WARSAW UNIVERSITY OF TECHNOLOGY Index 351733
FACULTY OF CIVIL ENGINEERING
COMMITTEE FOR CIVIL AND WATER ENGINEERING
POLISH ACADEMY OF SCIENCES ISSN 1230-2945

DOI: 10.24425/ace.2022.143061

ARCHIVES OF CIVIL ENGINEERING

Vol. LXVIII ISSUE 4 2022

 pp. 669 –682

Research paper

Estimate final cost of roads using support vector machine

Musaab Falih Hasan[1], Oday Hammody[2], Khaldoon Satea Albayati[3]

Abstract: The cost overrun in road construction projects in Iraq is one of the major problems that face the construction of new roads. To enable the concerned government agencies to predict the final cost of roads, the objective this paper suggested is to develop an early cost estimating model for road projects using a support vector machine based on (43) sets of bills of quantity collected in Baghdad city in Iraq. As cost estimates are required at the early stages of a project, consideration was given to the fact that the input data for the support vector machine model could be easily extracted from sketches or the project's scope definition. The data were collected from contracts awarded by the Mayoralty of Baghdad for completed projects between 2010–2013. Mathematical equations were constructed using the Support Vector Machine Algorithm (SMO) technique. An average of accuracy (AA) (99.65%) and coefficient of determination (R^2) (97.63%) for the model was achieved by the created prediction equations.

Keywords: estimate cost, roads, support vector machine

[1]MSc. Eng., General Directorate of Education Baghdad Rusafa First, Ministry of Education, Iraq, e-mail: musabmfh0000@yahoo.com, ORCID: 0000-0001-7036-0106
[2]Asistant Lecturer, Civil Engineering Department, University of Technology, Baghdad, Iraq, e-mail: 10984@uotechnology.edu.iq, ORCID: 0000-0001-5002-3882
[3]MSc. Eng., Iraqi Reinsurance Company, Ministry of Finance, Iraq, e-mail: k2a2c2h2a2n@yahoo.com, ORCID: 0000-0002-7317-6264

1. Introduction

Success in a company's project depends on completing pre-agreed tasks within the predetermined budget. Before agreeing on the contract terms, attention should be paid to all project implementation stages. Analysis of the costs of road construction projects is a necessity. To see if the potential project is acceptable to the contractor, which is done during the pre-contract stage to make a decision about involvement in the project, i.e., by making an offer. Many projects cost more than originally expected, as evidenced by the fact that actual project completion costs are almost always higher than initial estimates. Because the contractor has so little information about the job when forming a preliminary estimate, modern prediction methods are extremely valuable, and one such method is using a support vector machine. The important advantage of the support vector machine algorithm is that it can handle high dimensional data and this proves to be a great help taking into account its usage and application in the machine learning field, effective in instances where the number of dimensions is larger than the number of specimens and has better accuracy in results when compared with other algorithms used to predict.

2. Research methodology

In this paper, the following steps were carried on:

- The bills of quantity for the construction road were obtained from the Mayoralty of Baghdad and used to develop a Support Vector Machine (SVM) model to estimate the final cost.
- A model was statistically tested.

