact on the OCR.

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CONCLUSION

It is evident from this study that RVM can be successfully applied for the prediction of OCR of fine-grained soils based on PCPT data. Exactly 137 datasets have been utilized to construct the RVM model. The results indicate that the developed RVM model has the ability to predict OCR with an acceptable degree of accuracy (R=0.956, RMSE=3.375 and MAE=1.9783). The developed RVM outperforms some of the existing interpretation methods for predicting OCR. It achieves very good generalization performance and yields sparse models. The user can utilize the developed equation for the determination of the OCR. The developed RVM model has the added advantage of probabilistic interpretation that yields prediction uncertainty. The sensitivity analysis of the developed RVM model shows that q_t is the most influencing factor. The results clearly demonstrate that the developed RVM model has great potential and is capable of serving as a quick prediction tool for estimating OCR.

NOTATIONS

OCR=over consolidation ratio

R= coefficient of correlation

E=coefficient of efficiency

I_a=agreement index

q_t= cone resistance

σ_v= vertical total stress

u_0= hydrostatic pore pressure

u_1= pore pressure at the cone tip

u_2= pore pressure just above the cone base

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w=weight

σ^2=variance

S=sensitivity

ϕ'=drained friction angle

α =hyperparameter vector

σ=width of radial basis function

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FIGURE CAPTIONS LIST

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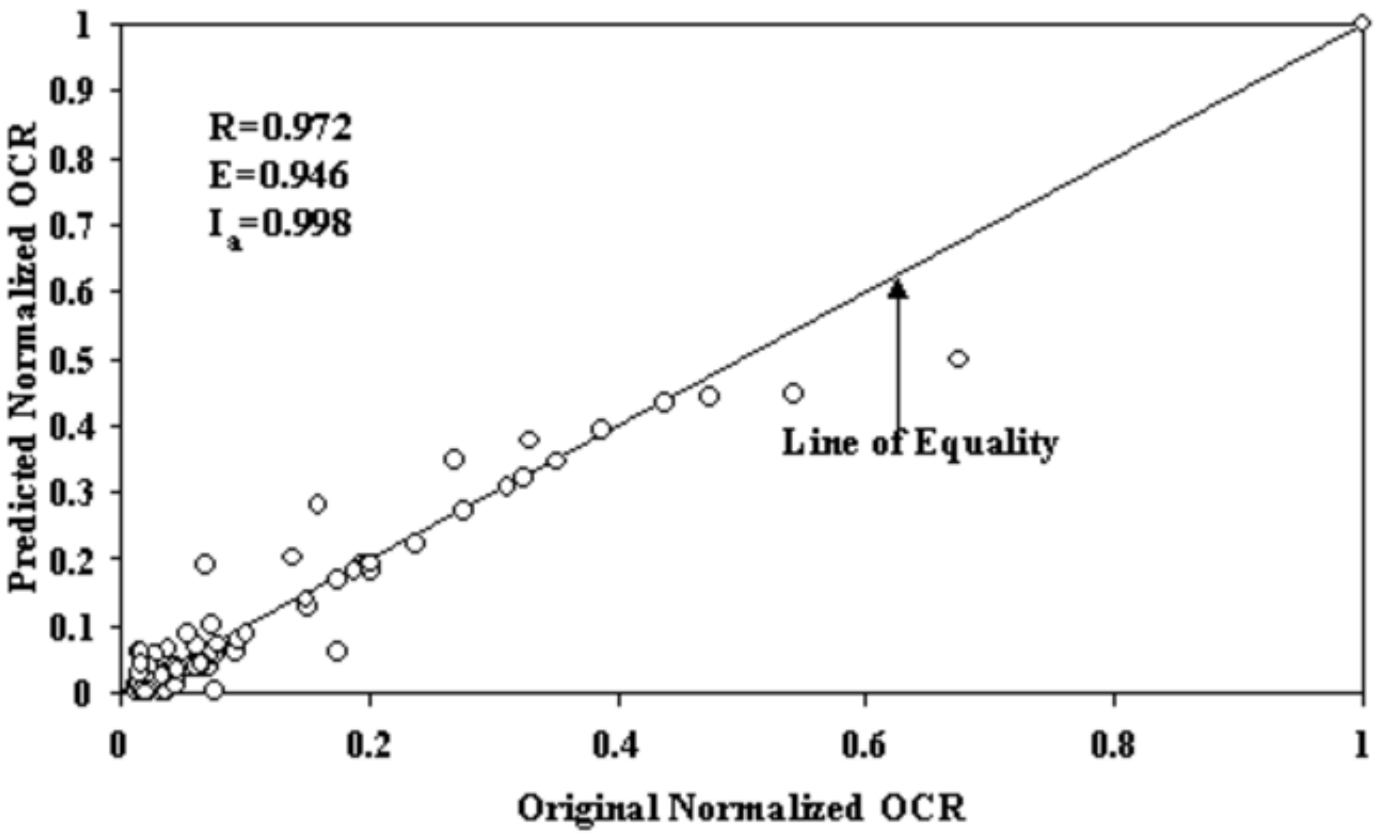

