Predicting Bidding Price in Construction using Support Vector Machine

Silvana Petruseva [1], Phil Sherrod [2], Valentina Zileska Pancovska [1], Aleksandar Petrovski [3]

[1] *"Ss Cyril and Methodius University", Faculty of Civil Engineering,Partizanski odredi 24, 1000 Skopje, Republic of Macedonia*
[2] *6430 Annandale Cove, Brentwood, TN 37027-6313, USA*
[3] *"Ss Cyril and Methodius University", Faculty of Architecture, Partizanski odredi 24, 1000 Skopje, Republic of Macedonia*

Abstract –**The bidding price can directly affect the construction firm business, so the decision what price to bid for a new project in order to sign a contract is a difficult and responsible decision. Data for fifty four tenders were collected from construction firms. Only data for twenty six tenders were contracts which were signed and used for further analysis. A model for forecasting the bidding price was developed. The model uses support vector machine. DTREG software package was used for predictive modeling. The obtained prediction was very accurate with only 2.5% error (mean absolute percentage error) of the model.**

Keywords – **Bidding price, construction, forecasting, support vector machine, DTREG software package.**

1. Introduction

An inadequate firm selection as participant in construction project can lead to sub-standard design, delays, disputes etc., so the selection of firms is a very important stage of every construction project. One of the ways for firm selection is a tender. The firm should win the tender in order to sign a contract and to become a participant in a project. For the firm, the decision not to bid could lead to losing the chance to get a profit [1], and the bidding decision can have influence on the success and existence of the firm.

DOI: 10.18421/TEM52-04
https://dx.doi.org/10.18421/TEM52-04

Corresponding author: Silvana Petruseva - Ss Cyril and Methodius University, Republic of Macedonia
Email: silvana@gf.ukim.edu.mk

© 2016 Silvana Petruseva et al, published by UIKTEN. This work is licensed under the Creative Commons Attribution-NonCommercial-NoDerivs 3.0 License. The article is published with Open Access at www.temjournal.com

A major characteristic of the bidding process is the high complexity and the many objectives [1]. Furthermore, the process of completing the bidding documentation consumes time and costs [2].

For the bidders the involvement in the bidding process leads to tension [3]. They have to decide what price to bid in order to maximize the profit on one side, and to bid a price that is low enough to win the bid, on the other side [4]. Therefore, in practice, when decision makers decide on the bidding price, they use their experience, intuition and personal bias, but the process can affect their emotions [5].

Usually, if other criteria are equal, the bid is awarded to the competitor with the lowest bidding price [6]. Then, the bidding price becomes a part of an agreement between the bidder firm and the investor, so the bidding price can attack the economic success of both agreement parties [7]. Therefore, for many firms, an important issue is to place the bid that will win [8].

With respect to the above mentioned, it can be concluded that the bidding price can have a direct influence on the firm's business. What price to bid for a new project is a responsible and very difficult decision during the process of preparation of the bid [9].

In many cases, decision makers don't support their decisions with mathematical expressions that are connected with the probability of winning and the price to bid [6]. Additionally, information and experiences about the past bids are not always available [10], and if they are, they are not always useful because of the different circumstances that are specific for each bidding process [6].

To support the bidding decision, there are support systems that are electronic [11], but the bidding process and the decision what price to bid is still a complex and crucial for each firm.

Acknowledging the above mentioned, the aim of this research is to develop a model for forecasting the bidding price for construction projects as a support in the decision process. The research is based on the investigation in the R. of Macedonia, but it can be generalized for any country.

2. Literature review

2.1 Bidding process and bidding price

Bids and bidding processes are examined by many authors.

Authors in [12] suggested the implementation of analytical hierarchy process to improve the selection of a contractor.

In [13] authors gave a model for selection of the contractor that is not based only on the bid with the lowest price, but on the bid that ensures the identification of contractors with the best potential to fulfill the contract requirements. The mark-up level and the bid winning probability are linked in a mathematical expression in [6].

The decision to bid or not to bid is attacked by numerous factors. They were ranked in [14].

The contract bids and their competitiveness are investigated in [15].

Authors in [3] gave a model for prediction of the mark-up decisions of the bid. They concluded that the size of the contract and the size of the bidder are in relationship.

The bidding process and the bidding price were also examined by other authors [16], [1], [8].

2.2 Neural network and bid decision process

Günther and Fritsch in [17] stated that many papers that examine the neural networks (NNs) application as a support in decisions making in the bidding process are worthy of attention.

