similar to ALBATROSS (Arentze and Timmermans 2000), TASHA (Miller et al 2003), FAMOS (Pendyala et al. 2005). The demand behaviors in POLARIS, however, are focused on modeling include time-dependent activity generation, dynamic activity attribute planning and re-planning, and an activity scheduling process which resolves schedule conflicts and maintains a consistent daily schedule. The demand components are also responsive to network and traffic management events, which can result in agent re-planning. The demand components implemented in the POLARIS demonstration model derive from previous work in modeling activity-planning and scheduling behaviors found in the development of the ADAPTS (Agent-based Dynamic Activity Planning and Travel Scheduling) model (Auld and Mohammadian 2009). The demand model is an activity-based computational process model, which simulates the underlying activity and travel planning and scheduling processes (Auld and Mohammadian 2009). Similar to the SIMTRAVEL framework (Pendyala et al 2012), the model continuously integrates with traffic simulation. In other words the generation, planning and scheduling of activities occurs in continuous time and are co-simulated with the time-dependent traffic state.

3.1.2. Traveler Information and Decision Making

Traveler decision making is represented in POLARIS as a set of route choice and route re-planning behaviors. The route choice model describes traveler agents' dynamic route choice decisions with response to pre-trip and en-route traffic information. All travelers are assumed to be able to access prevailing traffic information prior to departure. Equipped travelers can access real-time traffic information during their trip through their equipped devices with navigation services using real-time traffic information. Unequipped travelers can access real-time traffic information disseminated from a TMC through ATIS dissemination infrastructures such as VMS and Radio to respond to both recurrent and non-recurrent traffic congestions. A bounded rationality en-route switching model (Mahmassani and Stephan, 1988; Jayakrishnan et al. 1994) is used to realistically address the en-route switching behavior of traveler agents. This route choice modeling framework also incorporates traveler agents' dynamic route choice decisions with response to experienced traffic by comparing experienced route travel time to the expected travel time as each network node is traversed (i.e. if the current route is performing poorly the bounded rationality switching model is triggered), and by implementing a look-ahead function in which the real-time travel time for the next link is evaluated. This allows traveler routes to evolve and respond to congestion even in the absence of ATIS. Route switching is also triggered through interaction with VMS or radio by comparing messages against the links in the current trip, and evaluating the travel route incorporating the message information. In the route choice model for each traveler agent, we implement a weighted A-Star shortest path algorithm. This implementation allows the parallelization of route calculations by each individual, and enables heterogeneous route cost functions to be utilized.

3.1.3. Traffic Simulation

The traffic simulation model involves solving a set of partial differential equations for the Newell's Simplified Kinematic Waves Traffic Flow model (Newell, 1993), which is a link-based solution method and has been recently recognized as an efficient and effective method for large-scale networks (Zhou et. al, 2012) and dynamic traffic assignment formulations (Zhang et al., 2013). A notable implementation of this model is DTALite (2012). The traffic simulation model includes a set of agents for intersections, links, and traffic controls. Given as input a set of travelers with route decisions and the traffic operation and control strategies in the network, the network simulation model agent simulates traffic operations and controls to provide capacities and driving rules on links and turn movements at intersections. With these capacity and driving rule constraints, link and intersection agents simulate the traffic flows using cumulative departures and arrivals as decision variables based on the Newell's Simplified model, which then determines the network performance for the route choice model, the demand model, and the ITS model in the integrated framework. The traffic simulation model produces a set of individual vehicle trajectories, including each link traversed, the average travel speed, and stop time at each intersection.

3.1.4. ITS Infrastructure and Traffic Management Simulation

Traffic management is simulated in POLARIS through the Event Manager, ITS Infrastructure and Traffic Manager agents. The Event Manager provides information about network events, such as accidents, weather conditions, special events, etc. The ITS Infrastructure agents include simulations of various sensors and technologies such as VMS, VSS, advisory radio, etc. along with a Sensor Model that imitates sensor readings by adding noise to the ground truth speed data calculated in the Traffic Simulation Model. The locations and sensor types are specified in the input data that is stored in ITS Infrastructure object. The job of the Traffic Manager agent is to infer new network events (congestion, delays, etc.) and make decisions based on the inferred events, current network state as well as events provided by the Event Manager (model inputs). An automated Traffic Management agent models the response to the observed network events, by controlling the state of the ITS Infrastructure. The goal of the automated TMC agent is to monitor the status of the transportation network (speed, travel times, etc.) as well as network-related events (weather, incidents, etc.) and decide on a response that would allow to mitigate unusual congestion level on the network.

