

PARADIGMS FOR INTEGRATED MODELING OF ACTIVITY-TRAVEL DEMAND AND NETWORK DYNAMICS IN AN ERA OF DYNAMIC MOBILITY MANAGEMENT

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1 **ABSTRACT**

2 This paper describes various levels of an integrated transport modeling framework capable of
3 reflecting the impacts of dynamic traffic management strategies and real-time traveler information
4 provision on activity-travel demand and network dynamics. Many existing integrated model
5 systems involve a rather loose coupling of activity-travel demand models (ABMs) and dynamic
6 traffic assignment (DTA) models. These models do not have the capabilities necessary to simulate
7 the impacts of emerging dynamic strategies that rely on real-time connectivity, communications,
8 and proactive travel demand management to optimize network performance. In an effort to
9 advance the development of integrated modeling platforms that can address “planning for
10 operations”, this paper presents the design of increasingly detailed levels of the tightly integrated
11 modeling framework called SimTRAVEL. In this modeling framework, the ABM and the DTA
12 model communicate with one another along the continuous time axis with a view to reflect how
13 activity-travel patterns evolve in response to network dynamics, and how network dynamics
14 manifest themselves as travelers go about their daily activity-travel schedules. The highest level
15 of the framework is capable of reflecting the full suite of behavioral and network dynamics that
16 may result from a network disruption, information provision scheme, or dynamic mobility
17 management strategy. The efficacy of the framework is demonstrated by implementing the
18 platform using openAMOS as the ABM component and DTALite as the DTA model. Scenario
19 analyses conducted using the Sioux Falls network show that the integrated modeling framework
20 is able to provide behaviorally intuitive predictions of the impacts of real-time information
21 provision strategies.

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24 **Keywords:** integrated models, integrated modeling of travel demand and network dynamics,
25 integrated frameworks of activity-based travel demand models and dynamic traffic assignment
26 models, simulating dynamic mobility management strategies, real-time information provision
27 impacts
28

1. INTRODUCTION

The dawn of the era in which information is ubiquitous on a plethora of connected devices and vehicles has engendered many an opportunity to proactively influence, manage, and enhance transportation network performance with respect to a number of possible criteria (e.g., delay, congestion, energy and emissions footprint, mode share) under a wide variety of scenarios (e.g., regular traffic, work zones, evacuation situation, special events). In cities around the world, transportation and mobility professionals are exploring ways in which to leverage the power of technology to better manage congestion, influence travel choices, and optimize transportation system performance using analytics derived from big data streams. With the rapid development of connected and automated vehicles (CAVs), and the availability of a number of transportation-related apps on smartphones, the role of technology in shaping and managing the transportation system will undoubtedly increase in the years ahead.

In the United States, the US Department of Transportation (USDOT) has a number of intelligent transportation system initiatives underway with a view to provide jurisdictions around the country a suite of tools, strategies, and methods for enhancing system performance. The Applications for the Environment: Real-Time Information Synthesis (AERIS) Program (USDOT, 2016a), for example, included a suite of strategies to reduce the energy and emissions footprint of travel in a region through the use of connected vehicle technologies including vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. More recently, there has been a growing emphasis on and interest in the deployment of Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) strategies. Dynamic Mobility Applications include a number of technologies aimed at enhancing network operations for a variety of system users including auto users, transit riders, and freight transport providers (USDOT, 2016b). Active Transportation and Demand Management strategies include a suite of approaches to proactively manage travel demand (say, through the use of dynamic pricing schemes and the provision of information to system users), traffic flow (say, through dynamic speed limits and adaptive ramp metering), and parking operations (say, through dynamic parking pricing and dynamic way-finding) (FHWA, 2012). An examination of the strategies and techniques listed in the DMA and ATDM toolboxes clearly illustrate that the profession is moving to erase the line that divides and more closely integrate planning and operations.

The increasingly blended environment of transport planning and network operations calls for the development of analysis, modeling, and simulation tools capable of reflecting the dynamic interactions between planning strategies and network operations. In the past, travel demand model systems have been limited in their ability to consider such dynamic interactions. On the one hand, travel demand models purport to simulate choices related to activity generation, destination choice, and mode and route choices as a function of socio-economic, demographic, built environment, and network attributes. On the other hand, transportation network models and traffic microsimulation models have been used to simulate traffic flow dynamics at a fine level of spatial, temporal, and network level of detail. These two modeling enterprises have largely developed independent of one another, and connections between them have been achieved mostly through loose sequential coupling of demand and network model systems incapable of reflecting the impacts of real-time operational strategies on the full slate of travel choices and network dynamics. With ubiquitous connectivity provided by mobile technologies, it is now increasingly possible for travelers to adjust travel choices in response to prevailing or predicted network conditions. Unfortunately, integrated models of travel demand and network dynamics capable of fully accounting for such real-time phenomena have not yet matured to a stage where they can be implemented in practice.

