CMAP Microsimulation Extension of the Activity-Based Model (ABM)

Task 1: Methodology of ABM-DTA Integration

Draft Interim Report

Prepared for the Chicago Metropolitan Agency for Planning by Parsons Brinckerhoff and Northwestern University

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1 Introduction, Objectives, and Background

1.1 Basics of Agent-Based Modeling and Project Approach

Agent-based models are ideal for studying systems inaccessible to traditional analytical approaches due to complexity and large number of interacting agents. Emergent phenomena that cannot be either measured or observed as well as phenomena that cannot be mathematically modeled can be amenable to the agent-based framework. The main difference between inductive and deductive models like conventional microsimulation ABMs and agent-based models is that in the former, we try to reproduce previously recorded behavior, that is, we "teach" the model what we've learned; in the latter, we "teach" the model how to learn and adapt. While this concept itself is very appealing theoretically, using agent-based models for estimating travel demand and for traffic microsimulation presents several technical challenges. One important issue that requires addressing when dealing with network simulation models is how individual behavior affected by environment attributes, resulting from the individual choices, can be effectively captured at an aggregated ("neighborhood") level. For example, behavior of drivers in traffic stream affected by prevailing density (itself the result of previously made decisions of these drivers). Another example is how decisions of route and departure time made individually are affected by actions of all travelers in that corridor. In short, collective effects in these systems are quite robust and capturing them is important. Thus, a certain level of meso-effects is necessary in any microsimulation system and it cannot be completely broken into individual-level decisions and interactions between the agents.

In this regard, defining autonomous and intelligent agents that represent emergent collective behavior to estimate travel demand and network flows is quite challenging. Direct interactions of agents with each other should be complemented with interactions with the "environment". In the current project, we plan to apply the basic principle of "emergent" collective behavior where individual rules of behavior are specified with the maximum possible behavioral realism (individual schedule consistency and real-time adjustments based on the experience of trips already completed by the same individual) while there are some aggregate flows of information that provided to each agent (anticipated travel times) for planning.

The integrated model system is built using two major pieces developed for the Chicago Metropolitan Region: Activity-Based Model (ABM) of the CT-RAMP (Coordinated Travel and Regional Modeling Platform) type, and Dynamic Traffic Assignment (DTA) model of the DYNASMART (Dynamic Network Assignment-Simulation Model for Advanced Roadway Telematics) type. Both systems are planned to undergo substantial improvements to ensure a seamless integration. In the integrated model system the original concepts of travel demand and supply become intertwined in the framework of individual daily schedules. Thus, the final outcome of the project is a new integrated model rather than two existing models applied in an iterative fashion.

1.2 CMAP CT-RAMP Activity-Based Model

Parsons Brinckerhoff developed an ABM for CMAP specifically for highway pricing/tolling analysis in 2010-2011 (Final Report and User Guide are available by request from CMAP). The transit analysis framework for this ABM has been recently currently added by Parsons Brinckerhoff that resulted in many advanced features added to the ABM on the transit side (Final Report and User Guide are available by request from CMAP). Both these CMAP ABM models are briefly described below.

1.2.1 CMAP CT-RAMP ABM for Pricing

Parsons Brinckerhoff developed an ABM specifically for highway pricing/tolling analysis, which includes such features as 30 minute temporal resolution and work destination choice segmentation by person occupation. The car ownership, destination, time-of-day, and mode choice models were estimated using local data and the other sub-models were transferred from the Atlanta CT-RAMP and subsequently calibrated based on the aggregate local data. A number of enhancements were made to the model structure and parameters to account for various pricing sensitivities, such as distributed value of time and increased number of time-of-day periods (8 in the current version).

The Pricing CT-RAMP model is implemented for the 17-county Chicago region and microsimulates 10 million persons in the base year using approximately 6,000 zones (2,000 TAZs with three transit access sub-zones per TAZ) to represent the region. The CMAP model has eight time periods for highway skims, and two time periods for transit skims. Transit skimming is done separately for premium and local service by walk and drive access with EMME's headway-based optimal strategies algorithm, which is a probabilistic path-builder with transit sub-mode choice. The network procedures were implemented with EMME for network assignment and skimming. The model runs on 4 Windows 7 Enterprise machines each with 12 cores and 144 GB of RAM.

Highway pricing is a transportation policy where ABMs have clear and tangible advantages over 4-step models. The Chicago region already has toll facilities that allow for statistical analysis and estimation of impacts of congestion and pricing on travel demand. Following are the main modeling aspects of this project:

- User segmentation in the demand model and highway network procedures. One of the primary advantages of a microsimulation ABM is a practically unlimited population and travel segmentation. It is essential for pricing studies where different segments may have very different willingness to pay for travel time savings and reliability improvements. It is shown that 9-10 travel segments combined with 7-8 population segments provide a reasonable level of segmentation that can also be supported by the travel surveys used for model estimation. In aggregate network simulations like static traffic assignment, a parallel level of segmentation can be supported in multi-class assignments but the classes have to be grouped by value of time rather than travel purpose or person type.
- Distributed Value of Time (VOT) and other behavioral parameters. Within each segment, willingness to pay is subject to a significant variation across individuals and situations. A model that operates with discrete VOTs may exhibit illogical abrupt responses to small changes in toll values. Microsimulation framework allows for an effective randomization of VOT as well as other parameters across individual agents within the same segment. This approach was adopted for the CMAP CT-RAMP where each individual obtains VOT from the parameterized distribution.

- Travel dimensions affected by congestion and pricing. Pricing directly affects tour-level and trip-level choices (route, mode, destination and time of day) through the generalized cost component in the utility functions. However, a recently included advanced feature of ABMs allows for capturing impacts of congestion and pricing on activity generation and car ownership choice through a wide range of accessibility measures. In particular, in the Chicago region, household car ownership proved to be a strong function of the auto accessibility relative to the transit accessibility with an especially strong impact of accessibility to rail.

- Time-of-day choice with a fine temporal resolution. Modeling impacts of congestion and pricing (and peak spreading effects in particular) requires a level of temporal resolution of 30 min or less. This results in a large number of alternatives (thousands) when multi-dimensional tour-scheduling choices are modeled. In the recent ABM versions, special combinatorial methods for treatment of these choices were applied. The developed approach ensures a full consistency of individual daily schedules without gaps or overlaps in the sequence of activities and trips between them.

- Treatment of vehicle occupancy. Vehicle occupancy is a very important factor that strongly affects willingness to pay as well as frequently used for eligibility to use Managed Lanes (HOV/HOT lanes). Two different modeling approaches that have been used. The first one is simpler and considers occupancy as part of individual mode choice. The second one is more complex and based on an explicit modeling of joint travel as a separate travel segment. The second approach constitutes one of the advanced features of the CT-RAMP model structure. In both cases, VOT is scaled to account for car occupancy. It is implemented by "damping" the cost coefficient in the mode choice utility.

- Route type choice integrated with mode choice. All-or-nothing route choice framework embedded in a deterministic traffic assignment has inherent drawbacks in portraying the proportion between those who chose a tolled route and those who don't. In this regard, adding an explicit choice of route type (toll vs. non-toll) as the lower level in the mode choice structure helps compensate for this deficiency. Recently, a similar problem has been recognized with respect to all types of Managed Lanes (not necessarily tolled, like HOV lanes). Hence in the Chicago ABM, route type choice has been extended to incorporate distinctive route types explicitly.

1.2.2 Transit Modernization of CMAP CT-RAMP ABM

Parsons Brinckerhoff has recently developed a new version of the CMAP CT-RAMP ABM specifically for transit analysis. The model is based on the previously developed Pricing ABM. The transit modernization included a large number of additional model features to better address behavior of transit users in the complex multi-modal transit system in the Chicago Metropolitan Region. Both mode choice and transit assignment models were significantly extended to incorporate many attributes of premium transit services in addition to conventional parameters like travel time and cost. In particular, the following main innovative model components can be mentioned:

- Advanced "non-labeled" mode choice model formulation where differences in transit modes are quantified and explained by service attributes subject to policies rather than by fixed labels like "bus" or "rail".

- Enhanced spatial resolution where all location choices and corresponding transit access and non-motorized modes are modeled at the level of 17,000 Micro-Analysis Zones (MAZs); in particular, transit walk access is modeled by using a detailed navigation network.

- Incorporation of a wide set of station/stop characteristics such as station type (pole, shelter, plaza, station, and major terminal), provision of real-time information, ease of boarding (level platform, low floor, and staircase), cleanliness, density of commercial activities and crime rate in the station area. These parameters were quantified as components of boarding time as well as boarding time and/or wait time perception weights.

- Incorporation of a wide set of on-board service characteristics including comfort, cleanliness, convenience, social environment, productivity, etc. These parameters were quantified as perception weights on in-vehicle time.

- Total capacity constraints and crowding effects that required internal equilibration of transit assignment. Total capacity constraint was introduced by using the effective headway calculation method. Crowding effects were modeled using innovative methods developed by PB. Essentially, seating and standing passengers are distinguished on each transit segment and crowding penalty functions are developed for each group separately with the penalties for standing being most onerous.

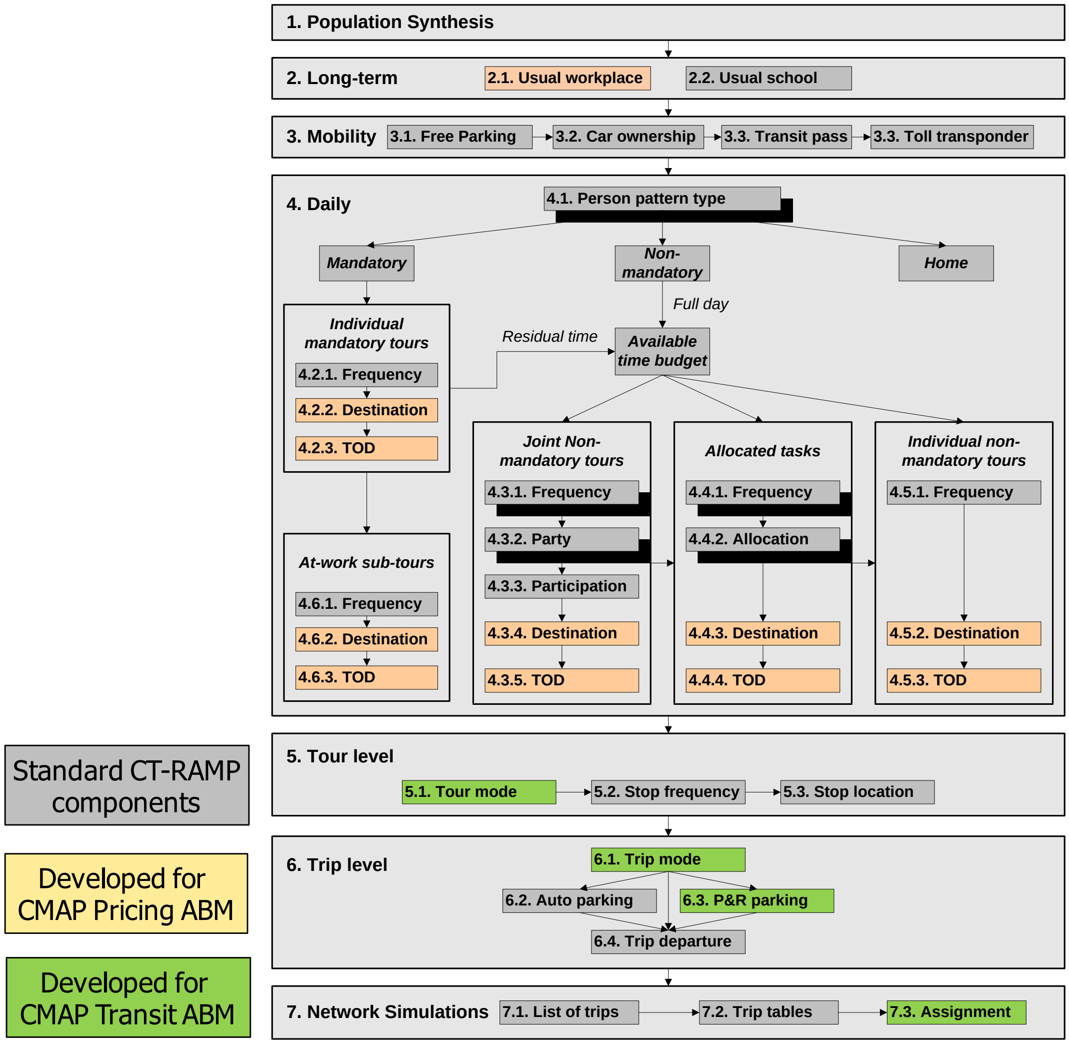
- Incorporation of transit service reliability. Special statistical function was developed for average extra wait time associated with bus “bunching” and other schedule non-adherence factors depending on the service frequency, number of boarding and alighting passengers, stop location on the route, time of day, etc. This function was incorporated in the transit assignment equilibration.

- Incorporation of probabilistic choice-base passenger arrival at the station instead of a random arrival hypothesis. This results in a wait time as non-linear function of headway rather than a simplified half-headway rule that is applied in many standard models.

- Addressing important details of actual fare structures including inter-modal and intra-modal transfers and zone-base fares for commuter rail.

The complete CT-RAMP ABM structure as developed for CMAP is shown in Figure 1.

Figure 1: CMAP CT-RAMP ABM Structure and Recently Updated Sub-Models



1.3 DYNASMART DTA (Application for Chicago Metropolitan Region)

Simulation-based dynamic traffic assignment has gained considerable acceptance over the past years as a practical analysis tool to evaluate a wide range of strategic and operational improvements to urban and regional transportation networks. Developed originally for the US Federal Highway Administration as a blueprint for simulation-based DTA functionality, DYNASMART-P has led to the development of a new generation of dynamic network traffic analysis tools that are increasingly gaining a foothold in practice (Mahmassani *et al.*, 1994). It models the evolution of traffic flows in a traffic network resulting from the decisions of individual travelers seeking to fulfill a chain of activities at different locations in a network over a given planning horizon.

