

Regional network microsimulation, level-of-service metrics and activity-based demand modeling

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Background

CMAP is developing a regional activity-based travel demand modeling system for evaluating planning policies outside the traditional realm of transportation infrastructure development². So far we have improved our capacity to evaluate long-range plan proposals for congestion pricing and transit modernization. Upon casual review, it seems that all activity-based travel demand models currently used by regional planning agencies rely on familiar origin-destination based level-of-service matrices — known as “skims” — to provide the agent-based choice equations with metrics of transportation system performance. These skim matrices are a by-product of the network assignment step that completes the conventional 4-step trip-based travel demand modeling method. Despite the convenience and manageability of skim matrices, their static nature undercuts the improved capacity of activity-based models to represent an agent’s true response to dynamic transportation conditions.

Over the past several years, TRB has sponsored — under the banner of SHRP2 C10 — research to develop an “Integrated, Advanced Travel Demand Model and a Fine-grained, Time-Sensitive Network.” This effort was a much needed exploration into the fundamental mechanics of functionally linking two new modeling paradigms — regional network microsimulation³ and activity-based demand — that up to this point have developed independent of each other. SHRP2 C10’s priorities emphasized incorporating transit vehicle operations, reconciling temporal definitions, establishing compatible data structures and streamlining run times. Other practical intrusions, such as generating emissions estimates and validating assignment results

appear to have left little time to examine whether the advanced network assignment procedure is producing results that might improve the predictive capacity of the activity-based model to which it is coupled.

Demonstrating that existing network microsimulation products can produce conventional level-of-service skims is certainly a worthwhile effort. But short of producing a time, distance and cost matrix for each individual for each minute of his prospective tours, the conventional transmission of skim data back to a travel demand model can never take full advantage of all the information resulting from a true network microsimulation. In fact, it is quite obvious that the origin-destination matrix format is not even the ideal way to organize network information if our goal is to extend activity-based modeling to predict an individual agent's reactions and subsequent choices while *en route*⁴. It seems that with the success of the initial SHRP2 C10 demonstrating a loose coupling of network microsimulation with activity-based modeling, the next challenge is to see if we can further improve the two by inventing more creative approaches for moving data between them.

Analysis framework

This paper is organized around the information presented in [A Primer for Dynamic Traffic Assignment](#)⁵. The primer is a useful introduction for practitioners and managers to the lexicon and basic approach to Dynamic Traffic Assignment. For practitioners well-versed in the procedures found in commercial travel demand software, the primer explains the fundamental differences between conventional static path-building algorithms and dynamic algorithms rooted more closely in the physics of traffic flow. Like SHRP2 C10, the primer is also a much needed resource for non-technical planning managers to understand the practicality of adopting a new and potentially more robust computational method into the production stream of their project and program evaluations.

For this paper, I will follow the primer's exposition of dynamic traffic assignment and highlight possible linkages with the agent-elements found in typical activity-based demand modeling. My perhaps naïve question is: is it possible to extend our current practice of static system

feedback to carrying individual trip rosters forward into network microsimulation thus allowing us to compare the conditions anticipated when planning the tour with the conditions actually experienced as they occur *en route*; and then, how the difference between expected and experienced conditions could be subsequently applied to the traveler's learning profile.

Defining the Agents

The primer begins by acknowledging that both paradigms of demand modeling—trip-based and activity-based models—have the common aim of explaining how travel behavior will change in the face of future conditions. Activity-based models, however, “seek to represent travel choices made by individuals” indicating that there is a capacity to systematically predict not only each traveler's sensitivity to personal preferences and environmental conditions when planning activities for the day, but also to monitor reactions and sensitivity to conditions experienced as the day progresses.

Because conventional static traffic assignment is time-invariant⁶ the knowledge gained by an agent about network conditions while *en route* is never actually modeled and therefore cannot be included in planning his activities or tours. Instead, the static conditions on the entire network are typically passed back to the head of the modeling stream—like a fresh set of traffic reports—allowing the agent to “try again”. While practitioners have invented a variety of metaphors to legitimate this practice, it is in truth only a crude approximation of the choices available to the agent during actual travel. Furthermore, plan and tour alterations necessitated by unexpected network conditions (both costly and beneficial) cannot be accommodated, though one would intuitively suspect them to be quite prevalent in a metropolitan region rich in opportunities for productive use-of-time.

