An equilibrium-seeking search algorithm for modeling the integration of supply and demand

Serio Agriesti*[1,2], Claudio Roncoli[1], and Bat-hen Nahmias-Biran[3]

[1]Department of Built Environment, Aalto University, Helsinki, Finland
[2]FinEst Centre for Smart Cities, Tallinn University of Technology, Tallinn, Estonia
[3]The Porter School of the Environment and Earth Sciences and the School of Social and Policy Studies, Tel-Aviv University, Tel-Aviv, Israel

*serio.agriesti@aalto.fi

Short summary

An iterative methodology integrating large-scale behavioral activity-based models and dynamic traffic assignment ones is presented in this abstract. The main novelty lies in the decoupling of the two sides, allowing an ex-post integration of any existing model, as long as certain assumptions are met. The abstract describes a measure of error characterizing an easily explorable search space. Within it, the equilibrium state is characterized by the joint distribution of number of trips and travel times, i.e. the distribution for which trip numbers and travel times are bound in the neighbourhood of the equilibrium between supply and demand. The approach is tested on a city of 400,000 inhabitants and the results suggest that it does perform well. Overall, values lower than 10% are reached in 15 iterations. The equilibrium state is then validated against baseline distributions to demonstrate the goodness of the results.
Keywords: Activity-based modeling, Model integration, Nested logit.

1 Introduction

Activity-based travel demand models and agent-based models (ABM) have some key advantages over more traditional four-step models, and their popularity is increasing accordingly. These advantages include framing disaggregate demand patterns, with individual choices based on socio-demographic features and sound behavioral models (Bastarianto et al., 2023). On the other hand, through ABMs traffic supply can be simulated down to the single agent (Kagho et al., 2020) and large-scale traffic assignment (TA) models can be as detailed as the input demand, with mesoscopic and microscopic applications considering each vehicle as a single agent in its interations with surrounding elements (Casas et al., 2010; Fellendorf & Vortisch, 2010; Krajzewicz, 2010). Still, the increased complexity is hindering the wider adoption of activity-based ABM models and, in general, disaggregate demand/supply modeling. To tackle this, this abstract presents an algorithm developed to integrate disaggregated supply and demand with close to no requirement on the adopted modeling tools, reporting results from a real life large scale case study (the city of Tallinn, capital of Estonia). Indeed, most integrations in literature rely on data exchange between the two models, often happening mid-simulation and requiring dedicated interfaces. Pendyala et al. (2012), for example, set up a data exchange between the two models happening every time a destination is reached, for the agents to update their behavior depending on the actual cost of the previous trip. Basu et al. (2018); Lu et al. (2015); Marczuk et al. (2015) build a tool where both users and vehicles are agent, and the demand is update in real time as the traffic assignment is carried out. Depending on the nature and complexity of the data exchange, Pendyala et al. (2017) categorize different integration types: sequential integration (L0), no real-time information (L1), only pre-trip information (L2), pre-trip and en route information with route diversion only (L3), and pre-trip and en route information with full activity-travel choice adjustments (L4). Already from L1, information between the two models is exchanged at regular intervals, e.g., every minute. Other works addressing the integration problem are (Heinrichs et al., 2018; Goulias et al., 2011).
We describe a L0 methodology (Figure 1) as to avoid any data exchange need and greatly increase the applicability of such integration methods, we do so by characterizing a measure of error (MoE) and perturbation techniques needed to reach equilibrium between demand and supply faster. The

