# Disaggregate simulation and some implications for calibration

Gunnar Flötteröd

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## An appeal for a more disaggregate perspective

- common sense is to "keep things simple"
- increased disaggregation
  - looks more at the "distributed" side of a simulation
  - may appear as if one was not keeping things simple
- this talk indicates relevance and feasibility of disaggregation



## One argument: calibration principles stay clear

calibration problem statement:

$$P(X \mid Y) \propto P(Y \mid X)P(X)$$

naive simulation of the solution:

$$E\{X \mid Y\} \propto \int XP(Y \mid X)P(X)dX$$

$$\approx \frac{1}{R} \sum_{r=1}^{R} X^{r} P(Y \mid X^{r}); \quad X^{r} \sim P(X)$$

• It is possible to do things like this for very large systems!



### Outline

Relevance: truthful modeling of uncertainty

Doability: avoiding to drown in details



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## Explaining deviations from reality

- when calibrating a (complicated) microsimulation...
  - one needs some kind of calibration model
  - this model must explain all deviations from reality
- essentially two approaches:
  - 1. use a deterministic calibration model and add random slack
  - 2. explicitly use a stochastic model to represent uncertainty

<sup>&</sup>lt;sup>1</sup>assignment matrix, OD matrix, linear dynamics, response surface, ...



#### Deterministic calibration model + random slack?

• (typical) measurement equation:

$$\mathbf{Y} = F(\mathbf{X}_1) + \varepsilon(\mathbf{X}_2)$$

- two extreme cases
  - 1. analyst really knows what is going on:  $\mathbf{Y} = F(\mathbf{X}_1)$
  - 2. analyst does not get the causality right:  $\mathbf{Y} = \varepsilon(\mathbf{X}_2)$
- in transportation, one seems to deal more with case 2...



#### Example: choice set uncertainties

(simulated) travel behavior with uncertain choice sets:

$$P_n(i) = \sum_{C_n \in C} P_n(i \mid C_n) P_n(C_n)$$

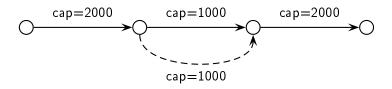
• operational version:

$$P_n(i) = P_n(i \mid \mathcal{C})$$

- not allowing for all alternatives can lead to inconsistencies
  - well known in choice modeling
  - have never seen this in OD matrix estimation



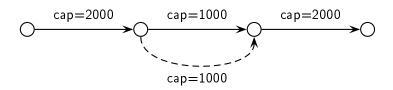
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- scenario:
  - peak hour demand of 1500 exceeds each route alone
  - congestion builds up upstream of the diverge
- best-response choice set generation never finds the detour
- even with a stochastic choice model, no one takes the detour
- effect on OD/path flow estimation when using random slacks?!





## Metropolis-Hastings sampling of paths (1/2)

- approach
  - give every path  $i \in \mathcal{C}$  a weight b(i) > 0
  - sampling probability q(i) shall be  $\propto b(i)$
- direct sampling from q(i) requires path enumeration

$$q(i) = \frac{b(i)}{\sum_{j \in \mathcal{C}} b(j)}$$

• MH does the job based on pair-wise comparisons only

$$\frac{q(i)}{q(j)} = \frac{b(i)}{b(j)}$$





## Metropolis-Hastings sampling of paths (2/2)

[[movie]]<sup>2</sup>

 $<sup>^2</sup> Fl\"{o}tter\"{o}d$  & Bierlaire (submitted). transp-or.epfl.ch/documents/technicalReports/FloeBier11.pdf





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## Where this is going

- this talks suggests to simulate and calibrate more "details"
- here: an idea of how a "gradual enrichment" is possible
  - first, introduce disaggregation without additional modeling
  - second, exploit the resulting structure whenever convenient





## Example: dynamic OD matrix estimation

- well-known to be utterly underspecified
- "macroscopic" approaches to deal with this:
  - non-negativity constraints
  - stay close to an (arbitrary) prior
  - assume (linear) dynamics





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- well-known to be utterly underspecified
- "macroscopic" approaches to deal with this:
  - non-negativity constraints
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  - assume (linear) dynamics
- problems arise when facing:
  - rigorous mass conservation
  - truthful representation of demand fluctuations
  - more than a handful of commodities





## Autoregressive OD matrix dynamics

• autoregressive model for OD flows (simplified):

$$x_{s}(k+1) = \sum_{r} a_{rs}(k)x_{r}(k) + \varepsilon_{s}(k)$$



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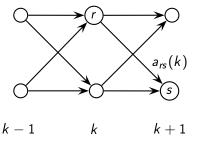
looking back at the original problem:

$$\Leftarrow \forall n: P_n(s|k+1) = \sum_r a_{rs}(k)P_n(r|k)$$





## Really more complex than the AR model?



- Markovian trip making dynamics at individual level
- truthful representation of original AR model
- but...



## Added value of traveler disaggregation

- constraints become simple in the disaggregate approach:
  - rigorous mass conservation
  - truthful representation of demand fluctuations
  - more than a handful of commodities
- in addition, one can add any behavioral model of trip chaining
- in this particular example, all of this is already possible<sup>3</sup>





<sup>&</sup>lt;sup>3</sup>Flötteröd & al. (2011). Transp. Science.

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- disaggregate simulation & calibration modeling
  - capture uncertainty where it occurs
  - contribute to unbiased calibration
- model complexity does not necessarily explode
  - in the 1st instance, only add physically existing structure
  - in the 2nd instance, add more complex model structure
- (very subjective) conclusion
  - calibration models benefit from increased disaggregation
  - possible without jumping right on activity-based models

