ESTIMATION OF THE NUMBER OF PARTICIPANTS IN GOVERNMENT TENDERS WITH COMPUTATIONAL INTELLIGENCE

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Abstract

Even though a lot of bureaucratic procedures are needed in order to enter government tenders, it is still very attractive for businesses to participate in that process, mainly due to the advantages that are related to guaranteed payments, reliable customers, etc. However, it is a challenging job for the participating companies and the government to establish the tender parameters where both sides will be satisfied with the outcome. In this study, we tried to estimate the number of companies that will participate at a particular government tender. We used a set of 85,052 tender data items between the years 2004 and 2006. We used 60% of the data as the training set, 20% for cross validation (CV) and 20% for the testing set. We implemented 5-fold CV and testing in order to use all available data during testing. We first performed regression by using several different computational intelligence methodologies and then modeled it as a classification problem and compared different techniques. The results indicate that we were able to correctly estimate the number of participants with a 58.5% success rate. This model can provide a rough estimate of the amount of participation of the interested companies at any future tenders that the government is planning to deploy. This can be beneficial for the government for establishing a competitive tender that can attract the right amount of companies.

Keywords: Government tenders, business, computational intelligence, machine learning, neural networks, Support Vector Machines (SVM)

1. Introduction

Public procurement comprises a significant part of GDP of a country. OECD (2011) report states that OECD member countries spend on average 12% of their GDP on public procurement. Most of these procurements are conducted using an auction mechanism, For example, in 2014, the value of procured goods, services and construction projects in Turkey was approximately US$34 billion, which corresponds to slightly more than 4% of the Turkish GDP. Accordingly, conducting public procurement efficiently is essential to lower budget deficits and attaining fiscal discipline. Besides, a lot of companies are interested in entering government tenders. Hence, having prior knowledge about the number of firms participating in the tender is very valuable for both the government and the potential bidders.

The level of competition determined by the number of bidders is one of the major features of public procurement efficiency. Lewis-Faupel et al. (2014) states that limited competition, collusion among contractors and corruption among public officials are important reasons for lacking efficiency. Empirical studies like Iimi (2006) and Onur et al. (2012) show that there is a significant negative relationship between procurement prices and number of bidders in government procurement auctions. An increase in number of bidders substantially lowers procurement prices. Consequently, governments take several measures to promote competition and receive enough developed bids like introducing electronic procurement systems.

On the other side of the coin, participating and preparing a bid for public procurement auctions are very costly for tenderers. When the public procurement is conducted using an auction mechanism, the probability that a firm wins the auction depends on the bids submitted by its competitors. Bajari and Ye (2003) show that the optimal bid of a firm is a function of the expected value of number of bidders. Hence, constructing a correct forecast about number of potential bidders in a public procurement auction increases the probability that the firm will win the auction and the expected profit of the firm.

Some researchers study the factors that affect the tender outcome (Onur et al., 2012) however, only a very limited number of published literature items exists that provided any prediction model for the tender parameters. Furthermore, to best of our knowledge, there has not been any work implemented using computational intelligence techniques to predict the number of participants in a tender. This is our main motivation in this study: to come up with a satisfactory computational intelligence model that will give the number of participants at a given tender. This prediction can be used by governments to take precautionary actions if the optimal competitive environment will not be achieved. When low numbers of firms submit bids then the auction process will produce an inefficient outcome with significantly higher procurement price. Firms can use the predicted number of bids when they are forming their bids. In the first priced sealed bid auction, the firms do not have any prior knowledge about the number of bidders and the bids of their competitors before submitting their bids. Hence, they form their bids by forming expectations about potential number of bidders and probability distribution of the bids of the other firms. Forming a correct prediction about the potential number of bidders allows firms to construct their bids such that their winning probabilities and their expected profits are maximized.

The structure of the paper is as follows. After this brief introduction, we will go through the previous work in Section 2. In Section 3, we will introduce briefly the computational intelligence models that we used in our study, in particular SVM, the technique that provided the best result. We will describe the data set and our prediction model in Section 4 where we will provide the details about the inputs, output, model parameters, running environment, etc. The estimation results will be provided and the outcome will be discussed in Section 5. Finally, we will conclude in the last section.

