Cost Estimates of Buildings’ Floor Structural Frames with the Use of Support Vector Regression

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Abstract. The paper presents some results of the research into a development of a cost estimating model that is capable of using information from building information model and implementing machine learning for cost prediction. Accurate estimates, provided throughout the whole construction project, allow for actual cost savings and assist in achieving sustainability goals. The model which is based on the support vector regression and radial basis kernel functions has been developed and proposed to support cost estimates of building’s floor structural frames. The author’s main assumption was to combine the benefits of building information modelling – namely the ability to extract certain information about the building and structural members of the floor frames from the models and the capabilities of machine learning. The research, presented in this paper, came down to solving a regression problem with the use of the support vectors approach. The training data for machine learning included inputs that represented features of the building and structural members’ belonging to the floor structural frames and outputs that represented corresponding real life cost estimates of the floor structural frames. The obtained results show that the proposed model allows predicting costs with satisfactory accuracy.

1. Introduction
The development of building information modelling (BIM) and its implementation in construction projects opens a broad variety of possibilities in terms of managing the data of construction projects. The access to the repositories of such data, (BIM models can be seen as repositories of that kind), along with the implementation of mathematical tools that are based on artificial intelligence and machine learning, bring a lot of capabilities in terms of analyses that support various processes in the course of construction projects. This paper aims at presenting some research results regarding the implementation of machine learning in cost estimation of higher level elements of buildings – namely floor structural frames. The author’s main idea and assumption was to combine BIM-based cost estimates and support vector regression for the purpose of development of a cost prediction model. The contents of this paper include a concise state of the review, description of the problem and a brief summary of the theoretical background of the support vector regression (SVR) method. The latter precedes the core part of the paper, namely the research results, discussion and conclusions of the study on model development. The research presented in this paper is a continuation of the previous work on the development of cost estimation models based on artificial intelligence for similar problems (reported previously e.g. in [1–3]).
2. Current state of the knowledge review
BIM, as a developing technology that brings a lot of benefits to the architecture, engineering and construction (AEC) industry, is discussed from various perspectives in the literature – some examples are given herein. The fundamentals of BIM can be found in many works (e.g. in [4]). General discussions on the trends, benefits, possible risks, and future challenges of BIM for the AEC industry as well as some findings for those willing to implement BIM in the projects can also be found there [5]. The study on the synergy of lean construction and BIM, the analysis that resulted in a proposal of a framework for research into the interactions between them and recognizing potential synergies, from which the AEC industry professionals may benefit, is presented in [6]. Another work [7] examines the importance of BIM in the UK construction sector – the authors focused on potential improvements in the area of cost management. The author of another paper [8] investigated the role of the project cost management professionals in the implementation and evolution of BIM in the construction industry. The research that aimed at developing an accurate, automated method for measuring construction progress on the basis of 4D BIM model validated by 3D data obtained from a construction site is introduced in [9]. The issue of linking BIM elements with cost and schedule data is considered in [10] – the authors proposed a model capable of linking such data automatically.

A support vector machine (referred to as SVM) is a theory belonging to a broad field of statistical learning developed by Vapnik and presented in many works – e.g. [11–12]. The theory is also discussed by other authors in various publications [13–16]. SVM can be implemented both for classification and regression problems - one can distinguish between support vector classification (SVC) and support vector regression (SVR), accordingly. The SVM method, as a machine learning tool, offers capabilities such as self-learning and knowledge generalization (compare e.g. [13]). The examples of works that report solving problems in a broad field of construction management with the use of the method can be given as follows. In [17] the authors present a methodology developed to improve the organization of information and access in construction management information systems based on the SVM classification of construction project documents. Another study [18] is focused on development of a legal decision support methodology which aims at mitigating the negative effects of conflicts that arise during the performance of construction projects. Another SVM based model is proposed in [19] for risk hedging prediction for construction material suppliers – the objective of the research was to develop a model to determine whether employing risk hedging based on the use of derivatives would be beneficial. The authors of [20] present a model that integrates SVM with a fast messy genetic algorithm for dynamical prediction of a project. In [21] machine learning is used for predicting construction project cost. The application of the SVM method in predicting construction project cost is also presented in [22], along with the introduction of the rough set theory. The authors of [23] developed and compared classification models based on SVM and artificial networks ensemble aiming at predicting project cost and schedule success, using status of early planning as the inputs. The paper [24] presents the comparison of models, developed for conceptual cost estimation of school buildings, based on regression analysis, neural networks and SVM.

