

A Random Forest Deviation Model for Predicting the Awarded Amount in Public Construction Procurement: Evidence from Morocco

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ABSTRACT

In construction procurement, forecasts of contract award values are typically driven by the initial estimate. Rather than directly predicting the awarded amount, as performed by the baseline Random Forest model, this study introduces a deviation-based decision-support model for public procurement that predicts the difference between the estimate and the eventual award value. The dataset was obtained from the Moroccan Portal of Public Procurement. Model performance was evaluated using RMSE and MAE. The findings show that the estimate accounts for 99.7% of the predictive influence in the baseline model. However, the proposed approach provides greater predictive accuracy, recording an MAE of 113,318.82 MAD, whereas the baseline model produces an MAE of 207,986.76 MAD. Moreover, while predictions generated by the baseline model remain strongly associated with the estimate, modelling the deviation reveals the relevance of contextual characteristics, including the contracting authority's name and geographical location, for data-driven public procurement analysis. The remainder of this paper is organised as follows. Following the introduction, the second section reviews the relevant literature, while the third section describes the research methodology and dataset. The subsequent sections report the results and discuss the strengths and limitations of the study. The final section concludes the paper and identifies directions for future academic research.

Keywords: Public Construction Procurement, Award Amount Prediction, Machine Learning, Random Forest, Project Procurement Management, Procurement Analytics, Decision Support

INTRODUCTION

Public procurement encompasses the acquisition of works, services, and goods by public institutions (Oliveira et al., 2024). Beyond its purchasing function, it provides public authorities with a mechanism for implementing public policies (Schotanus & Grandia, 2023) and managing public financial resources (Tkacova et al., 2017). Given its direct implications for public expenditure, procurement constitutes an important component of public financial management. Decision-making within this domain is nevertheless challenging because procurement processes are characterised by uncertainty and require the simultaneous consideration of structured and unstructured information. Public procurement professionals

therefore require robust analytical tools capable of supporting more informed decisions (Erridge & McIlroy, 2002; Thai, 2001).

Public procurement systems operate within regulatory frameworks that establish procedural requirements and govern the different stages of procurement. In the United States, procurement is regulated through the Federal Acquisition Regulation (Code of Federal Regulations, 1997), whereas the European context is governed by the European Commission (EC), (Janssen, 2023). In Morocco, responsibility for the regulatory framework lies with the Ministry of Economy and Finance (Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement, 2023). Before a tender is launched, Moroccan public institutions are required to determine an estimated cost in accordance with "Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement" (2023). The same regulatory framework requires this estimate to be made publicly available and communicated to all competitors (Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement, 2023).

The estimate serves several functions within the procurement process. Accurate prediction of the awarded amount can facilitate more effective management of project budgets. At the same time, regulations impose a threshold on the permissible deviation between the estimate and the awarded amount (Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement, 2023). A tender may therefore be declared unsuccessful when this deviation exceeds the prescribed limit. Efficient procurement management is also fundamental to good governance within public institutions. Preventing project overestimation can contribute to expenditure efficiency and generate substantial financial savings. The scale of this potential benefit is considerable, as even a 1% reduction in procurement expenditure could yield approximately 20 billion euros in annual savings (Garcia Rodriguez et al., 2021). Conversely, budgets that underestimate project requirements may result in cost overruns and impose additional pressure on public funds (Kandazoglu & Oz, 2025).

The importance of the estimate has consequently prompted considerable interest in the factors associated with its determination. Its value may reflect several dimensions of the procurement environment, including prevailing market prices, sectoral characteristics, competitive conditions, and the regulatory requirements applied by public institutions (Decarolis, 2014). From a financial perspective, research on construction procurement has devoted particular attention to differences between estimated and awarded amounts, including the uncertainty and biases that may contribute to such discrepancies (Flyvbjerg et al., 2002). These differences cannot necessarily be attributed to a single determinant, as regulatory requirements, tender technical specifications, and strategic bidding behaviour may all influence the final outcome. Bidders themselves respond strategically to the information available during the procurement process. Their offers may be formulated with reference to market prices, applicable regulations, anticipated bids from competitors, and the tender estimate (Shen, 2025). Given this combination of influences, identifying the factors and decision rules associated with tender outcomes is increasingly relevant to both bidders and public institutions (Shen, 2025).

Empirical evidence further indicates that, although the estimate is an important predictor of the awarded amount, it does not independently determine the eventual procurement outcome (De Silva et al., 2008). The final awarded amount may also be shaped by market prices and the administrative rules governing the tendering process. The mechanism through which a winning offer is selected also varies across regulatory environments. While many procurement systems award contracts to the lowest bidder, the Moroccan framework adopts a different criterion. Under Article 44 of Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement

(2023), the contract is awarded to the competitor whose offer is closest to the reference price, which is defined as follows:

$$\text{Reference Price} = (\text{Estimate} + \text{Mean of the offers received})/2$$

This requirement demonstrates that the regulatory framework is an important determinant of the awarded amount in public procurement. The increasing adoption of AI provides public procurement professionals with new opportunities to strengthen decision support and improve the efficiency of procurement processes. In relation to cost estimation, previous studies have demonstrated the potential of ML techniques to predict awarded amounts from historical observations (Hastie et al., 2009; James et al., 2021). By extracting meaningful patterns and converting historical records into actionable information, these tools can support more informed decision-making (Kache & Seuring, 2017; Wamba et al., 2017).

Despite their predictive capabilities, conventional ML approaches may become strongly associated with project size, thereby limiting the extent to which other explanatory characteristics are captured. Consequently, a model may achieve its predictions primarily through correlation with the estimate rather than by identifying the broader factors associated with the awarded amount. This issue is particularly important in the Moroccan public procurement context because contract award decisions are determined using a reference price that incorporates both the estimate and the mean of the submitted offers. A conventional prediction model dominated by the estimate may therefore provide limited insight into the additional factors underlying variations in awarded amounts. To address this issue, the present study introduces a deviation-based modelling framework in which the prediction target is the rate of deviation from the estimate rather than the awarded amount itself. Using Random Forest (Breiman, 2001), the empirical analysis demonstrates that the estimate contributes more than 99% of the explanatory power of the baseline model. Such dominance indicates that the baseline specification predominantly captures differences in project size rather than variations associated with bidder behaviour or contextual characteristics. Once the target is reformulated as deviation and the influence of the estimate is reduced, other explanatory variables become more prominent, including sectors, public institutions, project location, and year.