1 In light of the need for robust, and behaviorally sensitive, integrated transport demand and
2 network models, this paper presents a framework capable of reflecting travel demand and network
3 dynamics arising from real-time and proactive dynamic mobility/traffic management strategies.
4 The paper first presents the various levels of dynamic integrated transport demand and network
5 modeling in a conceptual manner, followed by illustrative results of the application of lower levels
6 of the framework to demonstrate the efficacy of the approach. The scope of the paper (and the
7 framework presented) is limited to the integration of activity-based travel microsimulation model
8 systems of travel demand with dynamic traffic assignment models of network dynamics. The
9 further integration of traffic microsimulation models, although meritorious in the context of
10 analyzing network performance at fine levels of detail, is beyond the scope of this paper.

11 **2. INTEGRATED MODELS OF TRANSPORT DEMAND AND NETWORK DYNAMICS**

12 Significant advances have been made in the development of integrated models that link state-of-
13 the-art activity-based travel demand models (ABMs) with dynamic traffic assignment (DTA)
14 models. Lin et al (2008) present the conceptual framework for an integrated ABM-DTA model
15 system in which the model components are loosely coupled together in a sequential fashion; the
16 travel times from the DTA model are fed back as input to the ABM only at the end of a full model
17 iteration. Bekhor et al (2011) discuss the results of an integrated model effort, where the Tel-Aviv
18 ABM was coupled with MATSim. For purposes of integration, the time-of-day choice in their
19 model was disaggregated into fifteen distinct time periods while taking into account activity
20 duration constraints. Goulias et al (2012) present the results of an integration of the CEMDAP
21 ABM with a multi-period static traffic assignment model. All of the model systems discussed
22 above are based on a loosely coupled or sequential integration paradigm where the ABM and DTA
23 models communicate and exchange data only at the end of a full iteration. This sequential
24 information exchange process hinders the use of such models to realistically represent the impacts
25 of network events or disruptions on activity-travel patterns. In recognition of this limitation,
26 integrated models that adopt a much tighter integration framework have been developed recently.

27 Balmer et al (2009) present results from an operational prototype of the MATSim
28 integrated model. MATSim is comprised of several modular components that work in concert to
29 link the activity-schedules obtained from an ABM with dynamic network phenomena. Pendyala
30 et al (2012) present a fully operational prototype of an integrated model called SimTRAVEL, in
31 which the ABM and the DTA model systems constantly communicate and exchange data with
32 each other on a minute-by-minute basis, thus rendering the integration process truly dynamic. Auld
33 et al (2015) propose a conceptual framework and present results of a test implementation of
34 POLARIS, which executes a continuous exchange of information between the ABM and DTA
35 components. Such a tight integration allows for realistic representation of impacts of network
36 dynamics, as well as real-time information systems and proactive traffic management strategies,
37 on traveler behavior.

38 Real-time information systems (RTIS) or advanced travel information systems (ATIS) may
39 impact various dimensions of travel behavior including, but not limited to, destination, time-of-
40 day, route, and mode choices. Several studies have attempted to model the influence of RTIS/ATIS
41 on travel behavior. In an empirical study using an interactive simulator, Srinivasan and
42 Mahmassani (2003) concluded that route-switching behavior is significantly influenced by the
43 nature, timeliness, quality, and extent of real-time information. Jang et al (2013) proposed a utility
44 maximization-based activity rescheduling model to allow adjustments in a traveler's daily activity-
45 travel schedule in response to time pressure or time surplus. Paz and Peeta (2009) proposed

1 paradigms that enhance the effectiveness of real-time traffic routing strategies by explicitly
2 accounting for a driver's likely response to path recommendations using an information-based
3 network control approach.

4 Considerable progress has been made in the recent past in modeling/representing the
5 influence of RTIS/ATIS on travel demand using integrated microsimulation model systems. Xiong
6 et al (2016) developed a model of enroute diversion by integrating an agent-based (microscopic)
7 enroute diversion model with a (mesoscopic) DTA model. Bellemans et al (2010) present the
8 implementation framework of FEATHERS, a comprehensive model system capable of modeling
9 travel scheduling decisions, within-day rescheduling, and learning processes of individual agents.
10 Bustillos et al (2011) studied the effects of pre-trip and enroute traveler information on route
11 choice. They developed models of congestion-responsive rerouting, pre-trip information-
12 responsive rerouting, and enroute information-responsive rerouting, and then integrated these
13 models into a DTA model. Konduri et al (2013) modeled the impact of network disruptions on
14 activity-travel choice patterns under varying levels of traveler information provision using
15 SimTRAVEL. POLARIS (Auld et al, 2015) is also an example of a model system capable of
16 simulating the impacts of real-time information systems by incorporating behaviors such as trip
17 re-planning and enroute switching.

18 Within the context of this paper, it is not possible to offer a comprehensive review of the
19 literature. However, examples from the literature cited above illustrate the depth of interest in the
20 development of integrated microsimulation models of activity-travel demand and network
21 dynamics. Efforts to develop such models continue to be rather fragmented and there is no
22 comprehensive modeling and simulation framework that can account for the full complement of
23 dynamic mobility management strategies. This paper aims to present and describe various levels
24 of a comprehensive conceptual framework for integrated microsimulation modeling of transport
25 systems that builds on the SimTRAVEL structure documented previously (Pendyala et al, 2012).