3.2. Vehicle Energy Use Modeling with Autonomie

Energy consumption is predicted using Autonomie vehicle models. Developed at Argonne National Laboratory, Autonomie (Rousseau et al 2010) is a modeling environment for vehicle powertrains that has a focus on energy consumption and performance. It allows a user to quickly build a powertrain model from individual configuration files, plant models, and controllers and to simulate it in a broad range of predefined processes (e.g., standard drive cycles). Autonomie includes dozens of ready-to-run advanced powertrain models for hybrids, plug-in hybrids, electric vehicles, fuel cell vehicles, etc. Many component and vehicle models have been validated using test data from Argonne's Advance Powertrain Research Facility (APRF). Typical use cases involve running one or several vehicles on predefined deterministic drive cycles (such as the U.S. Environmental Protection Agency's urban drive cycles). The POLARIS travel demand model, however, provides an unlimited number of stochastic speed profiles for a given itinerary. By running a fleet of representative vehicles on a large number of stochastic speed profiles, we can analyze energy consumption or other operations on a broad range of trips, for evaluating the energy impact of various policies of forecast scenarios.

3.3. Markov-Chain Monte-Carlo Process for Generating Vehicle Speed Profiles

Second-by-second speed profiles required for estimating vehicle energy use by Autonomie. A process was needed to convert the meso-level vehicle trajectories generated by POLARIS. The POLARIS simulator generates vehicle starts and stops on each link, along with average experienced travel speed, stop time at intersections and queue length at stopping. These inputs align with previous research on estimating detailed speed profiles from link-by-link profiles using NOKIA/HERE ADAS-RP data (Karbowski et al. 2014). The fundamental aspect of the approach is that vehicle speed can be modeled as a Markov chain: the next state only depends on the current state, and not on the sequence of past events. This translates into P_{ij}, the time-independent probability of the random variable being in state j at time $t+1$ knowing it is in state i at time t:

$$P_{ij} = P(X(t+1) = j | X(t) = i)$$

To model vehicle speed, the random variable can simply be the vehicle speed, or the tuple (speed, acceleration), which we use in our model. Given that acceleration at time t also depends on the speed at time $t-1$, the vehicle speed at a given time step depends of the state at the previous two time steps. The collection of transition probabilities in matrix form is the Transition Probability Matrix (TPM). The TPM is built from real-world observations, i.e., by counting all of the state transitions in the real-world data. The data was obtained from the Chicago Metropolitan Agency for Planning as part of a comprehensive travel survey for the greater Chicago area (CMAP n.d.). GPS loggers were provided to a subset of the 267 surveyed households that participated in the data collection, mostly for more than week. Close to 10,000 vehicle trips were recorded, for a total of 6 million data points. The data was filtered and then used to generate the speed TPM.

Speed profiles are generated as follows. Starting from an initial state, a random number is generated and the following state is computed using the TPM; this is continued until a stopping condition is reached (e.g., when the speed reaches zero after being strictly positive). Though our model is an accurate representation of real-world driving, it cannot be linked to a particular itinerary. Fortunately, however, there is also a deterministic aspect to speed prediction, in that there are stops, speed limits, and average speeds on all links of the trips. There will be of course stochastic variations of speed around those determined conditions. To combine those two aspects, we created an algorithm that consists of generating stochastic speed profiles until a result with characteristics “close enough” to the deterministic prediction emerges.

In a first loop, the Markov chain generation is stopped when the current distance is higher than, or close to the target distance and the speed is close to the target final speed (or equal to it if a stop is requested at the end of the segment). Once the candidate stochastic speed profile is generated, we check whether it satisfies a stopping criterion that depends on the target trip. If it does not, the algorithm computes a new vehicle speed profile.