The proposed model has potential applications for several stakeholders involved in public construction procurement, including directors of public institutions, professional buyers, procurement managers, and project managers. More accurate prediction of the awarded amount can support effective project budget management and strengthen procurement-related decision-making. Policymakers may similarly use predicted procurement outcomes as analytical inputs when formulating public policies. Furthermore, future research may build upon the proposed deviation-based framework to improve the accuracy of awarded amount predictions in public construction procurement. This paper aims to:

- Examine the contribution of the estimate to predictions of the awarded amount using a baseline ML model. Through empirical analysis, the study demonstrates that the model largely reproduces information embedded in the estimate, thereby restricting its capacity to capture the contribution of other variables and generate additional insights into procurement outcomes.
- Introduce a deviation-based modelling approach in which deviation from the estimate, rather than the awarded amount, constitutes the prediction target. This methodological framework provides an alternative means of examining the factors associated with procurement outcomes.

This paper is structured around the questions below:

1. To what extent does the estimate contribute to the explanatory power of a baseline ML model, and does this contribution limit its predictive accuracy in the context of public procurement?
2. Can the deviation-based modelling approach address this limitation and reveal other parameters that may influence the prediction of the awarded amount?

LITERATURE REVIEW

Machine Learning and Decision Support in the Field of Public Procurement

Recent developments in ML have accelerated the use of data-driven decision-support approaches within public procurement. Predictive techniques, including regression-based methods and ANN, have been applied to estimate awarded amounts and assist decision-making in procurement settings where complex data must be analysed (Baryannis et al., 2019; Wamba et al., 2017). By identifying meaningful patterns within such data, ML enables procurement professionals to generate useful predictive insights, improve estimation accuracy, and contribute to greater efficiency across the public procurement process.

The Impact of Estimation Errors in Public Procurement

Errors in public procurement cost estimation are widespread across countries and arise from a combination of technical, organisational, and strategic factors. Technical sources of estimation inaccuracies, examined by Ahmed H and Elshwadfy (2021) and Chimdi et al. (2020), include the quality of project documentation, the experience of cost estimators, and the materials specified for construction. Beyond these technical considerations, Flyvbjerg et al. (2002) identifies organisational inefficiencies and strategic misrepresentation intended to secure project approval as additional sources of estimation errors. The significance of these inaccuracies extends to procurement outcomes because the estimate serves both as a reference for bidders when preparing their offers and as an important determinant of the awarded amount (Berraida & Laila, 2025). Under the Moroccan regulatory framework, it also forms part of the reference price used to identify the most suitable bids (Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement, 2023). Consequently, deviations from realistic estimated values may directly influence the awarded amount and the eventual outcome of the procurement process.

Institutional Mechanisms and Bidding Behaviour in Public Procurement

Tender award outcomes in public procurement emerge from interactions between public institutions and competing bidders. When formulating their offers, bidders respond to the information available for a particular tender while also considering their expectations regarding the bids likely to be submitted by competitors (Krishna, 2009). Within this information environment, the estimate occupies a particularly important position because it can shape bidding strategies and influence how competitors position their offers (De Silva et al., 2008). Its relevance is further reinforced by its role within the mechanism used to determine the eventual tender award.

Tender outcomes, however, are not determined exclusively by bidding behaviour or the estimate. Institutional rules also shape award decisions (Bosio et al., 2022), meaning that submission of the lowest-priced offer does not necessarily result in contract award. This is particularly evident under Article 44 of Moroccan Decree No. 2.22.431 of March 8, 2023 on

Public Procurement (2023). Procurement outcomes should therefore be understood as the product of several interacting dimensions, including market behaviour, the number of competitors, the value of the estimate, and the institutional framework governing the award process. Accordingly, meaningful analysis of tender outcomes requires consideration of the broader contextual environment rather than reliance on a single explanatory variable.

The Role of Machine Learning in Public Procurement

The emergence of AI and ML has expanded the use of predictive analytics in procurement research, particularly for forecasting tender award amounts. Their ability to capture complex and nonlinear relationships within procurement datasets has encouraged the application of techniques such as neural networks, gradient boosting, and Random Forest for prediction, anomaly detection, and decision support (Hastie et al., 2009; James et al., 2021). Within this predictive setting, ML is primarily applied to maximise forecasting accuracy rather than to explain the mechanisms underlying procurement outcomes. Following a statistical learning approach, these models tend to place substantial predictive importance on variables that are strongly associated with the target (Hastie et al., 2009). In public procurement, the estimate represents such a variable because of its close relationship with the awarded amount. As a result, a model may predominantly learn the monetary scale of the tender through the estimate and use this information to forecast the awarded amount. Although this relationship can support predictive performance, its dominance may obscure other informative patterns within the data. Such dependence may become particularly limiting when the estimate is inaccurate or unavailable, as potentially relevant contextual variables may not be sufficiently captured by the model.

Gaps in Existing Methods and Pathways for Advancement

Research on public procurement has largely progressed along two complementary directions. One stream has examined inefficiencies within procurement processes, with particular attention to cost overruns and their underlying causes (Bajari et al., 2008; Flyvbjerg et al., 2002). A second, more recent stream has explored the increasing use of artificial intelligence, especially ML, to predict tender award amounts (Bosio et al., 2022; Decarolis, 2014). Within ML-based research, emphasis has primarily been placed on improving the predictive accuracy of the awarded amount. Given the strong association between the estimate and the eventual award value, predictive models may become heavily dependent on the estimate. Such dependence can reduce attention to model interpretability and limit the identification of other potentially relevant factors associated with procurement outcomes (Hastie et al., 2009). Consequently, rather than revealing additional patterns within procurement data, the model may predominantly reproduce information already contained in the estimate and thereby capture the monetary scale of the project. This limitation establishes the need for an alternative modelling framework that combines greater accuracy in predicting the awarded amount with the ability to uncover meaningful information about the factors associated with variations in procurement outcomes.