The primer argues for dynamic traffic assignment from both a transportation planner's and a traffic engineer's perspective, but assumes that only the latter is concerned with trying to resolve an agent's information gap based on *en route* conditions. Available DTA procedures are constrained to resolving the gap between instantaneous (i.e. pre-trip) and experienced (i.e. after-the-fact) travel times. “To account for this learning process, an iterative algorithm is needed.”

The algorithms offered suffer the same compromises found in static assignment; trading assignment precision for planning fidelity. The primer assumes that the traffic engineer prefers superior validation of assigned traffic flow (precision) to explaining the alterations to demand needed to accomplish it (fidelity) and favors modifying input demand to yield the correct assignment result. In transportation planning, the opposite is typically preferred. Planners are willing to tolerate wider error margins in network validation provided the demand profile remains true to our understanding of travel behavior.

To bridge this gap, we must find a way to attach “learning” variables to each ABM agent, track them as they pass through the DTA and then explain their route choice decisions in cognitive terms. Extending the definition of “learning” into the choice framework might provide a richer means by which to control equilibration of the ABM over successive global iterations.

Mapping the game

Even with advances in the granularity and explanatory depth permitted by activity-based models and network microsimulation tools, there remain fundamental dimensional constraints in current implementations that limit their ability to explain the full continuum of choices available to a traveler when reacting to *en route* conditions. On the demand side, there is an over-reliance on matching a discrete assembly of choices found in revealed preference surveys rather than understanding an agent’s calculus in planning his activities. On the network supply side, there is an over-reliance on matching instrument-derived link counts and speeds rather than understanding each agent’s calculus in choosing their route. Add to this the typically gross oversimplification of how agent’s will combine available travel modes, both during planning and while *en route* and we have a modeling system that can’t predict much outside of what we know only through very superficial system-wide observation.

Perhaps there is no practical escape from the discrete choice logit paradigm used to predict demand. But we should remember that—as entrenched as it is in our current framework—the result is no more than a generic “plan” for the day’s activities. In reality, once the day begins, uncertainty and risk begins to take its toll and the plan almost inevitably will change. It is

worth examining the distinction between “reaction” and “choice” and whether there is a continuous temporal or situational dimension along which learning variables can be mapped. For example, a typical auto commuter in a congested region might consult a live traffic report (radio, TV, web) immediately before departing for work. This is his last chance to change his daily plan while in the comfort of home with the greatest number of alternatives among the tours, times and modes of travel still before him. Once *en route*, the number of alternatives may diminish quickly as the traveler learns more about true conditions and gets further from home, but they never evaporate entirely.

Below is a simple, but real, example benchmarking the calculus of my morning commute. Let’s assume that CMAP’s AB model has accurately predicted that I plan to bike 8 miles to work and back. After my morning coffee, the happy moment has arrived that I should leave in order to arrive at work on time:

<i>En route Option</i>	Departing Condition	Choice	<i>En route condition</i>	Reaction	Arrival Condition
1	Sunny	Bike path	Still sunny	Bike path	Lock bike at work
2	Sunny	Bike path	Starts raining	Bus	Bus stop at work
3	Raining	Subway	Still raining	Subway	Walk 4 blocks from station to work
4	Raining	Subway	Stopped raining	Sidewalk	Walk 12 blocks to make up for not being able to bike.

Network assignments handle auto route diversions well enough based on prevailing congestion levels, but are not equipped to interpret equally viable choices of tour compression, on-the-fly mode changes and turning back. Like the route diversion algorithms, a traveler’s reaction to *en route* conditions is highly constrained by temporal and situational conditions. But while a traveler is not likely to abandon his car in the middle of a traffic jam just because he finds himself next to a train, he is very likely to engage in some on-the-fly probability math if he finds his regular park-and-ride full and he has only limited knowledge about nearby parking,

train headways and traffic jams. Similarly, a traveler with a couple of bad congestion experiences may have “learned” to permanently avoid using an unreliable expressway in favor of a much slower arterial with more opportunities to divert his path. These, and myriad other contextual variables are experienced only as a traveler passes through the network. While *en route*, he must be able to recall his planning choice alternatives at the same time he is reacting to immediate conditions.