The stopping criterion considers average speed, number of stops, excessive speed, and distance. It is given by the Performance Value (PV):

$$PV = w_1 \frac{|V_{avg} - V_{tgt}|}{V_{tgt}} + w_2 \frac{N_{stop}}{d} + w_3 \sum_{t=T_1 \dots T_2} \max\left((V(t) - V_{lim}), 0\right)^2 + w_4 \frac{|d - d_{tgt}|}{d_{tgt}}$$

where

- (w_1, w_2, w_3, w_4) are constants;
- V_{avg}, N_{stop}, d and V are explanatory variables for the generated speed profile: V_{avg} is the average speed, N_{stop} is the number of stops, d is the distance, and $V(t)$ is the speed at time t; and
- V_{tgt}, V_{lim}, and d_{tgt} are the constraints: V_{tgt} is the target average speed, $V_{lim}$is the speed limit, and d_{tgt} is the desired distance of the section.

This PV measures the capability of the generated speed profile to fit some constraints corresponding to the target trip: the average speed must be close to the experienced speed, the vehicle should avoid stopping for no reason (although we still allow unplanned stops), speed should not be higher than the speed limit, and the distance of the trip must be very close to the target distance. Once the loop is exited and there is a speed profile that matches the stopping criteria, the synthesized speed profile does not match the target distance exactly. We use an algorithm that “stretches” or “shrinks” the vehicle speed profile accordingly, mainly by adding or removing bits of constant speed segments.

4. CASE STUDY ANALYSIS

4.1. Chicago CBD ATIS Case Study

In order to demonstrate the energy use evaluation process, a case study was conducted for the Chicago metropolitan area. In this case study the model was used to analyze the energy impacts of a simple ATIS deployment. In this section we present the setup of the case study and the results that have been obtained. The case study is extracted from a larger regional model developed for the Chicago area, which includes 10 million individuals making 27 million trips. The various component models of the POLARIS ABM have been estimated using Chicago travel survey data, and initial calibration has been performed for each model component against observed data. Details of this validation of individual activity-based model components can be found in Auld and Mohammadian (2013). The study area has around 5,000 links, 3,000 intersections, 6,500 activity locations, and 400,000 travelers. The simulated ATIS infrastructure includes 20 VMS (Variable Message Sign) located along the expressways throughout the area. Three scenarios were studied, including a normal day scenario, a scenario with incidents but with the ATIS infrastructure disabled, and a scenario with incidents and the ATIS infrastructure enabled. The incidents in the case study include ten accident events which have been extracted from a database of historical incidents in the area for a representative day in June 2013. The CBD network, VMS and incident locations are shown in Figure 1. The impact of the accident events to the network traffic was modeled by the reduction of link capacity and free-flow speed per the rules introduced in the FHWA guidebook (FHWA 2013). The ATIS responses include notifications about accident events displayed on VMS signs which drivers are able to observe to trigger re-routing.

(a) (b)

Figure 1. (a) Vehicle Incident locations and times, and (b) Variable Message Sign locations

Finally, the fleet distribution used to estimate the energy consumption is shown in Table 1. During simulation in Autonomie, the vehicle types are randomly drawn from the distribution defined by market shares and assigned to individual trajectories. Autonomie, given the combination of vehicle type and second-by-second speed profile, is then able to estimate the energy consumption for a particular combination. The energy consumption distributions for each scenario can then be compared to evaluate impacts of ATIS.

Table 1. Vehicle Type Distribution

Vehicle Class	**Powertrain**	**Share (%)**
Compact	Conventional	27.0%
Midsize	Conventional	29.0%
Small SUV	Conventional	17.0%
Midsize SUV	Conventional	9.0%
Pickup	Conventional	15.0%
Compact	HEV	2.0%
Midsize	HEV	0.5%
Small SUV	HEV	0.3%
Midsize SUV	HEV	0.1%
Pickup	HEV	0.2%

4.2. Results

The three case studies have been analyzed using the combination of POLARIS and Autonomie. The models have been run in a deterministic mode, which allows a direct comparison for specific travelers between cases. This allows the benefits of ATIS to be evaluated at both the system-level and for affected travelers only. In the following results, the benefits are shown for affected travelers only, which are defined as travelers in the no-information (unmanaged) case who are directly impacted by the traffic incident – a total of about 21,000 individuals. The same set of travelers are then tracked in the ATIS deployment (managed) case, and changes in mobility and energy use are evaluated.