Contribution of this Paper

The gap identified in subsection 2.5 is addressed through an alternative modelling framework in which the deviation from the estimate is predicted rather than the awarded amount itself. By reformulating the prediction target in this way, the proposed deviation-based decision-support approach reduces the dominance of the estimate and enables other variables associated with the awarded amount to become more prominent. This contribution is particularly relevant to Moroccan public procurement, where the reference price reflects the influence of factors

beyond the estimate. The proposed approach therefore offers additional insight into the role of other determinants of the awarded amount, including institutional rules and competitive conditions.

RESEARCH METHODOLOGY AND DATASET

Research Methodology

The application of ML has been widely examined across previous studies ([James et al., 2021](#); [Mullainathan & Spiess, 2017](#); [Shmueli, 2010](#)). However, the effectiveness of these techniques, particularly in public procurement, is closely linked to how the prediction target is defined ([Domingos, 2012](#); [Hand, 2006](#)). Against this background, the present study adopts a supervised ML framework to evaluate two alternative modelling strategies: a baseline model and a deviation-based model. By comparing these approaches, the analysis demonstrates the importance of reformulating the target variable as a means of improving the effectiveness of ML in predicting the awarded amount.

Variables, Data Source and Pre-Processing

Study Sample

The data analysed in this study were obtained from the Moroccan Portal of Public Procurement, an e-procurement platform administered by the General Treasury of the Kingdom of Morocco ("[Moroccan Portal for Public Procurement \[Portail Marocain Des Marchés Publics\]](#)," 2023). The dataset comprises 375 tenders launched by Moroccan public institutions over the last five years, covering a range of contracting authorities, including ministries, universities, municipalities, and public agencies. The dataset contains key procurement-related variables, including the authority's name, location, year, sector, estimate, and awarded amount. The use of actual procurement records provides:

- Reliability and authenticity of the information.
- Transparency and reproducibility of the findings.
- Compliance with legal requirements.

Nevertheless, the information available through the Moroccan Portal of Public Procurement does not capture certain characteristics that may be relevant to procurement outcomes, including project complexity, supplier characteristics, and competition intensity. The absence of these variables may account for part of the unexplained variation observed in relative deviations and awarded amounts, since procurement outcomes may be associated with differences in these characteristics. Given that such information is unavailable in the dataset, however, these potential relationships cannot be quantified and should not be interpreted as causal effects. To incorporate categorical information into the predictive framework, categorical variables were transformed through one-hot encoding, allowing them to be represented appropriately during ML modelling ([Hastie et al., 2009](#)).

The complete sample was partitioned into training and testing subsets. The training set comprised 80% of the observations, corresponding to 300 tenders, while the remaining 20%, representing 75 tenders, formed the test set. An identical training–testing partition was maintained for both the baseline and deviation models to ensure comparability. The test set

remained entirely separate from model training, hyper parameter selection, and pre-processing decisions and was used exclusively for final performance evaluation. Figure 1 illustrates the composition of the dataset and the model development process. Moreover, Figure 1 illustrates the sample structure and validation procedure, including repeated cross-validation and model selection. Using the 300 tenders allocated to the training set, model performance was evaluated through five-fold cross-validation repeated 20 times. Within each repetition, the training data were partitioned into five folds of 60 tenders. Four folds were used for model fitting, while the remaining fold served as the validation subset. This process was rotated across all five folds so that every tender received an out-of-fold prediction. To maintain direct comparability between the two modelling approaches, identical folds were applied to both the baseline and deviation models.

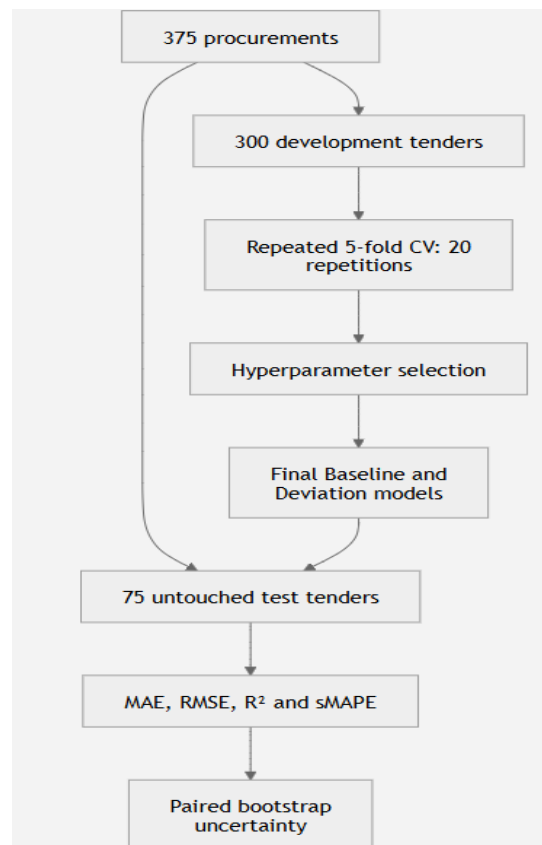


Figure 1: Model Development and Composition of the Sample

Descriptive Characteristics of the Sample

Descriptive statistics were used to characterise the study sample and summarise the distribution of the variables. Continuous variables were described using the mean, median, standard deviation, minimum, and maximum values. Categorical variables, including tender type, location, region, sector, procedure type, and authority name, were summarised through frequencies and percentages. Together, these measures provide an overview of the sample composition and the distributional characteristics of the variables incorporated into the modelling framework. Categorical features were summarised using frequencies and proportions.