Authors in [1] concluded that artificial neural networks are one of the most used for creating models for determination of the bid mark-up, while authors in [9] used artificial neural networks with combination with expert systems in order to find out the optimal mark-up for bids. Neural networks were also used in [11] where a model for customer behavior in order to support the bidding process in e-auctions is created.

For the bidding process, authors in [18] concluded that the artificial neural network has better capabilities of prediction than multiple linear regression.

Using artificial neural networks, author in [19] suggested a method that can be used for choosing the optimal value of bid mark-up.

To enhance online auctions, the model for forecasting the winning price for bid using the neural network and Bayesian network is created in [20]. Similarly, neural networks were used in [11] where a model for customer behavior in order to support the bidding process in e-auctions is created.

To support bid decisions in construction, artificial neural network is also used in [21].

In [22] authors used neural network for developing optimal bidding strategies, while in [23] authors developed models using neural network and regression to predict cost for bid for highway projects.

The paper [24] confirmed the power of neural network algorithms in creating a decision model for bidding process.

The author in [25] used neural fuzzy systems and multi-dimensional risk analysis for bid optimization.

3. Methodology

Bidding data for 54 tenders for structures design were collected from firms in the R. of Macedonia. Data were collected during 2014 for different types of structures financed by public funds. The collected data covered data about: the structure's type, bidding price, winning price and problems that occur for the firm during the bidding process.

From the 54 tenders' data, only 26 tenders had signed an agreement and were used for further analysis.

For forecasting the bidding price, support vector machine (SVM) predictive model was implemented. For modelling, the program package DTREG [26] was used.

4. Research

4.1 Support vector machine (SVM)

In recent years it has been proven that in many cases SVM learning algorithms are more superior to the neural networks learning algorithms, both for regression (function approximation) and also for classification tasks.

Below is a brief insight into this newer and rapidly developing learning paradigm implemented in support vector machines.

Support vector machines were first introduced by Vapnik et al. [27]. There are two main algorithms for support vector machines: support vector classification (SVC) and support vector regression (SVR). A version of a SVM for regression is called support vector regression (SVR).

Similarly to neural networks, SVMs are being considered as universal machines for approximation of any function to any degree of accuracy. Because of this, they are of specific interest for modelling partially known or unknown and highly nonlinear processes and complex systems.

In comparison to neural networks, SVMs were developed from sound theory to experimentation and applications, while the NN's were developed from extensive experimentation and application to sound theory [28].

One of the most significant features of the SVMs is that computational complexity of the SVM algorithm does not depend on dimensionality of the input space, and its sophisticated learning model matches the capacity of the model to the input data complexity, ensuring very good performances on previously unseen, future data.

Support vector learning algorithm has very broad applicability because of its more generic nature, and all feed-forward NNs have an ability of using support vector learning algorithms in their process of learning.

The learning problem for SVM is set up in the following way [29]:

There is a training data set $D = \{(x_i, y_i) \in X \times Y, \quad i = 1,2,...l\}$ which is the only available information. L is the size of the training set, **X** is some high dimensional input vector, whose components x_i are called *predictor variables or attributes.* **Y** is the output vector, whose components y_i are scalars and they are called *target variables*, or response from the system. Nonlinear dependent function **y(X)** is established between the input vector **X** and output vector **Y** in the process of learning.

SVMs are called “nonparametric” models because, in comparison to the classic statistical models, the parameters of the model are not predefined. This doesn't mean that SVMs do not have parameters at all. They are obtained in the course of learning and their number depends on the training data which isused. This means that the parameters which define the capacity of the model are data driven in order to match the model capacity to data complexity [28].

In case of solving very simple classification problems, for creating a classifier with a maximal margin, SVM uses a linear separating hyper-plane. If the classes can not be separated linearly in the original input space, the SVM transforms input space into a higher dimensional *feature space.* Predictor variable that is used to define the hyper-plane is called a *feature. Feature selection* is the task of choosing the most suitable representation. A row of predictor values, i.e. the set of features that describes one case is called a *vector*.

The transformation into multidimensional feature space can be accomplished using nonlinear mappings: sigmoid, polynomial, RBF (radial basis function) mappings (usually called *kernel functions*). After the nonlinear transformation, finding the linear optimal separating hyper-plane in the multidimensional feature space is a very simple task. The optimization problem in the new feature space is equivalent to the problem of finding maximal margin separating hyper-plane in the original input space. The vectors which are nearest to the hyper-plane are called *support vectors*. In N-dimensional space, the data points will be separated by N-1 dimensional hyper-plane.