From its earliest days, the DYNASMART platform, and its predecessors, was envisioned as a tool to capture the dynamic interactions among decisions made by individual travelers, and in turn capture the effect of the outcome of this interaction on traveler choices (Mahmassani and Jayakrishnan, 1991;

Jayakrishnan *et al*., 1994). To enable this interaction, several aspects had to be incorporated in the representation:

- Totally disaggregated representation of individual agents as decision entities throughout the simulation process, which implies (a) retention of the memory of the trajectories and experiences of each traveler through the simulation, (b) opportunities for exercising choices along the way, either ahead of nodes or in an event-based manner (e.g. triggered by thresholds or occurrences), and (c) availability of relevant supply-side attributes in dynamic manner throughout the simulation.
- Efficient network (graph) representation and associated data structures to enable fast-processing in optimum and feasible path computations for both real-time decisions as well as day-to-day iterative and consistency-seeking (equilibria) procedures.
- Different information availability states for the individual agents— including source or information and type of information, coupled with the corresponding decision rules appropriate to the extent of responsiveness to such information.
- Ability to load the network in various ways, including ability to load individual activity tours and schedules, with and without en-route adjustment; this feature is essential for correctly integrating with ABM for the demand side.
- Particle-based approaches to capturing the physics of traffic interaction in the network which retain the individual entity of the agents while exploiting robust relations among state variables in propagating vehicles and other entities.
- Consideration of multiple user classes in terms of system performance (supply-side), information availability, assignment and travel behavior rules.
- Sensitivity of network performance to prevailing weather conditions, including rain or snow intensity and visibility. This capability was introduced, calibrated, tested and demonstrated in over three years of development funded by FHWA's road weather traffic management program (Kim *et al*., 2013, Mahmassani *et al*., 2009; Hou *et al*., 2013).
- Consideration of heterogeneous user preferences in dynamic path-finding computations. For example, finding paths to consider for travel when some links are tolled, or more generally when users consider multiple attributes in their path selection, can be accomplished efficiently using a parametric algorithm that can be applied with any continuous or discrete distribution of users' value of time (Mahmassani, Zhou and Lu, 2005).

Simulation-based DTA models require detailed network information. Networks used in DYNASMART are typically built on the basis of existing static networks, which often do not contain necessary information such as cycle and green times and allowed movements at each phase at a signalized intersection, or definition of each movement at a node (e.g. left turn, right turn, U- turn, and through movement). Thus, in addition to data provided by static networks, information from several other external sources is necessary to achieve an accurate representation of the real-world network. Figure 2 illustrates the overall process for building and converting networks for DYNASMART. The main tool for the conversion is a software called DYNABUILDER, which is capable of converting many networks from different platforms into a DYNASMART-P network. DYNABUILDER requires input files in a certain format.

Therefore, several pre-processing steps are conducted using different codes and macros to re-format network data obtained from external sources.

For the CMAP Microsimulation Extension of the Activity-Based Model the Chicago regional network is used. The static network is provided by the Chicago Metropolitan Agency for Planning (CMAP). This static network (originally in TransCAD) was transformed into the DYNASMART-P format. Figure 3 presents a snapshot of the network.

Figure 2: Flowchart for the Conversion from the Static to the Dynamic Network Model

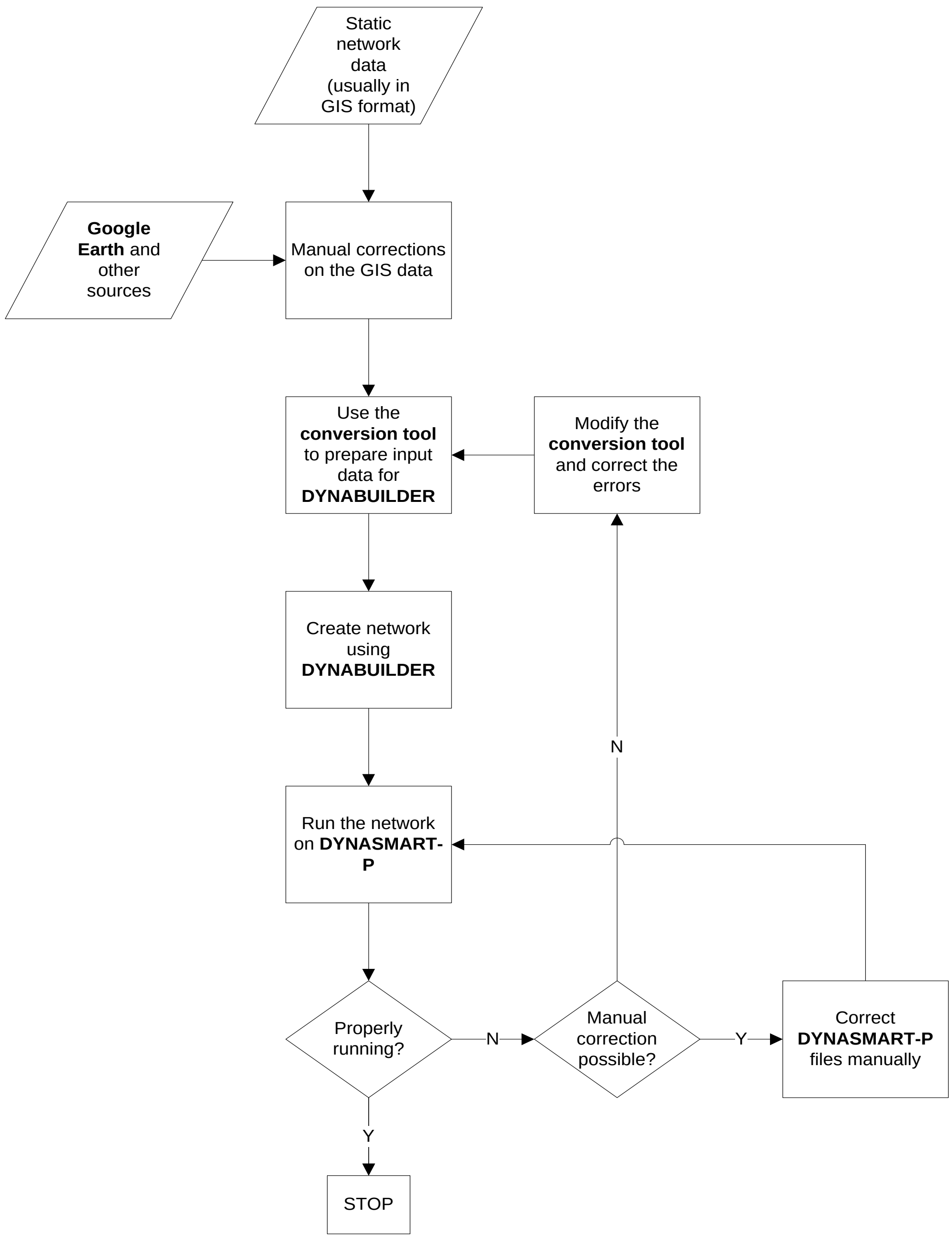
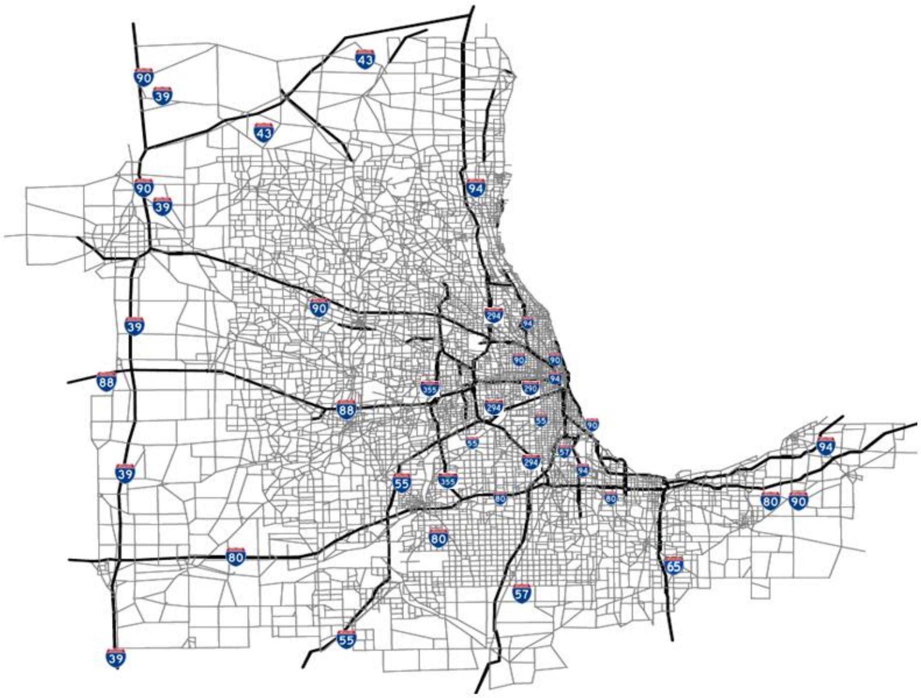


Figure 3: Chicago Network Configuration



The network has the following specifications:

- 40,443 links
    - 1,400 freeways
    - 201 highways
    - 2,120 ramps (96 metered ramps)
    - 36,722 arterials
- 13,093 nodes
    - 2,090 signalized intersections (Implemented as Actuated Control)
    - 2,196 no control
    - 8,655 all way stop sign
    - 152 Two way stop sign
- 1,961 zones
    - 1,944 internal
    - 17 external

The current network also includes 144 tolled links with a fixed price. The location of the tolled links is shown in Figure 4. Some additional lanes and new links are added to the current network to build the future network based on the CMAP congestion pricing study (CMAP 2012). The additional lanes are added to the current network in DYNASMART as new links. As a result, the future network has 79 new links and 32 new nodes and 66 of these 79 links are priced links. In total, the future network has 210 priced links.

Figure 5 shows the future network and highlights new tolled facilities.

Figure 4: Location of Tolled Links in the Current Network

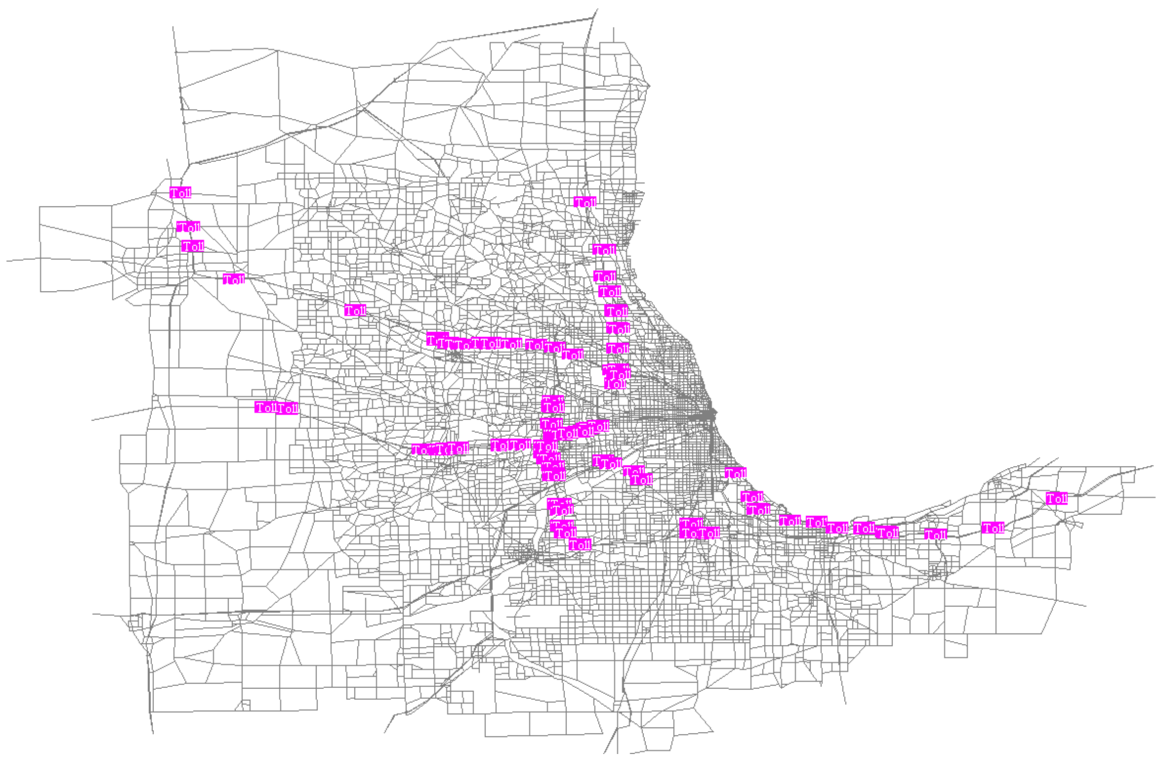
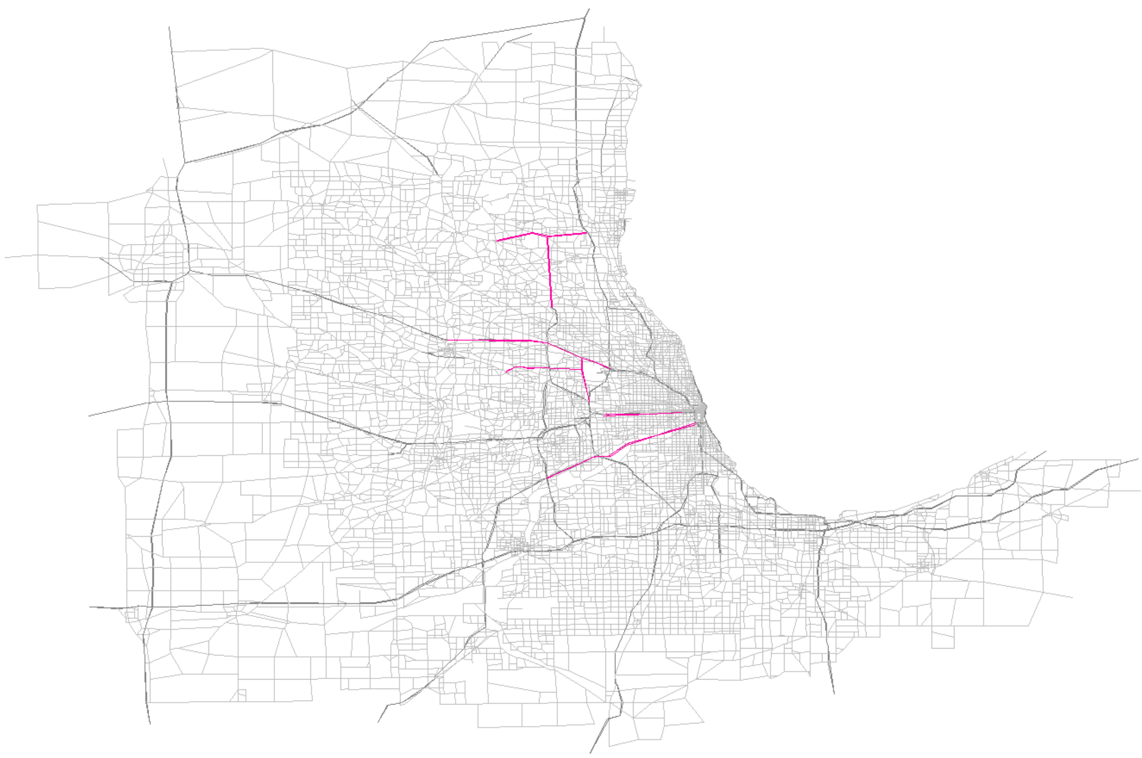