Table 1: Descriptive Statistics of the Sample

Variable	Median	Mean	SD	Maximum	Minimum
Estimate (MAD)	Value	Value	Value	Value	Value
Awarded amount (MAD)	Value	Value	Value	Value	Value
Year	Value	Value	Value	Value	Value

The sample covers a range of public institutions, regions, procurement types, and procedures, thereby capturing the diversity of procurement characteristics incorporated into the models. Table 1 presents the descriptive statistics of the most important variables, including the estimate, the awarded amount, and the year of tender.

Hyperparameter Sensitivity

A hyper parameter sensitivity analysis was undertaken to examine how alternative Random Forest configurations affected model performance. Six configurations were evaluated by varying the number of trees, maximum tree depth, minimum number of observations required in each terminal leaf, and number of predictors considered at each split. Each configuration was assessed using the 300 tenders allocated to model development, with the minimum number of observations required to split an internal node fixed at two. Performance was evaluated through five-fold cross-validation repeated three times, with identical folds applied to both models to ensure comparability. Mean cross-validation MAE was adopted as the primary criterion for hyper parameter selection, while RMSE was additionally examined to capture sensitivity to larger prediction errors. The remaining 75 tenders were held out entirely from the hyper parameter selection process. Table 2 presents the Random Forest configurations evaluated in the analysis. “Unlimited” indicates that no restriction was imposed on the maximum tree depth. A fixed random seed was applied across all configurations, while the minimum number of samples required to split an internal node was held constant at two.

Table 2: The Configuration of the Random Forest

Configuration	Trees	Maximum Depth	Minimum Observations Per Leaf	Predictors Used for Each Split
RF-500-Depth10	500	10	1	All Predictors
RF-300-Default	300	Unlimited	1	All Predictors
RF-500-Leaf2	500	Unlimited	2	All Predictors
RF-500-Half	500	Unlimited	1	Half of Predictors
RF-500-Sqrt	500	Unlimited	1	Square Root of the Number of Predictors
RF-500-Leaf4	500	Unlimited	4	All Predictors

Bootstrap Analysis and Final Evaluation

Following hyper parameter selection, each model was fitted using the 300 training tenders and subsequently evaluated on the held-out set of 75 tenders. Predictive performance was assessed against the awarded amount using MAE, RMSE, R², median absolute error, and sMAPE. To quantify uncertainty in the comparative performance of the two models, a paired bootstrap procedure was applied to their predictions on the test set.

The Models Studied in this Paper: Baseline Model and Deviation-Based Model

Baseline Model

The baseline model adopts a supervised learning framework in which the awarded amount is specified directly as the prediction target:

$$Y_i = g(x_i)$$

- Y_i : The awarded amount predicted
- X_i : Explanatory variables

The model is implemented using Random Forest (Breiman, 2001), an ML method that constructs an ensemble of prediction trees and generates the final predicted value by averaging the predictions obtained across the individual trees. Given the characteristics of the dataset and the presence of nonlinear relationships among the variables, Random Forest provides an appropriate modelling approach because of its ability to capture complex nonlinear patterns (Hastie et al., 2009). Predictive performance is assessed using RMSE and MAE, both of which are widely applied in empirical research to quantify prediction accuracy (James et al., 2021).

Deviation Based Decision Support Model

To address the limitation of the baseline model arising from the dominant contribution of project size to the predicted amount (Hastie et al., 2009), this study introduces a deviation-based modelling framework. Rather than predicting the awarded amount directly, the proposed approach reformulates the prediction target as the deviation from the estimate, thereby reducing the influence of the estimate on the modelling process. The deviation is calculated as follows:

$$D_i = (Y_i - E_i) / E_i$$

- D_i : Deviation for tender i
- Y_i : The predicted amount for tender i
- E_i : Estimate for tender i

By reformulating the prediction target as the deviation rather than the awarded amount, the model reduces its dependence on the estimate and places greater emphasis on other potentially informative parameters. Accordingly, the learning framework is defined as follows:

$$D_i = F(P_i)$$

- D_i : Deviation for tender i
- P_i : Explanatory variables (Sector, location, Authority's name)
- F : Random Forest

Once the deviation has been predicted, the awarded amount is reconstructed as follows:

$$Y_i = (1 + D_i) * E_i$$

- Y_i : The awarded amount for tender i
- D_i : Deviation for tender i

- E_i : The estimate for tender i

This formulation decomposes the awarded amount into two components: the estimate and the variation associated with market behaviour. This representation is consistent with [De Silva et al. \(2008\)](#); [Krishna \(2009\)](#), which recognise the relevance of these components in shaping the awarded amount.

Model Development

Both models were implemented in Python within the Google Colab environment, using the scikit-learn libraries for ML modelling. To ensure a consistent comparison, identical procedures were applied to the baseline and deviation models throughout pre-processing, training, and evaluation. The dataset was partitioned into two subsets, with 80% of the tenders allocated to training and the remaining 20% reserved for testing. This separation enables ML models to be evaluated on unseen data and provides an assessment of their ability to generalise beyond the observations used during training ([James et al., 2021](#)).

Evaluation Strategy

The evaluation strategy examines two complementary dimensions:

- Predictive accuracy, assessed by comparing MAE and RMSE. Both models were evaluated using the same test set of 75 tenders, with performance measured on the scale of the awarded amount. Accordingly, all prediction errors were calculated relative to the awarded amount.
- Model interpretation, examined by comparing the two approaches to determine which variables are associated with the prediction of the awarded amount.

This comparative framework therefore evaluates not only the predictive accuracy of each model but also its interpretability and capacity to provide meaningful insights into the factors associated with the prediction process.

RESULTS

Baseline Model

As defined in Section 3, the baseline model directly predicts the awarded amount as follows:

$$Y_i = g(x_i)$$

- Y_i : The awarded amount predicted
- X_i : Explanatory variables

The predictive accuracy of the model was assessed using MAE and RMSE, calculated as follows:

- $MAE = 1/n * \sum |Y_i - \hat{Y}_i|$
- $RMSE = \sqrt{1/n * (Y_i - \hat{Y}_i)^2}$

Where:

- Y_i : The actual awarded amount
- $\hat{Y}_i$: The predicted amount for tender i

Repeated Cross-Validation

The MAE and RMSE values obtained from repeated cross-validation of the baseline model are presented in Table 3.