Whether it is a problem of classification or regression, the problem will be solved in the new multidimensional space.

Figure 1. [29] shows the problem of classification which in the original input space is nonlinear. Linear separation is made in the new multi-dimensional space.

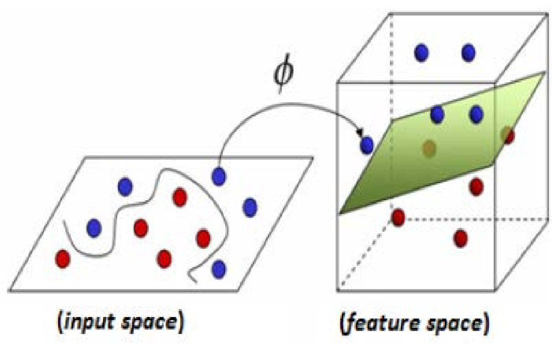

Figure 1. Mapping in multidimensional space

Using SVM method hyper-plane is found so that the margin between the support vectors is maximized (Figure 2.)[30].

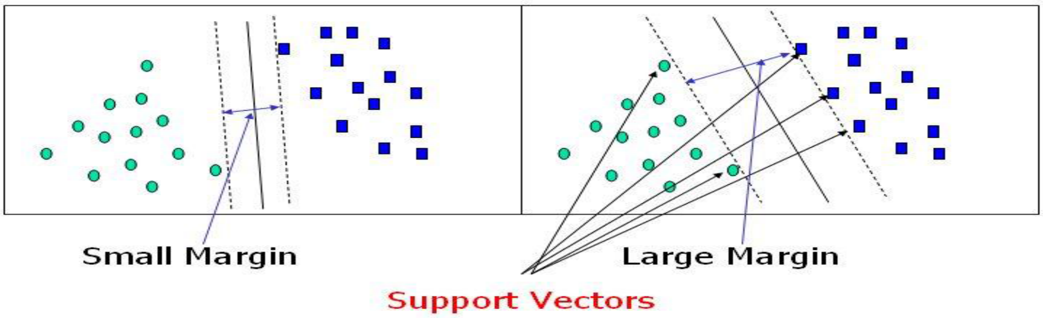

Figure 2. Margins and support vectors

The kernel mapping function in SVM modeling is a very powerful concept. It allows performing separations with very complex boundaries (Figure 3.) [30].

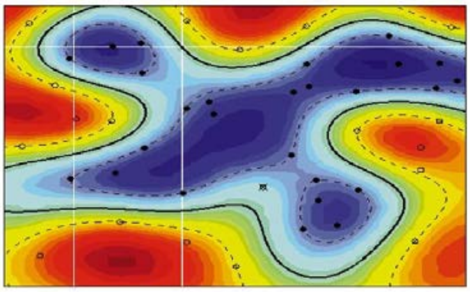

Figure 3. Separation with kernel mapping

In the tasks of learning from data there are 3 main components: 1) a generator of inputs X, 2) a system for training the learning machine with training responses y(d) , and 3) learning machine which should learn (model, estimate) the unknown dependency between these two sets of variables, the inputs x_i and systems responses y_i. This dependency will be defined by some weight vector *w*. In the course of the training phase, SVM will be able to find the relationship between the input space X and the output space Y, using data D - in regression tasks, or to find a function for separation of the data in the input space - in classification tasks.

As a result of the learning process SVM will find approximation function $f_a(x,w)$, also called hypothesis, which approximates the true dependency between input and output variables in the regression task (and the separation function in the case of classification). It is very important that this hypothesis minimizes some risk functional R(w).

An approximation function may be any function that maps inputs **x** into outputs **y**, for example: polynomial approximating function, multilayer perceptron, RBF network, SVM, or other. Here we use SVM. The parameters **w** are called weights and they are subject of learning. They may have different physical and geometrical meaning, depending on the hypothesis function; they are, for example, the hidden and output layer weights in multilayer perceptron, the coefficients of a polynomial, output layer weights of RBF network, or the weights of the support vectors in SVM [28].

4.2 SVM in regression problems (SVR)

SVM has been initially developed for solving classification tasks, but it can be very successfully applied also for functional approximation problems, i.e. for regression problems.