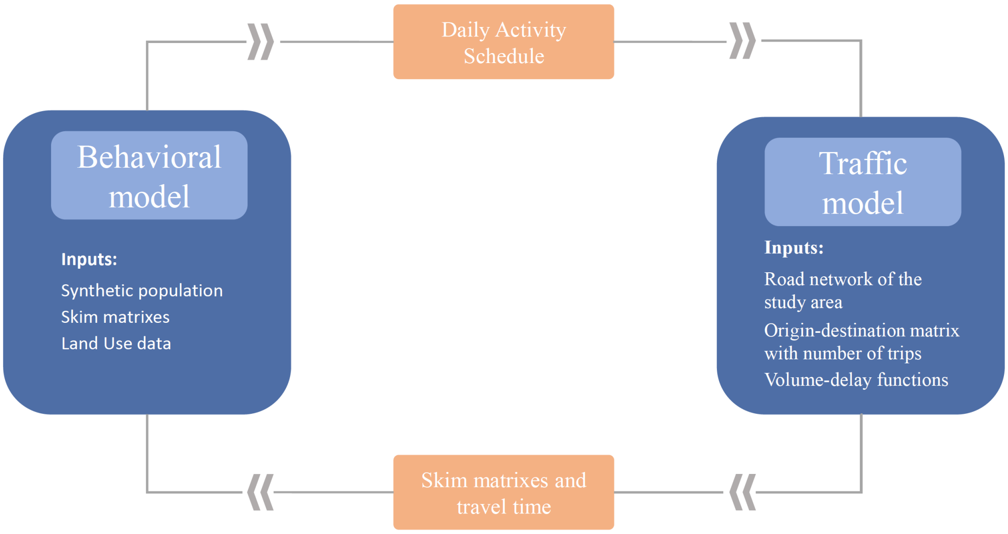

Figure 1: The proposed iterative approach

presented algorithm relies on a series of loops and is transferable by design. The trade-off sacrifices the communication to allow the integration between existing models, allowing, for example, to incorporate activity-based behavioral elements into large TA models relying on an aggregated demand. Another strength of the L0 approach is that it does not require specific software and applies to any meso/microscopic TA and activity-based tool. This, in turn, allows the usage of a multitude of TA tools, depending on the case study at hand.
The abstract is structured as follows. In Section 2 we describe the MoE, the iterative architecture and the perturbation techniques used to reach equilibrium; In Section 3 and 4 we report numerical results related to a real life experiment and show the stability of the reached solution; In Section 5 we discuss the presented results and the next research directions.

2 Methodology

Definition of a measure of error (MoE)

The MoE was conceived as one single measurement able to frame both dimensions of the problem (i.e. demand and supply modeling). To do so, a product matrix with origins and destinations as rows and columns was considered, with each cell filled by the corresponding value of $n \cdot tt$ (where n is the number of trips and tt the travel time). This matrix represents the quantity of traffic across the network resulting from one joint run of the activity-based model and of the traffic assignment one (in series). The MoE is defined as the difference between two consecutive matrixes, as it frames the changes in quantity of traffic (measured as number of trips $\cdot$ minutes travelled). We define the matrix M_{od} as follows:

$$M^{O \times D} = N^{O \times D} \circ T^{O \times D}, \tag{1}$$

Thus, each element m_{od} of matrix M is the resulting $n \cdot tt$ for each OD pair. It is worth highlighting how the proposed methodology is decoupled from any parameter involved in the calibration process of either model and is designed to reach an equilibrium with the existing, calibrated parameters of both demand and supply. The proposed MoE, being composed only of the outputs of each model (i.e., matrices N and T), fits the scope perfectly. The MoE is defined as:

$$\Delta A^i = |A^i - A^{i-1}| = \int |v^i(m_{od}) - v^{i-1}(m_{od})| \;\; d(m_{od}) \quad \forall m_{od}, \tag{2}$$

where A_i is the area under each distribution of values for an M matrix, i is the iteration index, od