26 27 **3. LEVELS OF INTEGRATED TRANSPORT MODELING**

28 This section presents conceptual designs of increasing levels of dynamic integration between an
29 ABM model and DTA model with a view to incorporate the ability to simulate the impacts of the
30 full array of dynamic mobility management strategies on the entire range of activity-travel choices
31 of agents in the system.

32 33 **3.1. Level Zero: Sequential Integration**

34 The simplest conceptual design of an integrated model system involves loose sequential coupling
35 of the two major model components, namely, the ABM and DTA models. In a sequential
36 integration paradigm, the ABM is run for the entire 24-hour period of the day to simulate daily
37 activity-travel patterns for all agents in a synthetic population of the region. The entire trip list
38 generated by the ABM is then input to the DTA model and the DTA model routes and simulates
39 all of the trips (or tours, in some instances) on the network. When travelers on the network can no
40 longer improve their travel times by switching routes, as evidenced by the computation of a gap
41 function (Chiu et al, 2011), the model generates assignment results by time of day together with a
42 new set of skim matrices that can be input to the ABM for the next iteration of the integrated model
43 system. The ABM uses these time-sensitive skim matrices to generate a new daily activity-travel
44 pattern for each agent in the population and the new set of trips/tours are input to the DTA model.
45 The DTA model assigns the trips and writes out an updated set of skim matrices. This process is
46 continued until there is convergence in the OD matrices output by the model system from one

1 iteration to the next. Other mechanisms to monitor and test convergence include a check of
2 consistency between time-dependent skim matrices output by the DTA model and those used to
3 simulate activity-travel demand choices in the ABM, and the use of a difference function that
4 demonstrates stability in link flows and end-to-end travel times across successive iterations of the
5 integrated model system. As the exchange of information between model components happens
6 only at the end of an iteration, this model integration platform is not responsive to network
7 dynamics and real-time information that may be available to a traveler.
8

9 **3.2. Level One: Dynamic Integration – No Real-time Information**

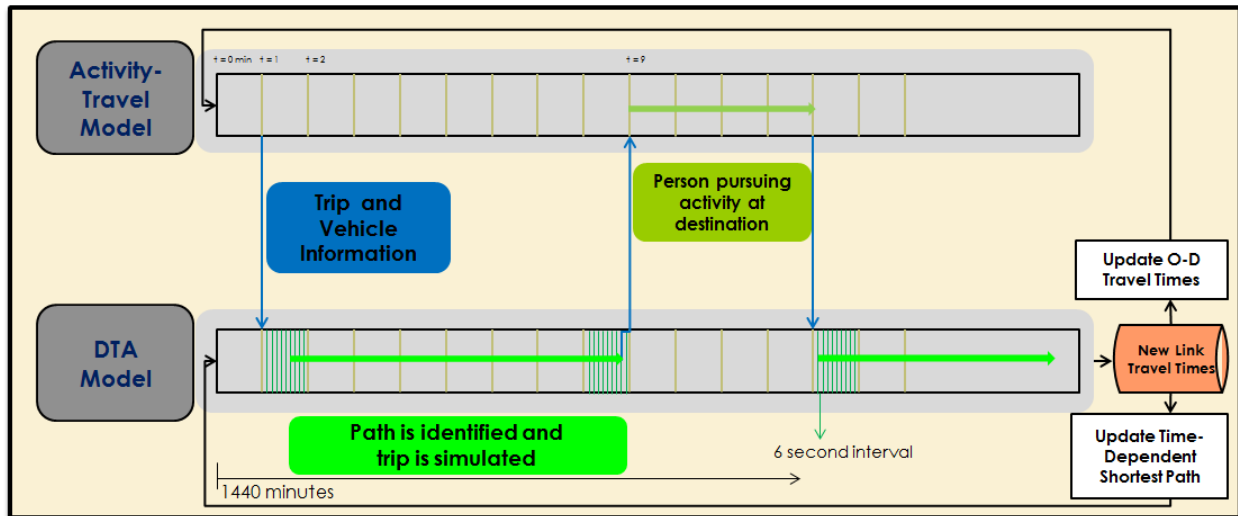
10 The first level of dynamic integration corresponds to the SimTRAVEL framework. SimTRAVEL
11 refers to a Simulator of Transport, Routes, Activities, Vehicles, Emissions, and Land and was
12 developed as part of an early Exploratory Advanced Research Program project of the US
13 Department of Transportation. The framework is inspired by earlier work presented by Kitamura
14 et al (2008), who envisioned a tightly integrated modeling platform to reflect behavioral dynamics
15 both on the demand side and network side. The framework is briefly presented here for the sake
16 of completeness; more details are available in Pendyala et al (2012).

17 The original SimTRAVEL framework is shown in Figure 1. In this framework, the ABM
18 and DTA models are run in parallel with data exchange happening along the continuous time axis
19 at a time-step specified by the analyst (set as one minute for the purposes of this discussion). An
20 initial set of coarse time-of-day specific network skim matrices are obtained from a set of bootstrap
21 runs in which the ABM and DTA models are run in sequence (Level 0). The dynamic integrated
22 platform is then launched with the ABM simulating activity-travel choices at the resolution of one
23 minute. In each minute of the day, the ABM provides a list of trips that are departing in that minute
24 to the DTA model. The DTA model then routes and simulates the trips on the network along time-
25 dependent shortest paths. In each minute of the simulation day, a set of travelers will arrive at
26 their destinations, and the DTA model will send to the ABM the set of trips (travelers) that have
27 arrived so that the ABM can determine the subsequent activity-travel choices based on destination
28 arrival time.

