Combinatorial Reverse Auctions in Construction Procurement

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Summary:
Construction procurement often involves negotiations between many parties over multitudes of components. In most cases, procurement processes do not consider combinatorial (or package) bids from suppliers. This research proposes the use of combinatorial reverse auctions to minimize construction costs. Various models were applied to real data to determine feasibility compared to the baseline of allocating all items to the lowest bidder. Results of the analysis provided justification for the use of combinatorial reverse auctions in construction procurements. Cumulative cost savings across all seven scenarios were 6.4% for unconstrained models and 2.7% for constrained models with limits on the number of awarded suppliers.

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KEY INSIGHTS

1. Traditional construction procurement processes do not consider combinatorial (package) bidding.
2. Combinatorial reverse auctions were found to reduce costs by an average of 6.4%.
3. Constraints were added to models to reflect business rules, such as limits on the number of awarded suppliers. In such cases, average savings of 2.7% were achieved.

Introduction

Due to ever increasing market competitiveness, construction companies face challenges in optimizing their supply chains. Specifically, managing the procurement of materials and services from multiple suppliers can be overwhelmingly complex. In other industries, such as the transportation industry, more sophisticated approaches are used to assign contracts to suppliers.

Reverse auctions (also referred to as tendering) are commonly used in construction procurement as a matchmaking process to select suppliers that best "fit" certain criteria. This is mainly done to minimize costs. The process is preceded by a detailed technical review of supplier proposals to ensure all participants in the auctions can deliver the products and services while meeting technical requirements.

Contracts with suppliers often include multiple line items, where each line item represents a component or group of components in a construction project. While a supplier may have the lowest total cost for supplying all items in a given contract, it may have overpriced a subset of the items relative to other suppliers. Auctions that consider combinations of items where sellers are bidders and buyers are the auctioneers are known as combinatorial reverse auctions. They have been shown to offer significant savings in other industries. This project introduces various approaches to procurement optimization using combinatorial reverse auctions. Their performance is measured in terms of potential cost savings. Real data, provided by a sponsoring company, is used in the analysis. Realistic business rules were incorporated into models to reflect management decisions.

Methodology

Using bid data provided by the sponsoring company, Shaksy Engineering Services (SES). A mathematical framework was designed to identify relevant items, aggregate them and apply various optimization models to determine optimal allocations. Sensitivity analyses were performed to determine the models' response to various supplier discount rates. The outline of the methodology is depicted in Figure 1.
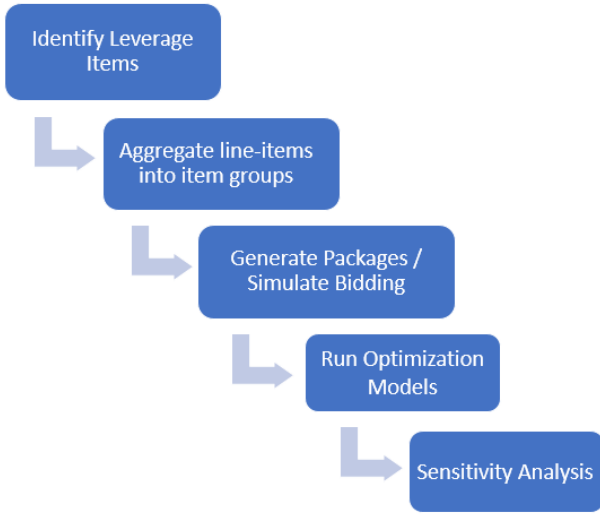

Figure 1: Methodology Outline

The relevant items were determined based on the Kraljic segmentation method. Each scenario included at least three suppliers and had a total budgeted value of at least 30,000 OMR ($78,000 USD). Line items were aggregated into logical groups based on similarity. Costs of aggregated groups (referred to henceforth as items) were tabulated into cost matrices where each column represented a supplier and each row represented an item. Seven scenarios were selected for this analysis.

All costs were adjusted to consider various extrinsic factors such operation and maintenance costs or cost of capital due to payment terms. Each row was then normalized and used as an input to a statistical model to generate packages (groups of items). The cost of each package was determined based on the item costs and a revenue-based discount model.

Definitions (units)

x: Package selection binary variable
y: Supplier selection binary variable
i: Item index
I: Set of all items in a scenario
p: Package bid index
P: Set of all packages in a scenario
s: Supplier index
S: Set of all suppliers within a scenario
c: Bid cost (OMR)
f: Supplier fixed cost (OMR)
Q: Item/package binary matrix
R: Supplier/package binary matrix
M: Number of items in a scenario
S^{max}: Maximum allowable number of suppliers selected per section
S^{min}: Minimum allowable number of suppliers selected per section
d: Discount rate based on supplier revenue (%/OMR)

Four optimization models were applied to each scenario to determine optimal contract allocations. Model 1 was the least constrained and was designed as a benchmark for future models. The formulation seeks to minimize the total cost by selecting packages that cover the full set of items within the scenario. The second model introduced supplier constraints and fixed costs. The model limited the number of awarded suppliers and assigned a fixed cost to each supplier. The formulation for the second model is shown in Figure 2.

$$\text{argmin } Z(x, y) = \sum_{p} c_p x_p + \sum_{s} f_s y_s$$

$$s.t \sum_{p} Q_{i,p} x_p = 1, \forall i \in I$$

$$\sum_{p} R_{s,p} x_p - M y_s \leq 0, \forall s \in S$$

$$S^{min} \leq \sum_{s} y_s \leq S^{max}$$

$$x_p \in \{0,1\}, \forall p \in P$$

$$y_s \in \{0,1\}, \forall s \in S$$

Figure 2: Model 2 Formulation

Model 3 is a simulation of an iterative auction process which begins with suppliers submitting single item bids. The auctioneer then analyzes the bids and proposes packages to suppliers. Package bids that are received from suppliers are then analyzed to produce new package recommendations. This process is repeated for a pre-defined number of iterations or until the solution converges. The math formulation of the model is identical to Model 2. A commercial integer

programing solver (Google OR-Tools) was used for Models 1-3.