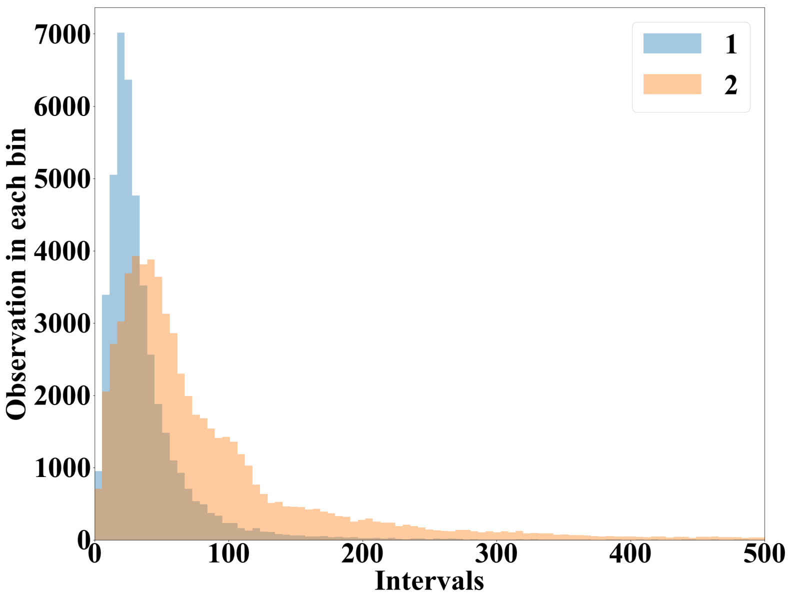

Figure 2: Area comparison between two iterations

represents each origin-destination pair for which the value m_{od} is computed, and v is the number of measurements (or cells) whose value falls in a certain range of $n \cdot tt$, as it will be explained in the following (refer also to Figure 2). Calculating the difference of areas (and of v) in absolute terms allows us to frame the overall "mismatch" between two matrices computed for successive iterations and avoid opposite differences to cancel each other out. To calculate v, we start by defining the interval size u as

$$u = \frac{\max(M) - \min(M)}{L}, \tag{3}$$

where L is the number of intervals; such intervals are equally distributed between the minimum and the maximum value of M, and are indexed by $l = 1...L$. The number of measurements in each bin, $v(m_{od})$, is calculated via

$$v^l(m_{od}) = \sum_1^O \sum_1^D \tau_{od}^l \quad \forall l = 1, \ldots, L, \tag{4}$$

where

$$\tau_{od}^l = \begin{cases} 1, & \text{if } u \cdot (l-1) \leq m_{od} < l \cdot u \\ 0, & \text{otherwise} \end{cases} \quad \forall l = 1, \ldots, L, o = 1, \ldots, O, d = 1, \ldots, D. \tag{5}$$

The distribution of values in M_{od} can be easily visualized and compared by dividing its values in the equal intervals $v(m_{od})$, as in Figure 2.
The closest the distributions, the closest the equilibrium between demand and supply as further iterations of the two models do not result in significant shifts in demand and supply performance.

The algorithm as a heuristic solution to a local search problem

The algorithm at the core solves an optimization problem for which the cost to be minimized, C, is the MoE value, namely the difference in the quantity of traffic calculated across iterations. This difference reflects how much each cell in the OD matrix oscillates around the point of equilibrium between demand and supply. To minimize this quantity means to minimize the cumulative distance across the matrix from the set of equilibrium points.
Figure 3 summarizes the described heuristic iterative local search algorithm (Lourenço et al., 2003; Johnson et al., 1988). It is worth formalizing it also in general terms, to maximize the generality of the proposed approach and to properly define the theory behind it. Local search algorithms look

