Improving Static Assignments Using Genetic Algorithms to Estimate Parameters for Complex Generalized Costs

Vince Bernardin, Jr, PhD & Steven Trevino
Bernardin, Lochmueller & Associates, Inc.

Seyed Shokouhzadeh
Evansville Metropolitan Planning Organization

Mike Conger, PE
Knoxville Regional Transportation Planning Organization
OVERVIEW

• Initial problem:
  Poor modeled route choices, especially trucks

• Solution:
  Add terms to generalized cost function
OVERVIEW

• **Initial problem:**
  
  Poor modeled route choices, especially trucks

• **Solution:**
  Add terms to generalized cost function

• **New problem:**
  How to get parameters for new terms?

• **Solution:**
  Genetic algorithm/metaheuristic
User equilibrium (UE) was first expressed by Wardrop purely in terms of minimizing travel time. Distance and tolls were recognized as key factors shortly thereafter and long been included in UE. Surveys in the 1960’s also identified driver preferences for: good signage, pavement conditions, grade, safety and aesthetics. Since 2000, reliability has also been considered as a factor in route choice – mostly in dynamic.
In practice, generalized costs have typically included only travel time, distance and tolls. The problem with ignoring other route choice factors manifested itself with a particular problem in the Knoxville regional model.
Trucks preference for I-75/I-40 over Frost Bottom Road cannot be explained by travel time or distance.

The preference is clearly reasonably considering:

- horizontal & vertical curvature/grade,
- lane width,
- turning radii,
- signage/route continuity,
- imperfect knowledge, etc.
PENALTIES

• No/incomplete data on design factors or knowledge

• Distance penalties by functional class for trucks

<table>
<thead>
<tr>
<th>Class</th>
<th>Urban</th>
<th>Rural</th>
<th>Penalty (sec/mi)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Principal Arterial—Interstate</td>
<td>Principal Arterial—Interstate</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>Principal Arterial/Other Freeways</td>
<td>Principal Arterial—Other</td>
<td>60</td>
</tr>
<tr>
<td>3</td>
<td>Other Principal Arterial</td>
<td>Minor Arterial</td>
<td>90</td>
</tr>
<tr>
<td>4</td>
<td>Minor Arterial</td>
<td>Major Collector</td>
<td>120</td>
</tr>
<tr>
<td>5</td>
<td>Collector</td>
<td>Minor Collector</td>
<td>150</td>
</tr>
<tr>
<td>6</td>
<td>Local</td>
<td>Local Collector</td>
<td>180</td>
</tr>
</tbody>
</table>

• Developed penalties using trial and error and assuming linear relationship across classes
  - *Clearly not ideal!*
IMPROVEMENT

• Fixed the Frost Bottom Road problem:

<table>
<thead>
<tr>
<th>Route</th>
<th>Travel Time (min)</th>
<th>Distance (mi)</th>
<th>Penalty (min)</th>
<th>Generalized Cost (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frost Bottom Rd</td>
<td>60.2</td>
<td>48.0</td>
<td>61.3</td>
<td>121.5</td>
</tr>
<tr>
<td>Interstates I-40/I-75</td>
<td>66.7</td>
<td>73.5</td>
<td>37.0</td>
<td>103.6</td>
</tr>
</tbody>
</table>

• And modestly improved truck assignment overall

<table>
<thead>
<tr>
<th></th>
<th>No Penalties</th>
<th>Penalties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multi-unit trucks</td>
<td>-7.7%</td>
<td>-3.2%</td>
</tr>
<tr>
<td>All Trucks</td>
<td>-5.0%</td>
<td>-1.8%</td>
</tr>
</tbody>
</table>
• New hybrid model for Evansville
  • Build on improvement in Knoxville – incorporate more factors in route choice for autos and trucks
  • Replace ad hoc trial and error with statistical estimation of all generalized cost parameters
NEW TERMS

• Generalized cost function for Evansville included terms for:

  Traditional
  • Travel time
  • Distance
  • Left turns
  • Right turns
  • Distance

  New
  • Functional Class Penalties
  • Truck Routes
  • Railroad Xings

• Separate parameters for Autos, Single Unit and Multi-Unit Trucks
ROUTE CHOICE DATA?

• For both new and traditional terms how to estimate parameters rather than pure trial and error?

• No survey data was available on route choice.

• Traffic counts only data available.
The Evansville network

- Small/mid-sized
  - 350,000 pop.
- 5,000 road miles
- 1,363 total counts
- 983 truck counts
LEAST SQUARED ERROR

• Least Squares Estimation (LSE) is broadly accepted with proven good behavior for many problems

• Problem is non-linear so there are no easy proofs of a unique solution, etc., here, but LSE is generally less susceptible to such problems than LAD, etc.