3. Literature review

To help owners and planners estimate the cost of a project, the construction conceptual cost estimate model is developed using Support Vector Machine (SVM). Literature review and expert interviews are used to identify the factors that influence cost estimations. The costs of 29 construction projects are used as training examples. Based on the training results, the average prediction error is less than 10% and the computation time is less than 5 minutes. The error is met during the planning and conceptual design phase of a project's conceptual cost estimate. Case studies have shown that SVM can assist planners in predicting the construction cost more effectively and more accurately [1]. This paper investigates the use of SVM to predict the elastic modulus of normal and high-strength concrete. The elastic modulus predicted by SVM was compared with the experimental data and those from other prediction models such as Artificial Neural Network (ANN) and Regression Analysis (RA). SVM demonstrated good performance and has proven to be better than other models [2]. To estimate steel structure productivity, the researcher used the SVM development model technique and discovered that among the developed models, the Naive Bayes (NB) model was the most appropriate [3]. Using the current state of early planning as model inputs, the researcher developed artificial neural network ensemble and support vector machine classification models to predict project cost and schedule success. Early planning and project performance data from 92 construction projects are gathered through an industry survey. Project success can be predicted using early planning status and the proposed artificial intelligence models [4]. One of the most accurate predictive models, the Support Vector Machine (SVM), was used to forecast construction time. Using Bromilow's "time cost" model, a linear regression model was first applied to the data for 75 objects. To improve the accuracy of the prediction, a support vector machine model was applied to this same data set [5]. This study compares the proposed Support Vector Regression model to the best-performing alternatives using earned value and schedule as benchmarks. Cross-validation and grid search procedures are used to adjust the SVM parameters before a large computational experiment is carried out. This study's findings show that support vector machine regression is superior to other methods for predicting the future. When the discrepancy between training and test sets becomes greater, an experiment is set up to test the proposed method's performance [6]. Researched a road construction project cost estimation model based on a support vector machine. SVM can be used to improve the ability of construction managers to estimate a road project's parametric cost estimate (support vector machine). Collecting historical cases of road executions served as the foundation for this project. The cost-estimation model was found to be most affected by these 12 factors. A total of 70 historical data case studies were randomly divided into three sets: 60 cases for training, 3 cases for cross-validation, and 7 cases for testing. With a 95% accuracy rate, the model could to forecast the project's costs accurately [7]. This study developed an AI model using SVM to predict project time and cost indices. This study used 21 tunnel projects in Kurdistan, Iraq. Input data include contract value, duration, change orders, conflicts, and company classification. WEKA, a machine learning and data mining software developed at the University of Waikato in New Zealand, was used to build the SVM model. The collected data were split by default into training, testing, and validation sets. SVM model I successfully predicted the cost index not only for the trained data, but also for projects with out-of-range input parameters. MAPE and AA for SVM cost index prediction were 13.9% and 86.1%, respectively. MAPE and AA for SVM model II were 3.4% and 96.6%, respectively [8].

4. Support Vector Machine

As a new statistical technique, SVM theory of SVMs has received much attention in the last few years. An alternative training method for polynomial, radial basis function, and multi-layer percept classifiers can be derived from this learning theory [9]. Based on Structural Risk Minimization (SRM) induction theory, SVMs are designed to minimize the generalization error, rather than to minimize squared errors. Regarding solving classification and regression problems, SVMs have proven to be more effective than traditional learning machines in many applications. Stated that only the target variables differ from the equations of classification problems in SVMs [1]. SVM is widely regarded as a promising and attractive tool in classification and regression. Optical character recognition and object recognition are the primary applications of SVM as a classifier thus far. Developed SVM as one of the computers learning methods based on statistical learning theory.

SVM has three distinct characteristics when compared to conventional artificial Neural Networks (NN) regression approximation. Linear functions defined in multidimensional space are used in SVM. To minimize risk, SVM uses loss functions and a risk function that includes the empirical error and a regularization term derived from the SRM [10]. Support vectors are defined as the points closest to the separating hyperplane. The hyperplane's location is all that they determine. All other factors are irrelevant. The normal vector of the hyperplane in Fig. 1 is the weighted sum of the support vectors. SVM outperforms other machine learning algorithms like Neural Networks (NN) in generalization and sparse representation, making it the better choice. The ability to deal with data that are sparse in input space is known as a generalization, while the ability to deal with data that are sparse in output space is known as sparse representation. In essence, a linear or nonlinear mapping function maps the input space into a higher-dimensional feature space for a set of training samples. As a result of these mapping functions (kernel functions), SVM creates an optimal hyperplane for class separation in higher dimensions that minimizes error and maximizes margin. This measures how far the hyperplane is from the data points in the surrounding classes. The SVM classifier's generalization error decreases as the margin increases. There are a few irrelevant features (dense concept), sparse document vectors (sparse instances), and text categorization problems that are linearly separable with SVM [11].

