Prediction of Pavement Performance

Application of Support Vector Regression with Different Kernels

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The pavement performance model is a basic part of the pavement management system. The prediction accuracy of the model depends on the number of effective variables and the type of mathematical method that is used for modeling the pavement performance. In this paper, the capability of the support vector machine (SVM) method is analyzed for predicting the future of the pavement condition. Five kernel types of SVM algorithm are formed and nine input variables of the proposed models are extracted from the range of effective variables on the pavement condition. The international roughness index is used as the pavement performance index. The results show that the Pearson VII Universal kernel can accurately predict pavement performance in its life cycle.

The pavement management system (PMS) concept was conceived in the mid-1960s to organize and coordinate the activities involved in achieving the best value possible for the available funds (*1, 2*). The American Public Works Association defines pavement management as a systematic method for the routine collection, storage, and retrieval of the kind of decision-making information needed to make maximum use of a limited maintenance budget (*3*). The pavement performance model is one of the critical parts of pavement management, and predicting the performance of a pavement affects the budget allocation for its maintenance in the future. Therefore, the accuracy of the pavement performance model should be at a significant level. Predicting the performance of a pavement with respect to estimating and simulating the deterioration process is very difficult, and the process is strongly connected to the assessment of pavement condition and serviceability level (*4, 5*). Pavement performance is affected by various parameters and an accurate model must take all of them into consideration. In this way, mathematical methods are used to find relationships between pavement performance and the parameters that affect it. Thus it is important to find a better mathematical method to predict the future of the pavement condition.

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In this paper, a data set consisting of nine effective variables on pavement condition is collected and modeled using a support vector machine (SVM) for regression. SVM offers the following advantages over conventional statistical learning algorithms (i.e., decision tree learning, maximum entropy method): (*a*) high generalization performance even with high-dimension feature vectors and (*b*) the ability to manage kernel functions that map input data to higher-dimensional space without increasing computational complexity (*6*).

The Long-Term Pavement Performance (LTPP) program is used to prepare data points for modeling and to investigate the accuracy of the examined model. The prepared data are used as training data to construct five types of SVM algorithms for the modeling of pavement performance. The results are then compared to indicate the capability of each proposed model.

The paper is structured in the following sections: pavement performance models and effective variables on pavement condition, specifications of the SVM method, an explanation of how the required data were collected, and results of the examined model for the prediction of pavement performance.

PAVEMENT PERFORMANCE MODELS

The PMS consists of several parts. The evaluation of pavement condition or performance and the prediction models that forecast its condition in the future are two of the main parts of the PMS (*7, 8*). A road pavement continuously deteriorates as a result of the combined actions of traffic loading and the environment. The ability of the road to satisfy the demands of traffic and the environment over its design life is known as performance (*9*). Attoh-Okine mentioned the importance of the pavement performance model (*10*). Without performance models, deferring maintenance would have no technical or economic consequences. The first comprehensive effort to establish an object indicator of pavement performance was made in the late 1950s. Until that time, inadequate attention had been paid to the evaluation of pavement performance; a pavement was considered to be merely either satisfactory or unsatisfactory (*9, 11*).

In general, there are two types of pavement performance. One refers to the structure of the pavement and includes such things as fatigue, while the other expresses the function of the pavement and includes riding quality. Various indexes have been used to describe the pavement performance as it relates to structural or functional condition. For example, the present serviceability index, pavement condition rating, pavement condition index, international roughness index (IRI), and riding comfort index are common indexes used to describe the condition of a pavement. With current pavement condition assessments, agencies are equipped with the information needed to predict the future condition of a segment. In pavement management, conditions are predicted with respect to performance models that estimate the average rate of pavement deterioration each year. In addition to forecasting future conditions, these performance models assist with the following activities (*4, 12*):

- Identifying the appropriate timing for pavement maintenance and the rehabilitation of each segment;
- Identifying the most cost-effective treatment strategy for the pavement segments in the network;
- Estimating pavement needs and associated budgets required to address agency-specified goals, objectives, and constraints; and
- Demonstrating the consequences of different pavement investment strategies.

Many models for the prediction of pavement performance are already available but, given the same input data, they tend to produce different predictions. Pavement performance models should be based on fundamentally correct standard engineering principles to be reliable and acceptable. It is also important that these models are easily adjustable to the available historical data and the engineer's knowledge of local materials, environmental effects, construction and maintenance practices, and so forth (*13*). Because making accurate predictions is important, the methods for predicting pavement performance should not be selected arbitrarily. Mistakes or a random selection of methods for performance prediction can be costly to the highway system (*10*). However, it is difficult to find a complete model that involves all properties; as Molenaar mentioned, in spite of the enormous efforts that have been made in the pavement engineering field, it still is not possible to make accurate and precise predictions of pavement life (*14*). Nonetheless, researchers have developed many methods, including regression models (*15–19*), Markovian approaches (*20–22*), neural network methods (*23–25*), fuzzy logic models (*1, 4*), and hybrid techniques (*26*). Each model contains distinct specifications about the mathematical approach used for modeling and the number of effective variables on pavement performance considered in the modeling. Thus the reasonable accuracy of the model is related to these two elements. Each of these models forecasts the effect of change in the effective variables on pavement condition. Each mentioned model has its own specific advantage and disadvantage and also exhibits different prediction accuracies.

A mathematical approach is used to find the relationships between pavement condition and the effective variables on it. Therefore, it is important to examine the various mathematical methods to find the best one for expressing the relationships between input and output factors of the pavement performance model. To date, modeling of pavement performance has been extremely complicated since no PMS can consider more than a few of the parameters (*27*).