• Since square root and arithmetic mean are monotonically increasing on positive reals, equivalently can minimize the RMSE
BI-LEVEL FORMULATION

• Simplifying by holding demand fixed, we can formulate the problem as a bi-level program:

\[ \min_{\beta} \sum_{a} (f_a - \bar{f}_a)^2 \]

such that:

\[ \min f_a \int_{0}^{f_a} c_a(x, y_a, \beta) \, dx \]

subject to:

\[ \sum_{r} f_{pqr} = d_{pq} \quad \forall p, q \]

\[ f_{pqr} \geq 0 \quad \forall pqr \]
METAHEURISTIC

Iterative Bi-Level Program

Genetic Algorithm
Evolve parameters to minimize squared errors versus counts

Assignment
Apply the base model given a set of parameter as inputs
WHY GENETIC ALGORITHM?

• No analytic gradients or guarantees of convexity – hence need metaheuristic

• Bi-level approaches require less programming because they can make use of assignment algorithms in modeling software

• Genetic algorithms are flexible and relatively easy to program
Overview

- Initial “population” of solutions
- Evaluate “fitness” of each solution
- Kill least fit solutions
- Create new generation of solutions by
  - Randomly mutating fit solutions
  - Combining fit solutions
INITIAL POPULATION

1 Best Guess

- Borrowed parameters from
  - Old model
  - Other models

17 Random Mutants

- Bounds on reasonableness
Least Squared Errors (LSE)

- Evaluate fitness by running assignment and calculating RMSE
- Diversity not currently considered
Mutation

- Draw new parameter randomly from normal distribution around previous solution parameter
- Currently only mutating best solution
- A couple of ‘hyper-mutants’ (mutate all parameters) each generation
Re-combination

- ‘Mate’ two attractive solutions
- ‘Child’ solution has a 50% chance of getting each parameter from either parent solution
TRUCK RUNS

• Genetic algorithm was run first for the truck preload, then for the auto assignment

• For the trucks, over 775 generations were run with more than 10,000 individual solutions in 13 days on a 12 core machine

• No formal convergence criterion, but the final solution remained unchanged for the last 300 generations
• Ran over 180 generations for autos with more than 2,200 individual solutions off and on as a computer was available over a span of about six weeks

• No formal convergence criterion, but the final solution remained unperturbed for the last 40 generations
RESULTS

• Only a modest improvement in overall RMSE
• Much larger improvement in the MAPE
  • Large impact on lower volume roads
• Larger effect on truck RMSE than autos

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Trucks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before</td>
<td>After</td>
</tr>
<tr>
<td>RMSE</td>
<td>36.3%</td>
<td>34.2%</td>
</tr>
<tr>
<td>MAPE</td>
<td>60.3%</td>
<td>41.8%</td>
</tr>
</tbody>
</table>
### Resulting parameters

<table>
<thead>
<tr>
<th>Factor</th>
<th>Penalty</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Autos</td>
<td>SU Trk</td>
</tr>
<tr>
<td>Left Turn</td>
<td>10.3</td>
<td>117.6</td>
</tr>
<tr>
<td>Right Turn</td>
<td>2.7</td>
<td>32.1</td>
</tr>
<tr>
<td>Length</td>
<td>86.9</td>
<td>147.1</td>
</tr>
<tr>
<td>- Freeways</td>
<td>3.0</td>
<td>0</td>
</tr>
<tr>
<td>- R. Min. Arterials/U. Princ. Arterials</td>
<td>6.7</td>
<td>42</td>
</tr>
<tr>
<td>- R. Maj. Collectors/U. Min. Arterials</td>
<td>10.1</td>
<td>63</td>
</tr>
<tr>
<td>- Urban/Minor Collectors</td>
<td>13.4</td>
<td>84</td>
</tr>
<tr>
<td>- Locals</td>
<td>16.8</td>
<td>105</td>
</tr>
<tr>
<td>Railroad crossing</td>
<td>6</td>
<td>*</td>
</tr>
<tr>
<td>Non-truck Route</td>
<td>35.5</td>
<td>0</td>
</tr>
</tbody>
</table>
FINDINGS

• Time generally dominates auto’s route choice

• But cars also prefer higher functional classes and avoiding railroad crossings

• Trucks weighed non-time factors much more than autos with strong avoidance of lower functional classes, especially for semis

• Very high SU turn penalties? – Non-convexity?

• No effect of truck routes on semis? – colinearity?
CONCLUSIONS

• Both Knoxville and Evansville experiments indicate a strong preference by truck drivers for higher class facilities

• Evansville also indicates a smaller but consistent preference by auto drivers

• Penalties on low class facilities can greatly improve their loadings

• Genetic algorithm for LSE GC parameters works, but not without some issues – feasible region, structure of parameters critical
FURTHER WORK

• Now using genetic algorithm for Knoxville update, incorporating non-linear penalties for autos as well as trucks

• Also using for Ohio DOT with statewide model – looking at vehicle operating costs and crash risk as well as reliability and penalties to improve consistency of assignment and economic analysis
THANK YOU!

- **Vince Bernardin, Jr., Ph.D.**
  VBernardin2@BLAinc.com
  812.479.6200

- **Steven Trevino**
  STrevino@BLAinc.com
  812.479.6200

- **Seyed Shokouzadeh**
  SShokouhzadeh@evansvillempo.com
  812.436.7833

- **Mike Conger, P.E.**
  Mike.Conger@knoxtrans.org
  865.215.2500