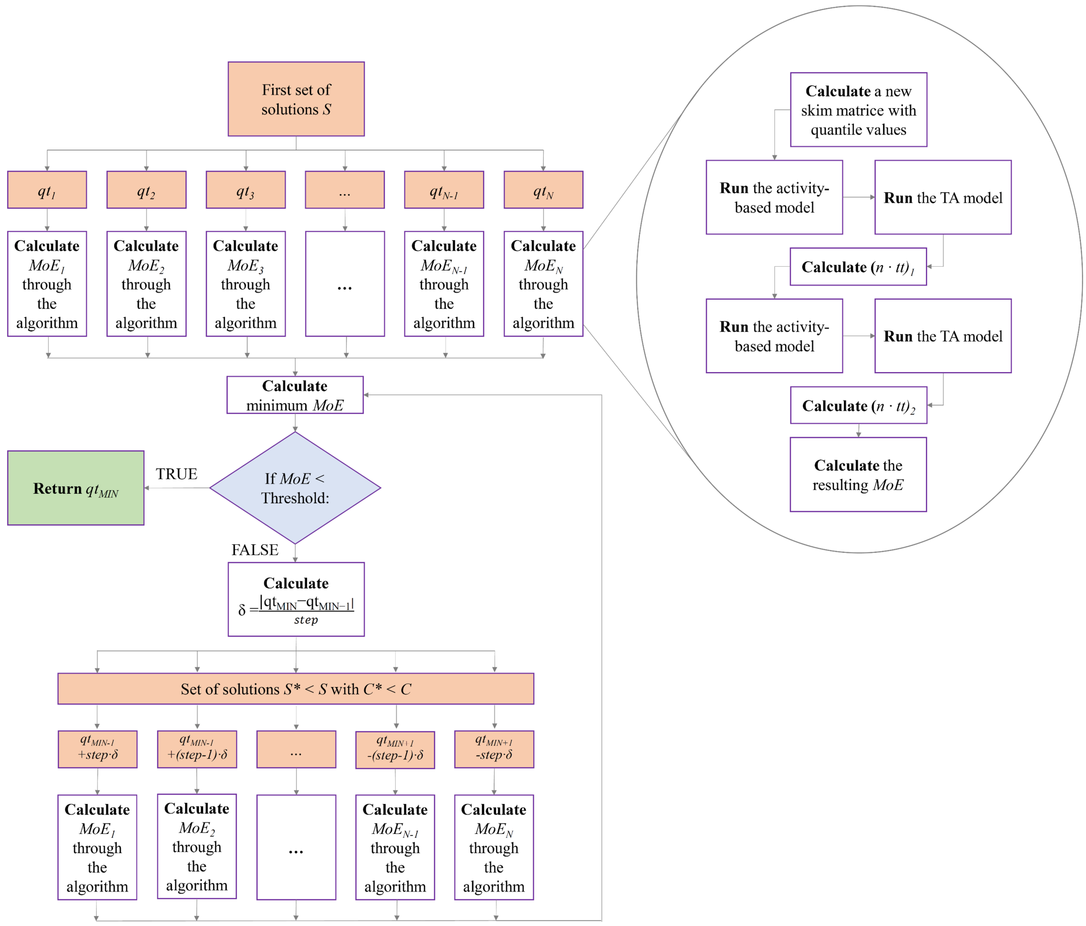

Figure 3: The proposed local search algorithm

for improved solutions $S*$ through perturbations of the current solution S. They do so by scanning the neighborhood of each solution and scoring, through minimization of the cost, each new area (Johnson et al., 1988). It is worth noting that the final solution is a local minimum of C. In the presented case, the cost is the MoE, the neighborhood is characterized by adjacent distributions of $n \cdot tt$ and the perturbations are applied through quantiles of tt. By adopting a threshold value to stop the iterations, we define an acceptance criterion and thus strongly favor intensification rather than diversification (Lourenço et al., 2003). Diversification,i.e., the scanning of the search space for different local solutions, is less important than intensification, i.e., acceptance of only improved sets of solutions, namely with a lower MoE. This greatly increases the efficiency of the algorithm, allowing a parallel search streamlined to the lowest MoE available. To accept worse MoEs through the search would instead disrupt the parallelization and greatly increase the number of branches and thus iterations needed (Figure 3). This concept is important as it justifies the approach and the final solution provided by the algorithm. Favouring intensification is justified as the number of combinations of n and tt across a large OD matrix for which $C^* \rightarrow \min(C)$ is unfeasible to treat but also of scarce interest. It is enough to imagine how little increases of 1 minute in a single cell may impact the whole network and/or population of agents. And then project such a small increase to all the possible combinations of both n and tt. It is impossible to escape such a conundrum due to the lack of mathematical formulations in both activity-based and TA models on a large-scale. So, the search for the exact distribution $n \cdot tt$ for which $C^* = \min(C)$ is not the objective of the algorithm (or rather, it is the general goal but the acceptance threshold can be placed at the suboptimal solutions). By characterizing the problem as the search of a set of equilibrium points, each in a convex supply-demand space, and by then identifying the local minimum in the solution's neighborhood, the algorithm guarantees a solution in a limited amount of iterations, while justifying the search for a local rather than the global solution.