2. Background

Most of the studies on government tenders / procurement auctions are concentrated on finding correlations between certain parameters that affect the tender outcomes. These studies aim to provide an insight into the complex workings and many factors of government tenders.

Levin and Smith (1994) theoretically present that under the optimal auction mechanism, the expected winning bid decreases when the number of potential bidders grows beyond a cut-off point. Li and Zheng (2009) present that equilibrium bidding behavior of the bidders can become less aggressive, meaning higher expected procurement costs, as the number of potential bidders increase.

A study by (Onur et al. 2012) investigates the relation between the number of bidders in government procurement auctions with the auction price, while also investigating whether the presence of foreign bidders also affect the auction price. The study concludes with establishing a significant negative relation between the number of bidders and the auction price.

Using data on tree planting contract auctions, Paarsch (1992) tests and rejects the hypothesis that the bid function decreases monotonically with the number of bidders, as expected for the standard first-price sealed-bid auctions within the private value model. He shows that the winning bid declines until the number of bidders reaches 5 to 10 for the tree planting contract auctions held in British Columbia. Gupta (2002) examines the number of bidders required for auctions to be competitive in highway construction auctions. He concludes that the procurement cost significantly decreases as the number of bidders rises to 6 to 8 firms.

While not focused on government procurement auctions, a study that was concentrated on eBay biddings by Bajari and Hortacsu in 2003 found out that the minimum bid set in auctions negatively influenced the number of bidders; with lower minimum bids attracting less bidders.

3. Computational Intelligence Models

Computational intelligence techniques have been used in different problems in a wide variety of application areas such as character recognition, stock market forecasting, weather prediction, credit risk evaluation, etc. (Theodoridis, 2009).

In this study, we compared the performance of a number of computational intelligence models for estimating the number of bidders in government auctions. The different computational intelligence models that we chose are Multilayer Perceptron, Radial Basis Function (RBF) Network, Decision Table and Regression Tree for the regression problem where we tried to directly estimate the number of bidders. Meanwhile, we also modeled the problem as a classification problem by trying to group the data into 3 different classes. Determining the groups using the number of participants in the tenders will be explained in Section 4. In the latter case we also used SVM in addition to the models that we used for the regression case. Furthermore, we compared the computational intelligence model results with the multivariate linear regression technique that is commonly used in such problems.

Multilayer perceptron is the most commonly used neural network model for regression/classification problems. The fundamental idea is to establish an input – output nonlinear relationship through several iterations by using one or more hidden layers for providing generalization capabilities and the learning is achieved by reducing the overall error between each output target value and the actual value to a satisfactory level. MLP is considered as a good generalizer. Radial Basis Function Network (RBF) is also considered as a neural network, but in this case there are no hidden layers. RBF generally converges faster than MLP, but the generalization capabilities are more limited compared to MLP. Regression tree is a type of decision tree that concentrates on the entropy for choosing the appropriate feature at each tree level, however instead of having discrete classes at the output, the average values of the output at that branch is used. Support Vector Machines (SVM) is a successful and widespread machine learning model used in many different fields. It was standardized as a machine learning tool by Cortes and Vapnik in 1995. Interested readers can get detailed information about the computational intelligence models in (Theodoridis, 2009).

SVM's versatility made it available for use in studies about government tenders. A study by Lam et al. in 2009 created an SVM model to improve the selection of bidders for government procurement auctions. Another study by Huang and Ying in 2007 used SVM to make credit analysis for bidders in government procurement auctions.

4. Dataset and Model

In this study, we used the government tender data which is provided by the Public Procurement Authority (PPA) of Turkey between the years 2004 and 2006, consisting of 131,000 tenders. Various tender methods are included in the initial dataset. To correspond with our study, we chose to use the first-price auctions, which consist of 85,052 tenders. The summary statistics of the used dataset is in Table 1.