The pavement deterioration process is influenced by many interacting parameters, including, but not limited to, pavement design, layer thicknesses, properties of materials, construction quality, underlying soil characteristics, climate changes, traffic loading, and maintenance activities (*28*). The interactions of these parameters result in a complex system. There is also a large variation in the characteristics of pavement materials and structures.

Moreover, the available performance prediction models have several limitations in that most of them involve large simplifications and some contain input factors that are difficult to quantify and do not consider all the effective factors. Each model used has specific advantages and disadvantages related to the type of applied model and the type of effective variable. For example, regression models are simple to understand and use in a PMS, but these are not adaptable to a wide range of road properties. Furthermore, heuristic methods, such as an artificial neural network, are able to model a complex system like pavement performance but they require historical data that are not always available for all types of roads. Some models concentrate on material properties, and others focus on traffic loadings or pavement structure. To date, the modeling of pavement performance has been extremely complicated since no PMS can consider more than a few of the parameters (*10*). The prediction accuracy of the models needs to be analyzed during the duration of a pavement life cycle because the prediction model may show a range of accuracies in the pavement life cycle (*23*). Thus, it is important for PMS users to identify the reliability of the models in both the short and long terms of the pavement life cycle for appropriate budget allocation to be made.

Machine learning techniques have been widely used in the literature to solve civil engineering predictions and classification problems (*29–36*). Also, some researchers used this technique in pavement evaluation (*37–41*). In this paper, SVM is used to predict pavement performance in an attempt to use more effective input variables of the prediction model. In addition, the accuracy of the proposed SVM models is analyzed in the short and long term.

SUPPORT VECTOR MACHINE FOR REGRESSION

SVM is a statistical learning method that was developed by Boser et al. (*42*). Maximizing the margin between the separating hyperplane and data rather than minimizing the trading error is one of the main advantages of SVM in comparison with traditional learning schemes. SVM was initially developed to solve classification problems in a simple binary classification problem with (x, y) data set where $y \in \{-1, +1\}$; it can separate two classes as follows by using a hyperplane where w is weight vector and b is bias:

$$\langle (w, x_i) + b \rangle \geq +1 \qquad \text{if } y_i = +1 \tag{1}$$

$$\langle (w, x_i) + b \rangle \geq -1 \qquad \text{if } y_i = -1 \tag{2}$$

which can be summarized as

$$y_i \langle (w, x_i) + b \rangle \geq +1 \tag{3}$$

The distance between point x_i and the classifier hyperplane is

$$\frac{\left| \langle (w, x_i) + b \rangle \right|}{\|w\|} \tag{4}$$

and with margin p then

$$\frac{y_i \left| \langle (w, x_i) + b \rangle \right|}{\|w\|} \geq p \tag{5}$$

for the canonical hyperplane numerator is equal to 1, and the distance of training instances that are closest to the hyperplane so-called support vectors is calculated as follows:

$$r = \frac{1}{\|w\|} \tag{6}$$

$$p = 2r = \frac{2}{\|w\|} \tag{7}$$

Thus, for finding the maximum margin, the $\|w\|$ needs to be minimized:

$$\text{minimize } \frac{1}{2}\|w\|^2 \tag{8}$$

subject to

$$y_i\langle(w, x_i) + b\rangle \geq +1 \qquad i = 1, \ldots, n \tag{9}$$

This model can be transformed into the dual space by using the Lagrangian function (*43*):

$$L(w, b, \alpha) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{n} \alpha_i \left(y_i\left(\langle(w, x_i) + b\rangle\right) - 1\right) \tag{10}$$

$$\frac{\partial L(w, b, \alpha)}{\partial w} = 0 \Rightarrow w\sum_{i=1}^{n} \alpha_i y_i x_i \tag{11}$$

$$\frac{\partial L(w, b, \alpha)}{\partial b} = 0 \Rightarrow w\sum_{i=1}^{n} \alpha_i y_i = 0 \tag{12}$$

It therefore can be considered as a dual optimization problem:

$$\text{maximize} \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_{j\langle x_i, x_j\rangle} \tag{13}$$

subject to

$$\sum_{i=1}^{n} \alpha_i y_i = 0 \tag{14}$$

$$\alpha_i \geq 0 \qquad i = 1, \ldots, n \tag{15}$$

where α_i are so-called support vectors that follow the Karush–Kuhn–Tucker (*44*) theorem.

$$\alpha_i\left[y_i\left(\langle w, x_i\rangle + b\right) - 1\right] = 0 \qquad i = 1, \ldots, n \tag{16}$$

$$\alpha_i \geq 0 \Rightarrow y_i\left(\langle w, x_i\rangle + b\right) - 1 = 0 \tag{17}$$

$$\alpha_i = 0 \Rightarrow y_i\left(\langle w, x_i\rangle + b\right) - 1 \geq 0 \tag{18}$$

Thus only support vectors that have nonzero α_i and x_i's with $\alpha_i = 0$ are beyond separating hyperplanes (*45*). Also, the similarly modeled soft margin in SVM (Equation 31) is valid for all misclassified instances.

$$y_i\left(\langle w, x_i\rangle + b\right) \geq 1 - \xi_i \tag{19}$$

Thus $\xi_i \geq 1$ must be minimized:

$$\text{minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \tag{20}$$

subject to

$$y_i\left(\langle w, x_i\rangle + b\right) \geq 1 - \xi_i \qquad i = 1, \ldots, n \tag{21}$$

$$\xi_i \geq 0 \qquad i = 1, \ldots, n \tag{22}$$

$$C \geq \alpha_i \geq 0 \qquad i = 1, \ldots, n \tag{23}$$

Cortes and Vapnik introduced SVM for regression by considering the regression as a single classification problem with a training set of N sample: (x_1, t_1), (x_2, t_2), . . . , (x_N, t_N) and ε-insensitive error function (*46*).