Table 3: Repeated Cross-Validation in the Development Set (5 Folds)

Model	Mean MAE (MAD)	Empirical 95% Interval	Mean CV RMSE (MAD)	Empirical 95% Interval
Baseline Model	851,407.00	726,175 – 1,065,057.00	7,612,593.00	6,959,010.00 – 9,090,821.00

As mentioned in Table 3, the reported intervals represent the empirical range of model performance observed across the 20 repetitions of the cross-validation procedure.

Final Test Performance

Table 4 presents the results obtained from evaluating the model on the held-out test sample of 75 tenders. Table 4 summarises the predictive performance of the baseline model, which achieved an MAE of 207,986.77 MAD, an R^2 of 0.9883, and an sMAPE of 3.226%. The difference between the RMSE and median absolute error indicates that a limited number of relatively large prediction errors occurred within the test sample, increasing the magnitude of the average error metrics.

Table 4: Baseline Model Performance

Metric	Value (MAD)
MAE	207,986.77
RMSE	1,021,623.21
Median Absolute Error	14,754.72
R^2	0.9883
sMPAE (%)	3.226

Deviation Based Model

As defined in Section 3, the deviation from the estimate is specified as the target variable as follows:

$$D_i = (Y_i - E_i) / E_i$$

- D_i : Deviation for tender i
- Y_i : The predicted amount for tender i
- E_i : Estimate for tender i

The predicted deviation is subsequently used to reconstruct the awarded amount as follows:

$$Y_i = (1 + D_i) * E_i$$

- Y_i : The awarded amount for tender i
- D_i : Deviation for tender i
- E_i : The estimate for tender i

Model performance was evaluated using MAE and RMSE, defined as follows:

$$\text{MAE} = 1/n * \sum |d_i - \hat{d}_i|$$

$$- \text{RMSE} = \sqrt{(1/n * (d_i - \hat{d}_i)^2)}$$

Where:

- d_i : Actual deviation with the estimate
- $\hat{d}_i$: Predicted deviation with the estimate

Repeated Cross Validation

The MAE and RMSE values obtained from repeated cross-validation of the deviation model are presented in Table 5:

Table 5: Repeated Cross-Validation in the Development Set (5 Folds)

Model	Mean MAE (MAD)	Empirical 95% Interval	Mean CV RMSE (MAD)	Empirical 95% Interval
Deviation Model	156,974.00	148,362 – 167,483	681,030	629,885 – 740,934

As mentioned in Table 5, the reported intervals represent the empirical range of model performance observed across the 20 repetitions of the cross-validation procedure. Based on the MAE and RMSE values, the deviation model demonstrates better predictive performance than the baseline model while maintaining consistent performance across alternative fold assignments.

Final Test Performance

Table 6 reports the predictive performance of the deviation model on the test sample of 75 tenders. Compared with the baseline model, the deviation model achieves a substantially lower MAE of 113,318.82 MAD, compared with 207,986.77 MAD for the baseline model. It also records an R² of 0.9985 and an sMAPE of 2.587%. The difference between the RMSE and median absolute error indicates the presence of a limited number of unusually large prediction errors, which increase the magnitude of the average error metrics.

Table 6: Deviation Model Performance

Metric	Value (MAD)
MAE	113,318.82
RMSE	369,326.17
Median Absolute Error	18,349.80
R ²	0.9985
sMAPE (%)	2.587

Distribution of the Relative Deviation

To assess the suitability of modelling deviations directly, the empirical distribution of the deviation variable was examined. The mean deviation was 2.3%, while the median was 1.2%, with a standard deviation of 4.6%. Positive deviations accounted for 76.8% of the sample, whereas negative and zero deviations represented 16.7% and 6.93%, respectively. Relatively large deviations were uncommon: only 4.53% of observations exceeded 10%, and 1.87% exceeded 20%. Although the distribution exhibited positive skewness, with a skewness coefficient of 3.22, extreme deviations occurred infrequently within the sample. Table 7 presents the distribution of deviations across the sample. Table 7 shows that the deviations are

concentrated around zero, with a mean of 2.3% and a median of 1.2%. Although the distribution is positively skewed, the relative deviation transformation remains stable across the sample.

Table 7: Distribution of the Relative Deviation

Statistic	Value
Tenders	375
Median Deviation	1.2 %
Mean Deviation	2.3 %
Negative Deviation $D_i < 0$	16.27%
Standard Deviation	4.67 %
Zero Deviation ($D_i = 0$)	6.93%
Positive Deviation ($D_i > 0$)	76.80 %
Deviation $> 20\%$	1.87 %
Deviation $> 10\%$	4.53 %
Skewness	3.22 %

Paired Bootstrap Analysis

The paired bootstrap analysis of the 75 test tenders further supported the improved performance of the deviation model relative to the baseline model. The deviation model reduced MAE by approximately 94,668 MAD and RMSE by 652,297 MAD, with the corresponding 95% bootstrap intervals remaining above zero. However, the bootstrap intervals for sMAPE and median absolute error included zero, indicating that the performance difference between the two models was less pronounced for these metrics. The complete paired bootstrap results are presented in [Table 8](#).

Table 8: Paired Bootstrap Analysis

Metric	Baseline Deviation	95% Bootstrap Interval	Interpretation
MAE (MAD)	94,667.95	705.80 – 261,932.11	Performance of Deviation Model
RMSE(MAD)	652,297.06	6,829.32 – 1,157,632	Performance of Deviation Model
Median Absolute Error (MAD)	-3,595.07	-12,400.36 – 16,777.44	Interval Includes 0
sMPAE (%)	0.638	-0,024 – 1.333	Interval Includes 0

Analysis of Feature Importance

In contrast to the baseline model, the predictions generated by the deviation model are associated with a broader set of features, as presented in [Table 9](#). [Table 9](#) highlights a clear difference in feature importance between the two models. In the baseline model, the estimate accounts for approximately 99.77% of the predictive importance, indicating a strong dependence on project size. In contrast, the predictive information captured by the deviation model is primarily associated with authority (79.61%) and location (20.38%). This shift indicates that reformulating the target as a deviation reduces the dominance of project size and allows other contextual features to contribute more prominently to the prediction.

