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A Graph-Based Framework for Analyzing Bidding Competition in Design-Bid-Build Highway Construction Contracts

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ABSTRACT: Bidding competition significantly influences bidding outcomes and bid prices in the project-letting phase for State Highway Agencies (SHAs). Prior research often quantifies competition by counting bidders, overlooking variations in competitive intensity among them. A small group of highly competitive bidders can exert greater pricing pressure than a larger pool of less competitive bidders. Additionally, existing methods lack predictive frameworks for identifying potential bidders based on contract-specific characteristics such as project bundling status. This study introduces a graph-based methodology that conceptualizes bidding competition as a bipartite network. In this framework, bidders and contracts are modeled as distinct node sets, with contract nodes incorporating attributes such as location, size, work type, bundling status, and letting year. Edges between bidder and contract nodes are formed based on historical bidding records. A graph neural network (GNN) is then employed to predict the probability of a bidder submitting a bid on a given contract. The framework was implemented using 11 years of bid data (1,590 contracts) from the South Dakota Department of Transportation, achieving an ROC-AUC of 90.62% and a weighted F1 Score of 83%, demonstrating strong predictive performance. This methodology provides SHAs and owners with a practical tool to assess competition intensity based on contract characteristics, ultimately enabling more data-driven decision-making in highway construction procurement.

1. INTRODUCTION

Design–Bid–Build (DBB) projects are primarily adopted for their potential to reduce bid prices, optimize project outcomes, and foster growth within the construction industry (Asaye et al. 2024; Tran et al. 2018). However, numerous studies suggest that the intended benefits of competitive bidding depend on the presence of a sufficiently high level of competition among bidders (Carr 2005; Cheung and Shen 2017; Heo et al. 2024; Lee 2022). When genuine competition is lacking, DBB projects not only fail to deliver the anticipated advantages but also lead to increased costs for the owner and suboptimal project outcomes (Cheung and Shen 2017).

Recognizing the critical role of adequate competition during the letting phase, the Federal Highway Administration (FHWA) requires State Highway Agencies (SHAs) to evaluate the level of competition during bid analysis to inform award or re-let decisions (FHWA 2021). However, the current practice among SHAs is to measure competition primarily by the number of bidders. Generally, if at least three bidders participate, the competition is deemed adequate (Liu et al. 2022). Although SHAs consider the percentage deviation from the engineers' estimate (EE), the main criterion remains the bidder count. Most previous studies have similarly relied on the number of bidders as the primary metric for measuring bidding competition (Baek and Ashuri 2019; Carr 2005; Padhi et al. 2016; Qiao et al. 2021; Shrestha and Pradhananga 2010).

Another important consideration related to anticipation of bidding competition arises during the project bundling decision process by SHAs (Qiao et al. 2021). Project bundling involves aggregating several projects into a single multi-project contract to enhance delivery efficiency, particularly through economies of scale (Do et al. 2023; Qiao et al. 2019). When implemented appropriately, bundling can lead to significant improvements in project outcomes. For example, FHWA has reported design cost savings of 25–50 percent and construction savings of 5–15 percent for bundled projects (FHWA n.d.). Nevertheless, these efficiency gains come with challenges, including a reduction in market competition (Assaf et al. 2024). In contracts that are already large or involve highly specialized tasks, incorporating dissimilar components tends to restrict the pool of qualified bidders (Qiao et al. 2021). Consequently, highway agencies remain ambivalent about the overall merits of bundling and seek clearer guidance on its effects on bidding competition. Moreover, existing studies assessing the impact of project bundling on competition also rely on the number of bidders as the key metric (Qiao et al. 2021).

Although it is intuitive to assume that more bidders indicate stronger competition, well-established competition theories characterize competition as a force of rivalry that drives innovation (Smith 1937). Recent research further demonstrates that a smaller group of highly competitive bidders may represent a higher intensity of competition than a larger pool of less competitive ones (Baek and Han 2024; Cheung and Shen 2017; Lu et al. 2021; Moriyani et al. 2024). For example, Moriyani et al. (2024) show that the level of competition within a contract depends on the competitiveness of its participating bidders. However, few studies have focused on assessing competition using predictive frameworks that identify which bidders are likely to participate (Baek and Ashuri 2018; Ballesteros-Pérez et al. 2019). One attempt modeled a bidder's participation preference using a log-normal distribution as a function of tender economic size (i.e., contract size) (Ballesteros-Pérez et al. 2016). Nonetheless, a limitation of such probability distribution models is the difficulty of simultaneously incorporating the synergistic effects of multiple explanatory variables. In reality, a bidder's likelihood of participating depends on various factors, including the project's location and complexity (Ahmed et al. 2024).