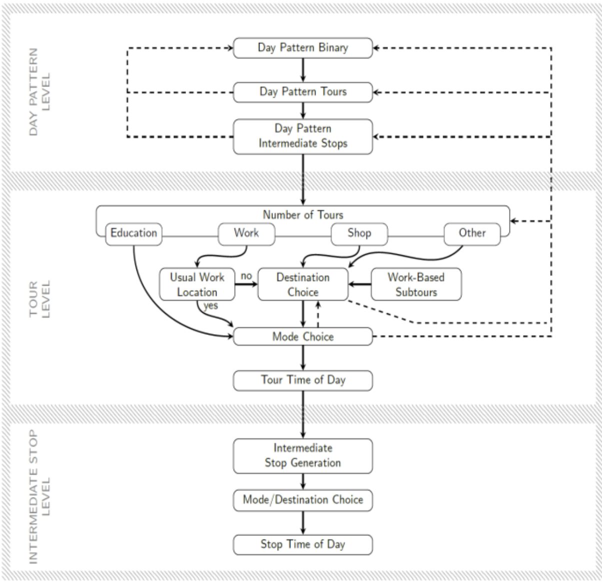

Figure 4: The nested logit structure used in the SimMobility-MT model; each level of the tree is characterized by a set of utility functions (Oke et al., 2019)

3 Case Study

The case study is focused on the city of Tallinn, the capital of Estonia. The city is home to ∼400,000 inhabitants and sees more than 1,100,000 trips in a typical day, of which almost half are carried out by private transport.

The activity-based model

The considered behavioral activity-based model is built in SimMobility-MT (Lu et al., 2015) and exploits a series of nested-logit models to characterize the schedule of each one of the inhabitants (agents) down to the single choice within the day. This is performed by computing and comparing utilities at each level of the mobility tree (Figure 4) while exploiting the logsum concept (Nahmias-Biran et al., 2021) to tie the utilities at the top of the tree with the ones on lower branches. SimMobility-MT takes into account stochasticity through random seeds. In the day pattern level, the choice of participating in one of the possible activities is characterized. It results in the list of tours for each agent (i.e. each individual user). The tour level builds the features of each tour such as mode choice, destination and subtours. In the same way, the intermediate stop level populates the tours with intermediate stops and defines the timing of each trip. The whole structure is hierarchical and consists of 22 behavioral models, described in detail in (Siyu, 2015).
Each behavioral model is a utility maximizing model exploiting utility functions such as the one reported in the Equation 6. Note that each weight variable in (6) is a vector of βs, including as many behavioral variables as categories considered. For example, $\underline{\beta}$ for age category is a vector with 5 βs, since 5 are the age categories considered. As in behavioral theory, these βs are alternative specific constants framing how much each feature (of the trip or of the person) weights towards the utility Siyu (2015).

$$
\begin{aligned}
U_{\text{bus}} = f(V_{\text{case\_study}}, &\underline{\beta}_{\text{cons\_bus}}, \underline{\beta}_{\text{tt}}, \underline{\beta}_{\text{walk\_time}}, \underline{\beta}_{\text{wait\_time}}, \underline{\beta}_{\text{cost}}, \\
&\underline{\beta}_{\text{cost\_over\_income}}, \underline{\beta}_{\text{central\_district}}, \underline{\beta}_{\text{transfer}}, \\
&\underline{\beta}_{\text{female\_num\_of\_cars}}, \underline{\beta}_{\text{number\_of\_cars\_in\_hh}}, \\
&\underline{\beta}_{\text{agecat\_num\_of\_cars}})
\end{aligned}
\tag{6}
$$

The model is built by defining 609 zones, which implies that 370,881 cells compose the $n \cdot tt$ matrix at hand (as many as the OD pairs). The model has been calibrated against relevant mobility patterns and socioeconomic features of the Tallinn population (Agriesti et al., 2022, 2023).