29 In simulating activity-travel choices (such as activity duration, next activity to be pursued,
30 destination and mode choice), the ABM explicitly recognizes and considers time-space prism
31 constraints associated with mandatory activities, household obligations, modal availability, and
32 history of activity-travel engagement throughout the day up to the decision point in question. If a
33 traveler is delayed on the network (say, because of congestion or an incident) and arrives later than
34 expected at the destination, then the ABM will simulate subsequent activity-travel choices
35 accordingly. By ensuring that activity-travel demand choices are precisely in sync with *actual*
36 travel times experienced by the travelers on the network, the dynamic integrated platform ensures
37 that there are no overlaps and gaps in the simulation of daily activity-travel patterns and schedules.

38 In the original SimTRAVEL integrated modeling framework, travelers do not have
39 information about prevailing network conditions when making decisions about activity-travel
40 schedules, routes, modes, and destinations. In this simplest level of the SimTRAVEL framework,
41 the DTA model outputs time-dependent skim matrices at the end of each iteration. These time-
42 dependent skim matrices are used by the ABM in the next iteration to simulate activity-travel
43 choices along the continuous time axis. The process continues until convergence is achieved,
44 wherein OD matrices show no appreciable change from one iteration to the next on the ABM side,
45 and the gap function shows no further decrease on the DTA model side. The model is said to have
46 converged when both criteria are met. This tight dynamic integration framework can be further

1 extended to incorporate the ability to simulate the impacts of dynamic mobility management and
 2 real-time information strategies.
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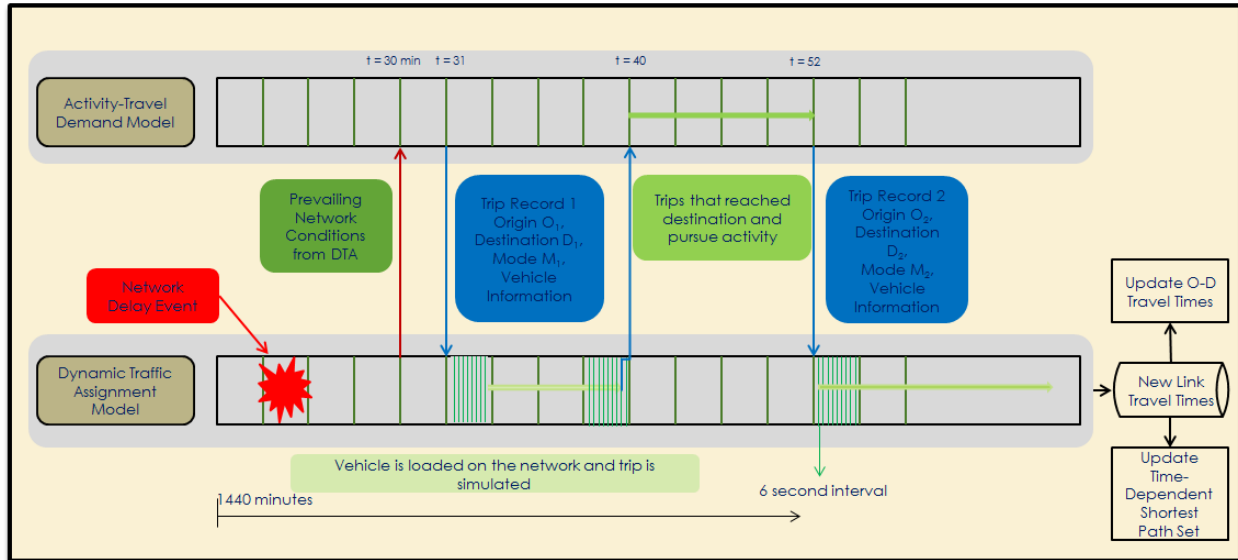


4
 5 **FIGURE 1 SimTRAVEL integrated modeling framework.**
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7 3.3. Level Two: Dynamic Integration – Only Pre-trip Information

8 In the next level of dynamic model integration, the SimTRAVEL platform is enhanced to
 9 accommodate the effects of the availability of pre-trip information about prevailing network
 10 conditions. That is, travelers are able to make activity-travel choices that are network-sensitive
 11 based on information they access prior to embarking on a trip. For example, suppose there is a
 12 network disruption (planned or unplanned) that affects prevailing travel times. A traveler will be
 13 able to access pre-trip information about prevailing network conditions and make activity-travel
 14 choices – subject to time-prism constraints – that take such information into account. A simplified
 15 representation of this conceptual design is shown in Figure 2.