	Min	Max	Mean	StdDev
covered	0	1	0.996	0.064
Good	0	1	0.458	0.498
Service	0	1	0.343	0.475
Construction	0	1	0.198	0.399
Open foreign	0	1	0.112	0.315
#bidders	1	67	3.011	3.234
Threshold	0	1	0.04	0.196
Estimated cost	0.693	20.261	10.387	1.812
Big city	0	1	0.227	0.419
Education	-0.75	3.645	0.272	0.109

Table 1 Variable statistics

The data distribution of the number of bidders is shown in Fig.1. The COVERED dummy variable takes the value one if the auction is conducted under the general or the annexed budget. Alternatively, the contracting authority might operate under its own budget if it is a state economic enterprise or partly owned by public administrations. The threshold values and procurement details are different for the auctions that are not covered by the general budget. The estimated cost is presented in Million Turkish Liras. Education parameter indicates the normalized education level around the country mean.

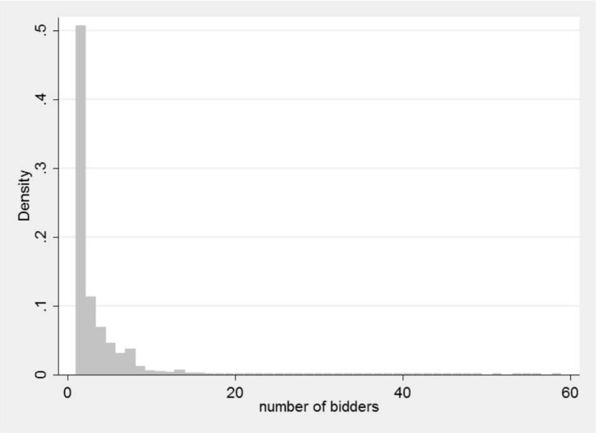

Fig. 1: Number of bidders' distribution

In this study, we used WEKA to train, test and predict the government procurement data. WEKA is a machine learning suite that is embedded with different models (Hall et al. (2009)). The performance metrics used for classification and regression (RMSE–Root Mean Squared Error and R - Correlation Coefficient) is given below:

$$R = \frac{\bar{l}\sum_{i=1}^{\bar{l}} f(x_i) y_i - \sum_{i=1}^{\bar{l}} f(x_i) \sum_{i=1}^{\bar{l}} y_i}{\sqrt{\left(\bar{l}\sum_{i=1}^{\bar{l}} f(x_i)^2 - \left(\sum_{i=1}^{\bar{l}} f(x_i)\right)^2\right)}\sqrt{\left(\bar{l}\sum_{i=1}^{\bar{l}} y_i^2 - \left(\sum_{i=1}^{\bar{l}} y_i\right)^2\right)}}$$

$$Accuracy = \frac{\#\,Of\ Correctly\ Predicted\ Data}{\#\,Of\ Total\ Testing\ Data} \times 100\%$$

$$RMSE = \sqrt{\frac{1}{\bar{l}}\sum_{i=1}^{\bar{l}} (f(x_i) - y_i)^2}$$

We split our datasets and used 60% for training, 20% for cross-validation and 20% for testing. We repeated this process 5 times, each time we used different 20% portions of the data for testing (and chose the 60% training and 20% CV data accordingly). As a result, we were able to test 100% of the data. In each process, we kept the data distribution of all training, CV and test portions representative of the overall data distribution. Our results reflect the testing performance.

The inputs to the model are listed in Table 1. Some of them are the tender types that represent goods, services and construction procurements, and the estimated cost for the tender before it is announced and the output is the number of participants.

Considering the wide distribution of the number of bidders, which is shown in Fig. 1, three approaches for prediction are used. In the first one, we tried to estimate the number of participants directly. In another model, we created a new dataset with three classes for the number of bidders. The first class, A, represented the tenders with only one bidder. The Class B, included more than one and less than six bidders tenders. And the Class C represented the rest (more than 5 bidders). Finally, in our third approach we normalized the dataset and equalized the number of instances in the classes by eliminating some tenders randomly from Classes A and B in order to equalize the number of instances in each class to be very similar without changing the data distribution. As a result, the total number of data points was reduced to approximately 3 times the number of data points in C.

5. Results and Discussions

In our first part of the study, we tried to find the number of bidders with regression. Using different computational intelligence methods that are listed in Table 2, we got slight improvements over linear regression. After that we examined our dataset in a detailed way.