The general regression learning problem is set in the following way:

l training data is given to the learning SV machine, from which it tries to learn input-output dependency (relationship) function **f(x,w)**.

The training data set **S** is given as $\boldsymbol{S} = \{(x_i, y_i) \in \boldsymbol{R}^n \times \boldsymbol{R},\quad i = 1,2,...l\}$, where inputs $\mathbf{x_i}$ are n – dimensional vectors($x_i \in \boldsymbol{R}^n$), and outputs, the responses of the model, have real values.

In the so called **ε** - support vector regression, the goal is to obtain an approximation function **f(x,w),** where **w** are learned through the process of training, so that the function **f** is as flat as possible and it has at most **ε** deviation from the actual outputs y_i**,** for all training data.

In SV regression, for estimation of the regression model, instead of measuring of the margin in the tasks of classification, we measure the error of approximation, using novel error (loss) function called linear loss function with **ε** insensitive zone, also called as Vapnik's general type of error. It is defined in Eq. (1):

$$|y-f(x,w)|_{\varepsilon}=\begin{cases}0 & \text{if } |y-f(x,w)|\le\varepsilon\\ |y-f(x,w)|-\varepsilon & \text{if } |y-f(x,w)|>\varepsilon\end{cases} \quad (1)$$

If the difference between obtained (predicted) value $f(x_i,w)$ and real, measured value y_i is smaller than ε, then the error is equal to zero. Vapnik's ε *insensitivity error* function defines ε tube (Figure 4.) [28].

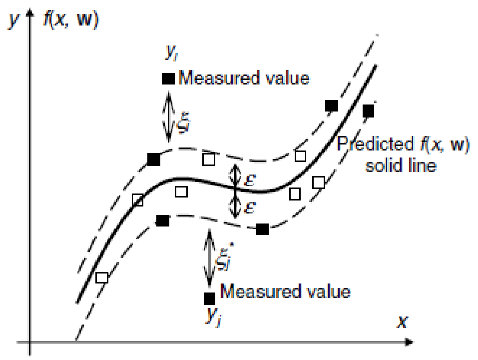

Figure 4. ε - tube. One dimensional support vector regression. Filled □ are support vectors, and the empty □ are not

In Figure 4. we can see typical graph of regression problem (nonlinear), where all needed mathematical objects required in the process of learning the unknown coefficients w_i, are presented.

Traditional training techniques usually focus on minimizing empirical risk, SVM tends to minimize effectively the upper bound of theoretical error (structural risk minimization, SRM). Empirical risk is the frequency of the error on the training set and it is computed as averaging the loss function on the training set (Eq. 2):

$$R_{emp}^{\varepsilon}(w)=\frac{1}{l}\sum_{i=1}^{l}|y_i-f(x_i,w)|_{\varepsilon} \quad (2)$$

SV machines implement new learning method which performs SRM and this leads to very good performance on previously unseen data, i.e. very good generalization, which makes SVM to be of exceptional importance, because the model which generalizes well is a good model, not the model which performs well on training data pairs.

Because SVM are developed in the frame of SRM (structural risk minimization) which tries to minimize expected, real error R, the most important goal in SVM modeling is to minimize this error R, which is given in Eq. (3):

$$R=\frac{1}{2}\|w\|^2+C\left(\sum_{i=1}^{l}|y_i-f(x_i,w)|_{\varepsilon}\right) \quad (3)$$

The parameter C is chosen by the user and it influences the value of approximation error and the weight vector norm $\|w\|$. Larger errors are penalized by increasing the parameter C. Another design parameter whose choice is easier than the choice of C and is also chosen by the user, is the desired precision, embodied in an ε value.

5. Results and discussion

In this paper, we use the software package DTREG [26] for forecasting the bidding cost.

Several types of SVM models are offered in this modeling software, depending on the kernel function which is used: sigmoid, linear, polynomial and RBF, for regression, and also for classification tasks.

Most often used and recommended function is the RBF (Eq. 4), but we do not know in advance the type of the kernel function which will be best for our task.

$$\Phi(x_i,x_j)=\exp(-gamma*|x_i-x_j|^2) \quad (4)$$

The iterative optimization process using DTREG can be stopped using control *tolerance factor*, called **Epsilon value.** For generating more accurate model, the tolerance factor can be reduced, and for reducing the computation time it can be increased, but very often the default value works well. After generating the SVM model, DTREG also gives a report on the relative significance of the predictor variables.