$$E_e(y(x) - t) = \begin{cases} |y(x) - t| - \varepsilon & \text{otherwise} \\ 0 & \text{if } |y(x) - t| < \varepsilon \end{cases} \tag{24}$$

The error then needed to be minimized is as follows:

$$C\sum_{i=1}^{N} E_e(y(x_i) - t_i) + \frac{1}{2}\|W\|^2 \tag{25}$$

Among the SVM techniques for regression, the authors selected SMO (sequential minimal optimization), which was originally developed by Microsoft (*47*) for classification. SMO regression is fast in solving large quadratic programming (QP) problems. It splits the QP problems into a series of simpler possible QP problems and then solves these small components analytically. SMO regression is able to deal with a huge number of attributes in training sets and is also flexible in avoiding overfitting by maximizing the margin around its hyperplane (*48*).

Kernels are used in SVM to deal with nonlinear classification and regression problems by reducing the complexity of the calculations (*49*). A kernel calculation is easy, but it reduces the complexity of feature vectors by providing an opportunity to linearly solve nonlinear functions in high-dimensional spaces. In this research, the authors used three nonlinear kernels as follows:

1. Polynomial (*d*th degree)

$$K(x, y) = (1 + (x, y))^d \tag{26}$$

2. Radial basis function (*C* is constant)

$$K(x, y) = \exp\left(-\frac{\|x - y\|^2}{C}\right) \tag{27}$$

3. Pearson VII Universal (*50*)

$$K(x, y) = \frac{1}{\left[1 + \left(\frac{2\sqrt{\|x - y\|^2}\sqrt{2^{(1/\omega)} - 1}}{\sigma}\right)^2\right]^\omega} \tag{28}$$

where ω and σ are constant and control the half-width and tailing factor of peak in the Pearson VII function (*51*).

DATA COLLECTION

The effective implementation and utilization of PMSs in generating and evaluating various alternative strategies based on engineering and economic principles is largely dependent on the ability to predict the future condition of pavement (*13*). The accurate prediction of pavement performance is very important for the efficient management of the road infrastructure. By reducing the prediction error of pavement deterioration, agencies can achieve significant budget savings through timely intervention and accurate planning (*52*). The accuracy prediction of the pavement performance model depends on the mathematical method and the number of effective variables used for modeling. The pavement deterioration process is influenced by many interacting parameters, including, but not limited to, pavement design, layer thicknesses, properties of materials, construction quality, underlying soil characteristics, climate changes, traffic loading, and maintenance activities (*28*).

In this research, the main effective variables on pavement performance were studied and the effective factors gathered from groups of pavement structure, climate changes, and traffic loadings. Each effective group consists of some factors that affect pavement performance directly or indirectly. There are some unknown factors that affect the pavement deterioration and also it is difficult to quantify some available factors. For example, the pavement structure group consists of several factors, such as surface thickness, base and subbase layers, percentage of asphalt content, percentage of air void of hot-mix asphalt, unit weight of hot-mix asphalt, percentage passing No. 200 and No. 4 sieves, and plasticity index of base, subbase, and subgrade (*24*). In this way, nine factors that affect pavement condition are extracted from the main effective groups. For the purpose of this paper, surface thickness and pavement thickness, including surface, base, and subbase, were selected from a group of pavement materials and structure. Equivalent single-axle load, annual average daily traffic, annual average daily truck traffic, annual average precipitation, annual average temperature, and annual average freeze index were selected from the traffic condition group and climate changes group, respectively. Pavement age (number of years since construction) is another effective factor. Each of the elements is measured annually in the pavement life cycle (*23*).

Several indexes have been invented to indicate pavement condition or deterioration. The most common indexes of pavement performance are fatigue, cracking, surface rutting, riding quality, and skid resistance (*9*). In this research, IRI was used as the pavement condition index. The IRI is a summary statistic of the surface profile of the road and is computed from the surface elevation. It is defined as the average rectified suspension motion to the traveled distance obtained from a mechanical model of a standard quarter-car traveling over the road profile at 80 km/h (*9, 53*). IRI value is raised by increasing pavement age and also by the effect of deterioration elements. In this paper, the proposed models predict the change of the IRI characteristic versus pavement operation time.

LTPP was used to provide the required data for modeling and analyzing the accuracy of the models. This LTPP program is primarily designed to provide state-of-the-art information to state highway agencies so they can build and maintain longer-lasting pavements (*54*). The accuracy of the LTPP database is acceptable and is used in different research. The LTPP data set is composed of a categorized set of data from various pavement types. The data set contains detailed information on pavement materials, environmental conditions, traffic, and maintenance and rehabilitation (*24*).

In this research, asphalt concrete pavement on a granular base was chosen as the study pavement and was selected from various types of pavement. The pavements without rehabilitation or reconstruction in their life cycle were used to show continuous change in IRI versus the age of the pavement. The type of the subgrade is limited to one type, so the effect of this factor is permanent in the modeling; it is also assumed that standard materials were used in the pavement construction. However, analyzing the effect of material properties is not the goal of this paper. To avoid a lack of data in a wide range of properties, the sections without any annual average daily traffic greater than 1,000 or annual average freeze index greater than 100 in their life cycles were not selected. The linear interpolation was used to determine the missing data. Thus 26 sections, including 205 observations of annual data, were extracted. The following list shows the specifications of the data from the general and specific pavement studies in LTPP for the prediction model of pavement performance:

- Type of surface layer: hot-mix asphalt concrete
- Type of base layer: granular
- Age: up to 17 years
- Annual average precipitation: 131.4 to 1,786.7 mm
- Annual average temperature: 3.9°C to 17.5°C
- Annual average freeze index: up to 1,360°C-day
- Annual average daily traffic: 225 to 14,629 (some sections have less than 1,000 in some years of the life cycle, but not in all years of the life cycle)
- Annual average daily truck traffic: 14 to 5,336
- 18-kip equivalent single-axle load: 8 to 1,128
- Pavement thickness: 9.52 to 40.9 in.
- Surface thickness: 1.4 to 11.7 in.
- IRI: 0.586 to 4.005 m/km

RESULTS AND DISCUSSION

This section reports and discusses the achieved results. As mentioned in the previous section support vector regression (SVR) with three different kernels (polynomial, Pearson VII Universal, and radial basis function) was used for predicting IRI. All learning schemes are trained and tested with one data set, which was described above. Parameter selection is a critical stage when SVR with different kernels is used (*55–58*). In this study, polynomial kernels with Degree 1 to 3 were tested to ensure the maximum capacity of polynomial kernels has been utilized. Therefore, SVR with five different kernels as numbered in Table 1 was used to predict asphalt IRI. A 10-fold cross validation was used for evaluating the selected algorithms, with 10-fold cross validation being the standard way of assessing a learning scheme on a particular data set (*59*). In this evaluation method, the data sets are divided into 10 folds, with around nine folds used for training; the remaining 10% of the data is used for testing. To assess the performance of the selected algorithms, three metrics of mean absolute error (MAE), root mean square error (RMSE), and correlation coefficient were used. The equations related to these performance criteria are presented in Equations 29 to 31.

$$\mathrm{MAE} = \left(\frac{1}{N} \sum_{i=1}^{N} \left(\frac{\left| \mathrm{IRI}_{i,\mathrm{act}} - \mathrm{IRI}_{i,\mathrm{pred}} \right|}{\mathrm{IRI}_{i,\mathrm{act}}} \right) \right) \tag{29}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\mathrm{IRI}_{i,\mathrm{act}} - \mathrm{IRI}_{i,\mathrm{pred}})^2} \tag{30}$$

TABLE 1 Tenfold Cross Validation Results of SVR with Different Kernels

Kernel	Algorithm ID	MAE	RMSE	Correlation Coefficient
Polynomial				
Degree = 1	1	0.341	0.4925	.5874
Degree = 1	2	0.25	0.3922	.7555
Degree = 1	3	0.2645	0.4245	.7499
Pearson VII Universal kernel	4	0.1489	0.2259	.9169
Radial basis function	5	0.3858	0.5787	.5592

$$\text{correlation coefficient} = \frac{\sum_{i=1}^{N}\left(\text{IRI}_{i,\text{pred}} - \overline{\text{IRI}_{i,\text{pred}}}\right)\left(\text{IRI}_{i,\text{act}} - \overline{\text{IRI}_{i,\text{act}}}\right)}{\sqrt{\sum_{i=1}^{N}\left(\text{IRI}_{i,\text{pred}} - \overline{\text{IRI}_{i,\text{pred}}}\right)^2 \times \sum_{i=1}^{N}\left(\text{IRI}_{i,\text{act}} - \overline{\text{IRI}_{i,\text{act}}}\right)^2}} \tag{31}$$

where

N = number of test instances,
IRI_{act} = actual value of IRI, and
IRI_{pred} = value of IRI predicted by the model.

A lower value of RMSE and MAE and a higher value of correlation coefficient close to 1 indicate better model performance.

In Table 1, the summary of 10-fold cross validation is reported using three different metrics (MAE, RMSE, and correlation coefficient). For SVR with polynomial kernels, increasing the degree (d in Equation 26) does not necessarily lead to an improvement in the accuracy, and from the results one can see that the degree of 2 outperformed other polynomial degrees. However, in general, SVR with Pearson VII Universal kernel outperformed other algorithms by achieving better values in all three metrics.

In Table 1, the average of the metrics achieved from 10-fold cross validation is reported but does not show the variation in predictions. In Figures 1 to 3, respectively, the variations of MAE, RMSE, and correlation coefficient achieved from 10-fold cross validation are depicted. It is clear that Algorithm 4 (SVR with Pearson VII Universal kernel) is the most stable learner and radial basis function is the worst.

To achieve a better understanding of the performances of the selected algorithms, the predictions are investigated in detail to reveal the strengths and weaknesses of each algorithm. In Figure 4, the predicted values versus the actual IRI values are illustrated. The blue line represents the desired situation when predictions and actual values are exactly the same. This figure indicates that the performance of SVR with polynomial kernels is very similar when Algorithm 1 (d = 1) slightly underestimates Algorithm 2 (d = 2) and Algorithm 3 (d = 3) but is not worse than Algorithm 5 (radial basis function). However, as expected, Algorithm 4 clearly achieves a better result.

For a deeper study, in Figure 5 the absolute residual of predictions versus actual IRI values is depicted. In this figure, the most desired situation is when the dots are overlain on a horizontal axis. This figure shows that for algorithms, with the exception of Algorithm 4, by increasing the IRI values the absolute residuals also increase. Similarly, in Figure 6 the sign of residuals is illustrated, and all algorithms, with the exception of Algorithm 4, have underestimated the IRIs between 0 and 1.5 and have mostly overestimated the IRIs over 1.5. Because of the dots overlapping, the only issue that cannot be perceived from Figures 4 to 6 is the distribution of errors for each algorithm. This issue has been investigated in Figure 7. Although this figure indirectly supports Figures 4 to 6, it also shows that Algorithm 3 and Algorithm 4 have obtained the highest number of relatively zero error predictions.