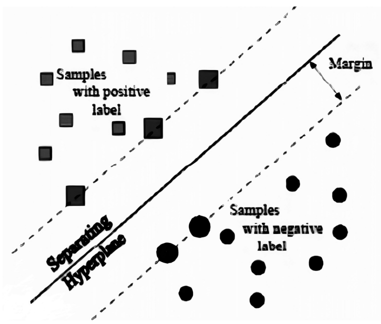

Fig. 1. Support vector machine maximal margin hyperplane in feature space [6]

The e-insensitive loss function and a slight modification to equation formation allow SVM theory to be easily applied to regression problems. It is through the process of mapping input data into a more complex feature space that SVM learns to do its work. The kernel function, $k(x_i,x_j)$, is used to identify the optimal hyperplane in this feature space, and various parameters, such as complexity, epsilon, tolerance, and the filtering method used, are passed on to the SVM. The type of kernel equations as follows [12]:

– Polynomial kernel:

$$k(x, y) = (x \cdot y + 1)^p \tag{4.1}$$

– Radial basis function kernel:

$$k(x, y) = \exp(-\gamma //x - y//^2) \tag{4.2}$$

– Sigmoid kernel:

$$k(x, y) = \tanh(kx \cdot y - \delta) \tag{4.3}$$

where: p, γ and δ are the kernel parameters: An important aspect of SVM regression is the use of a non-linear mapping to transform input data (x) into an infinitely large feature space (y), and then perform linear regression in this space (y). This is the regression model is defined as $y = f(x) + e$, Here, the high-dimensional feature space is used to define x and y as input and output functions. e: is the independently random error. Given a dataset $G = \{(x_i, y_i)\, i = 1, 2, \ldots, l\}$, This equation has three variables: l is the number of training data points, x_i is the input value, and y_i is the output value. The regression SVM aims to find an output that deviates by at least from the original. Assumptions about how the best regression performs are often made:

$$F(x) = w \cdot \varphi(X_i) + b \tag{4.4}$$

There are three components to this equation: the weight vector (w), the constant threshold (b), and the high-dimensional feature spaces (x_i) represented by $\varphi(X_i)$. Minimizing the regularized risk function is used to estimate the coefficients w and b:

$$R_{\text{reg}}(C) = C\frac{1}{I}\sum_{i=1}^{I} L\varepsilon\,(y_i, f\,(x_i)) + \frac{1}{2}||w||^2 \tag{4.5}$$

$$L\varepsilon\,(y_i, f\,(x_i)) = \{|y - f(x)| - \varepsilon, \quad \text{for } |y - f(x)| \geq \varepsilon \ \text{ or 0 otherwise}\} \tag{4.6}$$

where: the first term $C\frac{1}{I}\sum_{i=1}^{I} L\varepsilon(y_i f\,(x_i))$ is the empirical error, and the second term $\left(\frac{1}{2}||w||^2\right)$ measures the flatness of the function, $L\varepsilon\,(yi, f(x_i))$ is the ε – insensitive loss function. The parameter C determines the trade-off between the empirical error and the flatness of the model. Introducing the slack variables ζ_i and ζ_i^* into Eq. (4.5), it can be transformed into the dual optimization problem [12]:

$$\text{minimize} : R\,\left(w, b, \zeta_i, \zeta_i^*\right) = \left(\frac{1}{2}//w//^2\right) + C\sum_{i}^{I} = 1(\zeta_i + \zeta_i^*) \tag{4.7}$$

Subjected to:

$$\begin{gathered} Y_i - w \cdot \Phi\,(X_i) - b \leq \varepsilon + \zeta_i \\ w \cdot \Phi\,(X_i) - b \leq \varepsilon + \zeta_i^*, \quad \zeta i, \zeta i^* \leq 0, \quad i = 1, 2, \ldots, l \end{gathered} \tag{4.8}$$

Samples with an error more significant are penalized by the slack variables ζ_i and ζ_i^*, respectively. Since these data points are zero in the loss function, they do not need to be included in the objective function, which means that any error that is less than does not need to be included. It is possible to solve Eq. (4.7) and (4.8) of the optimization problem using Lagrangian multipliers, and the solution is as follows:

$$f\left(x, a_i, a_i^*\right) = \sum_{i=1}^{nsv} a_i - a_i^* \Phi\left(X_i, X_j\right) + b \tag{4.9}$$