3. Applying SVR to BIM-based cost estimates
The aim of the research was to develop a regression model capable of predicting construction costs of floor structural frames. If the variables of the model were denoted as:

\[ y \] – Dependent variable of the model – construction cost of a floor structural frame, output of the model,
\[ x \] – Independent variables of the model – selected cost predictors, inputs of the model, and the regression analysis problem came down to mapping \( x \rightarrow y \).

The main assumptions made by the author were: to use the information extracted from BIM model as the cost predictor and to implement support vector regression in finding the mentioned mapping. The proposed approach is supposed to aid cost estimation process in terms of the use of data and knowledge from the past, reliability of output and achieving cost targets, which altogether help in achieving sustainability goals.

In the two following subsections the general idea of the model is presented as well as a brief discussion of the SVR method theoretical background. In the third subsection the author presented the assumptions for the application of SVR method to the problem.
3.1. General description of a problem
BIM models include components that represent elements of a building which are, in the course of the modelling process, attributed with geometrical and non-geometrical information. This information provides the basis for various analyses, inter alia cost analyses. One of the assumptions of this study was that the data extracted from the BIM models and accompanying cost estimates will serve as a source of information and database including the training data for the regression analysis. Figure 1.a presents an exemplary BIM model with a floor structural frame highlighted, as a higher level element of the model including slabs, walls and columns as structural members. Figure 1.b depicts the ideogram of the model development.

![Figure 1. (a) Example of a BIM model with floor structural frame highlighted. (b) Ideogram of the proposed model development.](image)

As mentioned above, the output of the proposed model, denoted as $y$, was the construction cost of a certain floor structural frame, expressed in thousands of PLN excluding the value added tax. The input of the model included selected cost predictors that represented the features of a floor structural frame as well as features of a building. Table 1 presents cost predictors, $x_i$, selected to be the independent variables for the regression analysis. Cost predictors relate to: size of a building – $x_1$, $x_2$, $x_3$; location of a building – $x_{11}$; dimensions of a floor structural frame and structural members that constitute a certain frame – $x_4$, $x_5$, $x_6$, $x_9$; material characteristics and quality of construction works – $x_7$, $x_8$, $x_{10}$.

For the purposes of the support vector regression based analysis and model development the author used the database including 162 training patterns (as in the case of previous work [3]).

3.2. Theoretical background of the support vector regression
Support vector machine learning method is widely described in the literature. A theoretical background in this subsection is compiled from the following publications: [11–16]. Support vector regression allows approximating the mapping function as a linear regression hyperplane. If the training data set for a learning machine is given as $\chi$ such that:

$$\chi = \{x_i, y_i\} \in \mathbb{R}^m \times \mathbb{R}, i = 1 ... n$$

(1)
Table 1. Cost predictors – input for support vector regression analysis.

| Predictor’s description                                                                 | Coding                      | Values          | Symbol |
|-----------------------------------------------------------------------------------------|-----------------------------|-----------------|--------|
| class of building with regard to building’s height<sup>a</sup>                           | low                         | 1, 0, 0         | x<sub>3</sub> |
|                                                                                         | medium-high                 | 0, 1, 0         | x<sub>2</sub> |
|                                                                                         | high                        | 0, 0, 1         | x<sub>3</sub> |
| gross floor area                                                                         | surface                     | measured in m<sup>2</sup> | x<sub>4</sub> |
| volume of RCT horizontal structural members<sup>b</sup>                                  | cubic capacity              | measured in m<sup>3</sup> | x<sub>5</sub> |
| volume of RCT vertical structural members<sup>c</sup>                                    | cubic capacity              | measured in m<sup>3</sup> | x<sub>6</sub> |
| class of concrete                                                                        | C16/20 and C20/25           | 0.1             | x<sub>7</sub> |
|                                                                                         | C20/25 and C25/30           | 0.5             | x<sub>7</sub> |
|                                                                                         | C20/25 and C25/30           | 0.9             | x<sub>7</sub> |
| class of formwork execution                                                              | class 1                     | 0.1             | x<sub>8</sub> |
|                                                                                         | class 2                     | 0.5             | x<sub>8</sub> |
|                                                                                         | class 3                     | 0.9             | x<sub>8</sub> |
| volume of masonry vertical structural members<sup>d</sup>                                | cubic capacity              | measured in m<sup>3</sup> | x<sub>9</sub> |
| class of masonry works execution                                                         | class A                     | descriptive values scaled to the numerical values | x<sub>10</sub> |
|                                                                                         | class B                     | descriptive values scaled to the numerical values | x<sub>10</sub> |
| location of building                                                                     | voivodship of Poland        | descriptive values scaled to the numerical values | x<sub>11</sub> |