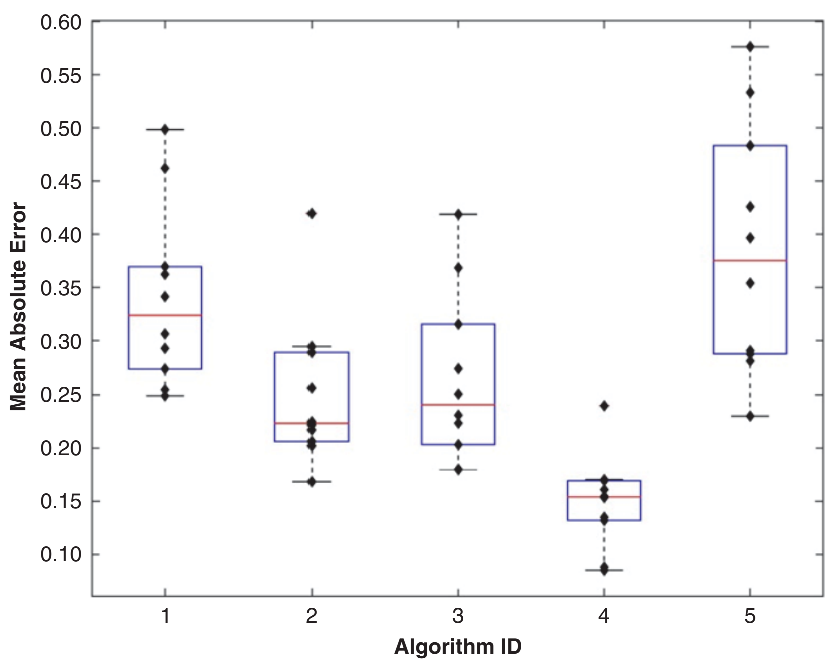

FIGURE 1 Variations of mean absolute error achieved from 10-fold cross validation.

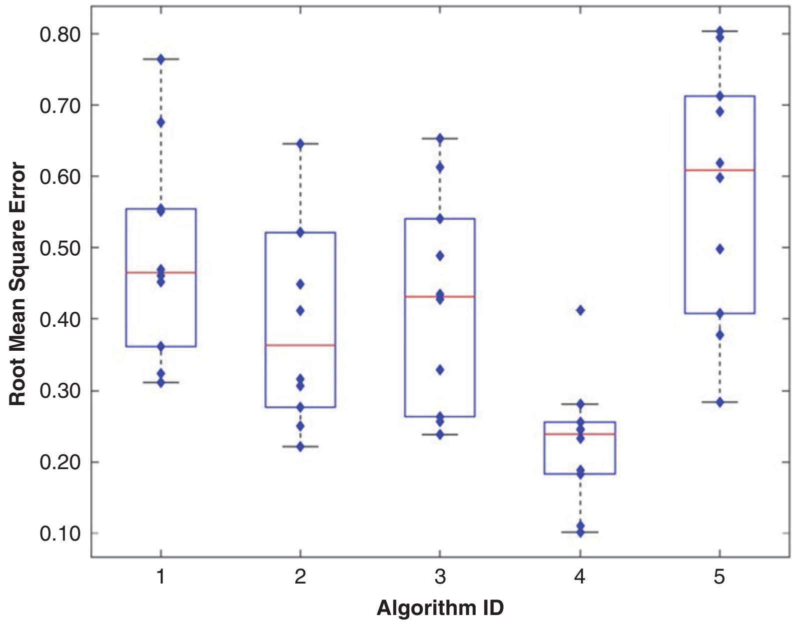

FIGURE 2 Variation in 10-fold cross validation for root mean square error.

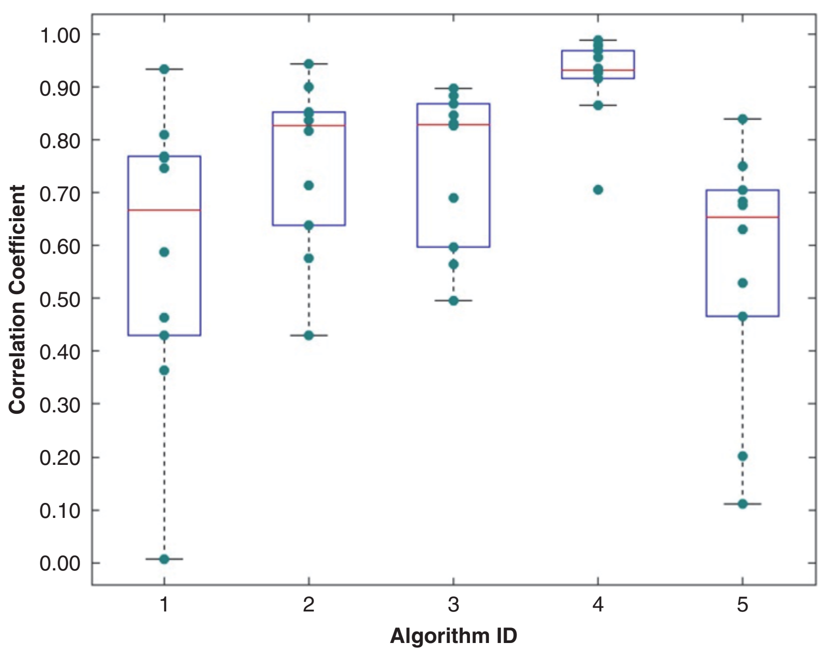

FIGURE 3 Variation in 10-fold cross validation for correlation coefficient.