Figure 1. Performance of training dataset.

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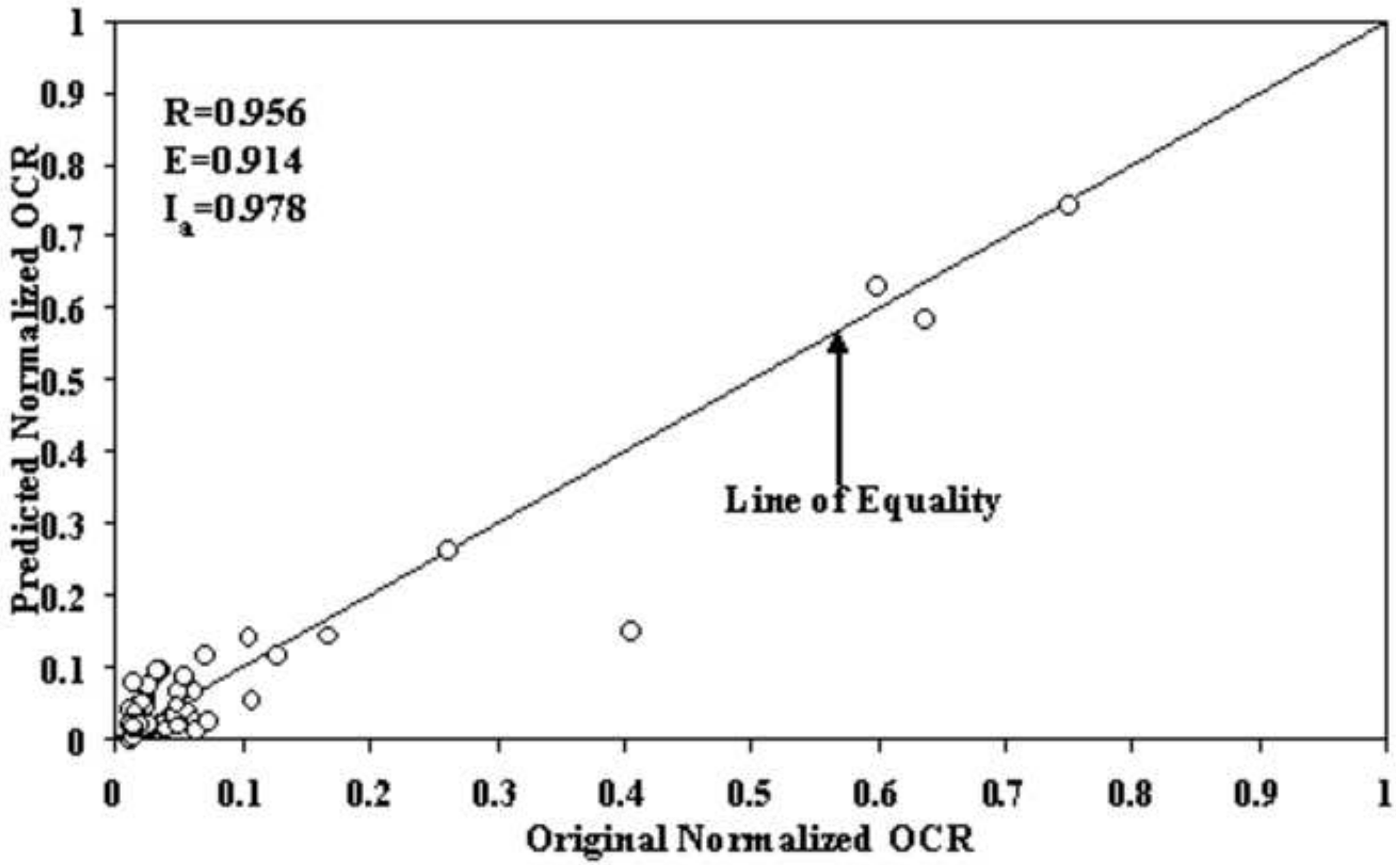

Figure 2. Performance of testing dataset.

