The conceptual cost estimate is the first estimate of the construction cost for a project. At this early stage in the project timeline there is very little information known about the project, yet this cost estimate is used for:

- Long-term budget allocation at state Departments of Transportation (DOTs)
- Benefit-to-cost analysis of different project options
- Allocating the preconstruction services budget

An incorrect conceptual estimate can result in misallocation of funds, inappropriate project selection and underfunding design effort which can lead to construction cost growth.

Artificial neural networks and multiple regression analysis are two data-driven techniques proven in the literature to calculate the conceptual construction cost using historical project data. The authors of these studies have solely focused on model performance and little attention has been paid to the effort required to compute/identify input variables for an estimating and the perceived influence that each variable would have on the construction cost.

A survey was conducted at Montana Department of Transportation (MDT) to help the research team identify those variables that best meet both objectives. A total of 31 preconstruction engineers answered perceptive questions on the effort required to compute/identify 29 potential input variables for an estimating and the perceived influence that each variable would have on the construction cost.

The survey results indicate that some project attributes require much less effort, yet only the same level of estimating performance obtained. If the correct 6-8 variables are selected then this is suitable to estimate conceptual costs then collection of further information is unnecessary. This saves on resources and reduces data storage costs.

A reasonable estimate of the project costs with less project detail enables improved budgeting and earlier cost-to-benefit analysis of future projects.

### Research Implications

- Significant and positive implications for practitioners willing to employ top-down data-driven methods to conduct a conceptual cost estimate. For the first time the preconceived notion, that more detail enhances estimate accuracy, was challenged.
- Once highway agencies are confident in the input variables required to estimate conceptual costs then collection of further information is unnecessary. This saves on resources and reduces data storage costs.
- A reasonable estimate of the project costs with less project detail enables improved budgeting and earlier cost-to-benefit analysis of future projects.

### Conclusions

- Conceptual cost estimating at transportation agencies need to focus on two objectives: (1) accurately estimate costs, and (2) expend the least effort.
- Survey results indicate that some project attributes require much less effort to be expended in order to calculate or identify.
- If the correct 6-8 variables are selected then this is suitable to estimate the construction costs. Collecting and using further variables will not enhance estimate accuracy.
- It is believed that selecting high-impact and low-effort variables essentially selects those variables which are known to a high degree of confidence at the early estimate stages.

<table>
<thead>
<tr>
<th>Proposed Input Variable Selection Method:</th>
<th>Data Management Level of Effort</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Preferred Variables</td>
<td><strong>High</strong></td>
</tr>
<tr>
<td><strong>Least Preferred Variables</strong></td>
<td><strong>Low</strong></td>
</tr>
<tr>
<td>Ideal input variable</td>
<td><strong>High</strong></td>
</tr>
<tr>
<td>Least Familiar Variables</td>
<td><strong>Low</strong></td>
</tr>
</tbody>
</table>

### Research Overview

Survey Results

- Input variables were added in the suggested dual-objective selection order. Model error was calculated each time the cumulative estimating error increased.
- Selection order was verified by repeating the process in the reverse selection order.
- Once 6-8 high-impact and low-effort variables added to the model then adding further input variables yielded no reduction in estimating effort.
- Using the reverse input selection required order almost twice the perceived level of effort, yet only the same level of estimating performance obtained.

Selection method tested with both artificial neural network (ANN) and multiple-regression analysis (MRA) models for validation

<table>
<thead>
<tr>
<th>Project Development Timeline:</th>
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<tbody>
<tr>
<td>Conceptual Estimate</td>
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### Results

- Effort required to identify/calculate points:
  - Maximum: 4 points
  - Minimum: 2 points

- Cumulative Estimating effort (points):
  - Dual-objective selection method
  - Reverse

- Performance of ANN model:
  - Cumulative Estimating Effort (points):
  - Dual-objective selection method
  - Reverse

- Performance of MRA model:
  - Cumulative Estimating Effort (points):
  - Dual-objective selection method
  - Reverse