To sum up, two significant limitations exist in the current literature. First, existing studies primarily rely on the number of bidders, even though bidding outcomes are more closely correlated with the intensity of competition among bidders rather than their sheer number. Second, no comprehensive framework currently exists to predict bidder identity while accounting for multiple contract-specific factors during the letting phase. To address these limitations, this study proposes a novel bipartite graph–based approach to model bidding competition. In our approach, bidders and contracts form two distinct sets of nodes, with edges connecting them only when a bidder has submitted a bid on a project, as indicated by historical bidding records. Contract-specific attributes are stored in the contract nodes. We then leverage a graph neural network to predict the probability of an edge existing between a given bidder and contract, thereby providing a more nuanced measure of competition.

2. METHODOLOGY

Figure 1 illustrates the proposed novel two-phase approach to modeling bidding competition. In the first phase, a bipartite graph is modeled using historical bid tabulation data, which typically includes information on contracts (along with contract-specific characteristics), the bidders participating in each contract, and the winning bidder. In the second phase, the competition is established by predicting bid probabilities and assessing the competitiveness of the predicted bidders to assess the level of competition in the contract. This approach serves two purposes. For project owners, it offers guidance for bundling decisions, and for potential bidders, it provides insights that help optimize their bidding strategies.

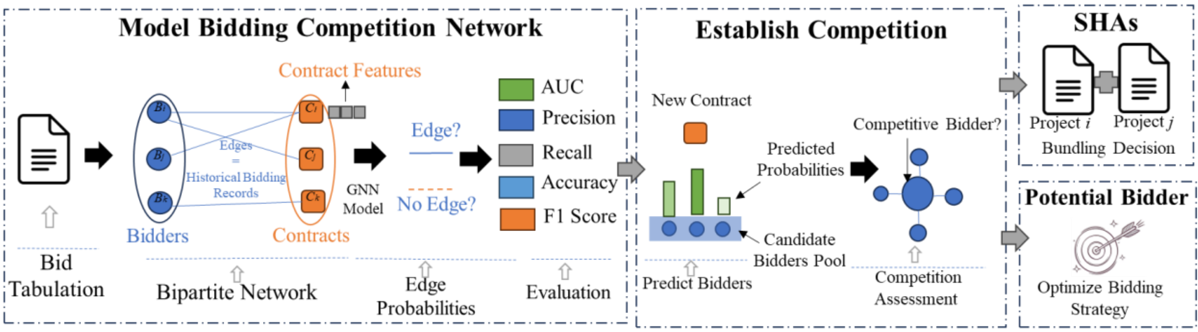


Figure 1: Proposed Novel Approach to Establishing Bidding Competition and its Application

2.1 Model Bidding Competition

2.1.1 Bipartite Network

A bipartite graph is defined by two distinct sets of nodes with edges only established between nodes of different sets (Xue et al. 2021). As shown in Figure 2, in the proposed bipartite graph, there exist two distinct sets of nodes: one representing a set of bidders and the other representing a set of contracts. An edge is established between a bidder and a contract if the bidder historically submitted a bid for that contract. Each contract node stores the contract-specific characteristics as node attributes. It is important to emphasize that our goal is not to predict the overall bid/no-bid decision, which is influenced by dozens of factors such as a bidder's current workload, availability of alternative projects, financial health, resource availability, and inflation (Chisala 2017). Rather, the goal is to assess bidding competition. Therefore, consistent with prior research on bidding competition, we consider only the contract features to model the bidding competition (Qiao et al. 2021). Among the various factors, we selected the six most significant factors affecting the bidding competition. 1) EE, reflecting project size; 2) Year of Letting (to incorporate the effect of macroeconomic conditions indirectly); 3) Letting Season (to incorporate the effect of seasonality); 4) Project Location; 5) Project Work Type, and 6) Bundling Status. The proposed graph is represented mathematically by using Equation 1, the contract features are represented by Equation 2, and the relationships are captured by the corresponding interaction matrix and adjacency matrices by Equations 3 and 4.