The primer acknowledges that “travelers are assumed to know, and accurately perceive, travel times throughout the network” and that this assumption is key to achieving network equilibrium. In addition to the typical conjectures about the self-correcting efficiency of traveler choice, the primer also defends equilibrium as a principle that “makes available methods from economics for evaluating the potential benefits” of transportation projects. While this is well-established practice, the current volatility in the world demonstrates just how dangerous blind faith in self-correction can be. Modern policy questions rely far less on maximizing the utility of a robust forecast than on avoiding the risks associated with a very uncertain future. As practitioners, not only do we know that no one actually experiences equilibrium in the fashion arrived at by the math we use in our models, but our habit of espousing such a condition acts as a palliative in what otherwise should be a very serious and ambitious inquiry into the long term social impacts of public policy. The primer points out, as a practical matter, that “experienced travel time cannot be realized at departure, but only at the end of the trip”. This very obvious statement also embodies the very real uncertainty faced by travelers as they embark on their daily tours.

A manageable direction

CMAP has been marginally engaged in assisting others to develop a functioning regional highway network microsimulation for the Chicago region. While the various clients have scoped these as strategic planning tools (e.g. evacuation, weather management), the resulting research products have also advanced the general functionality of the microsimulation tools and datasets available for continued development and new applications (if perhaps falling short of being as useful as hoped for in real-time application). By necessity, the bulk of development

has focused on database development, program flow and visualization. Scenario testing has been primarily limited to demonstrating path choice sensitivity to temporal network disruptions (no small feat). Initial demand data for each of these efforts was supplied by trip matrices from CMAP's trip-based models. In the absence of an activity-based model, the origin-destination trips pairs were arbitrarily reorganized into the diurnal list of tours needed to feed the network microsimulation procedure. While network validation has relied on the aforementioned demand-altering methods, there has been, to date, no attempt to reconcile the actual demand generating procedures with the results of microsimulation.

Our goal at the symposium is to identify some manageable first steps to implement network microsimulation in the context of our regional activity-based model, both to strengthen performance of the ABM and to advance the implementation of network microsimulation for production use.

En route choices

- What information (attributes of demand) can be carried forward from ABM to enrich network path choice? How would the data associated with these attributes be organized?
- Aside from accumulated travel time, what are other plausible determinants of path choice? How can an enriched set of path choice criteria be implemented?
- Can network microsimulation be made to incorporate multi-modal path choices in a practical and sequential fashion?

En route knowledge

- Can path-specifying data structures (i.e. trees) replace skim matrices in ABM?
- What information can be harvested from DTA for assimilation by agents? By what sequence is this knowledge best incorporated into the ABM?

- Can the route choices discovered by DTA be used to suggest demand profiles that are not present in revealed preference surveys?

¹ Disclaimer: This paper was written based the author's informal accumulation of observations over the course of planning and implementing advanced modeling practice at CMAP. The content was not exhaustively researched, vetted among peers or even meticulously edited. Its only purpose is to guide panel discussion at a one-day Symposium.

² CMAP has a robust advanced practice trip-based model that is rigorously maintained for evaluating capital programs and major capital project alternatives. Activity-based model development is focused on addressing broader public policy inquiries such as congestion pricing, freight's role in economic development and marketing a modernized transit system.

³ In this paper, the term "network microsimulation" is used generically to include Dynamic Traffic Assignment, TRANSIMS-style microsimulation and other similar applications. It is also intended to engender the concept of multi-modal assignment including walk, bike and transit legs of a tour.

⁴ This problem is widely recognized. This statement is taken from RSG's Interim C10 report: "Ideally, the network path choice would be fully integrated into an AB model such as DaySim.

When applying a time of day choice for a given tour or trip, for example, DaySim would evaluate all available paths through the network at each time of day for that given traveler on that given tour or trip. In other words, network path choice would be done "on the fly" in a fully disaggregate manner depending on each traveler's tradeoffs between travel time, toll, distance and any other important route characteristics that are known in the network."

⁵ TRB, Transportation Research Circular E-C153 , Dynamic Traffic Assignment A Primer, 2011.

⁶ i.e. like multiple exposures of many events printed as a single snapshot