Figure 5: Location of Tolled Links in the Future Network



Two scenarios are selected to illustrate application of DYNASMART-P for the Chicago regional network. The first scenario considers current network and the second one considers future network with the additional tolled facilities. Following simulation and DTA specifications are considered:

- 6:00 AM to 10:00 AM as simulation horizon (240 minutes)
- Forecasted demand for 2016
  - Provided by CMAP
  - Based on the Activity Based Model (ABM)
  - 6,332,185 generated vehicles with different values of time
- 5 iteration of user equilibrium for dynamic traffic assignment

- Three class of vehicles (if a vehicle uses tolled lanes it would be shared between its passengers and driver's value of time would be considered for that vehicle)
    - Single (driver only)
    - Joint2 (two passengers including driver)
    - Joint3 (three or more passengers including driver)

Figure 6 and
Figure 7 present some general output of the two above mentioned scenarios. Figure 6 presents cumulative vehicle generation of the network and also cumulative arrival of the vehicles to their destinations. It can be seen that both scenarios have similar performance and around 2 million vehicles have not reached their destinations at the end of the simulation. Note that many vehicles are generated at the last hour of simulation which need time to reach their destinations. In addition, due to the large estimated demand (6.3 millions trips), large gridlocks have formed in both scenarios which decreased the network output rate significantly.
Figure 7 presents dynamic traffic assignment convergence for both scenarios based on the average gap which is defined as following:

$$AGap(r) = \frac{\sum_{o\in O}\sum_{d\in D}\sum_{\tau=1}^{T}\sum_{m=1}^{2}\sum_{\alpha=\alpha^{\min}}^{\alpha=\alpha^{\max}}\sum_{p\in P^{m}(o,d,\tau)} r_{odp}^{\tau,m}(\alpha)\times\left|GC_{odp}^{\tau,m}(\alpha)-\pi_{od}^{\tau,m}(\alpha)\right|}{\sum_{o\in O}\sum_{d\in D}\sum_{\tau=1}^{T}\sum_{m=1}^{2}\sum_{\alpha=\alpha^{\min}}^{\alpha=\alpha^{\max}}\sum_{p\in P^{m}(o,d,\tau)} r_{odp}^{\tau,m}(\alpha)} \qquad \textbf{Equation 1}$$

where O is the origin sets, D, destination set, T, departure times, m, vehicle classes, α, value of time, P, set of paths, r, path flow, GC, experienced general cost, and π is the minimum calculated general cost. Note that each user equilibrium iteration has one internal iteration. Based on the user equilibrium assignment calculation at each UE iteration, one network simulation would be conducted. After the simulation, a path swapping algorithm is run (as part of the internal iteration). Then, based on the path swapping results, another simulation is run and the results of this simulation are used for the next user equilibrium assignment iteration. For simulating the above mentioned scenarios, including a 4-hour planning horizon with 6.3 million vehicles, about 3 hours and 45 minutes is needed. Each internal teration includes two simulation runs and a path swapping procedure which requires about 9 hours in total. The user equilibrium assignment calculation time depends on the iteration number. For the above mentioned example, it has the following calculation times (in hours) for iteration 1 to 5: 148.3, 57.5, 43.2, 29.7, and 23.1. Overall, the whole DTA simulation run with all the required steps takes about two weeks and the required memory for the calculations is about 10 GB for each scenario.

Figure 6: Cumulative Network Generation and Throughput for Three Pricing Scenarios

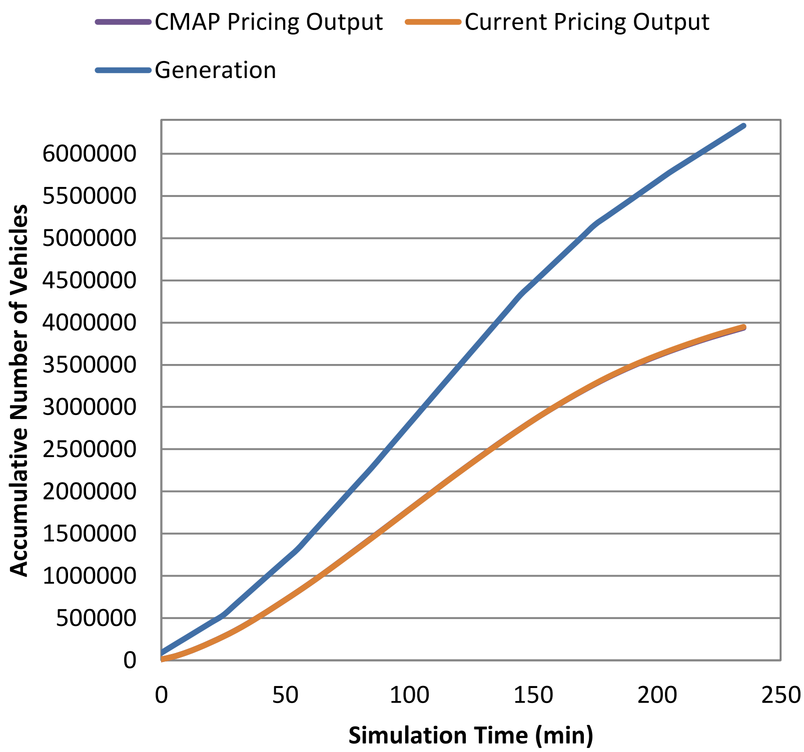
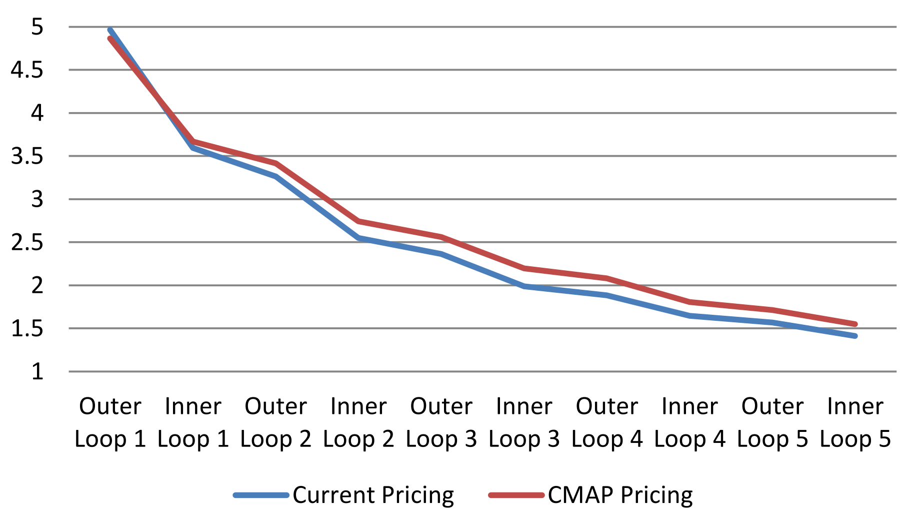


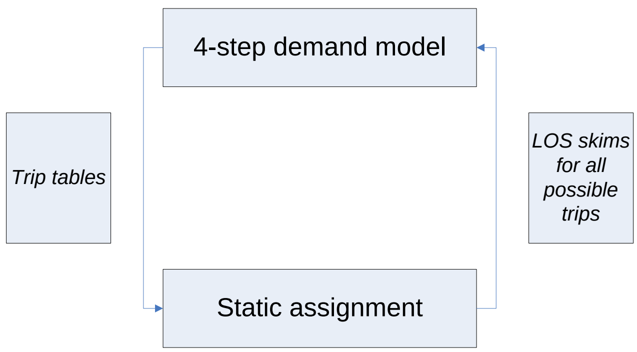
Figure 7: Convergence Patterns in terms of Average Gap



2 ABM-DTA Integration Approaches

This section describes the methodologies for the various levels of ABM-DTA integration. It also outlines the complexities associated with each approach. All ABMs currently in practice rely on conventional origin-destination based Level-of-Service (LOS) matrices (“skims”) to provide the agent-based travel choice utility functions. The techniques of LOS skim generation have been formed as an integral part of the 4-step modeling paradigm and are a result of the limitations of the static assignment framework. This traditional integration is shown in Figure 8.

Figure 8: Integration of Demand Model and Static Assignment



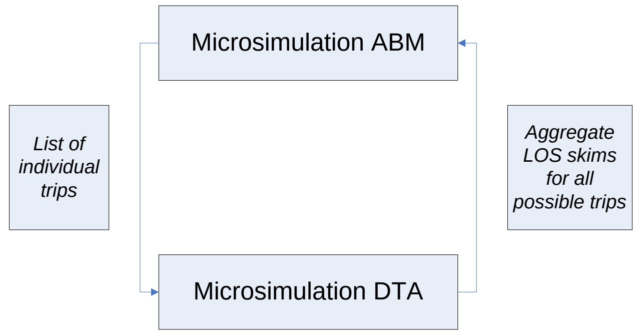
Despite the convenience and manageability of skim matrices, their static nature undercuts the improved capacity of ABMs to represent an agent’s true response to dynamic transportation conditions.

Thus, it is evident that dynamic network simulation represents a better counter-partner for an ABM; especially since both ABM and DTA operate with individual particles as modeled units (individual tours and trips) and have compatible levels of spatial and temporal resolution.

One possible way to integrate ABM and DTA was adopted in the SHRP 2 C10 project. It employed DTA to produce crude LOS matrices (the way they are produced by STA), and use these LOS variables to feed the demand model. This approach, in the aggregation of individual trajectories into crude LOS skims however, would lose most of the details associated with DTA and the advantages of individual microsimulation (for example, individual variation in Values of Time or other person characteristics). Essentially with this approach, the individual schedule consistency concept would be of very limited value because travel times will be very crude for each particular individual. The approach is shown in Figure 11.

This method does not take advantage of the additional beneficial dimension of an ABM—DTA integration -- consistent individual schedules (that can never be incorporated in an aggregate framework). Individual schedule consistency means that for each person, the daily schedule (i.e. a sequence of trips and activities) is formed without gaps or overlaps.

Figure 9: Integration of ABM and DTA (Aggregate Feedback)



The challenge is to develop creative and effective approaches for integrating ABM and DTA such that none of the additional benefits of both these advanced models are sacrificed. Any such approach should follow the following principles:

- *Considering individual agents and not only in a sense of decision-making units to which the choice models are applied (that is a rather trivial microsimulation approach) but also in terms of the realistic choice contexts and available information*. We consider individual decision-making units such as individual households and persons in ABM, individual vehicles and associated travel parties in DTA, and individual transit/non-motorized travelers rather than market segments. An important derived feature of this approach that is specifically requested by the RFP is that that each individual decision maker operates with realistic available (imperfect) information and under individual-level time-space constraints. It is very different from the loose coupling adopted in the SHRP 2 C10 Project where each traveler is assumed to have a simultaneous access to full information about LOS for all potential trips while the LOS used for this purpose is not individual but rather aggregate. In this regard, we want to exploit advanced concepts from agent-based modeling for integrating behavior processes in a network context, with special-purpose data structures geared to the physical and behavioral processes modeled. This allows for better representation of user heterogeneity (individual travel variations) in network-based choice processes, with implications for optimum path computations. In practical terms, it is essential to have different users choosing different paths in the network for the same trip origin, destination, and departure time with subsequently different time and cost parameters that cannot be achieved if aggregate skims are used. Conceivably, as was mentioned in the SHRP 2 C10 Report, network path choice should 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.

- *Maximum possible temporal and spatial resolution*. To the extent possible, we will consider maximum temporal resolution (essentially real-time continuous) through the entire model system and finer-grained spatial units like MAZ. The existing CMAP CT-RAMP structure operates with 30 min intervals at both daily level of planning tours and modeling actual trip departure time choice. This is not enough to seamlessly integrate it with dynamic network simulation. While, transferring the entire ABM to continuous time resolution may not be realistic within the current project time &

budget we have developed an effective hybrid approach (applied in the Phoenix-Tucson CT-RAMP ABM) where each individual plans the daily schedule in term of tours with a 30-min temporal resolution but subsequently details of each trip and activity are refined in continuous time (5 min or less). In terms of spatial resolution, the Transit Modernization CT-RAMP ABM is already being transitioned to the MAZ level for all location choices. We will also explore possibility to implement network simulations (including DTA) with the same level of resolution, i.e. a list of MAZ-to-MAZ individual trips rather than TAZ-to-TAZ trip tables. According to our preliminary analysis of the Chicago regional network, it may influence runtimes significantly, thus, some spatial aggregations might be inevitable to make dynamic path building and network loading realistic on the regional scale.

- *Individual daily pattern and schedule consistency*. This is an important unique measure of equilibrium between microsimulation demand model and network model that was largely overlooked in the SHRP 2 C10 Project, however, played a prominent role in the SHRP 2 C04 and L04 Projects. One of the essential outcomes of the entire process is an individual daily pattern and schedule formed for each person that contains all activities and trips. In reality, the observed patterns and schedules are always consistent in time and space since every person can be only in one particular place at a time. This consistency is essentially individual, i.e. activity schedules and durations are individual and travel times are specific to each individual and trip. Using aggregate skims in this context ruins this principle and can be classified as yet another aggregation bias that we would like to avoid. In this regard, as explained in the next section, our method is specifically designed to take advantage of simulated individual trajectories (as the only consistent representation of LOS) instead of synthetic aggregate skims. This concept is also beneficial for innovative, and more complete, formulations of demand-supply network equilibrium that are appropriate to the expanded set of choice dimensions included in an ABM.