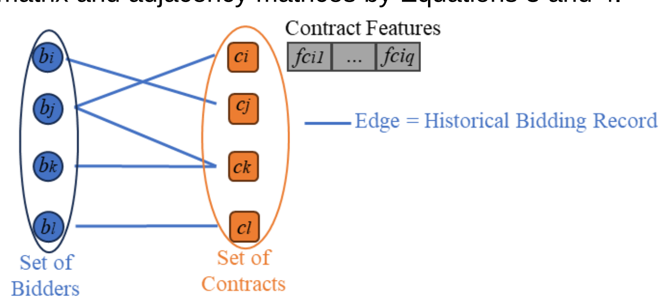


Figure 2: Proposed Bipartite Graph

[1] $G = (B, C, F_C)$

[2] $$fc_i = \begin{pmatrix} fc_{i1} \\ fc_{i1} \\ \vdots \\ fc_{iq} \end{pmatrix}$$

Where, G represents the bipartite graph; B is the set of bidders:$\{b_1, b_2, \dots b_m\}$; C is the set of contracts $\{c_1, c_2, \dots c_n\}$; m is the number of bidders; n is the number of contracts; F_C is the set of feature vectors associated with each contract Ci and q is the number of features for each contract.

[3] $I = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$

[4] $A = \begin{pmatrix} 0 & I_2 \\ I_2^T & 0 \end{pmatrix}$

Where, $a_{ij} = \begin{cases} 1 & \textit{if the bidder bi bid a contract cj} \\ 0 & \textit{otherwise} \end{cases}$; I= interaction matrix for the bipartite graph and A= adjacency matrix.

2.1.2 Edge Probabilities

Because bidders do not have inherent features, each bidder (denoted as bi) is assigned a learnable embedding. For contract nodes, the raw feature vector (fci) is transformed into a latent embedding via a learnable function. As shown in Figure 3, the initial node embeddings are then refined by passing them through a three-layer, multi-head GAT architecture (with dropout and ELU activations) to propagate and update node embeddings in the bipartite graph G. Since our proposed graph is a bipartite graph, we specifically preferred the GAT architecture, which leverages the self-attention mechanism to compute adaptive weights for each neighboring node, enabling the effective aggregation of heterogeneous node features, thereby achieving superior performance relative to other architectures (Veličković et al. 2018). To train the GNN effectively, we incorporate negative sampling. Negative samples are artificially generated examples of node pairs that do not exhibit a connection (Wang et al. 2024). In the case of our proposed network, a negative sample means a bidder is not interested in bidding on a contract based on its features. The negative sample ratio was kept twice as high as the positive sample. For link prediction tasks, it is crucial for the model to learn the distinction between valid connections (positive examples) and non-connections (negative examples). The network is trained using a weighted binary cross-entropy loss that addresses class imbalance through negative sampling. The model then predicts the edge probability through a dot product followed by a sigmoid activation function.