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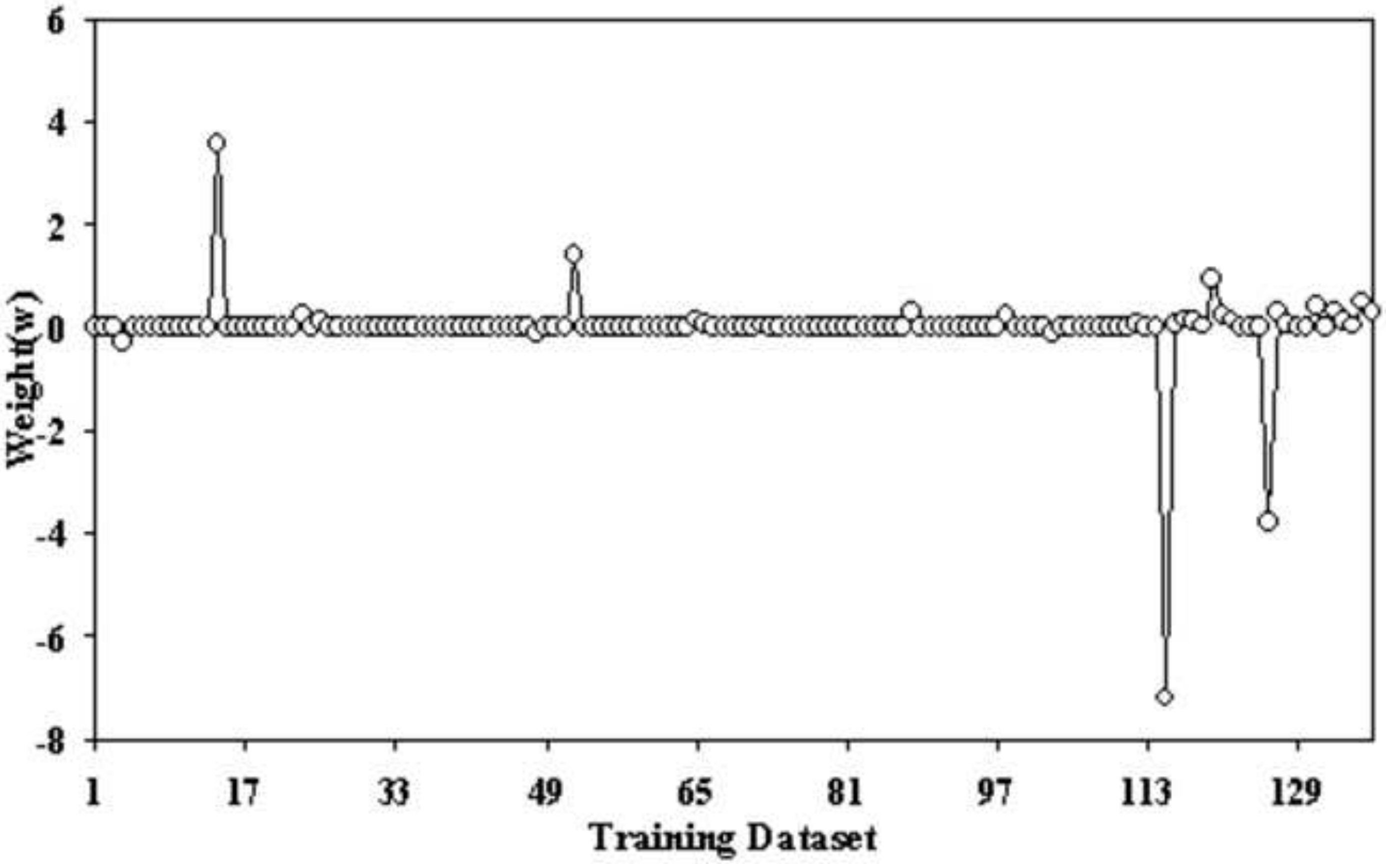

Figure 3. The values of w.

