Combinatorial Reverse Auctions in Construction Procurement

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Combinatorial Auctions

A **combinatorial auction** is a kind of smart market in which participants can place bids on combinations of discrete items, or “packages”, rather than individual items or continuous quantities.
Combinatorial Reverse Auctions

In procurement markets

Buyer (auctioneer) proposes packages to suppliers

Suppliers bid on packages

Buyer

Seller 1

$2

{{🍎}, {☕}, {🍕}}

Total Cost

= $9

Seller 2

$4

{{🍎, ☕}, {🍕}}

= $8

Seller 3

$2

{{🍎}, {☕, ▲}}

$5

= $7
Complexity – NP Hard

The graph illustrates the complexity of the problem as the number of items increases. The y-axis represents the number of packages and the number of feasible solutions. As the number of items increases, the number of feasible solutions grows exponentially, indicating the problem is NP Hard.
Other Issues

• How to determine packages?
• “Dead-lock”
• Bidding “Fatigue”
• Exploitation
• Auction Design
  • First price? Second Price?
  • Open? Sealed-Bid?
  • Bid language? (OR, AND/OR)

<table>
<thead>
<tr>
<th>Supplier</th>
<th>Items</th>
<th>Bid</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{A,B}</td>
<td>$10</td>
</tr>
<tr>
<td>2</td>
<td>{B,C}</td>
<td>$20</td>
</tr>
<tr>
<td>3</td>
<td>{A,C}</td>
<td>$30</td>
</tr>
</tbody>
</table>
Project Focus

• Construction procurement often involves negotiations between many parties over multitudes of different components.

• The process of allocating contracts to suppliers is a great challenge in minimizing project costs while meeting stringent specification and schedule requirements.

Can combinatorial reverse auctions be used to reduce construction costs?
Company Overview: Shaksy Engineering Services

- Based in Muscat, Oman
- Civil Contractor
- Founded in 2009
- $200M in projects
- Focus on Commercial & Residential projects
- Plans for regional expansion
Company Challenges

• Improve (and standardize) sourcing material and services
• Low supplier bidding participation
• High complexity, >1000 line items in projects
• Hard to capture supplier cost synergies
• Bid normalization
  • Quality
  • Lead time
  • Payment Terms
  • Risk
Motivation

• Good Procurement is important in construction *The Charted Institute Of Building
• $15.5 Trillion market by 2030 **Global Construction Perspective Report
• Procurement is not very sophisticated in construction projects
• Large body of knowledge on combinatorial auctions
• Not many empirical studies
• Not any studies focused on construction industry
Literature

Some relevant literature:


Methodology Outline

Identify Leverage Items based on:
- Number of suppliers (>2)
- Number of line-items (>10)
- Value (>30k OMR or $78k)

Aggregate line-items into item groups

Generate Packages / Simulate Bidding

Run Optimization Models

Sensitivity Analysis

-Kraljic Matrix-
Data

• **7 Scenarios** based on the **number of suppliers and number of items**
  (metal works, mechanical, electrical, plumbing, HVAC components, window and door panels, signboards, woodwork, etc.)

• 3 – 7 Suppliers per scenario (27 in total)

• 4 – 14 items per scenario (53 in total)

• Fixed costs (for each supplier)

• Discount rate (for each supplier)
  • Estimated based on experience

<table>
<thead>
<tr>
<th></th>
<th>Supplier 1</th>
<th>Supplier 2</th>
<th>Supplier 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>HVAC</td>
<td>15,720</td>
<td>13,650</td>
<td>24,502</td>
</tr>
<tr>
<td>Pipping</td>
<td>2,476</td>
<td>2,150</td>
<td>3,858</td>
</tr>
<tr>
<td>Electrical</td>
<td>3,945</td>
<td>3,525</td>
<td>6,148</td>
</tr>
<tr>
<td>Sanitary Ware</td>
<td>11,025</td>
<td>9,800</td>
<td>19,747</td>
</tr>
<tr>
<td>Lighting</td>
<td>7,936</td>
<td>6,200</td>
<td>12,524</td>
</tr>
<tr>
<td>Communication</td>
<td><strong>16,150</strong></td>
<td>41,570</td>
<td>22,351</td>
</tr>
<tr>
<td>Security</td>
<td>5,152</td>
<td>13,705</td>
<td>7,948</td>
</tr>
</tbody>
</table>
### Package Generation – Item Selection

#### Normalize each row

<table>
<thead>
<tr>
<th>Item</th>
<th>Supplier 1</th>
<th>Supplier 2</th>
<th>Supplier 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item 1</td>
<td>-0.38832</td>
<td>-0.7476</td>
<td>1.135917</td>
</tr>
<tr>
<td>Item 2</td>
<td>-0.38819</td>
<td>-0.7477</td>
<td>1.135892</td>
</tr>
<tr>
<td>Item 3</td>
<td>-0.42185</td>
<td>-0.71995</td>
<td>1.141801</td>
</tr>
<tr>
<td>Item 4</td>
<td>-0.46073</td>
<td>-0.68658</td>
<td>1.147315</td>
</tr>
<tr>
<td>Item 5</td>
<td>-0.29095</td>
<td>-0.82226</td>
<td>1.113211</td>
</tr>
<tr>
<td>Item 6</td>
<td>-0.79526</td>
<td>1.122661</td>
<td>-0.3274</td>
</tr>
<tr>
<td>Item 7</td>
<td>-0.86744</td>
<td>1.093764</td>
<td>-0.22632</td>
</tr>
</tbody>
</table>