<sup>a</sup> according to the classification present in the Polish legal acts

<sup>b</sup> reinforced concrete slabs, beams, landings, flights of stairs as construction members

<sup>c</sup> reinforced concrete walls and columns as construction members

<sup>d</sup> masonry walls as construction members.

And \( \varphi \) is a nonlinear transformation used to determine a new, high dimensional, linear feature space \( Z \) for the inputs:

\[
\varphi: \mathbb{R}^m \rightarrow Z, \quad \varphi(x) \in Z, \quad y \in \mathbb{R}
\]

Than the regression problem comes down to find an approximation function, in feature space \( Z \), given as:

\[
y = f(x, \beta) = \beta \cdot \varphi(x) + \beta_0
\]

For measuring an error of approximation the Vapnik’s function is used:

\[
|y - f(x, \beta)|_\varepsilon = \begin{cases} 0 & \text{if } |y - f(x, \beta)| \leq \varepsilon \\ |y - f(x, \beta)| - \varepsilon & \text{if } |y - f(x, \beta)| > \varepsilon \end{cases}
\]
Where \( \varepsilon \) determines borders within which the approximated hyperplane must lie. This loss function allows measuring the fit of a model for each element of the training data set. Both the idea of the regression function and the loss function are presented in Figure 2.

The aim of support vector regression is to find an approximation hyperplane which minimizes the generalization error - the optimal solution minimizes the capacity of machine learning and model complexity. The optimization can be given formally as:

\[
\frac{1}{2} \| \beta \|^2 + C \sum (\xi + \xi^*) \rightarrow \min
\]

(5)

Where \( C \) stands for the complexity of a model, regression parameter defined by the user. \( \xi \) and \( \xi^* \) are slack variables, calculated for each of the training data, introduced to make the method less prone to noise and outliers. For the data above the \( \varepsilon \)-border:

\[
|y - f(x, \beta)| - \varepsilon = \xi
\]

(6)

Whereas for the data below the \( \varepsilon \)-border:

\[
|y - f(x, \beta)| - \varepsilon = \xi^*
\]

(7)

The constraints for (5) are:

\[
\begin{align*}
    y - f(x, \beta) &\leq \varepsilon + \xi \\
    -y + f(x, \beta) &\leq \varepsilon + \xi^* \\
    \xi, \xi^* &\geq 0
\end{align*}
\]

(8)

Figure 2.a presents the idea of approximation with the use of the linear regression function in space \( Z \), whereas Figure 2.b presents the loss function. In both Figures one can see the visualization of the \( \varepsilon \)-border as well as slack variables \( \xi \) and \( \xi^* \).

![Figure 2.](image)

**Figure 2.** (a) Graphical interpretation of the linear regression function, \( \varepsilon \)-gutter, and \( \xi \), \( \xi^* \) slack variables. (b) The Vapnik’s \( \varepsilon \)-insensitive loss function.

For the purpose of solving the optimization problem, presented in the equation (8), the method of Lagrange multipliers has been implemented. The data points to which non-zero Lagrangian multipliers correspond and are called support vectors. The support vectors influence the position of the approximated hyperplane and thus the regression function. The quality of the regression model is influenced by parameter \( C \), as given in the equation (5), and by the choice of transformation \( \phi \), as in (2). As for the latter, in practice, it is enough to choose the function that allows computing scalar product \( Z \). In the SVR method a user is supposed to choose the kernel function which defines the scalar product as:

\[
K(x, x') = \langle \phi(x), \phi(x') \rangle
\]

(9)
The commonly used kernel functions are sigmoidal (10), polynomial (11) and radial basis (12):

\[ K(x, x') = \tanh(\gamma x \cdot x' + c) \]  
\[ K(x, x') = (\gamma x \cdot x' + c)^d \]  
\[ K(x, x') = \exp(-\gamma \| x - x' \|^2) \] 

Finally, the regression function can be given as:

\[ f(x) = \sum_i (\alpha_i - \alpha_i^*) K(x, x') + \beta_0 \]  

Where \( \alpha \) and \( \alpha^* \) are the Lagrangian multipliers for the optimal solution that correspond with the support vectors and \( K \) is the chosen type of the kernel function.