In practical terms, we consider three possible ways of integration between the demand ABM and dynamic network equilibrium models:

- *Daily level*. This means that an entire ABM is run to generate a daily activity pattern for each individual and then an entire-day network simulation is implemented at each global iteration of the process. This approach does not automatically mean a loose coupling that was applied in the SHRP 2 C10 Project since the equilibration feedback can provide specific details for each component of the daily schedule including dynamic characteristics of individual trajectories rather than aggregate LOS skims. This approach can be preferred for long-term planning when overall regional equilibrium is essential while details of individual responses to stress conditions in the network become of secondary importance. This process can be viewed as achieving consistency between the behavioral/cognitive level of ABM decisions, and the physical reality captured by the DTA model relations. Because of the focus on medium to longer-term consistency, it is important to devise a process that generates solutions that satisfy well-defined and reproducible notions of consistency (equilibrium) to enable comparison of different measures and policies. This approach has a practical advantage since it does not require a substantial change in the existing ABM or DTA software. Most of the integration aspects are handled through an interface that connects the existing pieces of software. It is also portable since it allows for a replacement or upgrade of either ABM or DTA (or transit simulation tool) in the future while the other two approaches are strongly wired to the ABM and DTA used in the initial development.

- *Trip/activity level*. This approach is more appealing from the behavioral standpoint than the first one although the difference is substantially mitigated when the overall equilibrium framework is considered rather than a single demand-network global iteration. With this approach, neither ABM nor DTA is programmed to work for an entire day with a fixed input but the multiple interactions between them occur during the simulation process somewhat mimicking the real time implementation of activities and trips during the day. However, these interactions are bound to entire activities and trips as the minimal units. In particular, an individual trip travel time is fed back to the activity adjustment module after completion of each particular trip that may result in rescheduling of the subsequent trips and activities of the same individual. This activity adjustment module can be defined inside the either of ABM or DTA environment. A complex activity adjustment module requires much more behavioral information and should be done inside the ABM environment which calls for more frequent data (travel times and list of activities) exchange between ABM and DTA. A Simpler and rule-based activity adjustment module can be performed inside the DTA environment, which would save time and memory usage as it does not requires data exchange between ABM and DTA. At the moment, it is recognized that this approach has strong advantages for analysis of short-term shocks, accidents, special events, holidays, and other situations where the system is apparently not in an equilibrium state. It is also called for to study day to day variability, under different realizations or instances from the "usual" pattern. In the context of regional equilibrium, the (more complex) trip/activity-level integration may (not necessarily) result in the same solution as the day-level approach since eventually a consistent individual daily pattern and schedule is built for each individual. Comparative testing will provide better insight in the dynamic behavior of alternative approaches.

- *Real-time level*. This approach in many regards is similar to trip/activity-level approach (especially in the activity rescheduling mechanisms of ABM). The main difference is that the feedback from the network simulation model to the activity adjustment module is implemented even earlier than the end of the trip, i.e. in the *en-route* status of the traveler. Incorporation of the real-time travel information in flexible rerouting is a routine feature of DYNASMART that we plan to use in the current project. We plan to take this feature to the next level that incorporates not only the driver's ability to re-plan the given route according to experienced conditions but to re-plan (or re-schedule) the rest of the trips. An initial capability was conceptually demonstrated by Abdelghany and Mahmassani (2003) more than 10 years ago. Compared to the trip/activity-level approach this additional feature is beneficial for modeling evacuation during a disaster with the ability for people to change their typical pattern that the non-disaster model determined. In the course of the current project, we plan to explore advantages of this (new) approach in detail. It also, should be noted that a hybrid construct is possible where en-route information would affect route choice but still would be fed back to the activity adjustment module after completion of the entire trip.

The described approaches are progressively more complicated from the first being the simplest and the third being the most complex in terms of integration between the ABM and DTA.

2.1 Day-Level Integration

2.1.1 Day-Level Integration Schema

This method of equilibration for ABM and DTA is presented in Figure 10 below, where two innovative technical solutions are applied in parallel. The first solution is based on the fact that a direct integration at the disaggregate level is possible along the temporal dimension if the other dimensions (number of trips, order of trips, and trip destinations) are fixed for each individual. Then, full advantage can be taken of the individual schedule constraints and corresponding effects. The inner loop of temporal equilibrium includes schedule adjustments in individual daily activity patterns as a result of congested travel times being different from the planned travel times. It might help the DTA to reach convergence (internal loop), and is nested within the global system loop (when the entire ABM is rerun and demand is regenerated). The convergence of the global system loop should be checked for both cases of including and not including the internal loop. All in all, either of these cases does not certify convergence. It is noted here, that the DTA should always report back dynamic travel times which are consistent with the activity schedule. This means, that for the full run of the ABM only LOS measures from the same activity plan should be used for utility comparisons.

The second solution is based on the fact that trip origins, destinations, and departure times can be pre-sampled and the DTA process would only be required to produce trajectories for a subset of origins, destinations, and departure times. In this case, the schedule consolidation is implemented through corrections of the departure and arrival times (based on the individually simulated travel times) and is employed as an inner loop. The outer loop includes a full regeneration of daily activity patterns and schedules but with a sub-sample of locations for which trajectories are available (it also can be interpreted as a learning and adaptation process with limited information).

2.1.2 Consistency of Individual Daily Schedule

The concept of a fully consistent individual daily schedule is illustrated in Table 1 below. The daily schedule of a person is modeled for 24 hours starting at 3:00 AM on the simulation day and ending at 3:00 AM next day (formally represented as 27:00). The integrated model operates with four schedule related types of events: 1) in-home activities, 2) out-of-home activities, 3) trips, and 4) tours. Start and end times of activities logically relate to the corresponding departure and arrival times of trips connecting these activities. Each tour spans several trips and related out-of-home activities and essentially represents a fragment of the individual daily schedule.

Figure 10: Integration of ABM and DTA (Split Feedback)

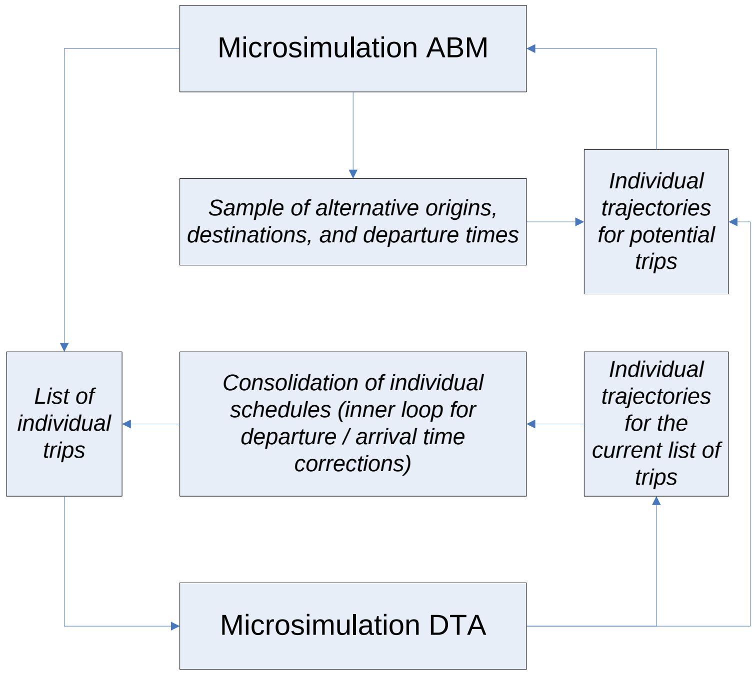


Table 1: Fully Consistent Individual Daily Schedule

In-home			Trips			Out-of-home			Tours		
Activity	**Start**	**End**	**Purpose**	**Depart**	**Arrive**	**Activity**	**Start**	**End**	**Purpose**	**Depart**	**Arrive**
Sleeping, eating at home, errands	3:00										
		7:30	Escort	7:30					Work	7:30	
					7:45	Drop-off child at school	7:45				
			Work	7:50				7:50			
					8:30	Work	8:30				
			Shop	16:30				16:30			
					17:00	Shop	17:00				
			Return home	17:30				17:30			
Child care, errands	18:00				18:00						18:00
		19:00	Disc	19:00					Disc	19:00	
					19:30	Theater	19:30				
			Return home	21:30				21:30			
Resting, errands, sleeping	22:00				22:00						22:00
		27:00									

In reality, the observed individual schedules are always consistent in the sense that they obey time-space constraints and have a logical continuous timeline, where all activities and trips are sequenced with no gaps and no overlaps. However, achieving full consistency has not been yet resolved in operational models. The crux of the problem is that all trips and associated activities have to obey a set of "hard" (physical) and "soft" (consideration of probabilistic choices) constraints that can only partially be taken into account without a full integration between the demand and network simulation models. Also, both models should be brought to a level of temporal resolution that is sufficient for controlling the constraints (e.g. 5 min or less).

The following constraints should be taken into account:

- *Individual schedule consistency*: Activity start time should correspond to the preceding trip arrival time and activity end time should correspond to the following trip departure time. This "hard" constraint is not controlled in either the 4-step demand models or the static trip-based network simulation models since they operate with unconnected trips and do not control for activity durations at all. Also, in 4-step models, the inherently crude level of temporal resolution does not allow for incorporating this constraint. In ABMs of the CT-RAMP family, certain steps have been made to ensure a partial consistency between departure and arrival times, as well as duration at the entire-tour level. This, however, did not include trip details and does not control for feasibility of travel times within the tour framework (though travel time is used as one of the explanatory variables). Certain attempts to incorporate trip departure time choice in a framework of trip chains have been made within DTA models, DYNASMART, in particular. However, these attempts were limited to a tour level only, and also required a simplified representation of activity duration profiles. This constraint expresses consistency (i.e. the same number) in each row of Table 1.

- *Physical flow process* properties: These "hard" constraints apply to network loading and flow propagation aspects in DTA procedures. Physical principles such as conservation of vehicles at nodes must be adhered to strictly (e.g. no vehicles should simply be lost or otherwise disappear from the system). This constraint accounts for feasibility of travel times obtained in the network simulation that are further used to determine trip departure and arrival times in the corresponding columns of Table 1.

- *Equilibrium travel times*: Travel times between activities in the schedule generated by the demand model should correspond to realistic network travel times for the corresponding origin, destination, departure time, and route generated by the traffic simulation model with the given demand. While most of the 4-step models and ABMs include a certain level of demand-supply equilibration, they are limited to achieving stability in terms of average travel times. There is no control for consistency within the individual daily schedule. The challenge is to couple this constraint with the previous one, i.e. ensure individual schedule continuity with equilibrium travel times. This "hard" constraint expresses consistency between trip departure and arrival times in the corresponding columns of Table 1 with the travel times obtained in the network simulation. Practically, it is achieved within a certain tolerance level.

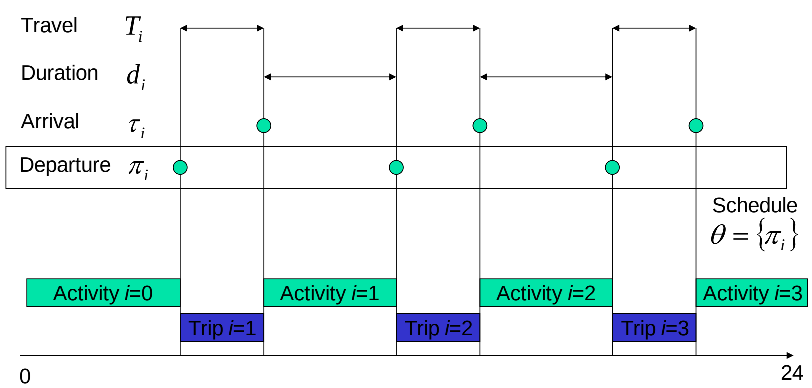
- *Realistic activity timing and duration*: Activities in the daily schedule have to be placed according to behaviorally realistic temporal profiles. Each activity has a preferred start time, end time, and duration formalized as utility function with multiple components. In the presence of congestion and pricing, travelers may deviate from the preferred temporal profiles (as well as even cancel or change order of activity episodes). However, this rescheduling process should obey utility-maximization rules over the entire schedule and cannot be effectively modeled by simplified procedures that adjust departure time for each trip separately. None of the existing operational ABMs explicitly control for activity durations, although some of them control for entire-tour durations as does the CMAP CT-RAMP ABM; or the duration of the activity at the primary destination, as implemented in the SACOG ABM. DTA models that incorporate departure time choice have been bound to a simplified representation of temporal utilities and limited to trip chains in order to operate within a feasible dimensionality of the associated choices when combined with the dynamic route choice. This "soft" constraint expresses consistency between activity start and end times in the corresponding columns of Table 1, with the schedule utility maximization principle (or in a more general sense with the observed timing and duration pattern for activity participation). In operational models, the focus has been primarily on out-of-home activities. It should be noted, however, that it is also important to preserve a consistent and realistic pattern of in-home activities (for example, reasonable time constraints for sleeping and household errands), as well as take into account possible substitution between in-home and out-of-home durations for work, shopping, and discretionary activities.

Schedule consistency with respect to all four constraints is absolutely essential for time-sensitive policies like congestion pricing. In reality, any change in timing spurred by the policy would trigger a chain of subsequent adjustments through the whole individual schedule. It can be shown, that under certain circumstances, an attempt to alleviate congestion in the AM period by pricing may result in worsening congestion in the PM period because of the compression of individual daily schedules that are forced to start later. In the next sub-section, we suggest a method to achieve a consistent individual schedule with respect to all requirements listed above. In this process, it is important to keep in mind that short-term adjustments generally follow different processes than long-term changes to one's "usual" activity patterns. Any given day will experience some variation from the usual pattern, due to factors that are both internal as well as external to the traveler (e.g. weather, accidents, etc.). The purpose of the short-term adjustments is to account for such variation while providing feasible schedules that are consistent with the actual travel times. On the other hand, the day-level integration presented here is intended to solve for the "usual" patterns for all travelers so as to achieve mutually consistent choices and *experienced* trip times, in other words a solution that is appropriately equilibrated over the long run. .

2.1.3 Individual Schedule Adjustments (Temporal Equilibrium in Day-Level Equilibration)

An individual's schedule is adjusted based on anticipated travel times. The scheduling component plays a role of interface that transforms the DTA output (individual vehicle or person trajectories) with departure and arrival times for each trip simulated with a high level of temporal resolution into schedule adjustments to the individual schedules generated by the ABM. The purpose of this feedback is to achieve consistency between generated activity schedules (activity start times and durations) and trip trajectories (trip departure time, duration, and arrival time). This feedback is implemented as part of temporal equilibrium between ABM and DTA when all trip destinations and modes are fixed but departure times are adjusted until a consistent schedule is built for each individual. Individual schedule consistency means that for each person, the daily schedule (i.e. a sequence of trips and activities) is formed without gaps or overlaps as shown in Figure 11 below. In this way, any change in travel time would affect activity durations and vice versa.