Model 4 (expressed in Figure 3) is a non-linear model that includes the revenue-based discount model in the objective function. It has the advantage of being able to search the entire solution space of possible allocations. However, due to the non-linearity of the formulation, a specialized genetic algorithm was developed to find optimal allocations. The formulation is expressed in Figure 3.

$$\text{argmin } Z(\boldsymbol{x}, \boldsymbol{y}) = \sum_s \left(\sum_i c_{i,s} x_{i,s} \right.$$

$$\left. - d_s \left(\sum_i c_{i,s} x_{i,s} \right)^2 \right) + \sum_s f_s y_s$$

$$s.t \quad \sum_s x_{i,s} = 1, \forall i \in I$$

$$\sum_i x_{i,s} - M y_s \le 0, \forall s \in S$$

$$S^{min} \le \sum_s y_s \le S^{max}$$

$$x_{i,s} \in \{0,1\}, \forall i \in I, \forall s \in S$$

$$y_s \in \{0,1\}, \forall s \in S$$

Figure 3: Model 4 Formulation

Sensitivity analyses were carried out on each scenario-model pair. The analyses used Monte Carlo simulations with different discount rates sampled from triangular distributions. All four models were solved in each run and the following statistics were recorded:

- Average total cost across all runs
- Average savings across all runs
- Coefficient of variation of savings
- Coefficient of variation of allocation
- Average computation time per run

Results and Discussion

Over all scenarios, the process achieved cumulative estimated savings between 58k OMR and 126k OMR or 2.7% and 6.4% (depending on supplier constraints). As expected, Model 1 attained larger savings than the other more constrained models, as it did not consider supplier constraints and fixed costs. It also had the computational advantage over Models 2 and 4 and converged to solutions faster. These two advantages can be leveraged

well in larger auctions with larger numbers of suppliers and items. Model 1's higher savings were most pronounced in scenario 4 where certain suppliers had significant fixed costs. In practice, Model 1 is recommended as a baseline and should not be used directly to make decisions. Rather, it should be used to gain insights into suppliers' cost structures. The model does not consider the cost of coordinating multiple suppliers (fixed costs). Disregarding the coordination hurdles of managing multiple suppliers on a project can lead to poor project performance.

Results of the sensitivity analysis highlighted low variance in total costs with coefficients of variations under 1% across all scenarios. This indicates that, in terms of total cost, the models are not significantly sensitive to variations in discount rates. However, supplier allocations had higher levels of sensitivity to the discount rates. This phenomenon was especially prevalent in Model 4 which used a genetic algorithm solver. This suggests an advantage of using non-deterministic methods. They can often generate a family of "good" solutions to choose from rather than providing only one "best" solution. Model 3 does not provide this advantage due to its inherently deterministic nature. In terms of computational performance, Model 3 achieved the fastest solve times on all scenarios. This is an interesting phenomenon since Model 3 requires solving the CRA winner determination problem multiple times. However, since the input of the problem is generally small in each iteration, the solve time is low. Model 3 also lends itself well to the structure of iterative auctions where multiple rounds are held. This is a significant advantage in practice because model 3 does not make any prior assumptions about the distribution of bids.

Conclusion

This research was aimed at determining the efficacy of combinatorial reverse auctions (CRAs) in the domain of construction procurement. A quantitative framework was established utilizing segmentation, optimization and simulation strategies built off prior research in other domains. Various business rules were incorporated into the processes to simulate real-world scenarios utilizing actual bid data. The methodology used the Kraljic segmentation strategy to identify leverage items. Items were then aggregated into item groups. The aggregated data (including seven scenarios) was then used as an

input to various optimization models that determined supplier allocations. Sensitivity analysis was used on each scenario-model pair to determine the effects of uncertain pricing structures on optimal costs and allocations. Results of this research justify the use of CRAs to reduce costs and incentivize supplier participation. In addition to cost reductions, models proposed in this research can be used to determine families of near-optimal solutions rather than just single best solutions. Having multiple solutions can often help management make more informed decisions when allocating contracts to suppliers. Areas for future research include applying the framework real-time during bidding phases of projects to determine their practical significance. Studies on bid distributions and the relationships between cost savings and item aggregation would help better refine the segmentation and aggregation stages of this framework.

The savings from deploying optimization-based procurement methods go beyond the quantitative findings of this project. In practice, allowing combinatorial bidding will generally increase the competitiveness of incumbent suppliers. In parallel, they also incentivize smaller suppliers with capacity limits to bid on subsets of scenarios. These intangible advantages may even outweigh the short-term cost savings associated with CRAs.