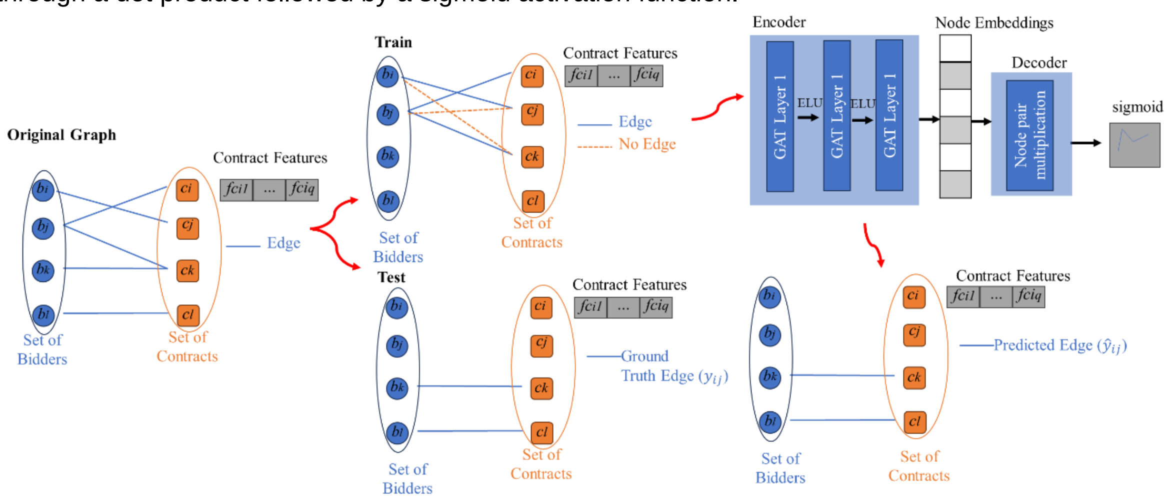


Figure 3: GNN Training Procedure to Predict the Edge Probabilities

2.1.3 Evaluation

The model's performance is evaluated using the Receiver Operating Characteristic Area Under the Curve (ROC AUC). The ROC AUC measures the probability that a randomly selected positive sample ranks higher than a randomly selected negative sample and is computed from the ROC curve, which plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. Furthermore, the confusion matrix, Precision, Recall, and F1 Score were also calculated to measure the model's performance.

2.2 Establish Competition

2.2.1 Predicting Bidders for new contract

GNNs rely on both the node structure (such as bidders' historical bidding records) and contract node embeddings to make predictions. However, this can lead to a cold start problem for new contracts, where historical bidding records are not available (Hao et al. 2021, 2023). To mitigate this, we leverage a common practice in many SHAs. In the existing practice, we know that Bidders are prequalified for certain work types and are only allowed to bid on projects for which they are prequalified (AASHTO 2013; FHWA 2021; SDDOT 2024). Since prequalification is an annual process that requires rigorous documentation, we first filter bidders based on whether they have bid on a specific work type. This filtered candidate pool of bidders serves as the initial pool of bidders willing to bid on a new project which is then used to generate recommendations for a new project by computing the dot product between the candidate bidders' node embeddings and the new contract's embedding.

2.2.2 Application to Project Bundling Decisions

Bundling multiple projects into a single contract can significantly alter the dynamics of competitive bidding (Qiao et al. 2021). Once the predicted bidders are known for a potential bundled project, we use the centrality measures proposed by Moriyani et al. (2024) to evaluate the competitiveness of bidders and therefore the competition level which ultimately can help SHAs make informed decisions regarding project letting.

2.2.3 Application to Bid Optimization Decision by Potential Bidders

During the letting phase, the plan holders list remains confidential, preventing individual bidders from identifying their competitors (AASHTO 2013; FHWA 2021; Liu et al. 2022). Preparing a bid requires a significant investment of resources (Chisala 2017); however, if a bidder can predict which competitors are likely to participate, they may adjust their bidding strategy accordingly. One such strategy is to analyze the competitor's historical average percentage deviation from the EE and optimize their own bid to improve their chances of success (Heo et al. 2024). During the letting phase of a project, FHWA suggests SHAs to keep EE confidential (FHWA 2021; Liu et al. 2022). Nonetheless, once the letting phase is complete, the EE is public information and is available to bidders (FHWA 2021). If a potential bidder can predict which competitors are expected to participate, their historical percentage deviations from EE can provide insights into the competitors' past bidding patterns. The potential bidders can then use these insights to optimize their own strategies, using the range for the EE provided by DOTs for a new project (FHWA 2021).

3. IMPLEMENTATION RESULTS

3.1 Input Data

The proposed approach was implemented on a historical dataset of highway contract bids provided by the South Dakota Department of Transportation (SDDOT) covering the period from 2009 to 2019. The dataset includes detailed records for 1,590 awarded contracts, each identified by a unique contract ID. For every contract, essential information, such as location, work type, EE, participating bidders, individual bid amounts, and the identity of the successful bidder, is present in the dataset. A total of 248 unique bidders are represented in the dataset, each assigned a distinct identifier. The dataset also contains 49 distinct work types, including 14 contracts categorized as "unknown." Among the 1,590 contracts, 91 were uncontested, meaning only one bidder submitted a bid, which provided no insight into competitive dynamics. These uncontested contracts were excluded from the subsequent network analysis, resulting in a refined dataset of 1,499 contracts.