Figure 11: Individual Schedule Consistency



New methods of equilibration for ABM and DTA are presented in **Equation 2** below, where two innovative technical solutions are applied in parallel. The first solution is based on the fact that a direct integration at the disaggregate level is possible along the temporal dimension if the other dimensions (number of trips, order of trips, and trip destinations) are fixed for each individual.

The schedule consolidation is implemented through corrections of the departure and arrival times (based on the individually simulated travel times).

Adjustment of individual daily schedule can be formulated as an entropy-maximizing problem of the following form (Vovsha et al, 2012):

$$\min_{\{x_i\}}\left\{\left[\sum_{i=0}^{I} w_i \times x_i \times ln\left(\frac{x_i}{d_i}\right)\right] + \left[\sum_{i=1}^{I+1} u_i \times y_i \times ln\left(\frac{y_i}{\pi_i}\right)\right] + \left[\sum_{i=0}^{I} v_i \times z_i \times ln\left(\frac{z_i}{\tau_i}\right)\right]\right\} \quad \textbf{Equation 2}$$

subject to:

$$y_i = \tau_0 + \left(\sum_{j=0}^{i-1} x_j\right) + \left(\sum_{j=0}^{i-1} t_j\right), \quad i = 1,2,\dots,I+1 \quad \textbf{Equation 3}$$

$$z_i = \tau_0 + \left(\sum_{j=0}^{i-1} x_j\right) + \left(\sum_{j=0}^{i} t_j\right), \quad i = 1,2,\dots,I$$ **Equation 4**

$$x_i > 0, \quad i = 0,1,2,\dots,I$$ **Equation 5**

where:

$i = 1,2,\dots,I$	=	trips and associated activities at the trip destination,
$i = 0$	=	activity at home before the first trip,
$i = I + 1$	=	(symbolic) departure from home at the end of the simulation period,
x_i	=	adjusted activity duration,
y_i	=	adjusted departure time for trip to the activity,
z_i	=	adjusted arrival time for trip to the activity,
d_i	=	planned activity duration,
π_i	=	planned departure time for trip to the activity,
τ_i	=	planned arrival time for trip to the activity,
t_i	=	actual time for trip to the activity that is different from expected,
w_i	=	schedule weight (priority) for activity duration,
u_i	=	schedule weights (priority) for trip departure time,
v_i	=	schedule weight (priority) for trip arrival time,

The essence of this formulation is that in the presence of travel times that are different from the expected travel times that the user used to build the schedule, he/she will try to accommodate new travel times in such a way that the schedule is preserved to the extent possible. The preservation relates to activity start times (trip arrival times), activity end times (trip departure times), and activity durations (**Equation 2**). The relative weights relate to the priorities of different activities in terms of start time, end time, and duration. The greater is the weight, the more important for the user to keep the corresponding component close to the original schedule. Very large weights correspond to inflexible, fixed-time activities. The weights directly relate to the schedule delay penalties as described below in the section on travel time reliability measures. However, the concept of schedule delay penalties relates to a deviation from the (preferred or planned) activity start time (trip arrival time) only, while the schedule adjustment formulation allows for a joint treatment of deviations from the planned start times, end times, and durations.

The constraints express the schedule consistency rule as shown in **Figure 11** above. **Equation 3** expresses departure time for each trip as a sum of the previous activity durations and travel times. **Equation 4** expresses arrival time of each trip as a sum of the previous activity durations and travel times plus travel time for the given trip. (Symbolic) arrival time for the home activity prior to the first trip is used to set the scale of all departure and arrival times. This way, the problem is formulated in the space of activity durations, while the trip departure and arrival times are derived from the activity durations and given travel times.

The solution of the convex problem can be found by writing the Lagrangian function and equating its partial derivatives (with respect to activity durations) to zero. It has the following form:

$$x_i = d_i \times \left\{ \prod_{j>i} \left[\left(\frac{\pi_j}{y_j} \right)^{u_j} \times \left(\frac{\tau_j}{z_j} \right)^{v_j} \right] \right\}^{\frac{1}{w_i}} \qquad \textbf{Equation 6}$$

This solution is easy to find by using either an iterative balancing method or Newton-Raphson method. The essence of this formula is that updated activity durations are proportional to the planned durations and adjustment factors. The adjustment factors are applied considering the duration priority. If the duration weight is very large, then the adjustments will be minimal. The duration adjustment is calculated as a product of trip departure and arrival adjustments for all subsequent trips. The trip departure adjustment $\left\{\frac{\pi_j}{y_j}\right\}$ and trip arrival adjustment $\left\{\frac{\tau_j}{z_j}\right\}$ can be interpreted as lateness versus the planned schedule if it is less than 1 and earliness if it is greater than 1. Each trip departure or arrival adjustment factor is powered by the corresponding priority weight. As the result, activity duration will be shrunk if there are many subsequent trip departures and/or arrivals that are later than planned. Conversely, activity duration will be stretched if there are many subsequent trip departures and/or arrivals that are earlier than planned. Overall, the model seeks the equilibrium (compromise) state where all activity durations, trip departures, and trip arrivals will be adjusted to accommodate the changed travel times while preserving the planned schedule components by priority.

SHRP 2 C04 and L04 Projects provided demonstration software with which we have implemented many numerical tests with this model. In particular, the iterative balancing procedure goes through the following steps:

1. Set initial activity durations equal to the planned durations $\{x_i = d_i\}$.
2. Update trip departure times with new travel times and updated activity durations using **Equation 3**.
3. Update trip arrival times with new travel times and updated activity durations using **Equation 4**.
4. Calculate balancing factors $\left\{\frac{\pi_j}{y_j}\right\}$ for trip departure times (lateness if less than 1, earliness if greater than 1).

5. Calculate balancing factors $\left\{\frac{\tau_j}{z_j}\right\}$ for trip arrival times (lateness if less than 1, earliness if greater than 1).
6. Update activity durations using **Equation 6**.
7. Check for convergence with respect to activity durations; if not go to step 2.

Applying this model in practice requires default importance weights for activity durations, trip departure times, and trip arrival times. This is an area where more specific data are welcome on schedule priorities and constraints of different person types. This type of data is already included in some household travel surveys with respect to work schedules. It should be extended to include non-work activities many of which can also have schedule constraints. At this stage, we suggest the following default values in **Table 2**.

Table 2: Recommended Weights for Schedule Adjustment

Activity type	Duration	Trip departure (to activity)	Trip arrival (at activity location)
Work (low income)	5	1	20
Work (high income)	5	1	5
School	20	1	20
Last trip to activity at home	1	1	3
Trip before work to NHB activity	1	5	1
Trip after work to NHB activity	1	10	1
NHB activity on at-work sub-tour	1	5	5
Medical	5	1	20
Escorting	1	1	20
Joint discretionary, visiting, eating out	5	5	10
Joint shopping	3	3	5
Any first activity of the day	1	5	1
Other activities	1	1	1

If some activity in the schedule falls into more than one category (for example, work and first activity of the day), the maximum weight is applied from each column.

It is possible to extend this approach in order to incorporate learning and adaptation. In the described procedure, the conditions anticipated when planning the tour/trip are compared with the conditions actually experienced as they occur *en route*; and then, trip departure time are adjusted to accommodate new travel times. In addition to that, the difference between expected and experienced conditions could be subsequently applied to the traveler's learning and adaptation profile. For example, we envision the following method. If the difference is not significant according to a pre-specified metric, the traveler is assumed to adjust the temporal equilibrium (schedule) only. If the difference is significant, the traveler is supposed to be seeking a different daily pattern in terms of tours and destinations that means going to the outer loop of equilibration where more travel dimensions could be changed.

This method is also one of the possible analytical ways to examine the distinction between "reaction" and "choice" and whether there is a continuous temporal or situational dimension along which learning variables can be mapped as was stated in the CMAP model vision document. In particular, schedule adjustments (especially minor ones) represent "reactions" with a minimal learning horizon while changing activities and/or trip destinations is an example of "choices" that are based on a longer-term information basis.

This flexibility in the manner feedback implemented from individual to individual is a completely new modeling paradigm that does not appear to have been explored yet. As mentioned in the CMAP vision documents, because conventional static traffic assignment is time-invariant 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 legitimize 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.

We believe that our suggested methods represent a breakthrough in this very direction. As further suggested in the same document, 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 (in our case, the entire sequence of choice of each individual is defined by the level of adaption) might provide a richer means by which to control equilibration of the ABM over successive global iterations.

2.1.4 Individual Schedule Adjustments and Relation to Schedule Delay Concept

We plan to explore addition version of individual schedule adjustments that are even more behaviorally appealing and consistent with the other theories and existing ABM structure. It should be noted that at this point of time there is no consensus on theory or prevailing practice in our profession regarding the individual scheduling process and associated responses to congestion, pricing, or other policy. In particular, there is no consensus regarding the relationship between two different time scales where individual schedule adjustment can take a place: day-level equilibration implemented for long-term planning (where multiple global iterations can be associated with individual learning and adaptation), and real-time non-equilibrium responses from certain time point on (end of particular trip). In reality, both processes can be intertwined, thus the schedule adjustment algorithm should be generic and should be based on the same behavioral principles. This is the main intention of the current project. On the other hand, modeling specifics become substantial from the practical perspective, for example, due to the equilibration process involved in the day-level schema only.

For the individual schedule adjustment procedure, we can outline two (seemingly inconsistent) behavioral foundations:

- Time-of-Day (TOD) choice model embedded in the CT-RAMP ABM that can be re-run with any constrained set of alternatives. This model is based on the estimated cross-sectional preference of travelers with respect to tour combination of departure-from-home and arrival-back-home times and trip departure time. This model provides utility functions for each individual and trip departure time alternative (as well as for other tour dimension including tour departure time)
- Schedule delay approach for each trip that provides estimates of perceived penalties associated with being early or late vs. the Preferred Arrival Time (PAT).

TOD choice and schedule delay concept are seemingly unrelated approaches that cannot be applied in one model system framework but they can be brought to a common denominator to ensure consistency between modeling “stressed” and “unstressed” households as discussed below.

The schedule delay approach has been widely accepted by the research community since its inception. According to this approach, the impact of travel time (un)reliability is measured by explicit cost associated with the delayed or early arrival at the activity location. This approach considers a single trip at a time and assumes that the preferred arrival time that corresponds to zero schedule cost is known. The essence of the approach is that the trip cost (i.e. disutility) can be calculated as a combination of the following three components:

α = value of travel time and cost,

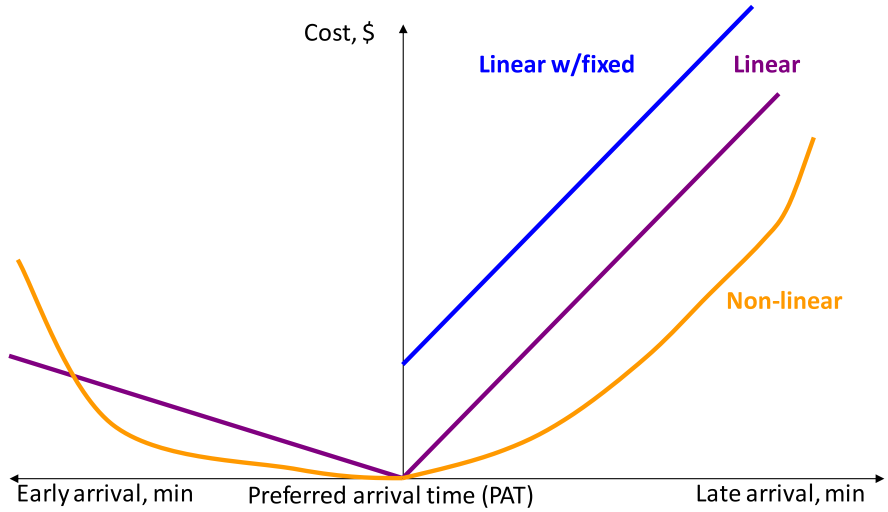
β = cost of arriving earlier than the preferred schedule,

γ = cost of arriving later than the preferred schedule.

By definition, only one of the schedule costs can have a non-zero value in each particular case depending on the actual arrival time versus the preferred one. There can be many analytical forms for the schedule cost as a function of the actual time difference (delay or early arrival). It is logical to assume that both functions should be monotonically increasing with respect to the time difference. It is also expected, in most cases, that the schedule delay function should be steeper than the early arrival function for most activities (being late is more onerous than being earlier). The details, however, depend on the activity type, person characteristics, and situational context.

The most frequently used forms include simple linear function (i.e. constant schedule delay cost per minute), non-linear convex function (assuming that large delays are associated with growing cost per minute), and various piece-wise functions accounting for fixed cost associated with any delay along with a variable cost per minute – see **Figure 12**.

Figure 12: Schedule Delay Cost Functions



Using the schedule delay approach the proposed individual schedule adjustment approach modified by replacing the entropy-maximizing objective function (**Equation 2**) with a linear combination of functions of following type (note that we also extend the original concept that applied to trip arrival time only to incorporate also trip departure time and activity durations):

$\sum_{i=0}^{I}[\beta_i \times max(\tau_i - z_i, 0)]$, for trip arrival earlier than planned,

$\sum_{i=0}^{I}[\gamma_i \times max(z_i - \tau_i, 0)]$, for trip arrival later than planned,

$\sum_{i=1}^{I+1}[\sigma_i \times max(\pi_i - y_i, 0)]$, for trip departure earlier than planned,

$\sum_{i=1}^{I+1}[\delta_i \times max(y_i - \pi_i, 0)]$, for trip departure later than planned, **Equation 7**

$\sum_{i=0}^{I}[\mu_i \times max(d_i - x_i, 0)]$, for activity duration shorter than planned,

$\sum_{i=0}^{I}[\nu_i \times max(x_i - d_i, 0)]$, for activity duration longer than planned.