where: (a_i) and (a_i^*) are the Lagrangian multipliers, and *nsv* is the total number of supports vectors used in the model; There are only a few nonzero values for Lagrangian multipliers (a_i, a_i^*) in the training data, and these data points have error estimates that are at least as large as. Support vectors are the training data with nonzero Lagrangian multipliers. In general, the fewer support vectors there are, the larger the. While a larger can reduce the approximation accuracy of the training data points, it can also reduce the model's accuracy. The kernel function $K(x_i, x_j) = (\Phi(X_i) \cdot \Phi(X_j))$ has been introduced to avoid computing explicitly the map $\Phi(x)$ [13]. It can be written as follows:

$$f\left(x, a_i, a_i^*\right) = \sum_{i=1}^{nsv} a_i - a_i^* K\left(X_i, X_j\right) + b \tag{4.10}$$

There are many different types of kernel functions in SVMs, and choosing the right one for each application is critical to ensuring a successful outcome. This is the main drawback of SVMs, as the kernel parameters are still determined heuristically [2]. This study will choose Kernel parameters using the least Root Mean Square Error (RMSE) and highest correlation (r) approach. It is also possible to solve the quadratic programming problem that arises during the training of support vector machines using the Sequential Minimal Optimization algorithm (SMO). In 1998, while working at Microsoft Research, John Platt came up with the idea. For training support vector machines, SMO is widely used, and a library for support vector machines tool implements it [14].

5. Data acquisition

The main precondition for the application of an SVM is the establishment of an adequate database. Within the framework of the research shown in this paper, data was gathered on completed projects from the Mayoralty of Baghdad for the construction of roads. It is important to mention that all of the completed projects were carried out in the same region under the same climatic conditions since they greatly influence the time taken for the completion of a project and, therefore, the total cost of its implementation [15]. The database established consists of (47) completed projects related to the construction of the new roads. Because of the most important part of the tender documentation, upon which the preliminary estimate of cost is based, the bill of quantities and works were divided in the following grouping way.

– Earthwork (Ew).
– Pavement works (Pw) consist of four layers each layer has a constant thickness, as shown in Table 1.
– Concrete curbs work (Cc).
– Drainage work (Dw) is taken into account basis on their total cost and divided into four levels depending on their limited cost of work, as shown in Table 2.

Table 1. Thickness of pavement layer

Layers	Thickness in (cm)
A layer of sub-base coarse	30
A layer of base coarse	10
A layer of binder coarse	5
A layer of surface coarse	5

Table 2. Thickness of pavement layer

Limitation ($\times 10^8$ ID*)	Level
Dw < 1	Level 1
1 ≤ Dw < 2	Level 2
2 ≤ Dw < 3	Level 3
Dw ≥ 3	Level 4

*Iraqi dinar

6. Data preparation

The data are divided into (training, testing, and validation) sets, allocating (70%) of data to the training set, (25%) to the validation (querying) set, and (5%) to the testing set for the model. As a result, the records of a total of (29) projects are used for training, (10) for validation, and (3) for testing this model. The input and output variables are pre-processed by scaling them to cancel their dimension to confirm that all variables receive equal interest throughout training. Table 3 shows the input and output data used to build the model with real and normalized scales. Scaled values are calculated for each variable with a minimum and maximum of ($x_{\min}/x_{\max}$) as part of this technique in Eq. (6.1):

$$\text{Scale Value} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{6.1}$$

A t-test determines the representativeness of the training, testing, and validation sets about one another. The t-test can be used on any two sets of data, and the null hypothesis

Table 3. Intervals of real and normalized input and output data

Input data	Symbol	Measure unit	Min (real)	Max (real)	Min (normalized)	Max (normalized)	Rang
The number of earthworks	EW	m^3	2250	125000	7.7187	11.7361	4.0174
The quantity of sub-base coarse	SB	m^2	5000	250000	8.5172	12.4292	3.912
The quantity of asphalt concrete (Base coarse)	BC	m^2	4500	225000	8.4118	12.3239	3.9121
The quantity of asphalt concrete (Binder coarse)	ECO	m^2	0	230000	0	12.3458	12.3458
The quantity of asphalt concrete (Surface coarse)	SC	m^2	17500	240000	9.77	12.3884	2.6184
The number of concrete curbs	CC	m	4500	66000	8.6125	11.0974	2.4849
Cost of drainage works	DW	level	1	4	1	4	3
Output data	Symbol	Measure unit	Min (real)	Max (real)	Min (normalize)	Max (normalized)	Rang
The final cost of roads	FCR	ID	1332700 $\times 10^3$	13103500 $\times 10^3$	21.0105	23.2961	2.2857