Table 9: Contribution of Features for Both Models

Variable	Deviation Model %	Baseline Model %
Estimate	0.000	99,77
Type of works	0.000	0.132
Sector	0.000	0.071
Authority	79,61	0.013
Location	20.38	0.008
Procedure	0.000	0.000
Year	0.000	0.000
Region	0.000	0.000
Total	100.00	100.00

Comparative Analysis

The baseline and deviation models are distinguished by how their target variables are defined. Whereas the baseline model directly predicts the awarded amount, the deviation model estimates the variation relative to the initial estimate. This reformulation of the prediction target leads the two models to capture different patterns during the learning process.

Models' Definition

Table 10: Deviation and Baseline Model Definition

Baseline Model	Deviation Model
$Y_i = g(x_i)$	$D_i = (Y_i - E_i)/E_i$
- Y_i : The awarded amount predicted	- D_i : Deviation for tender i
- X_i : Explanatory variables	- Y_i : The predicted amount for tender i
	- E_i : Estimate for tender i
	- The awarded amount is then calculated as bellow:
	- $Y_i = (1 + D_i) * E_i$
	- Y_i : The awarded amount for tender i
	- D_i : Deviation for tender i
	- E_i : The estimate for tender i

Table 10 presents the mathematical formulations associated with the definition of baseline and deviation models, providing the approach of each model to predict the awarded amount.

Models Performance Comparison

The MAE and RMSE results for both models are summarised in [Table 11](#). As shown, the deviation model achieves greater predictive accuracy than the baseline model, with its MAE decreasing from 207,986.77 MAD to 113,318.82 MAD.

Table 11: Models' Performance

Model	MAE (MAD)	RMSE (MAD)
Baseline	207,986.77	1,021,623.21
Deviation	113,318.82	369,326.17

Contribution of Variables for Each Model

Table 12 illustrates how the two models differ in their reliance on the explanatory variables. In the baseline model, the estimate accounts for approximately 99.77% of the predictive importance, indicating that the model predominantly learns the monetary scale of the project. In contrast, the estimate contributes negligibly to the deviation model, allowing contextual features, particularly authority and location, to become more prominent in the prediction process:

$$D_i = G(\text{Authority, location}).$$

This formulation demonstrates that, once the dominance of project size is reduced, other contextual characteristics become more informative for explaining variation in the awarded amount, alongside the institutional rules governing public procurement.

Table 12: Variables Contribution

Variable	Deviation Model	Baseline Model
Estimate	00.00%	99.77%
Authority's Name	79,61	00.00%
Location	20.38	00.00%

Robustness Testing

To assess model robustness, an additional test was performed using inaccurate estimates to examine how estimation errors affect the predictions generated by each model. The results of this analysis are presented in Table 13. Under the original estimate (Estimate bias = 0), the deviation model achieves a lower MAE than the baseline model (113,318.82 MAD vs 207,986.77 MAD). A similar performance advantage is observed under the +10% and +20% overestimation scenarios. These findings indicate that the deviation model performs well when estimates are realistic or moderately overestimated, although it does not outperform the baseline model under every scenario. Overall, the results also demonstrate that both models remain sensitive to substantial inaccuracies in the estimate.

Table 13: Robustness Test

Estimate Bias	Estimate Bias Percentage	Baseline MAE (MAD)	Baseline RMSE (MAD)	Deviation Model MAE (MAD)	Deviation Model RMSE (MAD)
-0.2	-20	1,019,793.74	2,182,389.10	1,068,115.85	2,360,517.02
-0.1	-10	552,723.83	1,434,500.19	566,004.38	1,322,730.14
0	0	207,986.77	1,021,623.21	113,318.82	369,326.17
0.1	10	571,088.85	1,592,934.92	440,463.36	865,462.19
0.2	20	1,107,716.61	3,166,630.34	943,065.93	1,892,315.30

DISCUSSION

Interpretation

This study compares two approaches for predicting the awarded amount in public procurement: the baseline model and the deviation model. Although both models demonstrate strong predictive performance, the deviation model achieves a lower MAE than the baseline model

(113,318.82 MAD vs 207,986.77 MAD). However, the main distinction between the two approaches lies in their learning behaviour. The baseline model relies predominantly on the estimate, resulting in predictions that largely reflect project size while providing limited information about the contribution of other variables. This pattern is consistent with statistical learning theory, whereby variables strongly associated with the prediction target can dominate the learning process (Hastie et al., 2009; James et al., 2021).

In contrast, reformulating the target as the deviation substantially reduces the predictive importance of the estimate (0.00% vs 99.77%), allowing other features, particularly authority and location, to become more prominent. These findings suggest that variation in the awarded amount cannot be understood solely through the estimate and may also be associated with contextual characteristics and the regulatory environment governing the procurement process (Bajari et al., 2008; De Silva et al., 2008; Krishna, 2009). The comparison therefore demonstrates the value of target reformulation when applying predictive analytics to public procurement. Rather than allowing a single highly dominant variable to determine model behaviour, the proposed deviation-based approach captures predictive information from a broader set of contextual features while also achieving improved predictive accuracy. In this way, the framework extends the role of predictive analytics beyond award prediction alone by providing additional interpretable insights that can support procurement decision-making.

Link to Procurement Regulations

The findings are consistent with regulatory frameworks such as Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement (2023), under which the awarded amount is determined not only by the estimate but also by competitors' bids. This regulatory setting reinforces the relevance of contextual factors when predicting procurement outcomes. From a tendering perspective, the awarded amount emerges from the interaction of competitors' bids, market behaviour, and competitive conditions (Klemperer, 2004; Krishna, 2009). Accordingly, procurement outcomes cannot be regarded as a simple reproduction of a single variable; rather, they reflect the combined influence of multiple factors, including characteristics of the procurement context. The deviation-based approach further reveals variation across public institutions, with authority accounting for 79.61% of the predictive importance in the empirical analysis. This result suggests that institutional characteristics are strongly associated with variation in the deviation from the estimate. Such evidence is consistent with previous research emphasising the role of governance and institutional practices in shaping the efficiency of public institutions (Bosio et al., 2022).