In this formulation, contrary to the entropy-maximizing approach, It is possible to differentiate between disutilities associated with earliness and lateness as well as disutilities associated with shorter and longer durations. This formulation of the objective function results in a simple Linear Programming (LP) problem with the same entire-day schedule consistency constraints (**Equation 3**-**Equation 5**). It is as efficient as the previously suggested entropy-maximizing approach and can be applied for millions of individual records with a very minor computational overhead. The utility components in **Equation 7** can be easily linearized by introducing intermediate variables in the LP framework in the following way (for trip departure time as an example):

$$min\left[\sum_{i=0}^{I}(\beta_i \times z_i^- + \gamma_i \times z_i^+)\right]$$

Subject to (additional) constraints: **Equation 8**

$$z_i^- \geq \tau_i - z_i;\ z_i^- \geq 0;\ z_i^+ \geq z_i - \tau_i;\ z_i^+ \geq 0.$$

This way the original schedule delay concept for a single trip can be extended to consider the entire daily schedule in computationally very efficient way. However, the reconciliation of the schedule adjustment algorithm and schedule delay theory does not solve the problem completely although it opens a way to apply this model in practice since there have been multiple publications on the ranges of values for the coefficients that could be borrowed for the current study. There is also a need for reconciliation of the coefficients applied in the schedule delay model with the TOD choice utility functions applied in the core CT-RAMP ABM. This step is outlined in the next section.

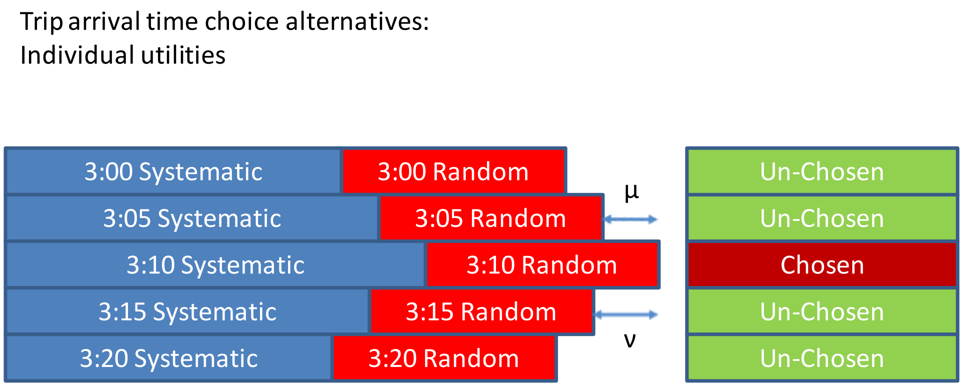
2.1.5 Individual Schedule Adjustments and Relation to Time-of-Day Choice

The TOD choice model is integrated in the CT-RAMP ABM with many other day-level, tour-level, and trip-level choices. In general it is very difficult to single out the TOD choice component without violating the logic of other choices and consistency across the entire model system.

However, the research team at the moment is exploring a new approach that resolves most of the issues and brings the core TOD choice component and schedule adjustments methodologically closer. In this approach, each person and household after completion of each global iteration is evaluated w.r.t to time pressure that is based on a proportion between travel time, out-of-home activity time, and in-home activity time (the corresponding analysis of the observed cases of travel budgets based on the available Chicago Household Travel Survey is currently underway). As the results, all persons and households are classified as “stressed” and “non-stressed”. The stressed households (in which at least one person is stressed) are re-simulated completely by the CT-RAMP ABM at the next iterations. Non-stressed households and persons are subject to individual schedule adjustments only.

The relationship between the coefficients used in the schedule adjustment model and full TOD choice model is shown in **Figure 13**. For each person and time choice dimensions (for example, trip arrival time) there is a set of random utilities associated with different timing choices where the highest utility alternative (including the random term) is chosen. In a normal ABM run setting this is the only information that is retained. However, for the schedule adjustment model, more useful information can be extracted from the choice utilities. In particular, the loss of utility associated with choosing the adjacent alternative can be easily calculated. This marginal disutility exactly corresponds to the schedule delay cost.

Figure 13: Time-of-Day Choice and Schedule Delay



2.1.6 Pre-Sampling of Trip Destinations

This method is intended to resolve one of the fundamental problems associated with integration of microsimulation ABM and DTA – the calculation of individual LOS variables for non-observed destinations and times of day (i.e. for characteristics of trips that were not simulated at the previous global iterations). The traffic microsimulation procedure embedded in the DTA produces robust estimates of average link travel times by time-of-day periods that can be used to construct average (shortest path) LOS skims similar to the conventional modeling procedures.

However, a more advanced approach is welcome that would take advantage of the simulated individual trajectories that might be quite different from the average LOS skims that are aggregated across individuals and within certain departure time bins (30-60 min). Individual driving style and route choice are among the factors that can contribute to a significant individual variation of travel times for the same departure time bin and travel segment. Application of individual randomized Value of Time (VOT) and/or Value of Reliability (VOR) is another important consideration in favor of individual LOS (in presence of tolls).

Yet another important consideration is the level of spatial resolution. LOS skims can be pre-calculated in matrix format only for several thousands of TAZs that result in millions of OD pairs. If smaller spatial units are applied, LOS skims cannot be pre-calculated and stored in a full-matrix format. It is also behaviorally more appealing to assume that an individual does not always scan all possible location in the region for each activity but rather operates within a certain spatial domain where he explores options over time and makes choices based on the past experience.

These considerations give rise to a concept of pre-sampling of destinations, where the same subset of destinations is reused for each individual at each global iteration of ABM-DTA equilibration. The modeled Chicago region has about 20,000 Micro Analysis Zones (MAZs). The following samples can be created in advance:

- Primary tour destinations:
    - 400 out of 20,000 for each (home or work) origin and travel segment,
    - 40 out of 400 for each individual and travel segment,
- Secondary stop locations:
    - 400 out of 20,000 for each OD pair and travel segment,
    - 40 out of 400 for each individual, primary destination, and travel segment.

We suggest a sampling without replacement from the expanded set of destinations, where each destination is attached a weight based on the attraction size variable and distance from the origin (for primary destinations) or route deviation (for secondary stops). The weights are normalized to ensure the total of 400×20,000 for first (segment) samples and 40×400 for the second (individual) samples. This is to ensure uniform unbiased samples. It should be noted that a similar sampling procedure is always applied for modeling individual location choices in ABMs. However, in a conventional setting, the sampling is applied independently for each individual record and the samples are normally regenerated at each global iteration of demand-supply equilibration. Thus, there is a very low probability of finding a trip from the same origin MAZ to the same destination MAZ, departing in the same time bin which individual trajectory could be used for the next iteration.

Pre-sampling of destination constrains the variation of destinations for each individual and allows for an efficient accumulation of individual trajectories in the microsimulation process. With this technique, LOS variables for the ABM applied at each subsequent iteration will be defined in the following way:

- First, individual trajectories to the same destination by departure time period for the same driver (or some other driver from the same household) are used if present in the previous simulation; behaviorally, this corresponds to personal learning experience; having only 30 possible destinations enhances this probability for each individual; if not:

    - Individual trajectories to the same destination by departure time period across all individuals are used if present in the previous simulation (if several of them are available, the average can be used); behaviorally this corresponds to social networking when the driver can hear from other people about their experience; having only 300 possible destinations for each origin MAZ enhances this probability, if not:

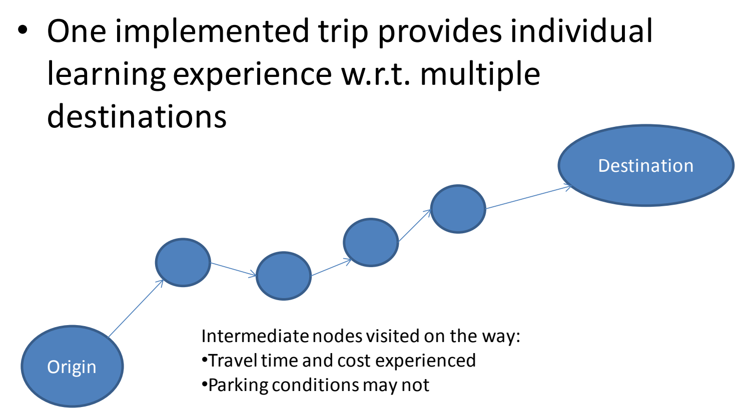
        - Aggregate LOS skims by departure time period will be used as the last remaining option; behaviorally it can be thought of as using an Advice from an advanced navigation device.

Updating individual travel times, cost, and reliability for accumulated observed choices means taking a full advantage of individual microsimulation. This is a new approach that has behavioral appeal (mimicking a learning and adaption process) and also avoiding aggregation of LOS variables. We plan to explore it in the course of the current project.

2.1.7 Pre-Sampling of Trip Destinations as Representation of Learning and Adaption

It is behaviorally appealing to further enrich the destination sampling component and associate it with individual learning and adaptation rather than a mechanical fixing of a certain number of sample destinations. In this regard, each implemented individual trajectory would provide valuable information about multiple destinations (nodes) visited on the way as shown in **Figure 14**. Essentially, if the trajectory included N nodes, it contains information on N×(N-1)/2 node-to-node travel times and cost that can be converted into zone-to-zone travel time and cost. It should be noted that parking cost is not directly experienced at each visiting node but this cost component can be specified separately at the node (zone) level since it is independent of the trip itinerary.

Figure 14: Learning about Space from Individual Trajectories



In the course of the project, we plan to explore a gradual choice set extension mechanism that would correspond to the behavioral notion of learning and adaptation. In parallel, we will investigate efficient ways to generate, store, and handle associated LOS attributes in a “tree” format rather than “matrix” format pertinent to conventional (all)zone-to-(all)zone skims. The CT-RAMP ABM model (as practically any other ABM in practice) utilizes zone (MAZ) sampling procedures for all destination choices, but they are currently implemented independently for each tour and trip. In this regard, the standard sampling practice (whatever sampling strategy is applied – random or by importance) assumes that an individual does not have any memory and cannot use the accumulated experience from the previous global iterations).

The following conceptual outline is currently being considered in parallel with the previously described fixed-sample approach:

- Every individual starts the simulation with a very limited sample (10 or so) of available destinations for each travel purpose chosen randomly. Crude skims are used to estimate LOS variables for each destination.

- For each individual, individual trajectories for the visited destination are stored and intermediate destinations are added to the choice sets if the corresponding purpose-specific size variable is positive.

- For each individual and travel purpose, a subset of non-chosen (never-visited) destinations is updated by randomly choosing a limited number (5 or so) of available destinations for each travel purpose randomly. Crude skims are used to estimate LOS variables for each never-visited destination.

- For each individual and travel purpose, a subset of never-visited destinations is evaluated and if it exceeds a set limit (say, 300) they are randomly dropped. This appears to be the case only if a large number of global iterations are implemented.

- Destination choice operates with the adjusted sample of MAZs. MAZs that correspond to actually experienced trajectories (visited as the actually chosen destination or on the way) are never dropped and the correspondent alternatives are evaluated based on the most recent travel time and cost from the previous global iterations experienced by the same individual for the same departure time bin. MAZ that corresponds to never-yet-visited destinations are updated at each global iteration randomly. They are evaluated based on the crude skims. In the process, after several global iterations, majority of the destination in the choice set would be based on actual experience and individual time and cost at least for some departure time bins.

2.2 Trip-Level Integration

2.2.1 Trip-Level Integration Schema w/Periodic Updates of Anticipated Times

This represents a more advanced ABM-DTA integration schema of the type that was proposed in research literature. The main focus of this project will be the implementation of this integrated ABM—DTA framework. The day-level interaction between the ABM and DTA where ABM would generate trips for the whole day to feed to the assignment model and at the end of each global iteration, updated LOS variables would be fed to the ABM can be criticized as not appealing behaviorally. In the real world, people revisit their schedules continuously and update them when necessary. Additional important practical consideration is that DTA is very sensitive to unrealistically high travel demand and simply cannot complete a daily simulation if a gridlock occurred due to unbalanced demand. However, it is practically impossible to guarantee that the list of trips created by the ABM will never exceed capacity at any local part of the network. Thus, an early feedback from DTA to ABM that informs about approaching gridlock is essential since it would allow for an early correction of the travel demand in order to complete the simulation at any given global iteration. The main application of trip level integration is to consider short term events such as extreme weather conditions, evacuation and etc,, to model daily variability in factors external or internal to the decision-maker, and to capture the impact of changes that may be localized in space or time. In this application it is assumed that an initial equilibrated list of activities with consistent schedule is available. This list of activities can be the output of the day-level integration of ABM and DTA. Trip-level integration in this regard can adjust the schedule of activities dynamically for each individual based on short term events that affect travel times significantly.

The CT-RAMP structure can be adjusted to have a capability to dynamically update schedules during the analysis period (from any time point on) rather than generate the entire daily plan from scratch. The proposed integration algorithm can be summarized in the following steps:

1. *Initial planning*. ABM produces a set of (planned) activities, tours, and trips in a way it is set now.

2. *Initial list of daily activity plans (which includes all tours and sequences of trips) for network simulation*. Activity plans with planned departure times for each individual are transferred to dynamic network simulation and all marked as "updated".

3. *Network routing*. Updated trips of tour chains are routed and re-routed with a specified time step (5-15 min in practical terms).

4. *Dynamic network simulation*. Routed trips of tour chains are implemented in a chronological order (by departure time). This process is similar to the conventional dynamic network simulation method but one important difference has to be mentioned. Vehicles and person trips are sent to the implementation queue from which they can be taken off and/or updated.

5. *Dynamic feedback*. Simulated travel times for completed trips are fed back to activity adjustment module and accumulated in the interface buffer for evaluation. While this operation is conceptually trivial it is challenging from the computational perspective since all individual daily patterns and schedules are distributed across multiple cores. It is important to feed back LOS experience of each individual user in a real time fashion for (possible) re-planning.

6. *Evaluation and re-planning*. Activity adjustment module takes the implemented trips from the buffer, compares the actual travel time to the planned, and reschedules, adjusts, or cancels subsequent trips/activities for the same household/individual if the discrepancy between the actual and planned travel times is greater than a set threshold. This component is a new addition to the CT-RAMP core structure that we plan for this project. This component uses the previously discussed schedule adjustment algorithm for each individual if the actual travel time is similar to the planned travel time. However, the difference is that this algorithm is applied only forward in time rather than to the whole day. Another important difference is that in case of significant discrepancies, activities and trips can be dropped or added. This is a more complicated mechanism than a pure rescheduling of a fixed sequence of activities and trips. We have developed an approach to this problem that is based on a rule-based mechanism that identifies the relevant travel dimension based on the time pressure index. If the time pressure exceeds a certain limit, the activity plan is subject to simplifications. We have currently experimented with the tour streamlining strategy that can resolve 70-80% of cases in practice. In this case the primary destination of the tour remains the same but intermediate stops are dropped sequentially from the least important to most important until the time pressure index is normalized. We also plan to add a tour-elimination rule to resolve major

conflicts where unexpected delays are significant (1 hour or more) to the extent that an entire tour can be eliminated and if the person is in the middle of the tour, he would proceed back home instead of pursuing the original plan. Interestingly, these rules can also be applied to add stops or even entire tours if the travel time proved to be shorter than expected. We have currently experimented with insertion of "opportunistic" stops.