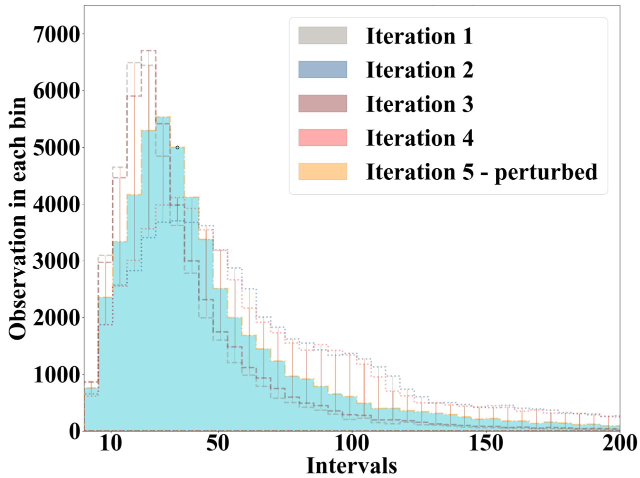

Figure 5: First round of iterations - perturbed iterations shaded in light blue

The traffic assignment model

A TA model is instead built with Aimsun (Aimsun, 2022). This model has the same set of origins-destinations as the one in SimMobility-MT and has been calibrated against traffic counts to match current guidelines (Beeston et al., 2021). The calibrated values rule over different aspects of the traffic assignment, with functions such as volume-delay ones or turn-delay ones, defining the performance of each route in terms of travel time and as a function of volumes and capacities. Defining these elements and the desired speed distribution means calibrating the main dimensions of the macroscopic assignment problem. Items such as reaction time, C-Logit, and node connections rule instead over the behavior of single vehicles in the mesoscopic assignment.

4 Numerical results

First set of iterations: Search space characterization

The two models are run iteratively, starting from an estimate of travel times based on distances as input for the first iteration. The first four iterations have produced the results shown in Figure 5, while the MoE values are reported in Table 1.

Table 1: MoE values across the first set of iterations - averaged for the morning and afternoon peak

Iterations	***MoE***
1-2	0.71
2-3	0.63
3-4	0.6

As it can be noticed, the iterations do not converge by themselves as the demand from the behavioral model is locked in a cycle of under and overestimation, which in turn generates over- and underestimated travel times. The equilibrium between the demand and the supply modules lies somewhere around iteration 5 in Figure 5. To find it, different distribution of the travel time matrix $T^{O \times D}$ are tested. These distributions are calculated as quantiles of the $T^{O \times D}$ from the first four iterations and then tested to determine which value results in the lowest MoE (as per Figure 3).

Second set of iterations: Perturbation and assessment of the equilibrium

Once the quantile resulting in the lowest MoE is identified, the resulting $T^{O \times D}$ is feed into the iteration loop, for the activity-based model to generate a corresponding demand. In the presented

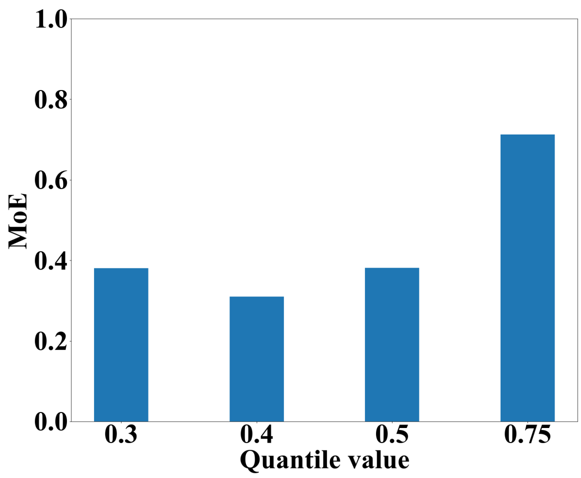

Figure 6: MoEs calculated for each quantile value - Initial values

Table 2: MoE values across the perturbed set of iterations - averaged for the morning and afternoon peak

Iterations	*MoE*
4-5	0.34
5-6	0.14
6-7	0.15
7-8	0.16

case study, the resulting $N^{O\times D} \circ T^{O\times D}$ is plotted as iteration 5 in Figure 5.