16 To illustrate this version of the framework, consider a network disruption that occurs in the
 17 middle of the day. If an individual has pre-trip information, then that individual would be provided
 18 data about prevailing network conditions and travel times rather than travel time matrices from the
 19 prior iteration. Those with no pre-trip information, on the other hand, will rely on historical (prior
 20 iteration) accumulation of travel time information to make activity-travel choices. In this
 21 conceptual design, the DTA model outputs network travel times at regular intervals (as small as
 22 one minute, but a 15 minute time step may be sufficient to reflect lag in information availability).
 23 Travelers with pre-trip information consult these travel time matrices (reflecting prevailing
 24 network conditions) when making activity-travel choices. Travelers with no pre-trip information
 25 rely on accumulated history of travel time information in decision-making, and may therefore
 26 encounter severe congestion and delayed arrival times as a result of the disruption. Presumably,
 27 those who have access to pre-trip information about prevailing network conditions are able to
 28 avoid the disruption effects (to the extent possible) and do not experience delays and setbacks as
 29 severe as those who do not have access to such information.
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FIGURE 2 Dynamic SimTRAVEL framework – level 2 pre-trip information.

It should be noted that Figure 2 does not represent an iterative process wherein the model components are run repeatedly to convergence. Whether or not the model system needs to be run in an iterative process may depend on the specific network disruption context being considered. For example, suppose the network disruption occurs due to an unexpected accident or spill. Then, it may be conjectured that the network will experience disequilibrium conditions where travelers encounter chaos and delay. In such a context, a single iteration of the integrated model run should suffice to study the impacts of network disruption on activity-travel patterns. On the other hand, suppose the disruption is a planned network event such as a work zone that is going to be present for several months or longer. In that case, it may be conjectured that travelers will learn from one day to the next, and use both accumulated history of experienced travel times as well as prevailing network conditions (if they have pre-trip information) to make activity-travel choices. Such a scenario would require the integrated model to be run in an iterative fashion (similar to Level 1).

3.4. Level Three: Dynamic Integration – Pre-trip and Enroute Information with Route Diversion Only

The next level of dynamic integration adds the ability to account for the effects of real-time enroute traveler information on route choice and route diversion that may occur in response to network dynamics. This level of the SimTRAVEL framework continues to account for the effects of pre-trip information that individuals may have about prevailing network conditions. Thus, the ABM in the SimTRAVEL framework simulates activity-travel choices in a network-responsive manner for those with pre-trip information, but continues to use accumulated history of travel time information from prior iterations for those with no information. In addition, individuals who have enroute travel information are able to adjust their route in response to network travel times. In every minute of the simulation time step (or a time step ' n ' specified by the analyst), the DTA model will check on the status of a portion of travelers in the network who have real-time enroute travel information. The DTA model will determine whether the prevailing travel time to the destination violates time-space prism constraints. If time-space prism constraints are not violated, then the individual (traveler or vehicle) continues on the same path until the next check is done n minutes later. If a traveler is on a path that is experiencing unusual congestion, then the DTA

1 model will search for alternate time-dependent shortest paths based on prevailing link travel times
2 and re-route the traveler to the best alternative. If there is no path that allows a traveler to reach
3 his/her destination without violating time-space prism constraints, then the best feasible path is
4 chosen and a violation of time-space prism constraints is permitted (e.g., being late for work,
5 school, child pick-up, or a business meeting).

6 Note that this level of model integration also supports a scenario where individuals do not
7 access pre-trip information, but have access to enroute information (say, via variable message
8 signs) to exercise route diversion. In this case, the traveler uses historical network travel time
9 skims from prior iterations to make activity-travel choices, and then adjusts route on the network
10 in response to enroute traveler information. In the interest of brevity, a separate figure is not shown
11 for this level of integration; the figure presented in the next subsection incorporates this level of
12 integration and therefore illustrates this conceptual design as well.

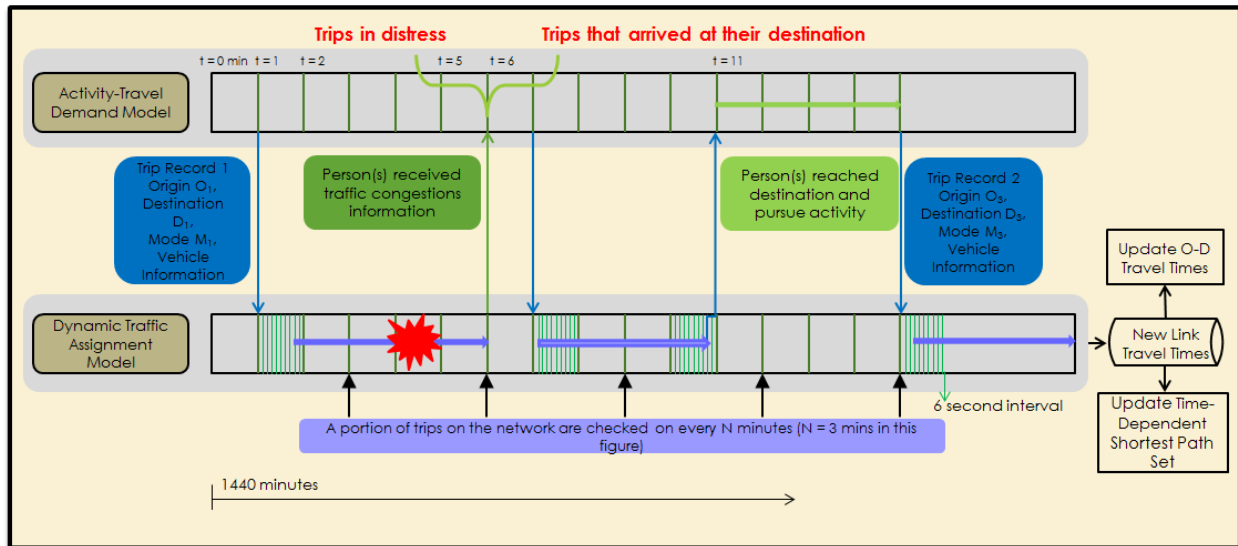
14 **3.5. Level Four and Beyond – Pre-trip and Enroute Information with Full Activity-Travel** 15 **Choice Adjustments**