DTREG uses V-fold cross validation method for validating the SVM model which is used.

The selection of the model parameters impacts very much on the accuracy of the SVM model. DTREG offers two methods for obtaining optimal parameter values. For finding optimal parameters for regression problems, a *criterion for minimizing total error* is used. [30].

Chang and Lin [31] have great contribution in both theoretical and practical development of the support vector machines and SVM implementation in DTREG modeling software is partially based on their outstanding LIBSVM project.

The results of the implementation of SVM model using package DTREG for predicting the real price of projecting is given bellow in Table 1. and Table 2.

Table 1.SVM model for predicting bidding price (input data, summary of variables and SVM parameters)

Target variable: ln (price received)
Number of predictor variables: 2
Type of model: Support Vector Machine (SVM)
Type of SVM model: C-SVC
SVM kernel function: Radial Basis Function (RBF)
Type of analysis: Regression
Validation method: Cross validation
Number of cross-validation folds: 10

============ **Input Data** ============
Input data file: TENDERS
Number of variables (data columns): 14
Data sub setting: Use all data rows
Number of data rows: 26
Total weight for all rows: 26
Rows with missing target or weight values: 0
Rows with missing predictor values: 0

--- Statistics for target variable: ln(received price) ---
Mean value = 13.126042
Standard deviation = 1.5542198
Minimum value = 10.164312
Maximum value = 16.28361
==========================**Summary of Variables** =====================

No. Variable	Class	Type	Missing rows	Categories
1 number of project	Unused	Continuous	0	
2 category of construction	Unused	Categorical	2	
3 year of construction	Unused	Continuous	0	
4 purpose of construction	Unused	Categorical	0	
5 in Skopje	Unused	Categorical	10	
6 outside Skopje	Unused	Categorical	16	
7 price offered	Unused	Continuous	0	
8 received an offer price	Unused	Continuous	0	
9 contract signed or no	Unused	Categorical	0	
10 time for prep. doc (days)	Unused	Continuous	0	
11 problems about the doc.	Unused	Categorical	9	
12 ln (price offered)	Predictor	Continuous	0	25
13 ln(pricereceived)	Target	Continuous	0	
14 ln(time for prepar. doc)	Predictor	Continuous	0	8

=========================== **SVM Parameters** =====================
Type of SVM model: Epsilon-SVR
SVM kernel function: Radial Basis Function (RBF)
SVM grid and pattern searches found optimal values for parameters:
Search criterion: Minimize total error
Number of points evaluated during search = 1110
Minimum error found by search = 0.215803
Parameter values:
Epsilon = 0.001
C = 40.7921156
Gamma = 0.76524768
P = 0.23479872
Number of support vectors used by the model = 13

Table 2.SVM model for predicting bidding price- Analysis of variance (training and validation data)

======================== **Analysis of Variance** ===================

--- Training Data ---
Mean target value for input data = 13.126042
Mean target value for predicted values = 13.13796

Variance in input data = 2.4155993
Residual (unexplained) variance after model fit = 0.1987342
Proportion of variance explained by model (R^2) = 0.91773 (91.773%)
Coefficient of variation (CV) = 0.033963
Normalized mean square error (NMSE) = 0.082271
Correlation between actual and predicted = 0.959911

Maximum error = 1.9269423
RMSE (Root Mean Squared Error) = 0.4457962
MSE (Mean Squared Error) = 0.1987342
MAE (Mean Absolute Error) = 0.2720582
MAPE (Mean Absolute Percentage Error) = 2.0801151

--- Validation Data ---
Mean target value for input data = 13.126042
Mean target value for predicted values = 13.148486

Variance in input data = 2.4155993
Residual (unexplained) variance after model fit = 0.2459916
Proportion of variance explained by model (R^2) = 0.89817 (89.817%)

Coefficient of variation (CV) = 0.037786
Normalized mean square error (NMSE) = 0.101835
Correlation between actual and predicted = 0.948581

Maximum error = 1.9475975
RMSE (Root Mean Squared Error) = 0.4959754
MSE (Mean Squared Error) = 0.2459916
MAE (Mean Absolute Error) = 0.3289504
MAPE (Mean Absolute Percentage Error) = 2.5109899

The target variable is chosen to be **ln(price received)** and predicted variables are chosen to be **ln(price offered)** and **ln(time for preparing documents)**, because in this way more accurate model is obtained.