refers to no difference between the two sets. A significant level is used to investigate the null hypothesis (0.05). This indicates that the statistical consistency of the training, testing and validation sets a confidence level of (95%). Table 4 shows the results of the t-tests. According to these findings, the population represented by the training, testing, and validation datasets is generally the same. Consistent results were found in all the hypothesis tests for statistical consistency in Table 4 (accepted).

Table 4. T-test for the model. SVM input and output variables

Statistical parameters	Actual input variables							Actual output
	LN(EW)	LN(SB)	LN(BC)	LN(ECO)	LN(SC)	LN(CC)	(DW)	LN(FCR)
Data sets	Testing							
t-value	–0.9447	–0.7824	–0.7603	–0.9477	–0.6364	–0.5616	0.2276	–0.7512
Lower critical value	–2.1130	–1.9546	–1.8832	–11.0756	–1.2614	–1.2579	–1.3289	–1.3196
Upper critical value	0.7765	0.8718	0.8614	4.0547	0.6620	0.7153	1.6623	0.6099
Sig.(2-tailed)	0.3524	0.4401	0.4530	0.3509	0.5293	0.5786	0.8215	0.4584
Results	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
Data sets	Validation							
t-value	–0.0296	–0.3974	–0.2372	–1.9895	–1.8490	–1.6059	–0.6185	–0.6797
Lower critical value	–0.7096	–0.8144	–0.7349	–6.6234	–0.8843	–0.8500	–0.9971	–0.6040
Upper critical value	0.6892	0.5471	0.5808	0.0575	0.0400	0.0980	0.5304	0.3004
Sig.(2-tailed)	0.9766	0.6933	0.8138	0.0539	0.0722	0.1166	0.5400	0.5008
Results	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept

7. Developing the SVM model

Table 5 shows the best kernel function model, with the poly kernel chosen in this model having the lowest root mean square error (0.1103). The kernel is thought to be the best option. In this model, it was used. SVM Model's root means square error (0.1074) and means absolute error (0.0746) are shown in Table 6, where the best value parameter C (5) and the highest correlation coefficient (98.34%) were used in this model. When it comes to the range of parameter C, the SVM model's performance is relatively unaffected (1 to 10). To illustrate the effect of epsilon on the SVM model, Table 8 shows that 0.001 epsilon had

Table 5. Effects of the kernel function on SVM

Kernel Function	MAE	RMSE	Coefficient Correlation (%)
normalized poly kernel	0.2307	0.2923	88.99
poly kernel	0.0753	0.1103	98.27
RBF kernel	0.1949	0.2378	97.56

the best correlation coefficient (98.34%) and the lowest root mean square error (0.1074) with mean absolute error (0.0746) so it was used in this model. According to the results, the SVM Model's various parameter epsilon has little effect on the model's performance, particularly in the range of epsilon (0.001 to 0.01).

Table 6. Effect of the parameter C in SVM model performance

Parameter C	MAE	RMSE	Coefficient Correlation (%)
1	0.0753	0.1103	98.27
2	0.0750	0.1099	98.29
3	0.0747	0.1090	98.31
4	0.0746	0.1086	98.31
5	0.0746	0.1074	98.34
6	0.0746	0.1079	98.33
7	0.0745	0.1083	98.32
8	0.0744	0.1078	98.33
9	0.0745	0.1081	98.32
10	0.0743	0.1081	98.32

Table 7. Effect of the parameter Epsilon in SVM model performance

Epsilon	MAE	RMSE	Coefficient Correlation (%)
0.001	0.0746	0.1074	98.34
0.002	0.0747	0.1071	98.35
0.003	0.0747	0.1069	98.36
0.004	0.0750	0.1067	98.36
0.005	0.0751	0.1067	98.36
0.006	0.0751	0.1069	98.35
0.007	0.0750	0.1074	98.33
0.008	0.0751	0.1072	98.33
0.009	0.0752	0.1070	98.34
0.01	0.0754	0.1066	98.35

8. Final equation

The optimal SVM model's connection weights are shown in Table 8 by the Weka program. There is no need for a scale because the program can choose whether or not to transform the data.