16 The final level of the SimTRAVEL framework considered in this paper is that in which travelers
17 have access to both pre-trip and enroute travel information, *and* are able to adjust the full
18 complement of activity-travel choices in response to the information they access. Thus, similar to
19 the previous levels, individuals with pre-trip information about prevailing network conditions will
20 rely on such information to make activity-travel choices in the ABM in contrast to individuals with
21 no information who use the historical accumulation of travel time matrices from prior iterations to
22 make activity-travel choices. Individuals with enroute travel information can now adjust activity
23 type choice, destination choice, mode choice, and accompaniment choice *in addition to* route
24 choice (which was accommodated in the prior level).

25 Similar to the prior level, individuals on the network with enroute travel information are
26 checked every n minutes to determine if the traveler should be diverted to an alternate path. In
27 general, it is assumed that individuals will first try to change path and find an alternate route to
28 their intended activity destination to minimize disruptions to the activity schedule. In previous
29 work, Ye and Pendyala (2007) have found that individuals first exercise choices that are least
30 constrained and minimize disruptions before modifying more constrained choices. If, however,
31 the best feasible alternative path is also deemed unacceptable (because a substantial violation of
32 the time-space prism constraints would occur), then the individual is tagged as a traveler in
33 *distress*. In each one-minute time step of the simulation, the DTA model now returns to the ABM
34 two sets of trips, namely, the set of trips that have routinely arrived at their destination and the set
35 of trips that are in *distress*. This is illustrated in Figure 3.

36 For the travelers that are tagged as being in distress, the ABM will determine if alterations
37 to their choices are in order. Travelers may choose to switch to an alternate destination if the
38 activity in question is discretionary in nature and has flexibility with respect to location. After
39 choosing a new destination (based on prevailing network conditions), the trip is sent back to the
40 DTA model (in the next one-minute time step) for routing and simulation on the network. If the
41 activity in question does not have location flexibility or there is no alternate destination that meets
42 time-space prism constraints, then the individual is assumed to switch modes or abandon the
43 activity altogether. Mode switching is generally unlikely to occur mid-journey and hence this
44 particular behavioral adaptation choice is suppressed in the current framework. However, with the
45 increasing advent of ride-sourcing and vehicle-sharing services, it is plausible that mid-journey
46 mode-switching will become increasingly feasible.

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FIGURE 3 Dynamic SimTRAVEL framework – levels 3 and 4.

An individual may abandon the activity in question and proceed to the next fixed activity defined by time-space prism constraints, or switch to a different (discretionary) activity type which would entail choosing a new destination, or simply return home (e.g., work or study from home). After the ABM simulates the choice adjustment made by the traveler, the information is sent to the DTA model and the DTA model routes and simulates the traveler on the network starting from the point where the traveler was originally tagged as being in distress. An abandoned activity may be pursued later in the day (the individual cannot go back in time) depending on time-space prism constraints.

It is plausible to envision levels of model integration that go beyond the ability to change route and activity-travel demand choices in response to real-time travel information facilitated by connectivity, communications, and technology. A further level of integration of the simulation framework would accommodate re-allocation of tasks and activities among household members. Thus, when a member of the household abandons a certain activity, the activity may be re-assigned to another (available and eligible) household member who has an open time-space prism that would accommodate the activity. Finally, the ultimate level of model integration would incorporate interactions across households or colleagues, where some tasks are reassigned to non-household-members.

4. AN ILLUSTRATIVE CASE STUDY APPLICATION

This section presents results of an illustrative case study application that demonstrates the efficacy of the framework and the increasingly detailed levels of integration that capture the effects of dynamic mobility management strategies and real-time traveler information on activity-travel patterns and network dynamics. For implementing the framework, it is assumed that any and all information about network conditions arising from the introduction of dynamic mobility management strategies or the occurrence of a network disruption can be translated into equivalent time and cost units, or mobility options (alternative routes, destinations, and modes). Thus, if there are dynamic pricing strategies, they will result in changes in travel times and costs. A dynamic parking management system will impact terminal times or parking costs. Thus, each and every

1 DMA or ATDM strategy that may be implemented to improve system performance is represented
2 in terms of the time and cost differences that the strategy engenders for different travelers.

3 All travelers in the synthetic population are tagged with an information type flag: no
4 information, pre-trip information only, enroute information only, and both pre-trip and enroute
5 information. These four information groups will exercise activity-travel decisions and route
6 choices based on different sources of information. The DTA model will provide information about
7 network conditions, both historical (saved from prior iterations) and prevailing (based on current
8 traffic), and agents will use the appropriate information depending on their information type status.