In terms of mobility, the deployment of ATIS assets for responding to traffic incidents has a clear benefit to the affected users as seen in Figure 2. The figure shows the total hours of delay experience by all affected travelers during each five-minute interval throughout the day, as well as the incident times for comparison purposes. The impact of the incidents on excess delay can clearly be seen as peaks in the figure, with the peaks being substantially lower in the managed case, indicating that the same travelers who are affected by the incident in the unmanaged case are finding better routes when informed by the ATIS. Overall experienced delay for informed travelers is reduced from 5,567 hours to 5,049 hours

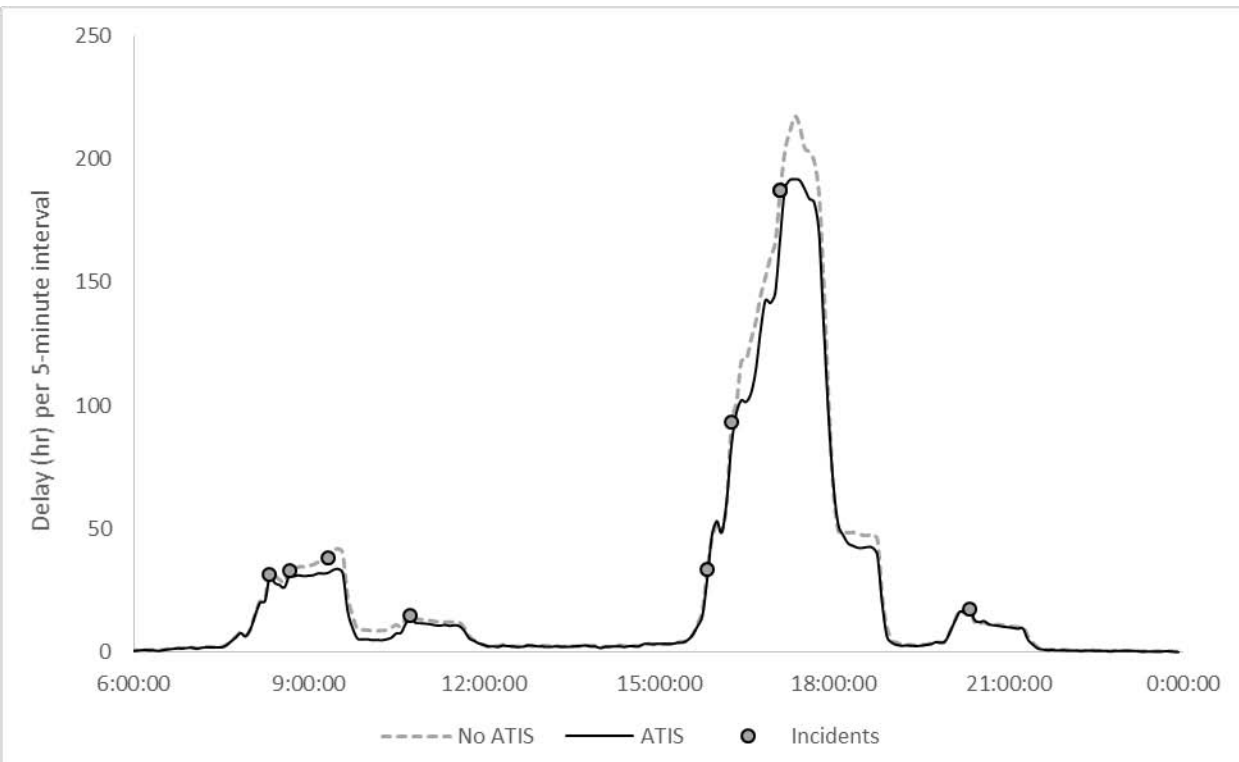

Figure 2. Vehicle Hours of Delay for Affected Travelers (per 5-minute interval)