	RMSE	APE	AAPE	R
RBF Network	3.2157	-72,8275	97,56122	0.1729
Multilayer Perceptron	2.8862	-7,0661	59,25341	0.5165
Decision Table	2.8011	-50,2858	74,11574	0.5147
REP Tree	2.7797	46,1117	69,79415	0.528
Linear Regresson	2.8749	-52,3396	79,07648	0.4741

Table 2 Root mean squared error (RMSE), Average Percent Error (APE), Absolute Average Percent Error (AAPE) and Correlation Coefficient (R) values of computational intelligence methods

When Table 2 is analyzed, it is seen that MLP provided the best overall error percentage due to its generalization capabilities. But the RMSE value was slightly higher than the others, indicating it was more successful in estimating the lower number of bids, but not as good in the higher ones. However, REP Tree provided the best RMSE and correlation values, indicating a slightly better match for the overall picture.

Due to using real world data, we faced the difficulty of having a non-uniform bidder number distribution. Concentration of data is mostly on the tenders with one or two bidders. Therefore, we got high percent error ratios at in the first approach. If the built model predicts two bids instead of one bid tender, the error ratio becomes 100%.

As a result, we tried a new approach. We tried to approach the problem as a classification problem. Instead of using the actual number of bidders, we put them into three classes as explained in the previous section.

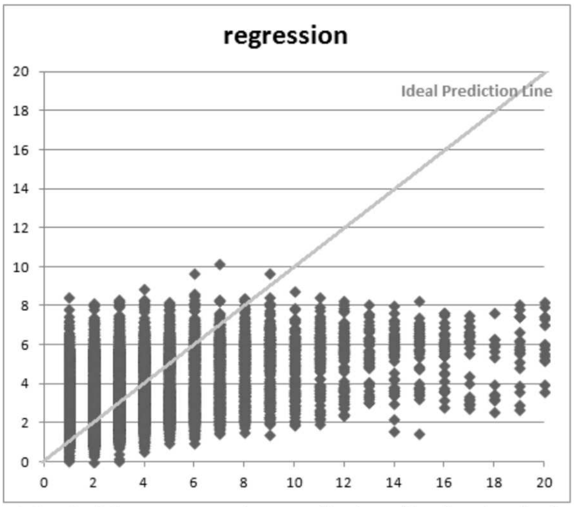

Fig. 2: Linear regression prediction distribution before data distribution normalization

Predicted values were generated with linear regression model. The distribution of actual and predicted values for linear regression can be seen in Fig. 2. and Fig. 3.

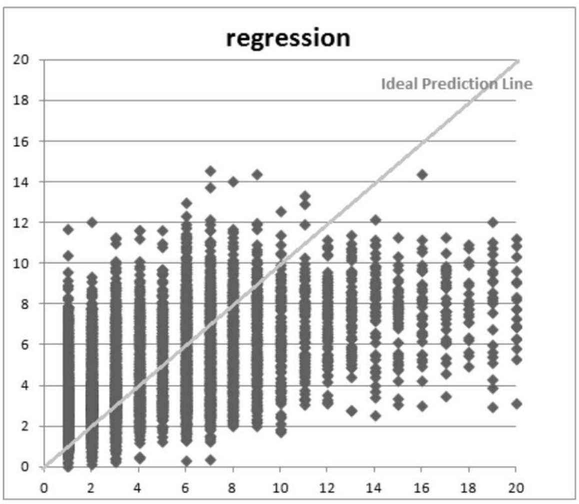

Fig. 3: Linear regression prediction distribution after data distribution normalization

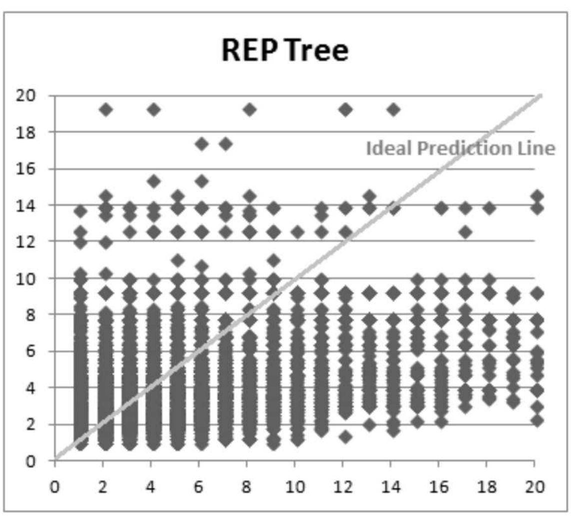

Fig. 4: REP Tree prediction distribution before data distribution normalization

Similarly, REP Tree performance is available in Fig 4 and 5. In Fig. 2,3,4 and 5, the x-axis represents the actual values and the y-axis represents the predicted values.