Contribution of this Paper

This paper examines the application of ML tools to predict the awarded amount in public procurement. Its main contribution is twofold:

- First, the empirical analysis demonstrates the dominant role of the estimate when the awarded amount is predicted directly using the baseline ML approach. The findings show that the baseline model largely reproduces information contained in the estimate, thereby restricting the contribution of other variables and limiting the additional insights that can be derived regarding procurement outcomes.

- Second, the study introduces a deviation-based framework in which the prediction target is reformulated as the deviation from the estimate rather than the awarded amount itself. The empirical results demonstrate that this reformulation substantially reduces the dominance of the estimate and allows the model to capture predictive information from other relevant features. By separating the deviation component from project size, the proposed approach provides additional insights into the role of contextual factors associated with variations in the awarded amount.

More broadly, this study extends the literature on ML-based procurement analytics by demonstrating how reformulating the prediction target can improve predictive accuracy while generating more informative insights into the factors associated with procurement outcomes.

IMPLICATIONS FOR PROFESSIONAL BUYERS

The findings of this study offer practical insights for professional buyers, particularly those involved in public procurement. First, the proposed model can serve as a decision-support tool by identifying variables associated with the awarded amount beyond the estimate alone. Second, its predictive capability can assist procurement managers in anticipating awarded amounts with greater accuracy, thereby supporting planning and resource management within public organisations. This is particularly relevant because tenders may be declared unsuccessful when the difference between the most favourable bids and the estimate exceeds the threshold established by the competent authority ([Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement, 2023](#)). More broadly, integrating predictive analytics into procurement processes can strengthen decision-making in an environment characterised by complex interactions and substantial volumes of structured and unstructured data.

LIMITATIONS OF THE STUDY

Despite its contributions, this study has several limitations that should be considered when interpreting the findings. First, although model performance was examined through a rigorous validation procedure comprising repeated cross-validation, hyper parameter sensitivity analysis, and paired bootstrap analysis, the final evaluation relied on a test sample of 75 tenders drawn from the original dataset. The reported results therefore constitute internal out-of-sample validation rather than independent external validation. Future research should evaluate the models using independent datasets obtained from different procurement portals, time periods, or jurisdictions. Second, because the empirical analysis is based on observational data, the identified relationships between the deviation and other variables cannot be interpreted as causal effects. The findings should therefore be understood as evidence of associations rather than direct causal relationships.

Third, the dataset contains a limited set of variables, including authority, sector, amounts, location, and year. Potentially relevant characteristics such as project complexity, competition intensity, and supplier characteristics could not be incorporated because of data availability constraints. Their omission may restrict the explanatory scope of the analysis and may influence the observed predictive patterns. Finally, the robustness analysis demonstrates that the deviation model remains sensitive to inaccuracies in the estimate. Under the -10% and -20% estimate-bias scenarios, the baseline model achieves better predictive performance. Consequently, the advantage of the proposed framework is not consistent across all estimation conditions, and its performance remains partly dependent on the reliability of the underlying estimate.

CONCLUSION

This study examines the prediction of awarded amounts in public procurement using ML and compares a conventional baseline model with a proposed deviation-based approach. While the baseline model directly predicts the awarded amount, the deviation model predicts the deviation from the estimate and subsequently reconstructs the awarded amount. The empirical findings reveal that the baseline model is strongly dominated by the estimate, which accounts for 99.77% of its predictive importance. This dependence limits the contribution of other variables. In contrast, the deviation-based formulation substantially reduces the influence of the estimate and allows contextual factors, particularly authority and location, to contribute more prominently to the prediction. These results demonstrate that target-variable formulation can significantly influence both model behaviour and the insights obtained from ML-based procurement analysis. The robustness analysis also shows that the deviation model remains sensitive to inaccurate estimates. Although it performs better under realistic and moderately overestimated conditions, its advantage is not maintained across all estimate-bias scenarios. The reliability of the initial estimate therefore remains important to model performance. Overall, this study contributes by demonstrating the limitations of directly predicting the awarded amount when the estimate dominates the learning process and by introducing a deviation-based decision-support approach that improves predictive accuracy while providing greater insight into contextual factors associated with procurement outcomes. Future research should validate the proposed approach using larger and independent datasets from different periods, procurement portals, and jurisdictions, while incorporating additional variables such as project complexity, competition intensity, and supplier characteristics.

CONFLICT OF INTEREST

Declaration of the authors: No conflict of interest for the publication of this article.

REFERENCES

- Ahmed H, I., & Elshwady, L. M. (2021). Factors Affecting the Accuracy of Construction Project Cost Estimation in Egypt. *Jordan Journal of Civil Engineering*, 15(3). <https://www.researchgate.net/profile/Lamiaa-Mohamed-4/publication/353147794>
- Bajari, P., McMillan, R., & Tadelis, S. (2008). Auctions Versus Negotiations in Procurement: An Empirical Analysis. *Journal of Law, Economics, and Organization*, 25(2), 372-399. <https://doi.org/10.1093/jleo/ewn002>
- Baryannis, G., Dani, S., & Antoniou, G. (2019). Predicting Supply Chain Risks Using Machine Learning: The Trade-Off between Performance and Interpretability. *Future Generation Computer Systems*, 101, 993-1004. <https://doi.org/10.1016/j.future.2019.07.059>
- Berraida, R., & Laila, E. A. (2025, 2025/06/11). *The Use of Artificial Intelligence to Calculate the Estimate of a Public Procurement Act* The 1st International Conference on Smart Management in Industrial and Logistics Engineering (SMILE 2025), <http://dx.doi.org/10.3390/engproc2025097007>
- Bosio, E., Djankov, S., Glaeser, E., & Shleifer, A. (2022). Public Procurement in Law and Practice. *American Economic Review*, 112(4), 1091-1117. <https://doi.org/10.1257/aer.20200738>

- Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5-32. <https://doi.org/10.1023/a:1010933404324>
- Chimdi, J., Girma, S., Mosisa, A., & Mitiku, D. (2020). Assessment of Factors Affecting Accuracy of Cost Estimation in Public Building Construction Projects in Western Oromia Region, Ethiopia. *Journal of Civil Engineering, Science and Technology*, 11(2), 111-124. <https://doi.org/10.33736/jcest.2617.2020>
- Code of Federal Regulations, 62 Federal Register 51230 (1997). <https://www.ecfr.gov/current/title-48/part-15/section-15.306>
- De Silva, D. G., Dunne, T., Kankanamge, A., & Kosmopoulou, G. (2008). The Impact of Public Information on Bidding in Highway Procurement Auctions. *European Economic Review*, 52(1), 150-181. <https://doi.org/10.1016/j.eurocorev.2007.07.003>
- Decarolis, F. (2014). Awarding Price, Contract Performance, and Bids Screening: Evidence from Procurement Auctions. *American Economic Journal: Applied Economics*, 6(1), 108-132. <https://doi.org/10.1257/app.6.1.108>
- Domingos, P. (2012). A Few Useful Things to Know About Machine Learning. *Communications of the ACM*, 55(10), 78-87. <https://doi.org/10.1145/2347736.2347755>
- Erridge, A., & McIlroy, J. (2002). Public Procurement and Supply Management Strategies. *Public Policy and Administration*, 17(1), 52-71. <https://doi.org/10.1177/095207670201700105>
- Flyvbjerg, B., Holm, M. S., & Buhl, S. (2002). Underestimating Costs in Public Works Projects: Error or Lie?. *Journal of the American Planning Association*, 68(3), 279-295. <https://doi.org/10.1080/01944360208976273>
- Garcia Rodriguez, M. J., Rodriguez Montequin, V., Aranguren Ubierna, A., Santana Hermida, R., Sierra Araujo, B., & Zelaia Jauregi, A. (2021). Award Price Estimator for Public Procurement Auctions Using Machine Learning Algorithms: Case Study with Tenders from Spain. *Studies in Informatics and Control*, 30(4), 67-76. <https://doi.org/10.24846/v30i4y202106>
- Hand, D. J. (2006). Classifier Technology and the Illusion of Progress. *Statistical Science*, 21(1). <https://doi.org/10.1214/088342306000000060>
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning*. Springer series in statistics New-York. <https://doi.org/10.1007/978-0-387-84858-7>
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). An Introduction to Statistical Learning. In *Springer Texts in Statistics*: Springer US. <http://dx.doi.org/10.1007/978-1-0716-1418-1>
- Janssen, W. A. (2023). Public Procurement Law in the European Union. In *Public Procurement* (pp. 39-56): Springer International Publishing. http://dx.doi.org/10.1007/978-3-031-18490-1_3
- Kache, F., & Seuring, S. (2017). Challenges and Opportunities of Digital Information at the Intersection of Big Data Analytics and Supply Chain Management. *International*

- Journal of Operations & Production Management*, 37(1), 10-36.
<https://doi.org/10.1108/ijopm-02-2015-0078>
- Kandazoglu, M., & Oz, B. (2025). *Resource Management for Public Construction Projects: The Economic Impact of Estimating Engineering Services Costs* 15th International Congress on Engineering, Architecture and Design, Istanbul, Türkiye.
<https://www.researchgate.net/publication/393745074>
- Klemperer, P. (Ed.). (2004). *Auctions: Theory and Practice*. Princeton University Press.
<https://doi.org/10.1515/9780691186290>.
- Krishna, V. (2009). *Auction Theory* (2nd ed.). Academic press San Diego.
<https://shop.elsevier.com/books/auction-theory/krishna/978-0-12-374507-1>
- Moroccan Decree No. 2.22.431 of March 8, 2023 on Public Procurement, Official Gazette of Morocco (2023).
<https://www.marchespublics.gov.ma/pmmp/textereg.html?rubrique6&lang=fr>
- Moroccan Portal for Public Procurement [Portail Marocain Des Marchés Publics]. (2023).
<https://www.marchespublics.gov.ma/pmmp/>
- Mullainathan, S., & Spiess, J. (2017). Machine Learning: An Applied Econometric Approach. *Journal of Economic Perspectives*, 31(2), 87-106. <https://doi.org/10.1257/jep.31.2.87>
- Oliveira, T. E. S. d., Pessôa, L. A. M., Frej, E. A., & Souza, A. C. d. (2024). A Combination of Fittradeoff and Cognitive Maps for Object Definition in Public Procurement. *Pesquisa Operacional*, 44. <https://doi.org/10.1590/0101-7438.2023.043.00273855>
- Schotanus, F., & Grandia, J. (2023). Public Procurement Policy and Purchasing Strategy. In *Public Procurement* (pp. 73-95): Springer International Publishing.
http://dx.doi.org/10.1007/978-3-031-18490-1_5
- Shen, T. (2025). Auction Theory: Applications in Real Estate Auctions. *Finance & Economics*, 3(6), 7562. <https://doi.org/10.61173/c6xgdy26>
- Shmueli, G. (2010). To Explain or to Predict? *Statistical Science*, 25(3).
<https://doi.org/10.1214/10-sts330>
- Thai, K. V. (2001). Public Procurement Re-Examined. *Journal of Public Procurement*, 1(1), 9-50. <https://doi.org/10.1108/jopp-01-01-2001-b001>
- Tkacova, A., Gavurova, B., Danko, J., & Cepel, M. (2017). The Importance of Evaluation of Economic Determinants in Public Procurement Processes in Slovakia in 2010?2016. *Oeconomia Copernicana*, 8(3). <https://doi.org/10.24136/oc.v8i3.23>
- Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. J. (2017). Big Data Analytics and Firm Performance: Effects of Dynamic Capabilities. *Journal of Business Research*, 70, 356-365. <https://doi.org/10.1016/j.jbusres.2016.08.009>