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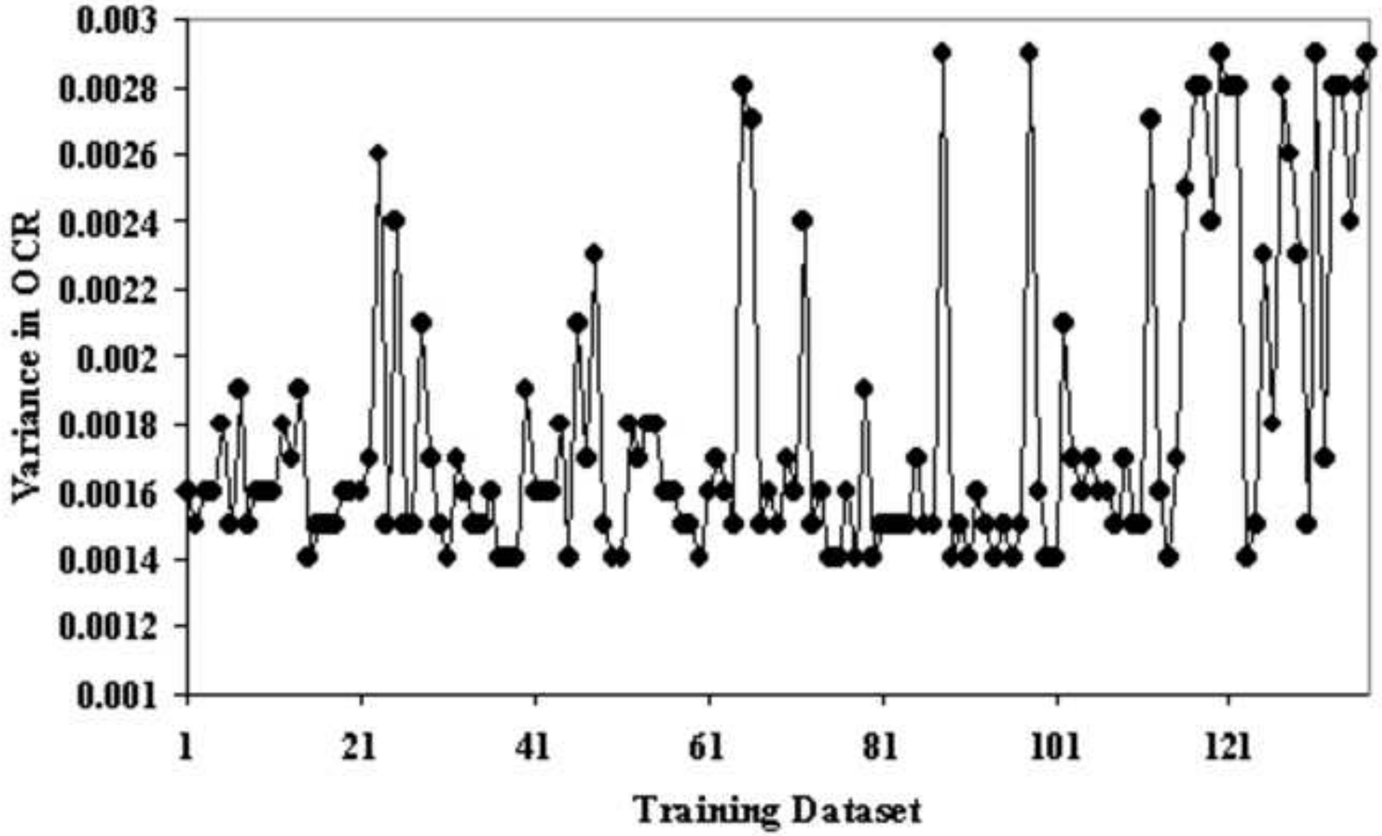

Figure 4. Variance of training dataset.