3.3. Assumptions for the application of SVR in the developed model

The application of support vector machine learning for regression problems requires several choices that are of key importance. The Kernel function that allows calculating scalar product (9) must be chosen, as well as the parameters of the model.

The research, presented in this paper, included investigations of models that were based on the use of the radial basis kernel functions (12). The complexity of developed model \( C \) as well as the parameter \( \epsilon \) was sought for with the use of 10-fold cross validation. The ranges of both parameters \( C \) and \( \epsilon \) are presented in Table 2.

Table 2. Ranges of investigated models’ parameters.

|     | min | max | step |
|-----|-----|-----|------|
| \( C \) | 2   | 15  | 1    |
| \( \epsilon \) | 0.1 | 0.5 | 0.1  |

For the purpose of the regression analysis and testing models, the whole set of training patterns was divided randomly into two subsets – subset L was used for learning, whereas subset T for testing. The division ratio L / T, in terms of subsets cardinalities, was assumed 75% / 25% accordingly.

On the basis of different combinations of the parameters presented in Table 2, on subset L a number of models have been investigated. The final choice of the model proposed to be the core for cost predictions relied on the comparison of prediction errors. The measures of models’ quality were as follows: correlation coefficient – \( R \), mean square error – \( MSE \), mean average percentage error – \( MAPE \), and percentage errors \( PE^p \). All of the measures have been calculated and given either for subset L and subset T separately, and for both subsets together.

\[ R = \frac{\text{cov}(y, \hat{y})}{\sigma_y \sigma_{\hat{y}}} \]  

Where \( y \) – real life values of the dependent variable, \( \hat{y} \) – predicted values of the dependent variable (model outputs), \( \text{cov}(y, \hat{y}) \) – co-variance between \( y \) and \( \hat{y} \), \( \sigma_y \) – standard deviation for \( y \), \( \sigma_{\hat{y}} \) – standard deviation for \( \hat{y} \);

\[ MSE = \frac{1}{n} \sum_p (y_p - \hat{y}_p)^2 \]  

\[ MAPE = \frac{100}{n} \sum_p \left| \frac{y_p - \hat{y}_p}{y_p} \right| \]  

\[ PE^p = \left( \frac{y_p - \hat{y}_p}{y_p} \right) 100\% \] 

Where \( y \) and \( \hat{y} \) as in (14), \( p \) – index of a training pattern belonging to either L or T, \( n \) – cardinality of either L or T subsets, or the whole training set. (In case of (17) it was intentional not to
calculate PE\textsuperscript{p} errors as absolute values to allow presenting the errors as either positive or negative numbers.)

4. Results and discussion

In the course of the research, over 50 models that varied in parameters presented in Table 2 have been investigated. As mentioned above, for each of the investigated models the parameters were determined with the use of cross-validation.

Table 3 presents the characteristics of 5 selected models for which best learning and testing results have been obtained. (In the case of correlation coefficients, as in the equation (14), the subscripts L, T and L&T indicate that the coefficients have been calculated for a learning subset, testing subset or both of them together accordingly). In Table 3 it can be seen that the complexity of the models, according to $C$, varied between 5 to 9, on the other hand the value of $\varepsilon$ is similar for all models. The number of support vectors ranged from 34 to 38 whereas the number of bounded vectors from 11 to 15. The correlation coefficients are close to 1 and are similar both for L and T subsets. Moreover, the values of $R$, compared for models 1-5 do not differ significantly.