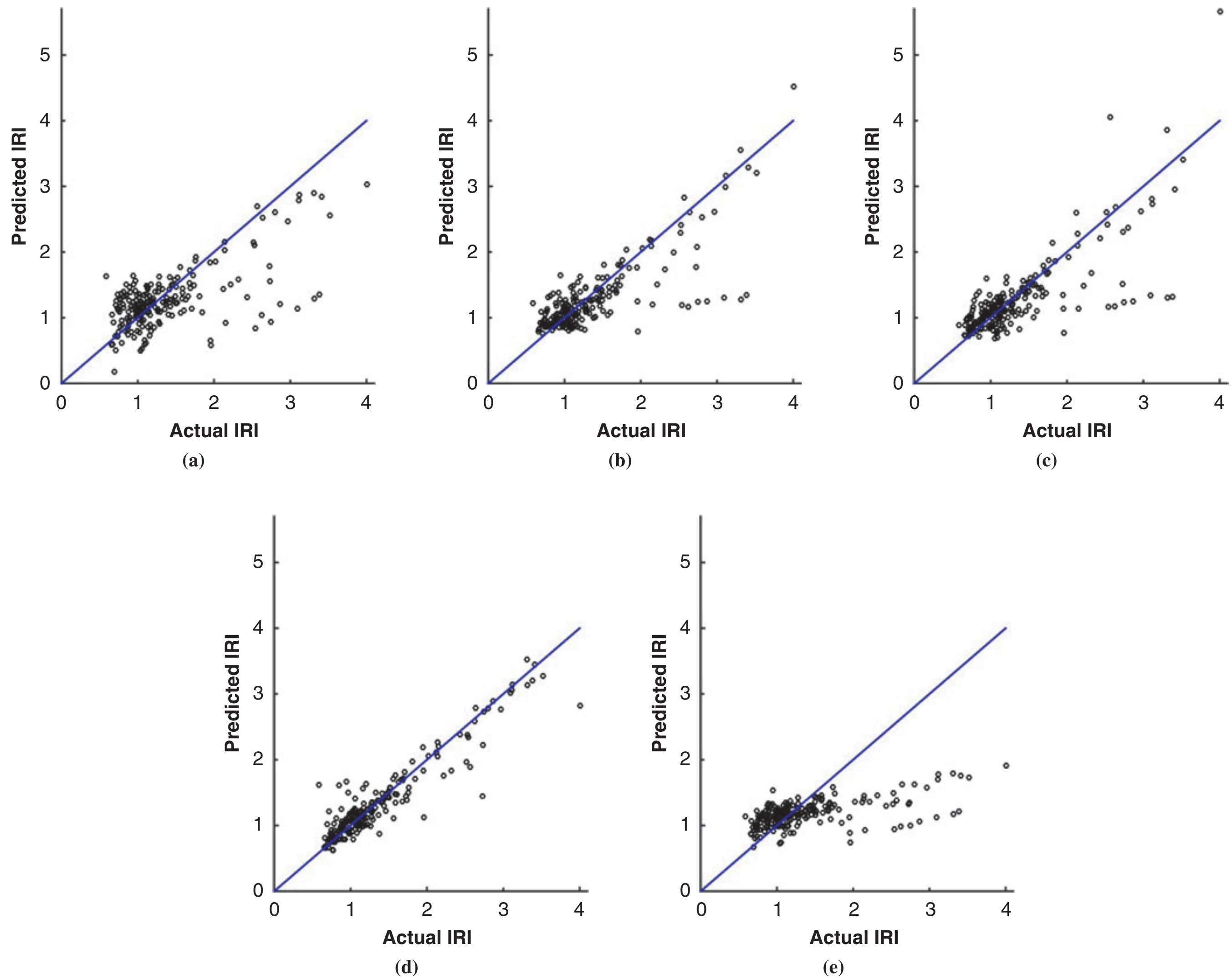

FIGURE 4 Correlation between actual IRI and predicted IRI.

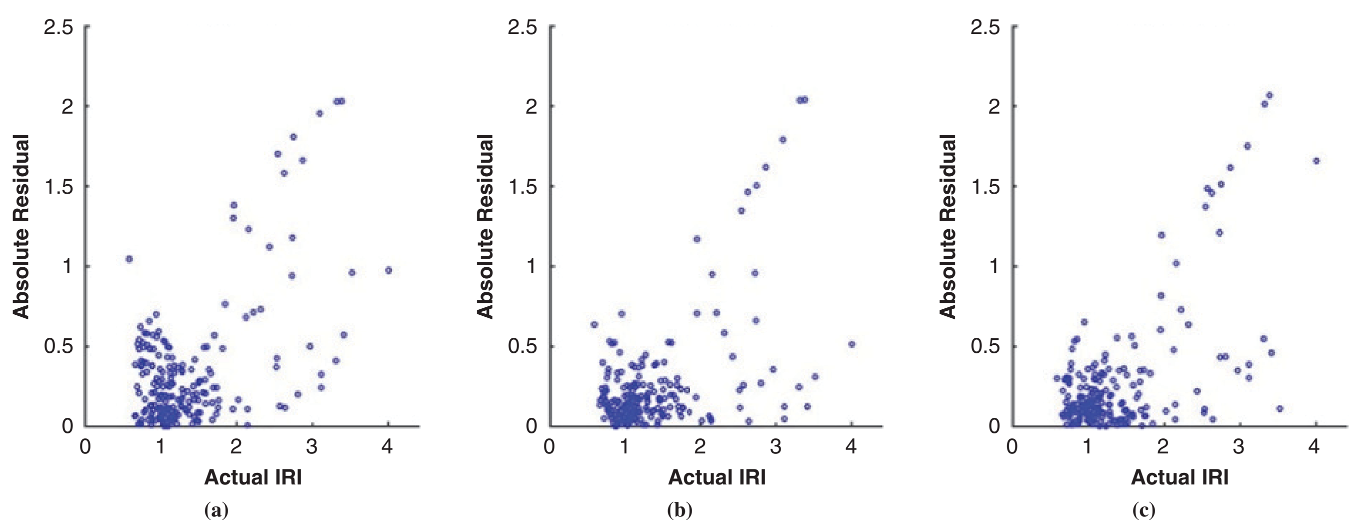

FIGURE 5 Correlation between actual IRI and absolute residuals of predictions.