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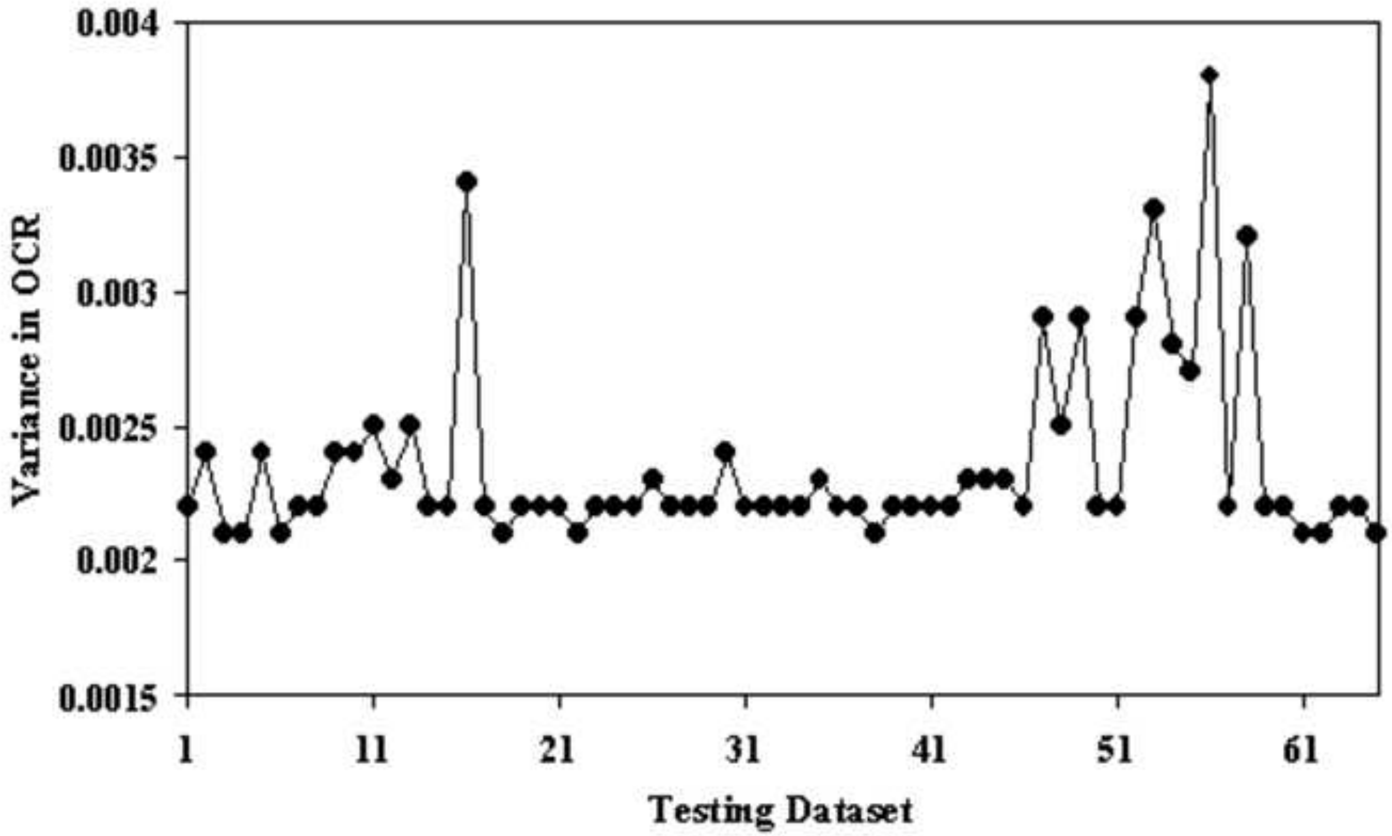

Figure 5. Variance of testing dataset.