Table 3. Characteristics of selected models.

| Model no. | C   | $\varepsilon$ | Number of support vectors | Number of bounded support vectors | $R_L$  | $R_T$  | $R_{L&T}$ |
|-----------|-----|---------------|----------------------------|----------------------------------|--------|--------|-----------|
| 1         | 8   | 0.1           | 35                         | 11                               | 0.967  | 0.986  | 0.975     |
| 2         | 5   | 0.1           | 38                         | 15                               | 0.970  | 0.979  | 0.973     |
| 3         | 5   | 0.1           | 36                         | 13                               | 0.972  | 0.972  | 0.972     |
| 4         | 9   | 0.1           | 34                         | 12                               | 0.974  | 0.977  | 0.975     |
| 5         | 6   | 0.1           | 36                         | 13                               | 0.972  | 0.972  | 0.972     |

For the purpose of the final selection of one model prediction errors have been analyzed. Table 4 presents values of $MSE$ and $MAPE$, set together for models 1-5, (the subscripts L, T and L&T indicate that the values have been calculated for a learning subset, testing subset or both of them together accordingly).

Table 4. MSE and MAPE errors calculated for selected models.

| Model no. | $MSE_L$ | $MSE_T$ | $MSE_{L&T}$ | $MAPE_L$ | $MAPE_T$ | $MAPE_{L&T}$ |
|-----------|---------|---------|-------------|----------|----------|-------------|
| 1         | 279.2   | 233.1   | 267.5       | 7.20%    | 7.06%    | 7.16%       |
| 2         | 294.3   | 261.3   | 285.9       | 7.39%    | 7.91%    | 7.52%       |
| 3         | 305.5   | 261.0   | 294.2       | 7.49%    | 8.46%    | 7.73%       |
| 4         | 280.1   | 220.9   | 265.1       | 7.31%    | 6.38%    | 7.08%       |
| 5         | 299.5   | 258.3   | 289.1       | 7.45%    | 8.36%    | 7.68%       |

The differences between the errors presented in Table 4, (both in terms of MSE and MAPE values), were not significant. The qualities of models 1-5 were comparable. However, the smallest errors for subset T were obtained for model number 4, which, therefore, became the one which was finally selected.

Figures 3, 4 and 5 depict the results of support vector machine learning process for the selected model. Figure 3 presents scatter plots of real life values of a dependent variable and predicted values of a dependent variable (model outputs). Figure 3.a presents a chart of $y$ and $\hat{y}$ for subset L, whereas Figure 3.b presents a chart of $y$ and $\hat{y}$ for subset T. In both charts the points decompose evenly along the line of a perfect fit.
Figure 4 and Figure 5 depict scatter plots of real life values of a dependent variable and percentage errors calculated on the basis of equation (17). Figure 4 presents the distribution of $PE^p$ for $y^p$ belonging to the subset used in the course of learning process, whereas Figure 5 presents the distribution of $PE^p$ for $y^p$ belonging to the subset used for testing. In both Figures it can be seen that most errors (either positive or negative values) fall into the range $<-20%; 20%>$. For subset L there are only a few cases, for subset T none which do not fall in this range.

![Figure 3. (a) Scatter plot of $y$ and $\hat{y}$ for subset L. (b) Scatter plot of $y$ and $\hat{y}$ for subset T.](image)

![Figure 4. Scatter plot of $y^p$ and $PE^p$ for subset L.](image)

![Figure 5. Scatter plot of $y^p$ and $PE^p$ for subset T.](image)
5. Summary and conclusions
The research allowed investigating the applicability of SVR to estimating costs of buildings’ floor structural frames. Some general conclusions about the method and its implementation for the presented cost estimating problem have been that the main capabilities of SVR are machine learning and generalization of knowledge. On the other hand, the drawbacks that can be mentioned are that a user is supposed to choose from a number of kernel functions and determine parameters of a model (in terms of the complexity and the width of \( \varepsilon \)-gutter. The choice of the parameters needs either a trial-error stage or the application of cross-validation.

The research specific conclusion is that the SVR machine learning results were stable for all investigated models. For the finally chosen model which is based on the SVR application and radial basis kernel function, the outputs of the model and the real life expected values of the dependent variable are highly correlated. The percentage errors of cost predictions fall in the range of <-20%; +20%> for the testing subset.

The obtained results are promising and justify further studies on the uses of the SVR method for cost estimation in construction. Applying machine learning in the estimates combined with the use of BIM technology can be considered as a potentially prospective, especially in terms of variant analyses, and, through this, supporting for achieving sustainability goals of a building. The forthcoming research will be devoted to the applicability of SVR in other problems of cost estimation in construction, as well as development of the models based on SVR committee machines.

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