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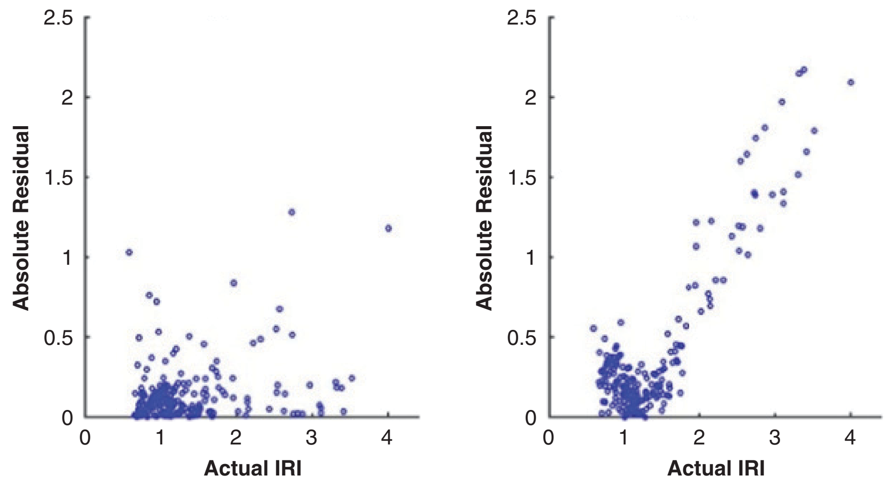

(d) (e)

FIGURE 5 *(continued)* Correlation between actual IRI and absolute residuals of predictions.

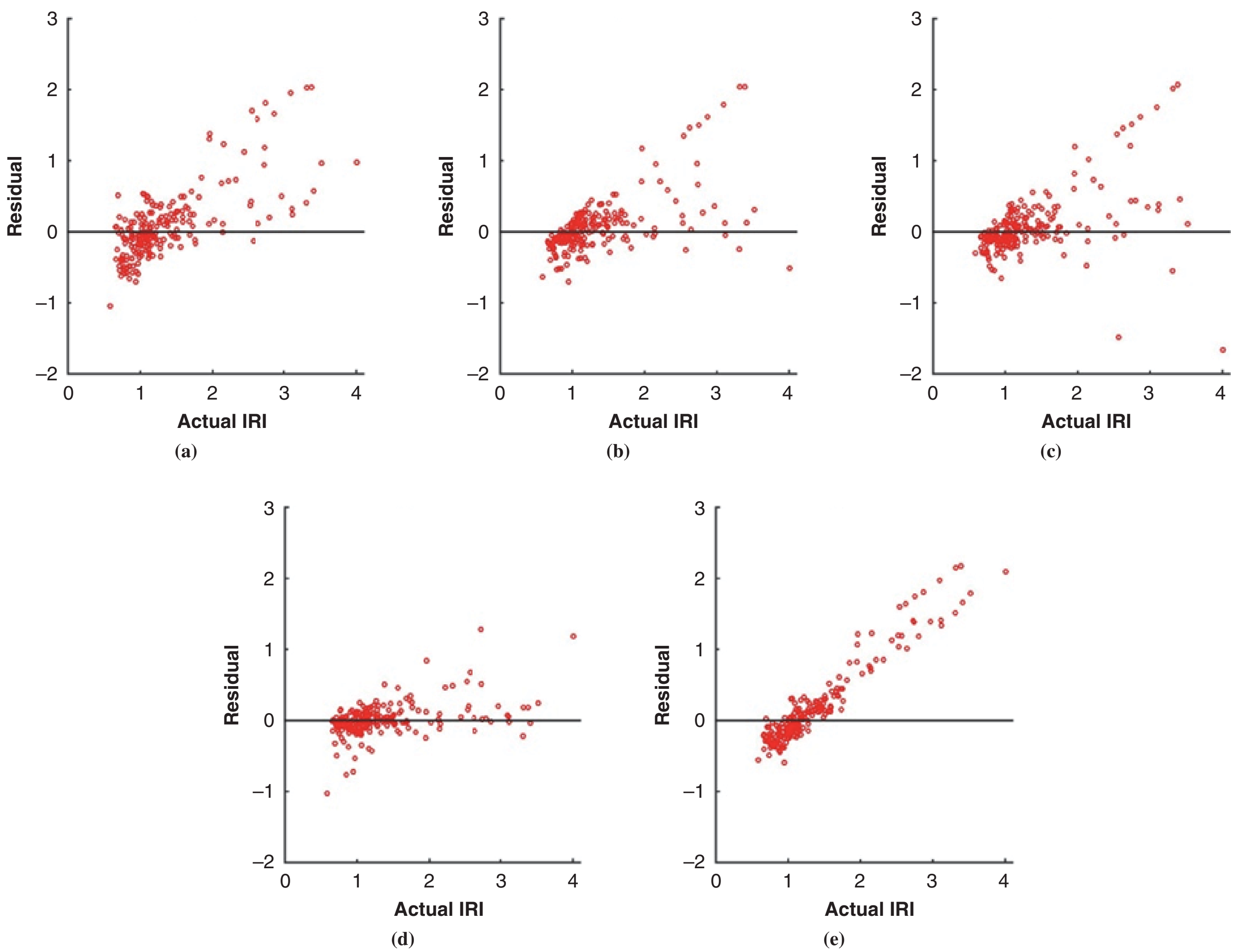

FIGURE 6 Correlation between actual IRI and residuals of predictions.