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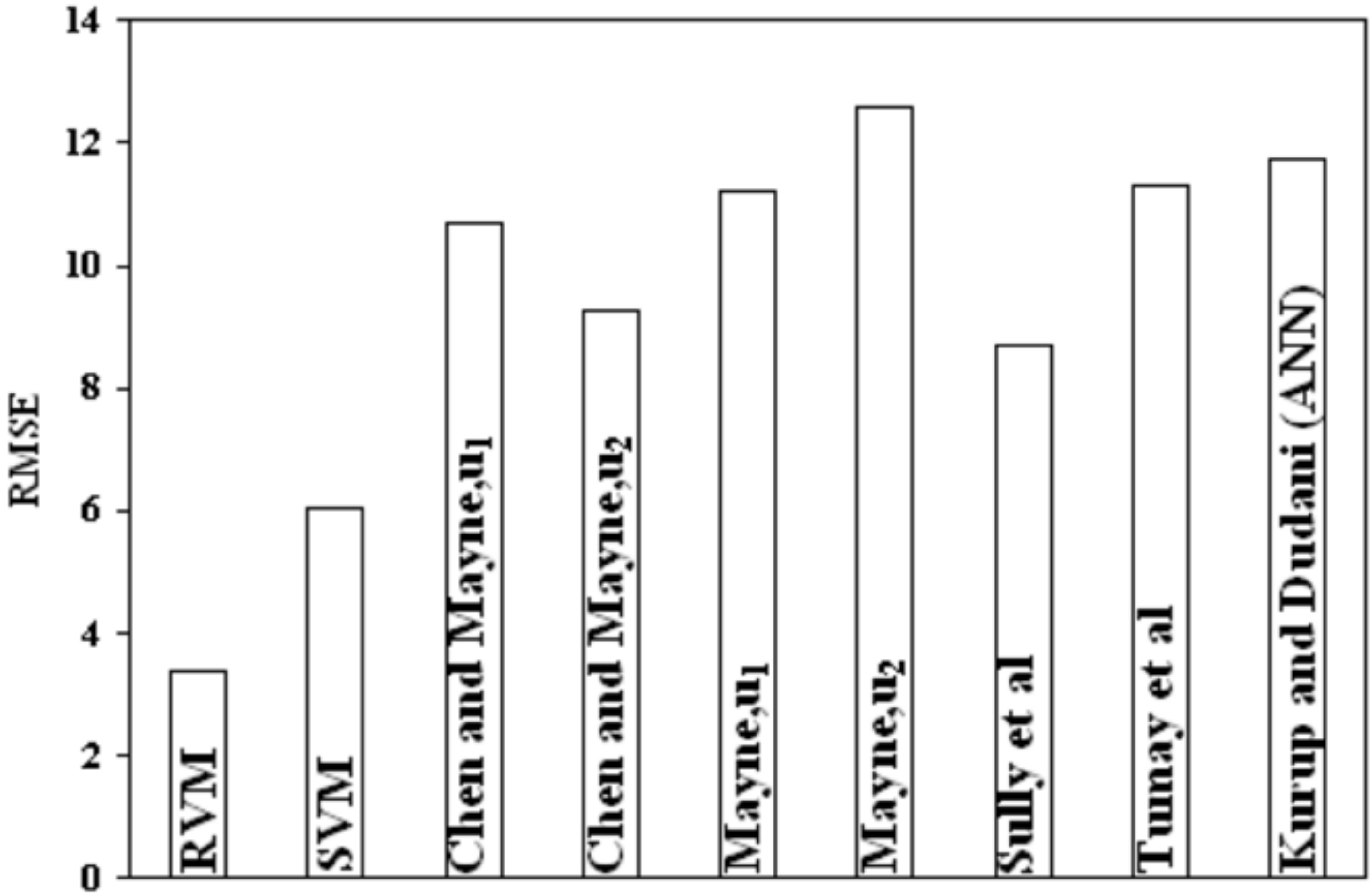

Figure 6. Comparison between RVM and traditional methods in terms of RMSE.