7. *Update of activity chains in the implementation queue*. Activity chains are dynamically updated at the end of each trip, future activities obtain a new duration or get canceled and trips that have not started yet obtain a new departure time.

The proposed integrated trip-level ABM-DTA model is presented in Figure 15. This integration is done at the trip level for every individual with the periodic updates of the prevailed or anticipated travel times for every simulation interval. It is assumed that the DTA simulation interval is *t*. That is, the list of activity chains with a trip departing an origin every time period *t* is available. This trip-level integration might work within the larger day-level integration scheme as well (See Section 2.1) where the day-level feedback is referred to as "global iterations". In this regard, the subsequent discussion refers to the inner-level loop that is subject to change in the trip-level integration. The main advantage of this trip-level integration is the ability to directly work with individual trajectories rather than aggregated LOS skims.

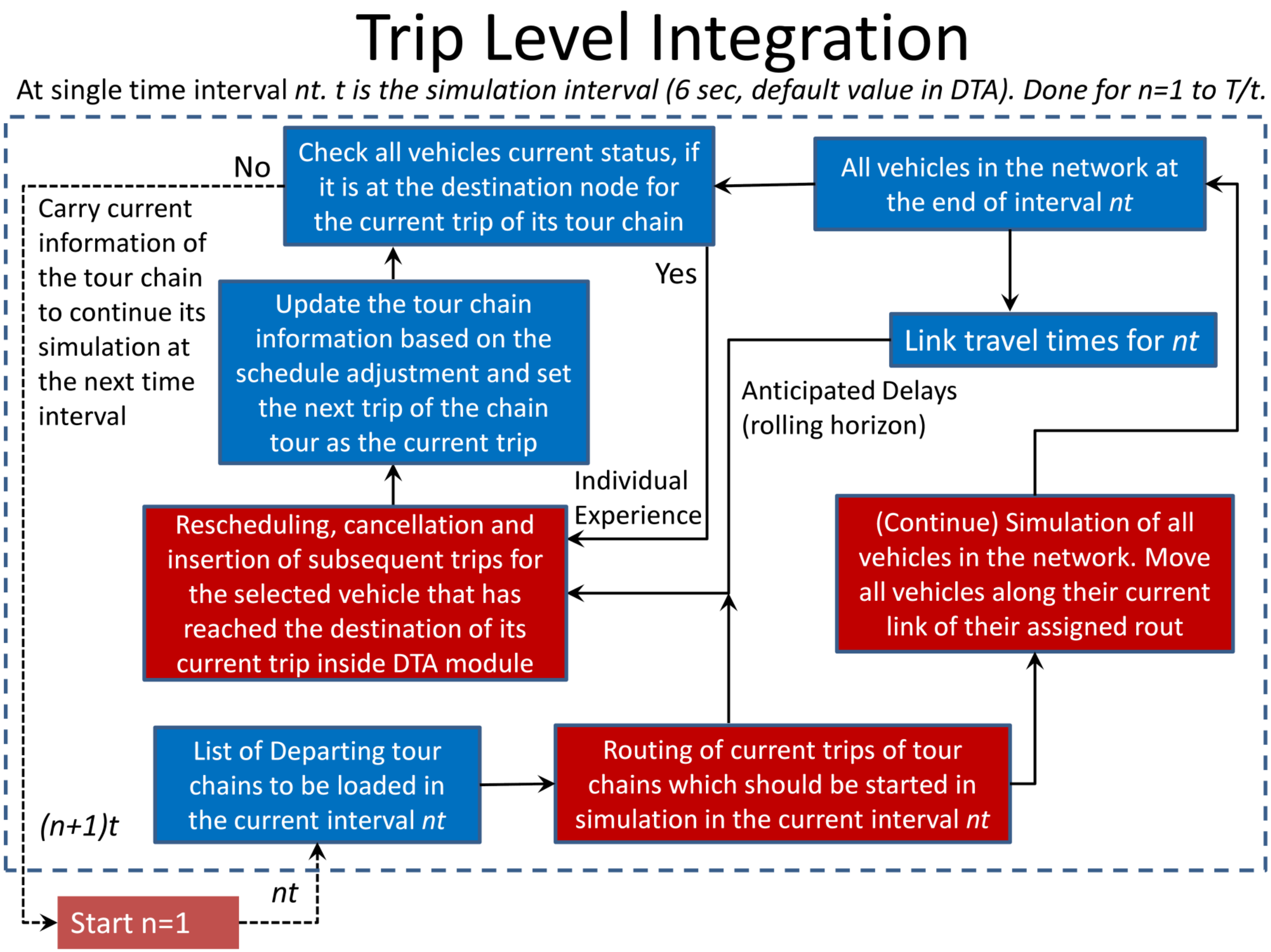
The algorithm begins at an arbitrary simulation interval *nt*. Currently, the network contains individuals who are en route to their destination and a list of activity chains with departing trips at nt. The trips are routed in the network, that is the time dependent shortest paths for these trips is computed and the paths that the individual trips will take is determined.

These trips, along with the trips that are already in the network are simulated for the current time period, that is, until the beginning of interval *(n+1)t.* At the end of interval *nt*, the following information is available:

a) Arrival information for completed trips till *nt*
b) List of trips of activity chains departing in interval *(n+1)t*
c) Link travel times
d) Network loading information including loaded chain of activity status

Given this information it is now possible to load the activity chains of trips that are only capable of starting at time *(n+1)t*. That is, suppose an individual trip was planned to start at *(n+1)t* in the initial schedule, but at the end of interval *nt*, it is learnt that that individual is still en route for its previous trip or doing an activity at one of the nodes and is physically unable to start the planned trip starting at *(n+1)t*, then this trip will not be included in the list of trips departing at *(n+1)t*. This (instant) rescheduling, cancellation and insertion of subsequent trips for the same individual for intervals (*n+1)t* or later is accomplished using a mathematical program, details of which are discussed later. Once the rescheduled and cancelled trips are computed, the schedule of activity chains at *(n+1)t* is updated and supplied to the next simulation interval and simulation continues till the end of the next simulation interval, at which point this process is repeated. The algorithm is presented formally below.

Figure 15: Trip level ABM-DTA Integration (inner loop)



2.2.2 Trip-level Integration Algorithm

Assume simulation interval is *t* (the default value for this parameter in DYNASMART is 6 seconds)*;* simulation duration is T

Set *n = 1*

At an iteration I:

For n = 1 to T/t

1. Route the list of trips in the current interval *nt* based on the current activity schedule.
2. Simulate the trips departing at *nt* and the incomplete trips already in the network
3. Examine all trips that can start in period *(n+1)t*

    a) If the current trip of any activity chain has not been completed at the end of *(n+1)t* time interval:

       Do not start the subsequent trips of that activity chain for DTA in the next period **(Experience)**

    b) If the current trip of any activity chain has been completed at the end of *(n+1)t* time interval:

        i. Route subsequent trips of the activity chain for period (n+1)t to obtain anticipated delays
        ii. Correlation between previous iteration and previous time periods to obtain anticipated delays

       Then based on **anticipation**, individual can postpone/cancel/depart immediately subsequent trips of the activity chain and update activity chains

4. Set *n = n+1*

End For

In this algorithm, Step 3 adjusts the schedule for every individual at the end of every trip. The details of which are presented below.

2.2.3 Individual Schedule Adjustments (Temporal Equilibrium in Trip Level Integration)

An individual's schedule is adjusted based on two factors – (a) experienced travel times for completed trips of activity chain by the individual and (b) prevailing/anticipated travel times of the subsequent trips of the activity chain that represent aggregate information.

a) **Experienced Travel Times:** The ability of an individual to make the succeeding trip is based on the travel time he/she experiences. If at the end of *nt* the individual has not yet reached the previous trip's destination/the next trips origin, then that trip cannot be included in the list of departing trips.

b) **Anticipated Travel Times:** In addition to experienced travel times, an individual's trip can also be rescheduled based on the travel time he/she anticipates for the following time periods. For a link a, in iteration *I* at time interval *nt;* Link travel time is: $C_a^I(nt)$. Let trp_i be the path taken by the individual during trip *i.* Then the anticipated delay is a function of both the travel times in the current iteration and the previous iteration. That is, $f\left(C_a^I(n-1t)\right) \quad a \in trp_{i-1}$ and $f\left(C_a^{I-1}(nt)\right) \quad a \in trp_i$. One way to calculate anticipated travel times is to find the routing cost (TDSP) of the next time interval. This is akin to a user listening to the radio for traffic delays or mapping his route using a mapping website prior to embarking on the trip. In the DTA context, before the rescheduling algorithm is employed, a routing is carried out to learn the travel times in the next time interval given the current network state. Another way to anticipate delays is to study the correlation of the link travel times with the link travel times in the previous iteration and the link travel times in the previous time period. The anticipated delays will consider adjustments in a rolling horizon timeframe. For example, in a given time interval, only delays anticipated within the next hour will be considered and those delays will be applied to all trips that are scheduled to leave in the next hour.

c) **Prevailing Travel Times:** Another approach for estimation of the anticipated travel times is to use prevailing travel times to calculate time dependent shortest path for the subsequent trips, which are already available in the network from the previous simulation steps. Note that these times are updated on a very frequent basis throughout the simulation, thereby providing opportunities for updating all activity choice dimensions with the latest available times. Prevailing trip times include estimates of delays associated with queues at junctions and along links, and may also be combined with the equilibrated trip times to emulate users' behavioral learning rules. These strategies may be more realistic in light of available information sources and human processing heuristics, and could also be implemented with limited software re-engineering to execute in a time-efficient manner.

2.3 Real Time Integration

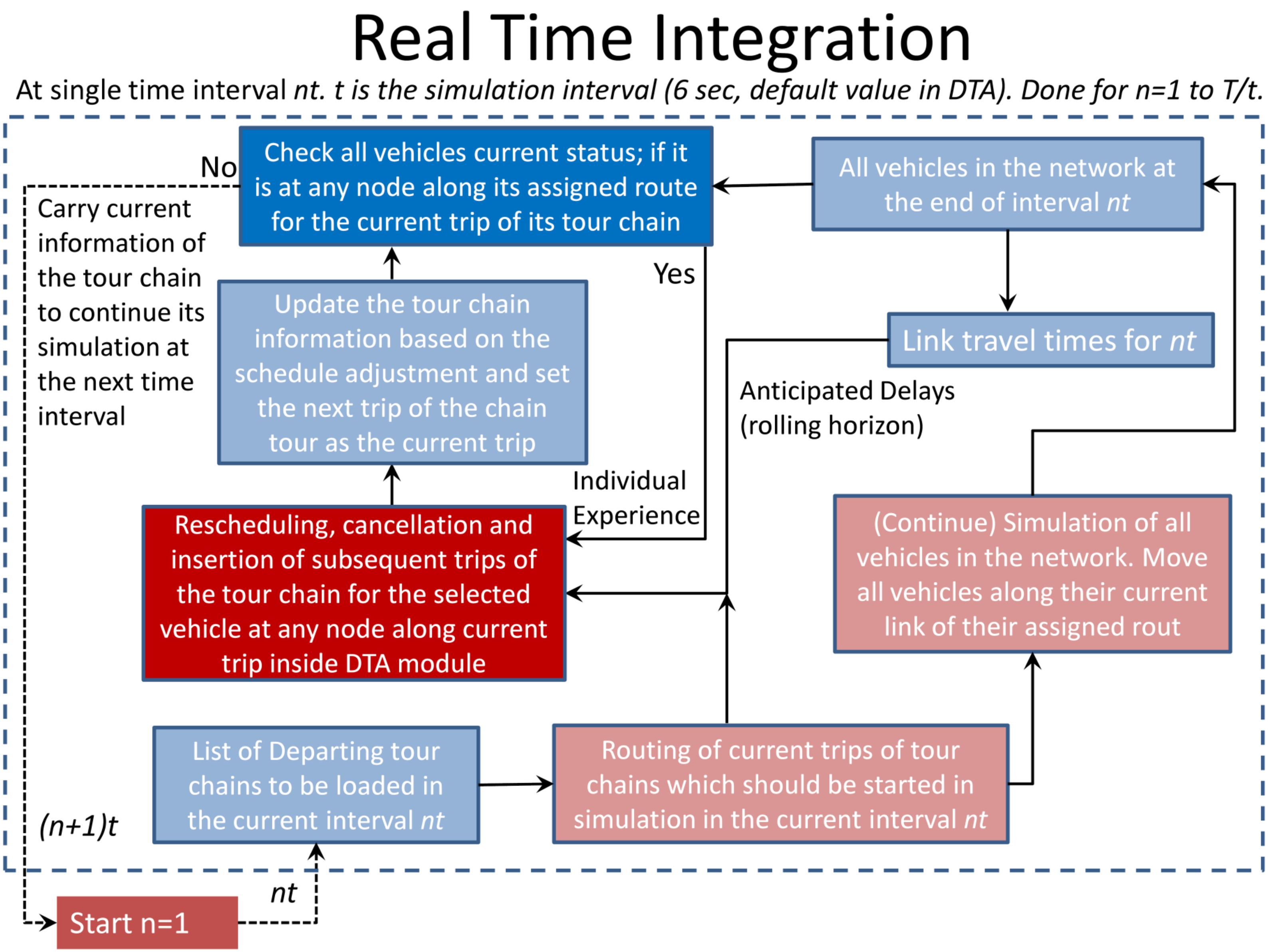
With the proposed trip level integration, real time integration becomes a specific case of trip level integration. In the trip level integration, the activity adjustment module is called at the each trip end node, while in the real time level integration the activity adjustment module is called at every node along the trip to a destination/activity node. This integration details is shown below in Figure 16. Note that this figure is similar to Figure 15. The repetitive steps are lighter in this figure and modified steps are highlighted. At each node of an activity chain along the network the planned and experienced travel times are compared. If the difference of planned and experienced travel time is larger than a specific threshold for an individual, the activity schedule adjustment module is called for that individual and the activity schedule is updated. As this module would be called much more frequently relative to the trip level integration, the real time integration is computationally more extensive.