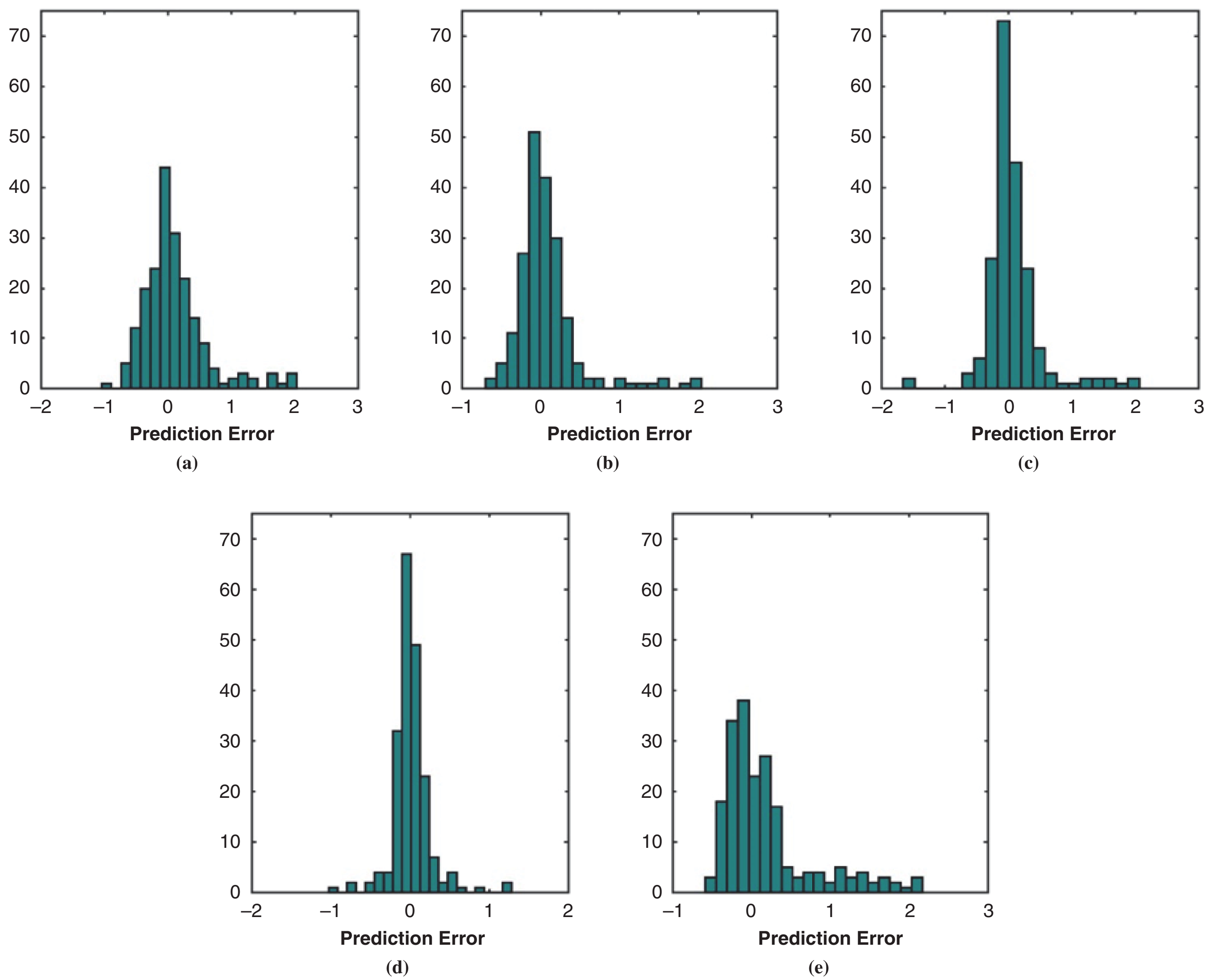

FIGURE 7 Histograms of prediction errors.

According to the concept of IRI, the IRI value rises by increasing pavement age because of the effects of deterioration factors (*24*), so the IRI value is low in the short term and is increased in the long term. As seen in Figures 4 to 6, all types of the SVM models, except Algorithm 4, demonstrate unacceptable errors in the short and long terms combined. For example, Algorithm 5 depicts a high correlation and low error in the short term while it depicts high data scattering around the correlation line and high error in the long term. Algorithm 4 exhibits good distribution of data points around the correlation line and a reasonable rate of error in the short and long terms combined.

It is essential for a tuned model to meet all performance criteria for having a reliable model. In this study SVM with Pearson VII Universal kernel predicted pavement performance when it was trained and tested with a field data set consisting of nine effective variables. The qualified SVM method obtained a correlation coefficient of .916 and MAE of 0.148 (equal to 14.8% error, which is accepted) and RMSE of 0.225, which is reasonable. So it can be concluded that in this context SVM with Pearson VII Universal kernel can predict pavement performance in the PMS with acceptable accuracy.

CONCLUSION

The accurate prediction of pavement performance directly affects budget allocation for the maintenance and rehabilitation of the PMS. In this paper, the SVM method was applied to predict the future of pavement performance. To this end, nine effective variables on pavement deterioration were considered and used in five types of SVM algorithm. The results show that the Pearson VII Universal kernel of SVM is capable of predicting pavement performance in the short and long terms of the pavement life cycle. Some other types of SVM, such as the radial basis function kernel of SVM, exhibit a reasonable accuracy of prediction but only in the short term. In general, the SVM method by Pearson VII Universal kernel and the nine effective variables could be proposed as a pavement performance model in the PMS. Further research could examine more effective variables and other mathematical methods for the modeling of pavement performance.

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