3.2 Bipartite Graph

A bipartite competition network was constructed using Python's NetworkX library. In this network, one set of nodes represents the 248 bidders and the other represents the 1,499 contracts. An edge between a bidder node and a contract node indicates that a bid was submitted for that contract. In total, there were 6085 edges which means that a bidder submitted approximately 24.5 bids, and each contract received around 4.1 bids on average. Due to the complexity of displaying the entire network, a representative subnetwork is presented in Figure 4. In this subnetwork, for example, bidder ID 3 is shown as having submitted bids for contract IDs 3675 and 3934. Additionally, Figure 4 includes annotations detailing the contract features stored within each corresponding contract node.

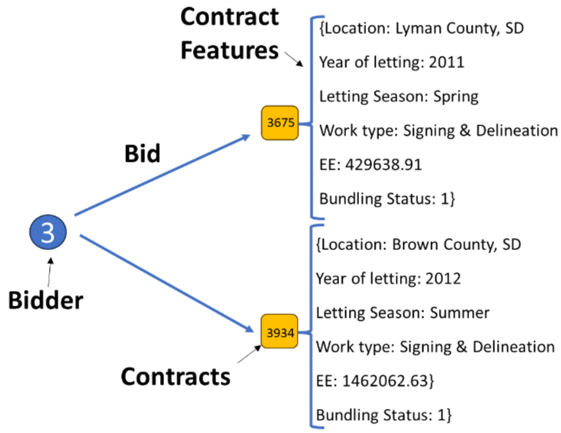
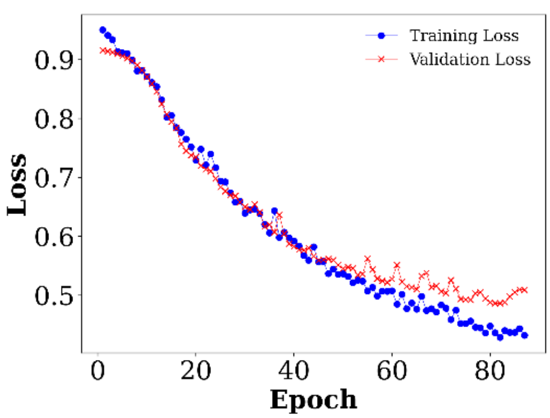


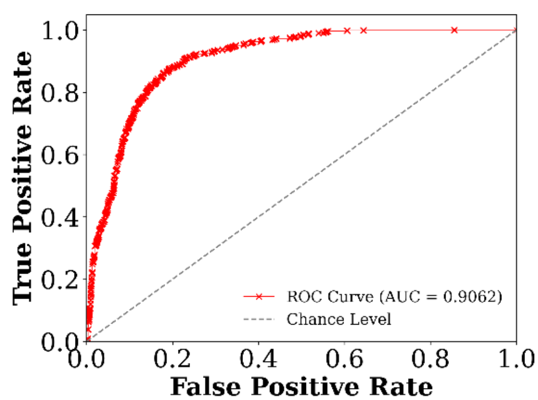
Figure 4: A Sample Subgraph of the Modeled Bipartite Graph

3.3 GNN Training and Evaluation

The GNN model was trained following a conventional procedure, using 80% of the edges for training, 10% for validation, and the remaining 10% for testing. During training, bidder nodes were assigned learnable 128-dimensional embeddings, and ELU activation functions were applied. Additionally, a dropout rate of 0.5 was introduced after the first two layers to help generate more expressive node embeddings. The model was optimized with the Adam optimizer (using a learning rate of 0.001 and L2 regularization set at 1e-4) and a ReduceLROnPlateau scheduler. Training was configured for up to 250 epochs, with early stopping triggered after 86 consecutive epochs (Figure 5a), ultimately achieving its performance as measured by ROC AUC of 90.62% on the validation set as shown in Figure 5 (b).



(a)



(b)

Figure 5: (a) Training and Validation Loss Curve (b) Receiver Operating Characteristic (ROC) Curve

Figure 6 presents the confusion matrix derived from the test dataset, which comprises 10% of the total edges (609 positive and 1,218 negative cases). The model accurately classified 967 negative instances and 532 positive instances. However, it misclassified 249 negative cases as positive (false positives) and 76 positive cases as negative (false negatives).