After the training phase, when the model is trained and established, SVM model can predict the values of the target variable for new values for the predictors. From the DTREG‘s ***Validation data row report file*** one can read all predicted values for the actual target variable, in this case **ln(price received)**, from where **price received** can be easily computed.

The accuracy of the model will be estimated from the statistics of validation data.

$\mathbf{R^2}$ and **MAPE** are used most often as estimators of a model**.**

The *coefficient of determination* $\mathbf{R^2}$ is a measure of global fit of the model, it indicates how well data points fit a line or curve. $\mathbf{R^2}$ is often interpreted as the proportion of the response variation “explained” by the explanatory (independent) variables in the model, and it is an element of [0,1]. The value $\mathbf{R^2=0.89817}$ from our model may be interpreted: around **89.8%** of the variation in the response can be explained by the independent variables. The remaining, around **10%,** can be ascribed to inherent variability or some unknown variables.

MAPE (mean absolute percentage error) is a measure of accuracy of a predictive model expressed as a percentage. For this SVM model **MAPE=2.5109899** means that the error of the model is around 2.5**%,** which is very high accuracy considering that the data are real.

6. Conclusion

The bidding process for a construction firm is affected by many internal and external firm factors that are complex and changeable. Additionally, in many cases, required bidding documents are extensive and the timeline for tendering is short. Furthermore, the bidding price can have a big influence on the construction firm's business. Hence, one of the most crucial issues for the firm is to determine the probability of a winning bidding price.

Decision concerning the bidding price has multi-disciplinary nature, so it is normally carried out by the firm team representatives. But, the decision for the bidding price stays a critical and a crucial decision.

Despite the big importance of the firm bidding price in the construction industry, it has not been given enough attention by researchers.

In this paper, the support vector machine (SVM) model was applied for forecasting the bidding price. Predictions by support vector machine model showed high accuracy that emphasized the fact that the SVM is one of the most accurate predictive models recently.

The proposed model in this paper is a tool for forecasting the bidding price in construction. Also, the model can be used as a support in decision for the price for tendering process by the project participants.

Although the model is based on data from the R. of Macedonia construction practice, this paper aims at giving a contribution to the body of knowledge for forecasting of the costs in the bidding process.

References

[1] Bagies, A., & Fortune, C. (2006). Bid/ no-bid decision modeling for construction projects. *Boyd, D (Ed): Procs 22nd Annual ARCOM Conference,* 4-6 September 2006, Birmingham, UK, Association of Researchers in Construction Management, 511-521. http://www.arcom.ac.uk/-docs/proceedings/ar2006-0511-0521_Bagies_and_Fortune.pdf (12.12.2014.)

[2] Ravanshadnia, M., & Rajaie, H., Abbasian, H.R. (2011). A comprehensive bid/no-bid decision making framework for construction companies. *IJST, Transactions of Civil and Environmental Engineering,* Printed in The Islamic Republic of Iran, Shiraz University. 35(C1), 95-103.

[3] Hartono, B., & Yap, C. M. (2011). Understanding risky bidding: a prospect-contingent Perspective. *Construction Management and Economics,* 29(6), 579-593.

[4] Wang, W. C., & Dzeng, R. J.,& Lu, Y. H. (2007). Integration of Simulation Evaluation Model for Bid Price Decisions. *Computer-Aided Civil and Infrastructure Engineering,* 22(3), 223-235.

[5] Xu, T., & Tiong, R. (2001). Risk assessment on contractors' pricing strategies. *Construction Management and Economics,* 19, 77-84.

[6] Ribeiro, J.A., & Pereira, J.P.,& Brandao, E. (2013). Reaching an optimal mark-up bid through the valuation of the option to sign the contract by the successful bidder, *SSRN ELECTRONIC JOURNAL, MAY 2013*

[7] Mitkus, S., & Trinkuniene, E. Reasoned decisions in construction contracts evaluation. (2008). *Technological and Economical Development of Economy,* 14(3), 402-416.

[8] Skitmore, R. M., & Pettitt, A. N., & McVinish, R. (2007). Gate's Bidding Model. *Journal of Construction Engineering Management,* 33(11), 855-863.

[9] Li, H., & Love, P.E.D. (1999). Combining rule-based expert systems and artificial neural networks for mark-up estimation. *Construction Management and Economics,* 17(2), 169-176.