Overall, the figure demonstrates that in the unmanaged (no-ATIS) case, affected travelers spend a substantial proportion of overall travel time (50.8%) moving at very low speed (<20% of free flow), due to being stuck in congestion with few alternate routes as expected. Alternatively, in the managed case (with-ATIS), travelers spend less of the overall travel time (48.3%) on highly congested links and more time traveler near free flow speed (22.4% vs. 20.9% for unmanaged case). This can also be seen in Table 2 which shows the hours and miles traveled, average speeds and experienced delay for the unmanaged and managed cases for affected travelers and for the system as a whole. The results show a statistically significant increase in average travel speed in the managed case of 4.5%, and a decrease in hours traveled of 6.3% and delay of 9.3%.

Table 2. Aggregate Travel Characteristics for Affected Travelers and All Travelers

	Affected travelers			All travelers		
	No ATIS	**ATIS**	**% change**	**No ATIS**	**ATIS**	**% change**
VHT	8,189	7,673	-6.3%*	198,892	198,287	-0.3%*
VMT	108,229	107,852	-0.3%	5,451,218	5,450,853	0.0%
Avg. speed (by time)	18.1	18.9	4.5%*	31.8	31.9	0.3%*
Delay	5,567	5,049	-9.3%*	67,010	66,383	-0.9%*

* *differences statistically significant at p=0.05*

The impacts shown above can also be seen at the overall system level, which is important as it is possible that improving the situation for informed travelers could be detrimental to the system as a whole, for example by pushing more travelers onto congested arterial streets when routing around incidents. However, the results in Table 2 show this to not be the case. In fact, there is minor, though significant, improvement at the system-wide level, with the delay reduced approximately 100 hours beyond the reduction for affected travelers alone, and average speed increasing from 31.8 to 31.9 mph, which affects the overall energy consumption, and no significant change in the miles traveled.

The primary purpose of the proposed modeling effort is on estimating the energy impacts of transportation policies and system investments (i.e. ATIS deployment in this case) as these policies interact with various vehicle technologies. Previous research has shown that there are complex interaction effects between transportation policies and vehicle powertrain technologies which can either multiply or inhibit the expected benefits from either in isolation, as in the case of heavy vehicle hybridization and managed lane deployment (Sokolov et al 2014). The results of the vehicle simulation using the generated speed profiles demonstrate this to an extent. The overall distribution of fuel consumption for affected travelers in each case is shown in Figure 3, where fuel consumption is measured in kilograms of gasoline. The results show that the deployment of ATIS to travelers does result in a fuel consumption savings of approximately 2.5% in terms of the overall weight of fuel used by affected travelers. There is a clear reduction in trips using more than 0.6 kg of fuel, which are shifted closer to the 0.2-0.4 kg range in the managed case. This is likely due to improved performance in long-distance, highway trips coming into the CBD, which subsequently route around the traffic incidents using local streets.