While the overall framework of real-time integration is similar to the trip/activity level of integration there are some particular details that have to be addressed. For instance, it is computationally more effective to implement the readjustment decisions within the supply-side simulation, hence viewing the latter as a true platform for modeling user decisions in networks. This has been the philosophy guiding the development of DYNASMART from its earliest days, as one of the main motivating concerns was to capture the effect of real-time information and advanced system management interventions on user choices and the resulting performance of the system.

Accordingly, DYNASMART provides the opportunity for each agent to exercise a choice or series of choices at each update time interval, which for practical purposes is real time or quasi-continuously. The most obvious example of this capability is to allow drivers to switch routes at every possible decision point—where such a switch is feasible. Similarly, users pursuing an activity chain may opt to extend the duration of their stay at a particular destination along the chain, and/or go to a different destination than originally planned for their next activity, and/or cancel it altogether. From a software implementation standpoint, and associated computational execution time, it makes sense for such decisions to be executed within the simulation, using information shared in RAM rather than read or retrieved from external files.

There are also behavioral factors that weigh in favor of such implementation. The mechanisms governing real-time or en-route or in-activity choices are generally different from those underlying a priori choices. Experimental evidence in connection with commuting behavior is clear in this regard—en-route models tend to be in the form of deviation from a plan, switching from a default choice, whereas a priori choices tend to include consideration of a more complete set of alternatives, and more comprehensive information on these alternatives. Accordingly, switching models tend to follow simpler mechanisms, which can be readily built onto the simulation platform, rather than the need to invoke an elaborate ABM that may be heavy-in-data and long on computation. Such a real time implementation recognizes the differences between a priori decisions, that are reached over a longer-term process, versus those that are purely reactive or short-term anticipative of unfolding conditions.

Figure 16: Real Time ABM-DTA Integration (Inner Loop)



Furthermore, real-time decisions would generally rely more on recent experience and/or information received en-route, which is generally based on prevailing conditions, word of mouth, tweets and the like. While the state of the art of information provision calls for predictive information, existing systems available commercially do not yet deliver accuracy in prediction that leads to better user decisions. However, research studies (e.g. Dong et al., 2011) have demonstrated the value of such predictive information and controls under certain conditions. The proposed predictive travel times in Section 2.2.3 could be built into the DTA tool as well. In fact, the same DTA simulation platform could be used to solve for consistent predictive information— which for evaluation purposes over the long run is equivalent to solving for an equilibrium solution (Dong, Mahmassani and Lu, 2006).

For this project, we propose to enhance the number of choice dimensions for updating one's planned activity schedule through adjustment decisions that would be triggered and executed as part of the simulation platform, by taking advantage of the existing flexibility already built into the DYNASMART platform. We will also identify areas that could be enhanced in this regard with only limited restructuring of the software implementation. More extensive and comprehensive real-time integration requires additional research on the behavioral side, which would dictate the kinds of models and implementation requirements for these models.

3 Vision of Software Implementation and Data Exchange API

The ABM-DTA model will be implemented by integrating two existing software platforms – CT-RAMP and DYNASMART. CT-RAMP is implemented in Java, is multi-threaded, and is also distributed. CT-RAMP uses the Java Parallel Processing Framework[1] (JPPF) and Remote Method Invocation (RMI) to distribute work to additional machines on a cluster. DYNASMART is implemented in FORTRAN and runs in a single multi-threaded process. Since each program is a closed system, it requires all inputs and outputs to be files (or databases). Both programs run on 64-bit operating systems in order to utilize large amounts of RAM.

In terms of highway LOS measures, CT-RAMP currently reads aggregate zone-to-zone LOS measures. After calculating trips, CT-RAMP outputs either microsimulated trips or aggregate demand matrices for network assignment. DYNASMART currently reads microsimulated trips or aggregate demand matrices as input. In terms of outputs, DYNASMART can produce microsimulated trip trajectories (i.e. paths) and/or aggregate LOS measure matrices.

As currently implemented, CT-RAMP and DYNASMART can only be integrated at the day-level using microsimulated trip files as input to DYNASMART and aggregate LOS matrix files as input to CT-RAMP. In order to efficiently implement trip-level integration, two significant revisions to the existing platforms are required. The first is to integrate Java with FORTRAN so they programs can run in a truly integrated fashion. Java's platform independence makes it difficult to easily integrate with FORTRAN (or C/C++) programs which are compiled for specific platforms. However, there are Java technologies such as Java

[1] http://www.jppf.org/

Native Interface[2] (JNI) and the newer Java Native Architecture[3] (JNA) that allow Java programs to call FORTRAN programs and vice versa. The second significant revision is to share data between programs without reading and writing to the disk. This is required as the amount of data to be shared is substantial. The remainder of this section describes the software integration data requirements and proposed implementation strategies.

3.1 Day-Level Integration

As described earlier in this document, there are three types of ABM-DTA integration: day-level, trip-level, and real time. Day-level integration requires the following data be shared between the two software platforms:

1) ABM Output / DTA Input: Microsimulated trips
2) ABM Input / DTA Output: Microsimulated trip trajectories at the path level

The ABM outputs trips with attributes such as Trip Id, Origin, Destination, Planned Departure Time Period, Vehicle Class, Value-Of-Time, and other market segment attributes.

The DTA outputs trip trajectories at the path level with attributes such as Trip Id (to join to the ABM trip record), Various path level LOS measures such as free-flow travel time, experienced travel time, distance, cost, etc. Note that day-level integration does not require link level (i.e. path component) trajectory information.

In addition to trip trajectories, the DTA needs to supply generic LOS measures by Origin, Destination, Planned Departure Time Period, etc for use by the ABM in situations where there are no observed trips.

3.2 Trip-Level Integration

In the day-level approach, the ABM and DTA are integrated as closed systems. Trip-level integration calls for data sharing between the programs during model runtime. This means for example that after a trip arrives at its destination, the trajectory LOS measures can be used by the ABM to modify later travel. Trip-level integration requires no addition data beyond what is required for day-level integration. It does however require the two software packages to be truly integrated. Integrating the two programs is discussed in more detail in section 3.4 below.

3.3 Real Time Integration

Real time integration integrates the DTA and the ABM data mid-trajectory (i.e. at a node along a trip's path for example). Real time integration requires the following data be shared between the ABM and the DTA software:

1) ABM Output / DTA Input: Microsimulated trips
2) ABM Input / DTA Output: Microsimulated trip trajectories at the link level

[2] http://en.wikipedia.org/wiki/Java_Native_Interface
[3] https://jna.java.net/javadoc/

Instead of one set of LOS measures by trip, there is a set of LOS measures for each link that make up each trip path. Link level trip trajectories are a significant increase in the amount of data being shared between programs. Based on the current model design, link level data sharing is not currently required.

3.4 Data Exchange API

The previous description of the data sharing required by level of integration focused on inputs and outputs. This input/output approach is a convenient description of the software requirements when the implementation is framed as two separate software packages. However, these software packages cannot simply be implemented as separate programs that work with files (or databases) since it will not be computationally efficient to read and write the large amounts of data.

What is proposed instead is a data exchange application programming interface (API) that both software modules (instead of programs) implement. An API is a contract for how software components can interact, what components are exposed through the interface, and how they are exposed (i.e. their objects, attributes, and methods). In addition, both modules will operate in the same process/memory space in order to avoid the costly disk I/O and the API will allow for threaded access since components of the model may be threaded.

In order to integrate the two programs in a shared manner, the ABM or the DTA becomes the master program, and the other program becomes a slave process within the master. This allows the two programs to share one memory space. For example, the DTA becomes the master program and the ABM (or components of the ABM) is exposed as a series of dynamic link libraries[4] (DLLs) that are loaded at runtime by the DTA. The master manages the data and exposes it via the agreed upon data exchange interface to the slave process. The slave can access and modify the data according to the interface.

The data exchange API will consist of a series of objects and methods that describe the data interface. The final API will be specified once the model design is finalized. A basic description of what the API may look like is below.

1) Trip Object
    a. Attributes
        i. Id
        ii. Household Id
        iii. Person Id
        iv. Origin
        v. Destination
        vi. Planned Departure Time Period
        vii. Vehicle Class
        viii. Value-Of-Time
        ix. Assigned (T=Assigned by DTA, F=Yet to be assigned)
        x. Actual Departure Time
        xi. Actual Arrival Time

[4] http://en.wikipedia.org/wiki/Dynamic-link_library

xii. Actual Travel Time
xiii. Free Flow Travel Time
xiv. Travel Distance
xv. Travel Cost
xvi. Links (for real time integration)
xvii. etc

b. Methods
   i. HasTripBeenAssigned()
   ii. etc

2) Link Object (for real time integration)
   a. Attributes
      i. From Node
      ii. To Node
      iii. Free Flow Travel Time
      iv. Actual Travel Time
      v. Distance
      vi. Cost
      vii. etc

3) Trip LOS Engine Object
   a. Attributes
      i. Trips
      ii. Links
      iii. LOS Measures = (“TRAVEL TIME”, “DISTANCE”, “COST”, etc)
   b. Methods
      i. AddTrip(Trip, Household, Person, etc)
      ii. RemoveTrip(Trip, Household, Person, etc)
      iii. Trip = GetTrip(Id)
      iv. Trips[] = GetTrips(Household, Person, etc)
      v. Trips[] = GetTrips(Origin, Time Period, etc)
      vi. Trips[] = GetTrips(Destination, Time Period, etc)
      vii. Trips[] = GetTrips(Origin, Destination, Time Period, etc)
      viii. LOS = GetLOSAcrossTrips(LOS Measure, Origin, Destination, Time Period, etc)
      ix. LOS = GetLOSAcrossHHTrips(LOS Measure, Origin, Destination, Time Period, Household Id, etc)
      x. LOS = GetGenericLOS(LOS Measure, Origin, Destination, Time Period, etc)
      xi. PreCalculateGenericLOSMeasure(LOS Measure)
      xii. etc

4 Conclusions and Work Plan for Tasks 2-4

4.1 Improvements Planned for CT-RAMP ABM

The following improvements to the CMAP CT-RAMP will be implemented in the course of Tasks 2 & 3:

- Enhanced temporal resolution allowing for generation of trips by 5-min departure time bins.
- Individual schedule adjustment interface (delay-response and delay-avoidance version). This interface can be implemented as a stand-alone subroutine (for a trip-level integration schema) or embedded in the real-time event-driven response of DTA (for a real-time integration schema).
- Person-to-vehicle translation of the demand parameters (car occupancy, VOT). This feature will allow for creation of an individual list of (auto) vehicle trips with the driver characteristics for SOV and entire travel party characteristics for HOV out of the list of person trips that is generated by the current version of the CMAP ABM.

4.2 Improvements Planned for DYNASMART DTA

The following improvements to the DYNASMART DTA will be implemented in the course of Tasks 2 & 3:

- Integration of transit simulation, generation and extraction of additional level of service attributes required for the expanded set of activity and travel choice dimensions considered in the ABM.
- Ability to call and apply ABM adjustment modules on an event-driven basis, and integrate the outcomes of the adjustment choices into the simulation.

4.3 Development of a Transit Assignment and Simulation Platform

As part of Task 2, a stand-alone transit network assignment and simulation platform will be developed that will work in parallel with DYNASMART:

- The network will have a very high resolution. All stops and stations in the real transit network will be included along with all transit links, transfer links and centroid connectors.
- Time-dependent movement of vehicles and passengers will be simulated. This will enable the modeling of transfers and bus loads explicitly. As a result, the intricacies of the fare structure due to transfers will be possible to model, as well.
- Walking will be allowed on most of the links so that passengers will have the option to walk a certain distance to catch better service at a different location.
- The movements of buses in traffic will be simulated in DYNASMART in parallel, so that the time-dependent bus link travel times are updated in the transit platform.
- Based on the updated link travel times,bus loads and user experience, new time-dependent shortest paths will be calculated and passengers will be re-assigned in an iterative manner until equilibration.

4.4 Work Plan for Tasks 2-4

Our proposed work plan for the remaining Tasks 2-4 reflects our original proposal with no principal changes. The following tasks will be completed:

- **Task 2: Produce a working multi-modal network microsimulation of the Chicago region**. The main deliverable of this task is a functioning demonstration of a multi-modal network microsimulation of the Chicago region. In this task, we plan to build upon the existing regional networks provided by CMAP and existing DTA and multi-modal simulation models developed by NU. This Task will be fully completed by 6/30/2014.

- **Task 3: Integrate network microsimulation with activity-based demand model**. The main deliverable of this task is a functioning demonstration of the means by which *en route* knowledge and other disaggregate data gained from the network microsimulation is incorporated into a regional activity-based model of travel demand. This includes implementation of the interface between ABM and network simulation models, individual schedule adjustment algorithms, and other (real-time) integration linkages. The integrated network micrsimulation/demand model will be completed and available for use at CMAP by March 30, 2015.

- **Task 4: Final Documentation and technical support**. The final months of the contract period are reserved for preparing final documentation and providing technical support to CMAP staff in using the new product. Required documents include: a final report documenting the research effort, findings, data summaries and recommended next steps; and a user guide giving step-by-step instructions for interpreting and executing the code, data development and maintenance requirements and hardware and software needs. Final documentation will be completed to a standard acceptable by CMAP by June 30, 2015.

The time and main personnel associated with accomplishing each task and preparing each deliverable is summarized in **Table 3**.

Table 3: Schedule and Main Personnel Responsible for Each Task

Task	Main personnel	Deliverable	Schedule
Task 2: Produce a working multi-modal network microsimulation of the Chicago region	Hani Mahmassani – lead Jim Hicks Peter Vovsha	A functioning demonstration of a multi-modal network microsimulation of the Chicago region.	July 1, 2013 – June 30, 2014

Task	Main personnel	Deliverable	Schedule
Task 3: Integrate network microsimulation with activity-based demand model	Ben Stabler – lead Peter Vovsha Jim Hicks Hani Mahmassani	A functioning demonstration of the methods by which disaggregate data gained from the network microsimulation is incorporated in a regional activity-based model of travel demand.	July 1, 2014 – March 30, 2015
Task 4: Final Documentation and technical support	Peter Vovsha – lead Hani Mahmassani Jim Hicks Ben Stabler	Final documentation and technical support to CMAP staff in using the new product. Required documents include: a final report documenting the research effort, findings, data summaries and recommended next steps; and a user guide giving step-by-step instructions for interpreting and executing the code, data development and maintenance requirements and hardware and software needs.	April 1, 2015 – June 30, 2015
Complete project			March 2013 – June 2013

5 References

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