Table 8. Weight estimates for model FCR

Input	Weights	Bias
EW	0.4353	–0.1887
SB	0.1358	
BC	–0.0772	
ECO	0.0168	
SC	0.2762	
CC	0.3057	
DW	0.1178	

According to the procedure mentioned above, the following final cost of road estimation equation was developed using (SVM):

$$\text{FCR}_{\text{nor}} = -0.1887 + \{(0.4353\ \text{EW}) + (0.1358\ \text{SB}) - (0.0772\ \text{BC}) + (0.0168\ \text{ECO}) + (0.2762\ \text{SC}) + (0.3057\ \text{CC}) + (0.1178\ \text{DW})\} \tag{8.1}$$

$$\text{FCR}_{\text{act}} = \ln v\text{Ln}\,(\text{FCR}_{\text{nor}}\ \text{range} + \text{min}) \tag{8.2}$$

$$\text{FCR}_{\text{act}} = \ln v\text{Ln}\,(\text{FCR}_{\text{nor}}\ 2.2857 + 21.0105) \tag{8.3}$$

Before using Eq. (8.1), it should be noted that all input variables must be converted to values between (0–1) because Eq. (8.1) was built using Eq. (6.1). To get actual data out of normalized ones, conversions to actual values were made using Eq. (8.3) and Table 3.

9. Models accuracy and validity

Testing the accuracy and validity of a model is a critical step in its development. Using some test or validation data, the model is tested and evaluated. The model's validation data should include some representative samples from the intended audience that were omitted during the model's creation. Eq. (8.1) to (8.3) are used to estimate the final cost of road. Table 9 shows the results of the experiment. The residual values in this table show that the model is performing well.

To determine the validity of the SVM model's estimate of the final road costs, the coefficient of determination is used (FCR). FCR predictions are plotted against actual validation data as shown in Fig. 2 using the natural logarithm (Ln).

This figure shows that the SVM model can generalize to this data type. The coefficient of determination for this model was (97.63%). As a result, it's safe to say that this model's predictions match up well with the data collected.

Table 9. Comparison of observed and predicted data of model FCR

Ln (FCR) Observed	Ln (FCR) Predicted	Residual value
22.192	22.198	0.006
21.796	21.853	0.057
22.233	22.186	-0.047
21.287	21.364	0.077
22.419	22.511	0.091
22.659	22.797	0.138
22.717	22.770	0.053
22.532	22.739	0.207
22.052	22.048	-0.004
22.064	22.153	0.090

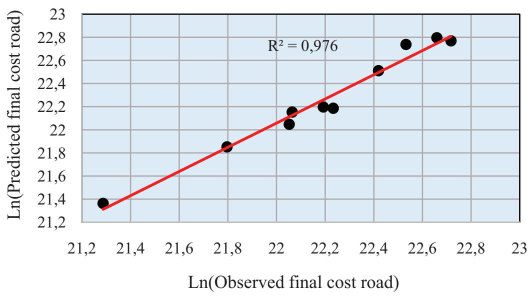

Fig. 2. Observed vs. Predicted final cost of roads using SVM

10. Model evaluation

Table 10 statistical measures were used to evaluate the performance of prediction models, according to [16].

Table 10. Statistical tests results for the SVM model (FCR)

Description	Statistical Parameters
MPE	–0.2990%
RMSE	0.0961
MAPE	0.3454%
AA	99.65%
R	98.81%
R^2	97.63%

Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) measures of average error are only applied to independent test data. Table 10 shows the statistical parameters for the model (FCR), including the MAPE and the Average Accuracy Percentage (AA%) generated by the SVM model.

11. Conclusions

The following are the findings of this research:

- The developed model (FCR) showed an excellent performance in estimating construction costs for roads in Baghdad city.
- The generalization and validity of the (FCR) model were realized by applying the statistical validation measures of Mean Absolute Error (MPE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Average Accuracy Percentage (AA%), coefficient of determination (R^2). The (R^2) for SVM model (FCR), it was 97.63%.
- The application of SVM for the simultaneous conceptual estimation of works to be carried out based on the analysis conducted and the results obtained proved to be acceptable. It is acceptable for the conceptual estimation of the real cost to have a maximum deviation of the estimation output data from real values. It significantly improves the quality of decision-making and reduces the risk of overspending on potential projects.