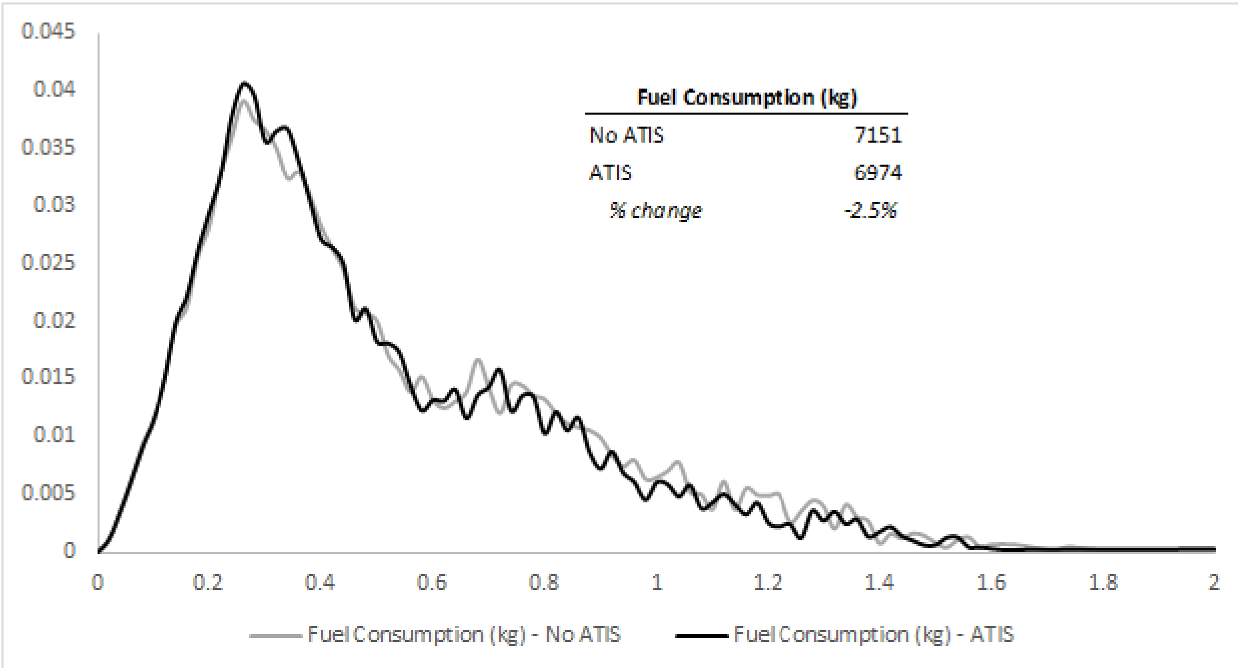

Figure 3. Plot of fuel consumption distribution shows managed case reduce energy use by 2.5% for affected travelers