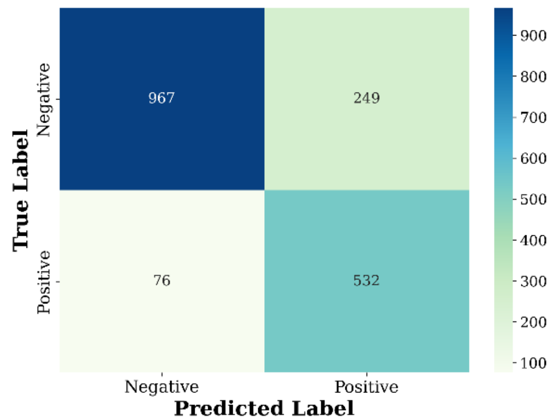


Figure 6: Confusion Matrix for the Testing Edges

Table 1 presents the classification report, which demonstrates robust overall predictive performance as evidenced by a substantial number of true positives and true negatives. For the positive class (i.e., where an edge exists), the model achieved a precision of 0.68 and a recall of 0.88, resulting in an F1 score of 0.77. In contrast, for the negative class (i.e., where an edge does not exist), the model achieved a precision of 0.93 and a recall of 0.80, yielding an F1 score of 0.86. When accounting for class imbalance, the weighted averages are 0.85 for precision, 0.82 for recall, and 0.83 for the F1 score. Overall, the model achieves an accuracy of 82% on 1824 samples, highlighting its effectiveness in both detecting true edges and correctly dismissing non-existent ones.

Table 1 Classification Report on the Testing Edges

	Support	Precision	Recall	F1 Score	Accuracy
Positive Sample (Edge Exist)	608	0.68	0.88	0.77	-
Negative Sampe (Edge do not exist)	1216	0.93	0.80	0.86	-
Weighted Average	1824	0.85	0.82	0.83	-
Overall	1824	-	-	-	0.82

Notably, the model excels in predicting negative samples (F1 score: 0.86), indicating that it is more reliable in identifying the absence of an edge between a bidder and a contract than in confirming its presence. This conservative approach is particularly beneficial in practical applications involving SHAs when determining project bundling. For example, if the model predicts only two bidders while more actually exist, this conservative bias can help prevent overestimation of bidder interest, thereby supporting more risk-averse and accurate decision-making in the bundling process.

3.4 Application to Project Bundling Decisions

To demonstrate the practical application of our proposed approach for project bundling decisions, we present a hypothetical example. Suppose that SHAs are considering bundling two projects, Project A and Project B, in the Spring of 2025. Project A involves milling, which removes the deteriorated pavement layer to create a textured surface, and Project B involves micro-surfacing, which applies a thin polymer-modified asphalt layer to seal cracks and improve durability. Intuitively, these work types are complementary because milling prepares the pavement for better adhesion of the microsurfacing layer and ideal for bundling (Qiao et al. 2019). Additionally, both projects are located in close proximity, with their counties nearby (Campbell and Walworth, SD) which is ideal for bundling (Qiao et al. 2019).

Table 2 Hypothetical Example of Project Bundling

Contract Attributes	Project A	Project B	Bundled Project
EE	$1.7 Million	$2.3 Million	$4.0 Million
Work type (s)	WT48 Mill	WT19 Microsurfacing	WT48 Mill and WT19 Microsurfacing
Letting Year	2025	2025	2025
Letting Season	Spring	Spring	Spring
Locations	Campbell, SD	Walworth, SD	Campbell and Walworth, SD
Bundling Status	1	1	2

The potential predicted bidders from the proposed model are presented in Table 3. For Project A, the model identifies four bidders with a probability greater than 0.50, indicating sufficient competition (note that while the model predicted additional bidders, only the top four are shown). In contrast, for Project B, only two bidders exceeded the 0.50 probability threshold, suggesting limited interest. Moreover, when these two projects are bundled into a single contract, no bidder achieves a probability greater than 0.50, indicating that such a bundling may not be favorable. One possible explanation is that bidders may lack expertise in both work types (i.e., milling and micro-surfacing). Alternatively, since milling and micro-surfacing projects are generally smaller in scale, attracting smaller bidders, these bidders might not possess the bonding capacity required for a larger, bundled contract.