9 Two specific model systems were used for this illustrative demonstration of the
10 SimTRAVEL framework. The activity-based travel demand model system is openAMOS, an
11 open-source activity mobility simulator (SimTRAVEL, 2016). Unlike many tour-based models
12 that have been implemented in practice (e.g., Outwater and Charlton, 2006), openAMOS is a
13 continuous-time evolutionary ABM where the activity-travel pattern evolves over the course of a
14 day as individuals make decisions regarding activity engagement at various decision-points in the
15 day subject to a variety of constraints. Such a design is ideal for tight coupling with a DTA model
16 in which the ABM and DTA models exchange information about trips and travelers on a
17 continuous (one-minute time step) basis. The DTA model used in this illustrative exercise is
18 DTALite (Zhou and Taylor, 2014), a dynamic traffic assignment model capable of routing and
19 simulating trips through a network while recognizing the time-dependent nature of shortest paths.
20 Although this exercise utilizes these specific model components, the SimTRAVEL framework
21 may be implemented using any ABM and DTA models that can be tightly coupled together and
22 engineered to exchange data at a fine temporal resolution. By tightly integrating the two models
23 so that specific travelers can be tracked through both the ABM and DTA models, the SimTRAVEL
24 framework constitutes a true agent-based simulation model system.

25 In this illustrative example, the first three levels of the SimTRAVEL framework are
26 demonstrated using the small Sioux Falls network that includes 24 traffic analysis zones (TAZs)
27 and 76 network links (at 60 mph free-flow speed). In order to ensure that significant traffic
28 volumes and congestion levels would be realized on the network, a synthetic population of 24,853
29 persons residing in 8,259 households was generated using the population synthesizer embedded
30 within openAMOS. The SimTRAVEL framework was applied to a number of network scenarios
31 to demonstrate the ability of the framework to reflect the impacts of network dynamics and traveler
32 information on activity-travel patterns and system outcomes. The scenarios are as follows:

- 33 • Baseline Scenario: No network disruption
- 34 • Scenario 1: Network disruption with no traveler information (SimTRAVEL Level 1)
- 35 • Scenario 2: Network disruption with pre-trip traveler information only (SimTRAVEL
36 Level 2)
 - 37 ○ Individuals in 50 percent of households have pre-trip information; others have no
38 information
- 39 • Scenario 3: Network disruption with pre-trip and enroute traveler information allowing
40 only route changes in the middle of a journey (SimTRAVEL Level 3)
 - 41 ○ Individuals in 50 percent of households have pre-trip and enroute information;
42 others have no information

43 The network disruption involved severely constraining three of the 76 links during key periods of
44 the day. Heavily traveled links were selected for disruption. One link was assumed to have a
45 speed of 10 mph during 8 AM to 9 AM, another link was assumed to have this speed between 12
46 noon and 1 PM, and a third link was assumed to experience 10 mph speed during 5 PM to 6 PM.

1 DTALite identified alternate paths for individuals who had enroute travel information, and
2 provided skim matrices with information about prevailing network conditions so that individuals
3 with pre-trip information could make informed activity-travel demand choices.

4 Results of the scenario analyses are presented in Table 1. For purposes of brevity, only
5 aggregate measures are presented in the table. The first column shows travel characteristics for the
6 baseline case where no disruption is introduced in the network. Average trip duration is 9.26
7 minutes per trip and average trip length is 8.23 miles. Given the high free-flow speed of the links
8 in the network, these statistics are not inconsistent with expectations. In scenario 1 where a severe
9 disruption is introduced, it can be seen that average trip duration increases as expected. In the
10 absence of any information, and in view of the disruption, DTALite routes individuals on
11 somewhat more circuitous paths leading to an increase in trip length as well. The trip length and
12 trip duration are both higher during the disruption period when compared with the overall daily
13 average.

14 Results of Scenario 2 clearly demonstrate the benefit of providing information about
15 prevailing network conditions to travelers. Armed with real-time pre-trip information, travelers are
16 able to make more informed decisions with respect to activity-travel schedules and location
17 choices. As a result, the average trip duration and average trip length for travelers with pre-trip
18 information is considerably lower than corresponding values for individuals without any traveler
19 information. Travelers with pre-trip information are better off during the disruption period as well.
20 Compared to the case where nobody had any information, travelers with no information are better
21 off in the scenario when individuals in one-half of the households are equipped with information.
22 As the individuals with information make more informed decisions, travelers with no information
23 benefit as well due to reduced congestion and delays.

24 Finally, results of Scenario 3 demonstrate the case where individuals in one-half of the
25 households have pre-trip and enroute travel information about prevailing network conditions. It
26 is interesting to note that those with information are better off than those without information
27 (similar to Scenario 2). However, these individuals (with both pre-trip and enroute information)
28 actually experience a degradation in average trip duration and trip length in comparison to the case
29 where they had only access to pre-trip information. The differences are modest, but very
30 systematic, suggesting that these differences are not attributable to stochastic randomness inherent
31 to microsimulation model systems. A further examination of the phenomena at play suggested
32 that re-routing of travelers resulted in longer trip lengths as DTALite attempted to re-route travelers
33 in the middle of a journey, resulting in more circuitous paths and increased trip durations.