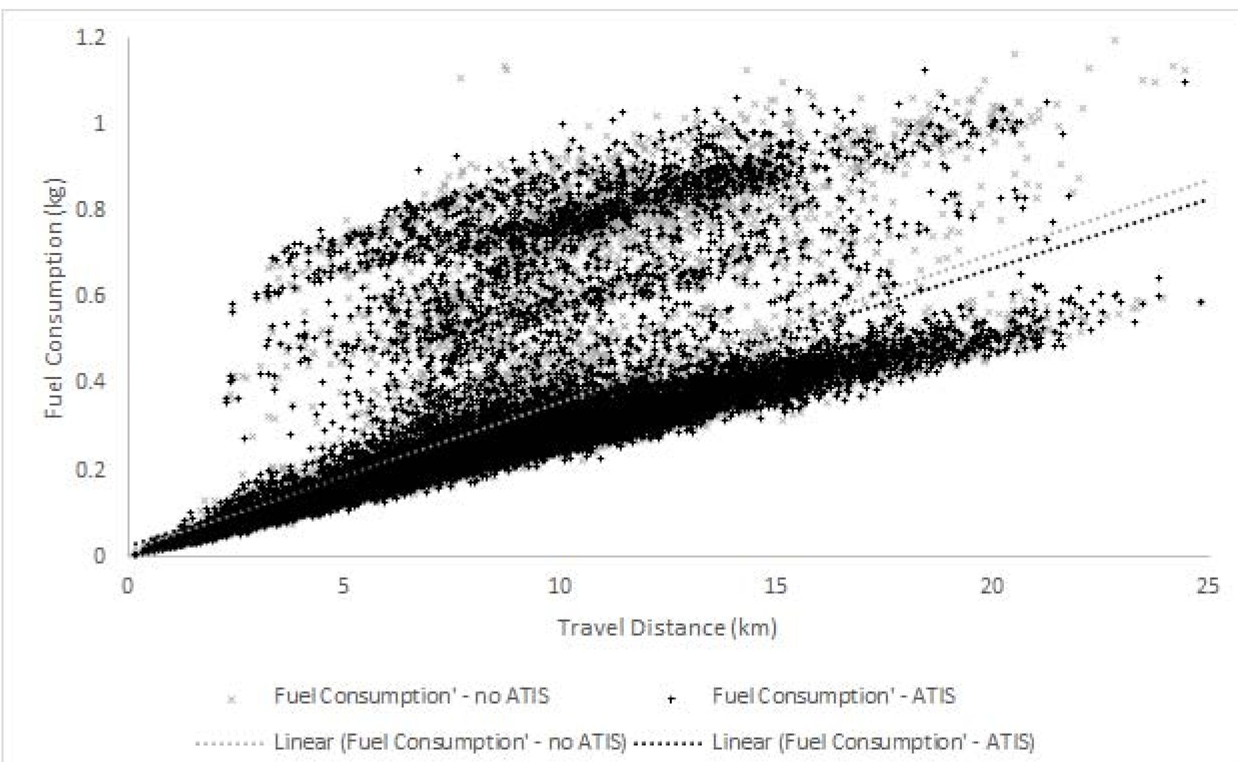

Figure 4. Fuel consumption by travel distance

This result can clearly be seen in Figure 4. There is very little difference in fuel consumption between the managed and unmanaged cases for short distance trips (0-5 km) as the local trips in the CBD largely avoid the affected highway segments. However, in the unmanaged case there is a large cluster of trips in the 5-15 km range which have very high fuel usage, in the 0.6-1.6 kg range, which are largely reduced, as previously observed. The trend lines in the figure clearly show the improvement in fuel consumption with increasing distance as expected. The variability in fuel consumption for a given distance is a result of the combination of various vehicle technologies as specified by the fleet mix and differing drive patterns (i.e. highway vs. arterial where variability due to traffic signals is introduced. However, it is clear that this variability is reduced in the managed case, where highly congested travel segments are mostly eliminated.

5. DISCUSSION AND CONCLUSIONS

This case study has demonstrated how multiple levels of model integration, i.e. connection between travel demand, traffic flow and network operations for POLARIS, and between POLARIS outputs and Autonomie, can be leveraged to assess the energy use impacts of transportation system policies and operations. The model process made use of a new methodology for extracting detailed second-by-second speed profiles from aggregated link performance measures which are generated by the POLARIS model. The speed profile generation process is guided by the constraints imposed by the POLARIS link performance measures, but is estimated using real-world travel data obtained from the Chicago GPS travel tracker survey. In other words, the speed profiles are synthesized statistically, but in such a way that the replicate observed driving cycles and behavior to an acceptable degree (Karbowski et al. 2014). The process stands in for detailed traffic flow microsimulation when such is either infeasible due to scale, data limitations, etc., or when such detail is unnecessary.

The ATIS deployment analyzed in this case was a fairly simplistic example, but a clear benefit was identified, both in terms of mobility and energy use. Users who are affected by the traffic incidents save approximately 500 hours of excess delay when they are informed of incidents via the ATIS system as compared to the case where they are not informed. Their average travel speed increases from 18.1 to 18.9 mph, primarily due to a reduction in time spent in highly congested links. The results in terms of energy usage are more mixed. While there was a reduction in overall fuel consumed of 2.5%, which is smaller than the travel time savings and speed increase. This is most likely due to increases in non-highway driving, stopping at intersections, and interfering with existing surface street traffic. This result, however, is clearly dependent on context, i.e. the mix of long-distance vs. local trips, the time of day, the location of the ATIS infrastructure, and the availability of suitable alternatives. The availability of such a wide range of complex and interacting effects indicates the importance of this type of integrated modeling when planning for such deployment scenarios.

The process demonstrated in this work is extensible to more complex scenarios, especially those pertaining to future connected and autonomous vehicle technologies and the intersection with such technologies with advanced vehicle powertrains (Sokolov et al 2014), which complicates the analysis even further. Future work in this area will include more detailed analysis of fleet characteristics and forecasting of fleet vehicle technology market penetration. The addition of individual level vehicle choice models, rather than assigning vehicle technologies randomly to trajectories, will add another dimension of interest to the work. Finally, comparisons of the speed profile disaggregation approach with both real world data on speed and energy use, as well as alternative traffic microsimulation approaches will be undertaken.

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