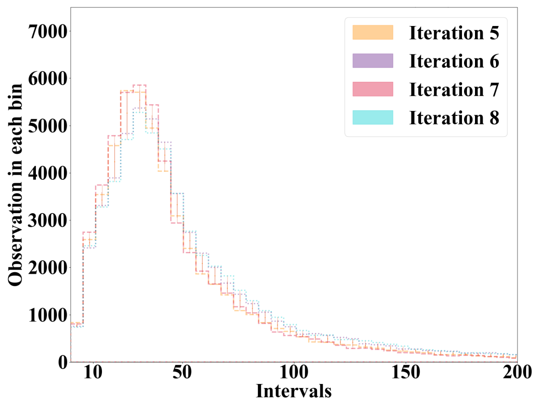

Figure 7: Static iterations after perturbation

As can be noticed from Figure 7, the oscillations between iterations are sensibly smaller than in the previous set of iterations. The reduced oscillation around an equilibrium distribution of $n \cdot tt$ is reflected also in the MoE that drops to the values reported in table 2.

From static to dynamic traffic assignment

To reduce computational times, the TA simulations up to this point have been ran as static rather than dynamic. Still, it is important to verify that the found equilibrium between supply and demand is not disrupted by the congestion propagating properties of the dynamic TA (Aimsun, 2022; Casas et al., 2010). To do so, a further round of iterations is run, this time with a dynamic TA. Nothing else is changed at this point, as these iterations continue the iteration loop from iteration 8 in Table 2. The MoE progression is showed in Figure 8

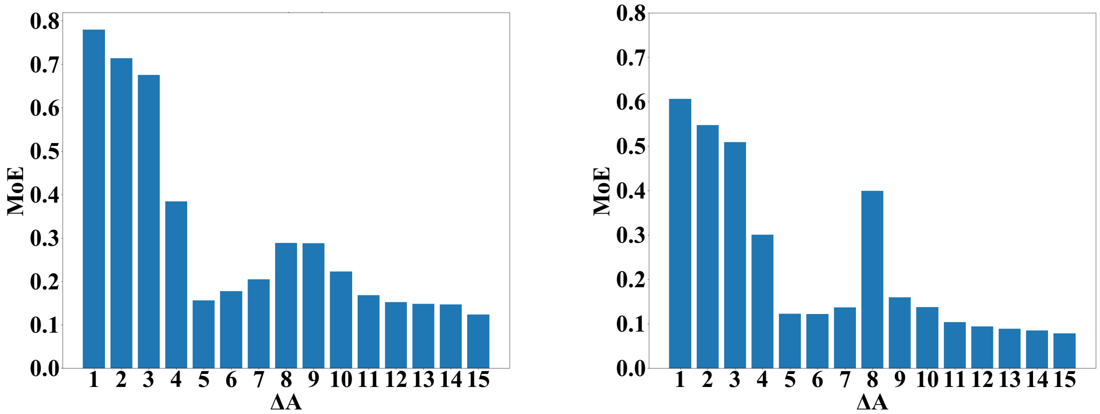

Figure 8: Progression of the MoE across all the iterations for the morning and the afternoon peak

As it can be noticed, after an initial sharp increase between iteration 8 and 9 (the first one including the dynamic element in the TA), the equilibrium settles back to initial values of the MoE. This and the low MoEs from iteration 5 to 8 point to a robust stability of the found equilibrium between demand and supply.

5 Conclusions

The paper proposed a framework to integrate large-scale activity-based models and traffic assignment models, with close to no requirements concerning the tools themselves. A MoE transferable and comparable among case studies is defined and tested on a large scale urban case study, with a very detailed activity-based behavioral model and a state-of-the-art TA tool. The search space definition and perturbation are detailed while the resulting equilibrium is assessed for an existing case study. Overall the paper aims to provide an easily replicable blueprint for the integration of existing models and hopefully foster wider adoption of this kind of modeling both in academia and among other stakeholders. Numerically, the case study results in negligible errors in the modal share ($\sim$1%) and overall number of trips, while the MoE value stabilizes at 10%.

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