34 In the case where travelers adjust their route during the course of the journey, two factors
35 may contribute to increased travel times and distances. First, travelers switch to a more circuitous
36 path in an attempt to divert and abide by time-space prism constraints, and second, the alternative
37 paths themselves experience greater congestion as individuals are diverted by DTALite. In other
38 words, it appears that travelers are being switched to alternative paths even when the path will
39 eventually prove to be detrimental (as more and more travelers switch to the alternative path). To
40 address this issue, multiple iterations internal to DTALite need to be executed so that travelers are
41 diverted to alternative paths in a more optimal fashion. In this exercise, multiple iterations of
42 DTALite were not performed, resulting in a diversion pattern that was suboptimal.

43 This illustrative demonstration shows that the SimTRAVEL framework is able to capture
44 dynamics of activity-travel choices and network attributes and reflect the impacts of real-time
45 traveler information and dynamic mobility management strategies.

1
2 **TABLE 1 Results of Illustrative Demonstration of SimTRAVEL Integrated Modeling Framework**

Travel Characteristic	Baseline - No disruption	Scenario 1: Disruption	Scenario 2: Disruption		Scenario 3: Disruption	
		100% No Information	~50% No Information	~50% Pre-trip Information	~50% No Information	~50% Pre-trip + Enroute Information
Total trips	115683	115625	59216	56393	59060	56404
Total number of persons	24853	24853	12729	12124	12729	12124
Trip rate	4.655	4.652	4.652	4.651	4.640	4.652
Total travel time	1071410	1079195	553535	523511	552639	525363
Total travel distance	952196	959232	491991	464132	491308	466323
Average trip duration (min)	9.26	9.33	9.35	9.28	9.36	9.31
Average trip length (mile)	8.23	8.30	8.31	8.23	8.32	8.27
During time interval of disruption						
Total travel time	232011	236504	204531	202808	205787	203622
Total travel distance	205343	209824	181202	179587	182556	180569
Average trip duration (min)	9.26	9.40	9.33	9.30	9.37	9.34
Average trip length (mile)	8.19	8.34	8.26	8.23	8.31	8.28

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5. CONCLUSIONS

The advent of the information era has ushered in a new suite of dynamic mobility management strategies for proactively managing travel demand, freight and passenger travel choices, and network performance. The suite of strategies included under the Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) umbrella include measures that affect both travel demand choices as well as network attributes. As the profession seeks to increasingly erase the line that divides planning and operations through the deployment of proactive dynamic mobility management strategies, there is a growing need for integrated model systems that are capable of adequately reflecting behavioral dynamics and network dynamics, and the continuous interaction that exists between them.

This paper presents various levels of a dynamic integrated modeling framework where an activity-based travel microsimulation model is tightly coupled with a dynamic traffic assignment model. In the proposed framework, the two model components are able to communicate with one another along the continuous time axis so that trips or tours generated by the activity-based model are routed and simulated on the network as they happen, and activity-travel demand choices made by travelers recognize actual experienced network conditions as travelers go about their daily lives. Through such a tight coupling, it is possible for the framework to simulate the impacts of real-time information provision and operational strategies aimed at influencing traveler behavior and optimizing network performance. Various levels of the integrated modeling framework, referred to as SimTRAVEL, are described in detail. The increasingly detailed and capable levels of the framework accommodate scenarios where a portion of the travelers are equipped with pre-trip information or enroute travel information (or both) about prevailing network conditions at all times.

The efficacy of the integrated model system is demonstrated through an illustrative case study of the small Sioux Falls network, albeit with a sizeable population to realize network congestion. It is found that the model is capable of simulating network performance under alternative information scenarios and provides results that are consistent with expectations with improvements in performance seen in the information provision scenarios. The scenario where travelers had both pre-trip and enroute information showed that they actually experienced a degradation in performance (travel time and trip length) compared to the scenario where they had only pre-trip information. It appears that travelers are being diverted to longer alternative paths in the enroute information scenario, resulting in congestion on the alternative paths; this calls for the execution of route switching patterns in the network model such that diversion is done in a more user optimal fashion. This would require that the dynamic traffic assignment model be run through multiple iterations until an equilibrium (in terms of route switching) is achieved.

There is much work that remains to be done. The efficacy of running large scale integrated model systems for large networks is yet to be demonstrated. When integrated model systems are applied in the context of emerging travel demand management and technology-based scenarios, they generally provide predictions that are consistent with the patterns of behavior found in the survey data sets that informed the model specifications to begin with. While this is reasonable as a point of departure, there is still a severe paucity of information on how individuals actually respond to dynamic mobility management strategies when implemented in the field. The predictions from SimTRAVEL or any integrated transport model system need to be validated against real-world data before they can be applied for “planning for operations”. In addition, additional references such as the TCRP Report 95 Collection (TCRP, 2016) could provide data

1 about traveler response to system changes that can be used to validate predictions from novel
2 integrated model systems such as that presented in this paper.

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