Using Error Distributions with Model Output to Acknowledge Prediction Uncertainty: Results using Travel Demand and Transit Flow Models

Mark R. McCord^{a,b}, Serkan Bicici^a and Rabi G. Mishalani^a ^aCivil, Environmental & Geodetic Engineering ^bCity & Regional Planning

The Ohio State University, Columbus, OH

15th TRB National Transportation Planning Applications Conference

> Atlantic City, New Jersey May 20, 2015

Uncertainty in Transportation Demand and Flow Models

Postulates

- There is uncertainty in predictions/forecasts: "Models are off"
- It is better to recognize than ignore the uncertainty
- Practice
 - Transportation demand/flow models generally produce point estimates

Propose and validate an approach to "add" uncertainty to model point estimates

Recognizing Differences between Models and the "Truth"

- Empirical-based studies
 - Measures of difference (e.g., RMSE) to compare models
 - Do not provide measure for prediction uncertainty
- Theoretical/Numerical (Monte Carlo)-based studies
 - Provide measures for prediction uncertainty based on distributions of inputs or parameters
 - Do not account for model/assumption uncertainty
- This approach
 - Use differences between past model-based and observed values to determine distribution of true value, conditional on model output

Developing Uncertainty Distributions Difference between Model Values and Observations: Δ MORPC Network



1990 Link i Volume

MORPC Model Output (M	1 _i) : 26,844 *
Observation (T_i)	: 29,340 *
$\Delta_i = M_i - T_i$	-2,496

* Ferdous et al. (2011) Comparison of Four Step Versus Tour-Based Models in Predicting Travel Behavior Before and After Transportation System Changes

Determining Difference (Δ), Bias (b), and Error (ϵ) Distributions



1041 Segments in Ferdous et al.

Determining Difference (Δ), Bias (b), and Error (ϵ) Distributions



Determining Bias Distribution



Prediction/Forecast on Link i: $F_i(T_i|M_i)$



Validation Study

- Use subset of model/observation data to estimate bias and error distribution
- Use estimated bias and error distributions with remaining model output to produce uncertainty in model predictions/forecasts
- Use observations for remaining data ("known outcomes of prediction/forecast") with modeled uncertainty to determine empirical distributions of probabilities of observations
- Compare empirical distributions to theoretical distributions

Prediction/Forecast on Link i: $F_i(T_i|M_i)$



Validation Logic: Probabilistic Forecast of Observation *Tobs* on Link i





In 2005 Model link k: $M_k = 59,050$ Observation link k: $T^{obs}_k = 54,025$







Monte Carlo Logic: Well-calibrated uncertainty should produce points around 45° line

Metrics of discrepancy w/ 45° line

- AAD: |Avg. Dif. (45°, pts.)|
- MD: |Max. Dif. (45^o, pts.)|
- Area (45⁰, pts.)

Larger metric values imply poorer empirical distributions

Empirical Applications

- Link volumes from traffic assignment
 - Mid-Ohio Regional Planning Commission model outputs and observations
 - Values from *Ferdous et al. (2011)*: Tour-based model
- Bus passenger OD (B2A) flows from estimations based on boarding and alighting data
 - The Ohio State University Campus Transit Lab OD flow observations (http://transitlab.osu.edu/campus-transit-lab)
 - Boarding and alighting data from observations used with Iterative Proportional Fitting (IPF) method to produce model estimates

Traffic Assignment Validation Using Ferdous et al. MORPC Data

- Model/Observation years: 1990, 2000, 2005
- Calibrate using two years to predict third year: All (3) combinations
- Calibrate one bias and one error distribution using all segments: "Aggregated Calibration"
- Pool results



Traffic Assignment Validation Aggregated Calibration for Segmented Predictions



Traffic Assignment Validation Aggregated vs. Segmented (Bias and Error) Calibration



Calibrating Bias and Error Distributions for Each Functional Class Improves Results

Empirical Applications

- Link volumes from traffic assignment
 - Mid-Ohio Regional Planning Commission model outputs and observations
 - Values from *Ferdous et al. (2011)*: Tour-based model
- Bus passenger OD (B2A) flows from estimations based on boarding and alighting data
 - The Ohio State University Campus Transit Lab OD flow observations (http://transitlab.osu.edu/campus-transit-lab)
 - Boarding and alighting observations for six academic terms
 - Model output using Iterative Proportional Fitting (IPF) method



Calibrating Bias and Error Distributions for High/Low Volume Cells Improves Results

Conclusions

- Preliminary validation studies indicate the approach is capturing uncertainty appropriately
- Additional studies needed to refine approach and produce more robust validation studies ("spin-off" research investigations also envisioned)
- Request for agency model validation data mccord.2 @osu.edu, mishalani.1 @osu.edu, bicici.1 @osu.edu

Acknowledgements

- US DOT RITA: Region V University Transportation Center, NEXTRANS
- OSU Transportation and Traffic Management
- OSU College of Engineering Transportation Research Endowment Program
- Mid-Ohio Regional Planning Commission (Zhuojun Jiang)

The views, opinions, findings, and conclusions reflected in this presentation are the responsibility of the authors only and do not represent the official policy or position of USDOT, RITA, OSU, or any other entity or person.