[10] Fayek, A.(1998). Competitive Bidding Strategy Model and Software System for Bid Preparation. *Journal of Construction Engineering Management,* 124(1), 1-10.

[11] Chan, C. C. H.(2005). Online Auction Customer Segmentation Using a Neural Network Model. *Journal of Applied Science Engineering,* 3 (2), 101-109.

[12] Wang, W. C., & Yu, W. , & Yang, I.T., & Lin, C. C., & Lee, M.T., & Cheng, Y.Y.(2013). Applying the AHP to support the best-value contractor selection-lessons learned from two case studies in Taiwan. *Journal of Civil Engineering Managment*, 19(1), 24-36.

[13] Fong, P. S.W., & Choi, S. K. Y.(2000). Final contractor selection using the analytical hierarchy process. *Construction Management and Economics*, 18(5), 547-557.

[14] Enshassi, A., & Mohamed, S., & Karriri, A. E. (2010). Factor affecting the bid/no bid decision in the Palestinian construction industry. *Journal of Financial Management of Property and Construction*, 15 (2), 118-142.

[15] Drew, D.S., & Skitmore, R. M. Competitiveness in bidding: a consultant's perspective. (1992). *Construction Management and Economics*, 10(3), 227-247.

[16] Skitmore, M. (2004). Predicting the probability of winning sealed bid auctions: the effects of outlines on bidding models. *Construction Management and Economics*, 22(1), 101-109 .

[17] Günther, F., & Fritsch, S.(2010). Neuralnet: Training of Neural Networks. *The R Journal*, 2(1), 30-39. http://journal.r-project.org/archive/2010-1/RJournal_2010-1_Guenther+Fritsch.pdf (10.10.2014)

[18] Dissanayaka, S. M., & Kumaraswamy, M. M.(1999). Evaluation of factors affecting time and cost performance in Hong Kong building projects. *Engineering, Construction and Architectural Management*, 6(3), 287-298.

[19] Christodoulou, S.(2010). Bid mark-up selection using artificial neural networks and an entropy metric. *Engineering. Construction and Architectural Management*, 17(4), 424-439.

[20] Hongil, K., & Seung, B. (2004). Forecasting Winning Bid Prices in an Online Auction Market – Data Mining Approaches. *Journal of Electronic Science and Technology of China*, 2(3), 6-11.

[21] Dias, W. P. S., & Weerasinghe, R. L. D.(1996). Artificial neural networks for construction bid decisions. *Civil Engineering Systems*, 13(3), 239-253.

[22] Hota, A.R., & Bajpai, P., & Pratihar, D. K.(2012). Evolutionary neural networks for strategic bidding in electricity markets. *International Journal of Energy Sector Management*, 6(3), 321-342.

[23] Williams, T. P. (2002). Predicting completed project cost using bidding data. *Construction Management Economics*, 20(3), 225-235.

[24] Wanous, M., & Boussabaine, H. A., &Lewis, J. (2003). A neural network bid/no bid model: the case for contractors in Syria. *Construction management Economics*, 21(7), 737-744.

[25] Christodoulou, S. (2004). Optimum Bid Markup Calculation Using Neurofuzzy Systems and Multidimensional Risk Analysis Algorithm. *Journal of Computing in Civil Engineering*, 18 (4), 322-330.

[26] Sherrod, P. (2013). *Predictive Modelling Software*, www.dtreg.com, 02.08.2014.

[27] Vapnik, V., & Golowich, S., & Smola, A.(1997). Support vector method for function approximation, regress estimation and signal processing. *In M. C. Mozer, M. I. Jordan and T. Petsche (Ed.): Advances in Neural Information Processing Systems*, MIT Press, Cambridge, 281-287.

[28] Kecman, V. (2005). *Support Vector Machines – An Introduction.* School of Engineering Report 616, The University of Auckland, Auckland, NZ, Springer-Verlag, Berlin Heidelberg.

[29] Pesko, I.(2013). *Model for estimation of costs and time of construction for urban traffic arteries*,(in serbian), Phd Thesis, Novi Sad, R. of Serbia .

[30] Sherrod, P.(2013). *DTREG Predictive Modeling Software – tutorial*, www.dtreg.com , 15.07.2014.

[31] Chang, C. C., & Lin, C. J.(2011).LIBVSM – A library for Support Vector Machines, *ACM Transactions on Intelligent Sysems and Technologies*, 2 (3), 27.