References

[1] M.Y. Cheng, Y.W. Wu, "Construction conceptual cost estimates using support vector machine", in *22nd International Symposium on Automation and Robotics in Construction ISARC'05, Ferrara, Italy*, 2005, pp. 1–5.

[2] K. Yan, C. Shi, "Prediction of elastic modulus of normal and high strength concrete by support vector machine", *Construction and Building Materials*, 2010, vol. 24, no. 8, pp. 1479–1485; DOI: 10.1016/j.conbuildmat.2010.01.006.

[3] T. Mahfouz, "A productivity decision support system for construction projects through machine learning (ml)", in *Proceedings of the CIB W78 2012: 29th International Conference–Beirut, Lebanon, 17–19 October, 2012*.

[4] Y.R. Wang, C.Y. Yu, H.H. Chan, "Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models", *International Journal of Project Management*, 2012, vol. 30, no. 4, pp. 470–478; DOI: 10.1016/j.ijproman.2011.09.002.

[5] S. Petruseva, V. Zileska-Pancovska, V. Zujo, "Predicting construction project duration with support vector machine", *International Journal of Research in Engineering Technology*, 2013, vol. 11, no. 2, pp. 12–24.

[6] M. Wauters, M. Vanhoucke, "Support vector machine regression for project control forecasting", *Automation in Construction*, 2014, vol. 47, pp. 92–106; DOI: 10.1016/j.autcon.2014.07.014.

[7] N.I. El-Sawalhi, "Support vector machine cost estimation model for road projects", *Journal of Civil Engineering Architecture*, 2015, vol. 9, pp. 1115–1125.

[8] F.K. Jaber, F.M. Al-Zwainy, S.W. Hachem, "Optimizing of predictive performance for construction projects utilizing support vector machine technique", *Cogent Engineering*, 2019, vol. 6, no. 1, pp. 1–13; DOI: 10.1080/23311916.2019.1685860.

[9] C.F. Lin, S.D. Wang, "Fuzzy support vector machines", *IEEE Transactions on Neural Networks*, 2002, vol. 13, no. 2, pp. 464–471; DOI: 10.1109/72.991432.

[10] K. Gopalakrishnan, S. Kim, "Support vector machines approach to HMA stiffness prediction", *Journal of Engineering Mechanics*, 2011, vol. 137, no. 2, pp. 138–146; DOI: 10.1061/(ASCE)EM.1943-7889.0000214.

[11] N. Tabatabaee, M. Ziyadi, and Y. Shafahi, "Two-stage support vector classifier and recurrent neural network predictor for pavement performance modeling", *Journal of Infrastructure Systems*, vol. 19, no. 3, pp. 266–274, 2013; DOI: 10.1061/(ASCE)IS.1943-555X.0000132.

[12] V. Kecman, "Learning and soft computing: support vector machines, neural networks, and fuzzy logic models", *MIT press*, 2001.

[13] Y. Shi, Y. Tian, G. Kou, Y. Peng, and J. Li, "Optimization based data mining: theory and applications", *Springer Science & Business Media*, 2011.

[14] C. C. Chang and C. J. Lin, "LIBSVM: a library for support vector machines", ACM transactions on intelligent systems technology, vol. 2, no. 3, pp. 1–27, 2011; DOI: 10.1145/1961189.1961199.

[15] I. Peško, M. Trivunić, G. Cirović, and V. Mučenski, "A preliminary estimate of time and cost in urban road construction using neural networks", *Tehnički vjesnik*, vol. 20, no. 3, pp. 563–570, 2013.

[16] Z. S. Khaled, R. S. A. Ali, and M. F. Hassan, "Predicting the Delivery Time of Public School Building Projects Using Nonlinear Regression", *Eng. &Tech.Journal*, vol. 34, no. 8, pp. 1538–1548, 2016.

Received: 2022-07-20, Revised: 2022-09-20