### Formula

\[ Q'_{i,p} = \text{round}[-N(T_{i,s} + R)] + 1 \]

<table>
<thead>
<tr>
<th>Item</th>
<th>Package 1</th>
<th>Package 2</th>
<th>Package 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item 1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Item 2</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Item 3</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Item 4</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Item 5</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Item 6</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Item 7</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Apply discount rates ($d$) to each package/supplier pair

\[
c_p = \left( \sum_{p \in P^1} c_p \right) \left( 1 - d \sum_{p \in P^1} c_p \right)
\]

- $c_p$: Package Bid Value
- $P^1$: Single Item Packages
Optimization – Model 1

- Most basic Integer Programming model (Andersson et al., 2000)
- Doesn’t distinguish between suppliers
- Doesn’t consider costs
- Lowest total cost
- Fast

\[
\begin{align*}
\text{argmin } Z(x) &= \sum_p c_p x_p \\
\text{s.t } \sum_p Q_{i,p} x_p &= 1, \forall i \in I
\end{align*}
\]

- \( x_p \): Binary decision variable
- \( c_p \): Package cost
- \( Q_{i,p} \): Item/package matrix
- \( Z(x) \): Total cost (objective)
Optimization – Model 2

\[ \arg\min Z(x, y) = \sum_p c_p x_p + \sum_s f_s y_s \]

s.t \[ \sum_p Q_{i,p} x_p = 1, \forall i \in I \]
\[ \sum_p R_{s,p} x_p - M y_s \leq 0, \forall s \in S \]
\[ S^{\min} \leq \sum_s y_s \leq S^{\max} \]
\[ x_p \in \{0,1\}, \forall p \in P \]
\[ y_s \in \{0,1\}, \forall s \in S \]

- \( f_s \): supplier fixed cost
- \( y_s \): supplier selection decision variable
- \( R_{s,p} \): supplier/package matrix

**Linking constraint**
**Supplier limits**
Optimization – Model 3

- **Iterative** solver
- Same formulation as Model 2
- Use solver to generate packages
- Initialized with single item packages
- Stops when no new unique package is generated
- Deterministic model - always gives the same answer
Optimization – Model 4

\[
\begin{align*}
\text{argmin } Z(x, y) & = \sum_s \left( \sum_i c_{i,s} x_{i,s} - d_s \left( \sum_i c_{i,s} x_{i,s} \right)^2 \right) + \sum_s f_s y_s \\
\text{s.t. } & \sum_s x_{i,s} = 1, \forall i \in I \\
& \sum_i x_{i,s} - M y_s \leq 0, \forall s \in S \\
& S_{\text{min}} \leq \sum_s y_s \leq S_{\text{max}} \\
& x_{i,s} \in \{0, 1\}, \forall i \in I, \forall s \in S \\
& y_s \in \{0, 1\}, \forall s \in S
\end{align*}
\]

- Non-linear
- Discount term moved to objective function
- Assumes we know pricing functions
- Genetic algorithm
Optimization – Output

- Allocation matrix
- Values assigned to final allocation
- Total cost
- Compare to baseline (all items to lowest supplier)
- Computation time

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<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Pipping</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Electrical</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Sanitary Ware</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Lighting</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Communication</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Security</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
# Summary of Optimization Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Reason for use</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Baseline CRA</td>
<td>Test various solvers and benchmark performance of other models</td>
<td>Easiest to solve and can be solved using a variety of solvers</td>
<td>Doesn’t differentiate between suppliers and doesn’t model fixed costs</td>
</tr>
<tr>
<td>2</td>
<td>CRA with supplier constraints</td>
<td>Model supplier fixed costs and constraints</td>
<td>Faster to solve than subsequent models if a limited number of packages are used</td>
<td>Will usually not find a better solution than subsequent models if packages are sparse</td>
</tr>
<tr>
<td>3</td>
<td>Iterative CRA</td>
<td>Better simulate real auctions where bidding is limited and doesn’t take place simultaneously</td>
<td>More realistic and has the potential to converge to a better solution than previous models on auctions with many items and suppliers</td>
<td>May take longer to carry out due to multiple rounds</td>
</tr>
<tr>
<td>4</td>
<td>Non-linear Model</td>
<td>Including the pricing function in the objective function allows the solver to search over the entire allocation space</td>
<td>Reduction in number of decision variables and does not require package bids as inputs</td>
<td>Involves solving a non-linear objective function and may not be feasible for larger auctions</td>
</tr>
</tbody>
</table>
Sensitivity Analysis

Considering 7 scenarios with different number of items and suppliers;
• Assume discount rates \( (d_s) \) are triangularly distributed
• Monte Carlo simulation
• Measure average savings
• Measure variability of total cost
• Measure variability of allocations
Results

• 6.4% savings for unconstrained models ($320k)
• 2.7% for constrained models ($150k)
• Model 3 produced the lowest costs and was fastest
• All models had low cost variability (<2%)
• Models 1, 2 and 4 had a higher allocation variability
Limitations

• Proxy bidding, realistic?
• Pricing function – not monotone
• Supplier capacities not considered
• Cost of implementation?
• Understandability, black box?

Quadratic Pricing Function
Recommendations

• Use models as decision support systems
• Navigation tool for negotiations (iterative model)
• What-if analyses with different:
  • Bid adjustments
  • Item aggregations
  • Discount distributions
  • Supplier constraints
Areas for Future Research

• Practical experiment with real package bidding
  • Data analytics on bidding

• More theoretical pricing function

• Stochastic optimization
  • Consider variability in pricing structures
THANKS

Q & A