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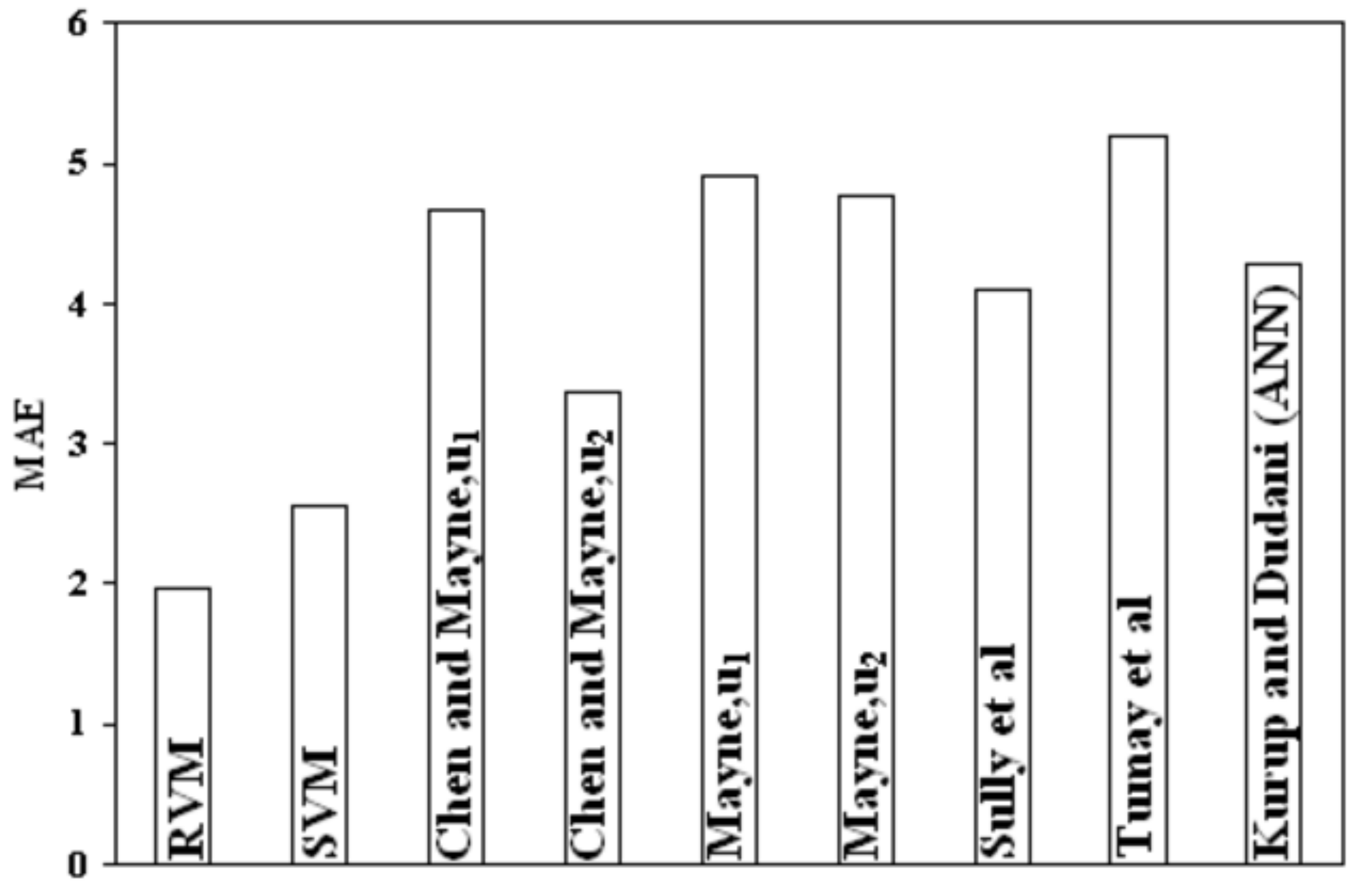

Figure 7. Comparison between RVM and traditional methods in terms of MAE.