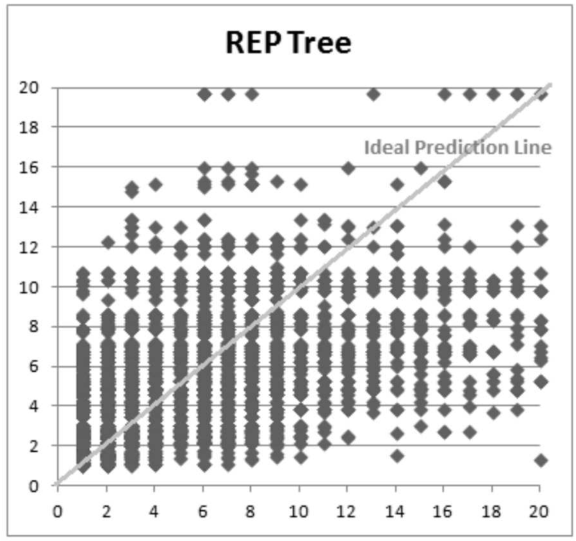

Fig. 5: REP Tree prediction distribution after data distribution normalization

In our second approach we classified the data into 3 groups as explained before. Then we performed the classification of the number of bidders. We are only presenting the results of the SVM model, since it outperformed the other models. The confusion matrix and true-positive, false-positive rates of SVM runs' results before normalization can be seen in Table 3 and Table 4.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
A	0.448	0.089	0.777	0.448	0.569	0.68
B	0.856	0.589	0.555	0.856	0.673	0.634
C	0.258	0.021	0.645	0.258	0.369	0.619

Table 3 Statistics before data distribution normalization

		Predicted Values		
	Class	A	B	C
Actual Values	A	3115	3800	31
	B	845	6718	285
	C	51	1593	573

Table 4 Confusion Matrix before data distribution normalization

According to Powers (2011) True and False Positives (TP/FP) refer to the number of correctly/incorrectly labeled instances. F-Measure, Recall and ROC Area are used to compare and evaluate the performance of the algorithms. These values are calculated using the number of True/False Positive and True/False Negative examples classified by algorithms.

After dividing the data into three classes, we got improvements in our results but not much as was desired. However, this was mostly due to the uneven distribution of the data into classes. The A, B, C classes' percentages in the dataset are 40.8%, 46.13% and 13.07% respectively, indicating the small number of bidders dominated the data set, it was very hard for the classifier to identify the class which consisted of the tenders characterized by high number of bidders (class C). Therefore we applied a normalization process and equalized the number of instances in each class. The confusion matrix and true-positive, false-positive rates of SVM runs' results after normalization can be seen in Table 5 and Table 6.

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
A	0.46	0.066	0.776	0.46	0.578	0.697
B	0.593	0.351	0.459	0.593	0.518	0.621
C	0.701	0.206	0.629	0.701	0.663	0.747

Table 5 Statistics after data distribution normalization

		Predicted Values		
	Class	A	B	C
Actual Values	A	1020	946	249
	B	240	1318	664
	C	54	607	1547

Table 6 Confusion Matrix after data distribution normalization

As can be seen from the tables, the percentage of correctly classified instances increased after the normalization process. In our initial dataset, we classified 52.41% of the instances correctly (Class C was very poorly classified). On the other hand, after the data distribution normalization process, we were able to classify 58.46% of the instances correctly.

6. Conclusions

In this study we provided a prediction model that will provide the number of participating companies at a given government tender. We used different computational intelligence techniques for this purpose. Several different models are tested and compared. Our best model was able predict the correct class of participants with 58.46% accuracy. By analyzing the results, we see that the proposed model can be used to provide a general estimation that can assist the government to take necessary action about the tender if needed. As a result, the government can set or adjust the initial tender requirements such that the optimum number of companies might participate in the tender to achieve the best competition. Future work will involve the estimation of the tender bid and the actual cost along with more accurate results for similar tender parameters.

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