Table 3 Predicted Bidders for Example presented in Table 2

Project A		Project B		Bundled Project
Bidder ID (Top 4)	Probability	Bidder ID	Probability	Bidder ID
115	0.5375	18	0.5114	None
210	0.5348	201	0.5023	
121	0.5344			
151	0.5313			

Another important consideration is that for Project B, the model identified Bidders 201 and 18. Bidder 18 was ranked 4th in competitiveness according to PageRank centrality, and Bidder 201 was ranked 10th based on authority score (Moriyani et al. 2024). This suggests that although only two bidders are present, the high competitive standing of these bidders indicates robust competition. Such insights are not captured by conventional measures of competition, which typically infer a lack of competition solely from a low bidder count (Baek and Ashuri 2019; Carr 2005; Padhi et al. 2016; Qiao et al. 2021; Shrestha and Pradhananga 2010).

3.5 Application to Bid Optimization Decision by Potential Bidders

Another advantage of the proposed methodology is its support for bid optimization by potential bidders. For example, consider Project B. A potential bidder interested in this project can review the historical bidding patterns of the two predicted competitors. As illustrated in Figure 7, the average deviation from the EE shows that Bidder 18 bids approximately 1% above the EE, while Bidder 201 bids about 5% above the EE. Therefore, to maximize their chances of winning the contract, a potential bidder might consider bidding below these levels.

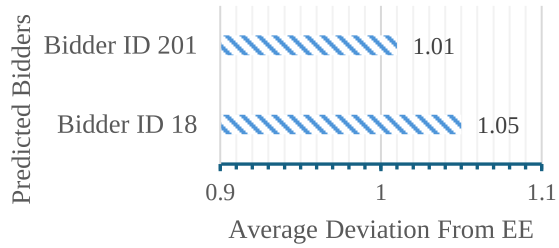


Figure 7: Average Deviation from Engineer's Estimate (EE) by Predicted Bidders

4. CONCLUSIONS

This research presents a novel idea of using a bipartite graph to model bidding competition in DBB projects. The main contribution of this approach is the advancement from the traditional reliance on bidder count and integration of multiple contract-specific features to predict the interest of bidders and ultimately capture the intensity of competition. The empirical evaluation, conducted on a comprehensive dataset from the South Dakota Department of Transportation, demonstrates robust performance, evidenced by an ROC AUC of 90.62% and an overall accuracy of 82%, thereby validating the effectiveness of our model in predicting bidder participation. The proposed methodology offers significant practical applications. The framework provides deeper insights into bidding competition for State Highway Agencies, informing more detailed predictions to facilitate project bundling decisions. Similarly, the model delivers actionable intelligence regarding competitors for potential bidders, enabling them to fine-tune their bidding strategies to enhance bidding competitiveness. However, there are limitations to this study, which we will address in future studies. First, we will evaluate the model using additional metrics such as recall@k, which will help better understand the real-world impact of false positives and false negatives as indicated from the presented confusion matrix. Second, we will use content-based filtering to address the cold start problem. Furthermore, some studies suggest that the work type is a weak indicator of a project description; we will test a better methodology to address the limitations of using work type in the future. Additionally, this paper aims to demonstrate a novel approach using South Dakota DOT data as a case study. Nonetheless, since contractor pools, regulations, and project scales vary among SHAs, the model must be recalibrated before application to other SHAs. Moreover, since our model relies on historical bidder participation data, it does not capture new market entrants. In the context of project bundling, SHAs are interested in identifying potential bidders for a bundle that our model highlights. When the actual number of bidders exceeds the forecasts of the model because new competitors have entered the market, it suggests increased market interest and a likelihood of more bidding outcomes, which does not limit the applicability of our model. Additionally, this approach is intended to guide only public owners and contractors competing for public projects, as private projects often involve client biases influenced by favoritism and reputation. In future studies, additional factors (such as those related to market conditions) can be incorporated as the contract features for the enhancement of the model. Even with these limitations, our research introduces a paradigm shift to transform competition assessments beyond the number of bidders alone, and we contribute to the body of knowledge with the hope of igniting a wave of innovation and inspiring future generations to uplift the construction industry for the better.

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