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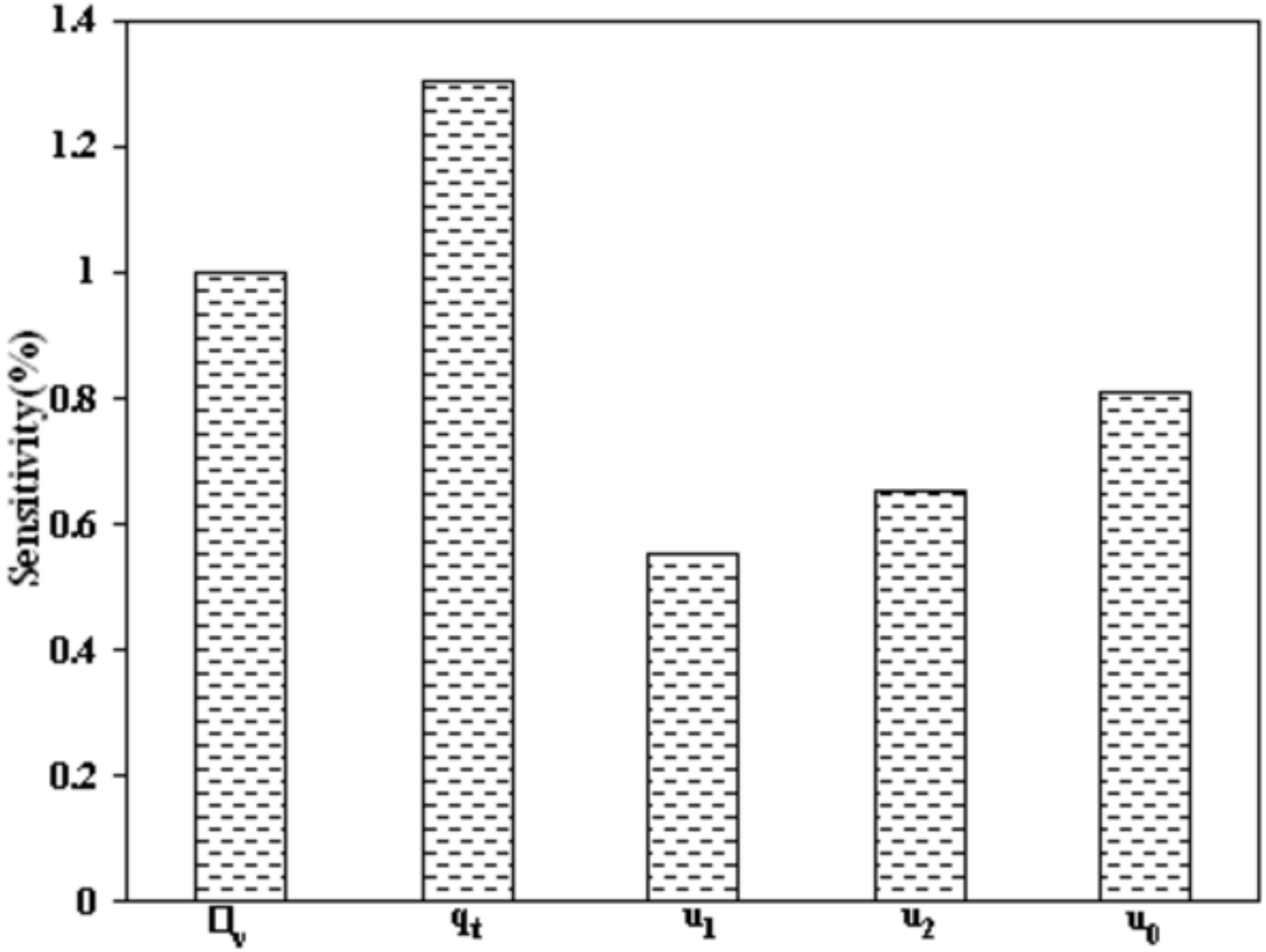

Figure 8. Sensitivity analysis of input parameters.

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Table 1. Statical parameter of the dataset.

Variables	Minimum	Maximum	Average	Standard Deviation	Skewness	Kurtosis
σ_v(KPa)	0.9	922	186	156.4	1.4159	5.7095
q_t(KPa)	34	7902	1071.3	1112.1	2.4547	11.6145
u_1(KPa)	24	5633	689.6	655.9	2.9120	18.9191
u_2(KPa)	1	2422	397.4	386.7	1.9508	8.5004
u_0(KPa)	0	512	93.2	90.7	1.7029	6.7373
OCR	1	80	6.5	11.5	3.4143	16.2547

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Table 2. Performance of different kernels.

kernel	Training performance(R)	Testing performance(R)
Polynomial	0.902	0.856
Spline	0.897	0.834
Radial basis function	0.972	0.956

Figure Captions list

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Figure 1. Performance of training dataset.

Figure 2. Performance of testing dataset.

Figure 3. The values of w.

Figure 4. Variance of training dataset.

Figure 5. Variance of testing dataset.

Figure 6. Comparison between RVM and traditional methods in terms of RMSE.

Figure 7. Comparison between RVM and traditional methods in terms of MAE.

Figure 8. Sensitivity analysis of input parameters.