TUM ABM Symposium

UIC ENGINEERING
Civil, Materials, and Environmental Engineering

Argonne NATIONAL LABORATORY

Enhancing ADAPTS/POLARIS Agent-Based Transportation System Simulation Framework

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ADAPTS/POLARIS implements an agent-based activity-travel demand framework using variety of statistical/behavioral models

- **ADAPTS models dynamic activity-travel engagement**:
  - *Generation: deciding what needs to be done on a given day*
    - Activities are generated continuously on-the fly
    - Based on needs growth over time, household requirements, mandatory acts…
  - *Planning: determining the who/where/why/when/how of activity episodes*
    - Attribute choices made dynamically and updated throughout the simulation
    - Dependent on the order / priority in which activities are planned
  - *Scheduling: maintaining a consistent daily activity-travel plan*
    - Order in which activities are planned and executed is reflected
    - Activities (including travel, work, charging…) compete for time resources
    - Intra-person, intra-household, resource scheduling, all accounted for
  - *Execution: moving from planning to physical moves on the simulated network*
    - Continuous integration with multi-modal network model
    - An agent-based execution – persistent agents moving through networks based on their individual choices.

ADAPTS/POLARIS, initiated by UIC TransLab, has been further developed by Argonne National Lab to address key research questions

- Originally proposed:
  1. Flexible activity planning/scheduling
  2. Improve model integration / Enhance Interoperability among existing tools
  3. Model technology / ITS Systems for planning applications

Core Goals of the Effort:
- Modeling Standards and Protocols
- Open Source Modeling Environment
- Listen to the Transportation Community
- Common Modeling Language
- Maintain Flexibility and Modularity

- FTA funding to:
  1. Understand transit rider behavior and response to disruptions
  2. Develop system short-term forecasting tools from big data sources
  3. Simulation for transit planning and response and recovery to emergencies

Multi-modal
- Freight and logistics
- Ridesharing, car-sharing
- Enhanced bus service
- Bike-sharing
- Intermodal travel
- Modal energy use

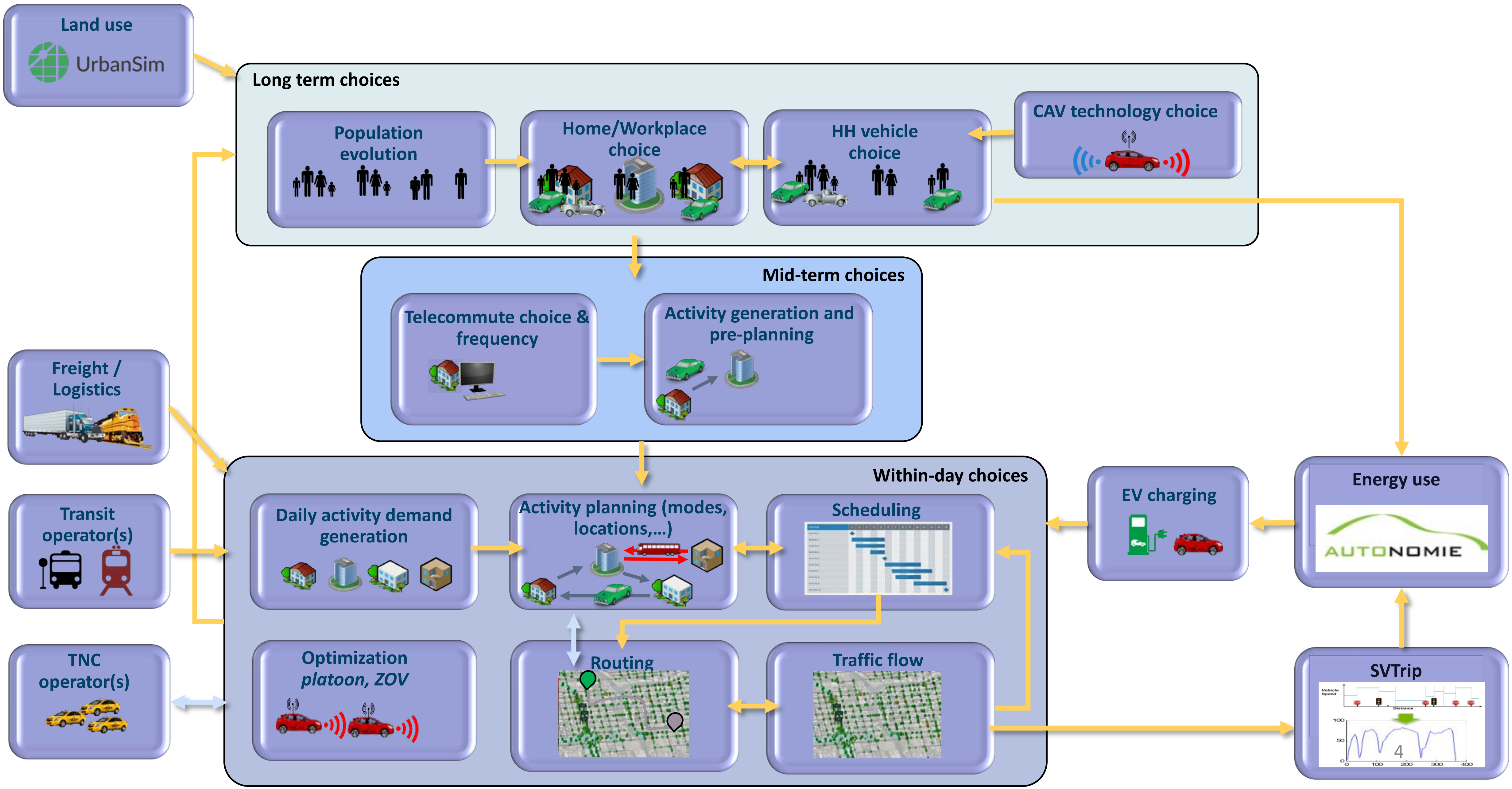
Connectivity and Automation
- Autonomous vehicles / fleets
- ACC / CACC
- Transit signal priority
- Eco-approach / departure
- Traveler information
- Impacts of level 3/4/5 automation

Urban Science
- Data collection from vehicles and infrastructure
- Supporting future growth plans
- Land use

Vehicles and Infrastructure
- Refueling infrastructure
- Traffic management center
- Connected signals
- Bike-share stations
- Bike and walk lanes

Decision science
- Understanding mode choice behavior
- Providing useful information to travelers
- Incentivizing energy efficiency
- Increasing ‘choice’ ridership
- CAV impact on behavior

Transportation Systems Simulator Design…



POLARIS Workflow

- **Key modeling features:**
  - Full-featured **activity-based** model
  - **Integrated** demand, network assignment and traffic flow
  - Includes **freight** shipments and local deliveries
  - High-fidelity **vehicle energy** consumption
  - **EV charging** and **grid** integration
  - Connection to **UrbanSIM** land use
  - Traveler behavior impacts of **VOTT** across many choices

Computational performance:

- Fully **agent-based**
- Integration with external **optimization** solvers (CPLEX, Gurobi, GLPK)
- High-performance **C++ codebase**
- Large-scale models with **100% of agents**
- **4-6 hr runtime** for up to 10 million agents
- Cross-platform implementation can run on Linux **HPC** clusters

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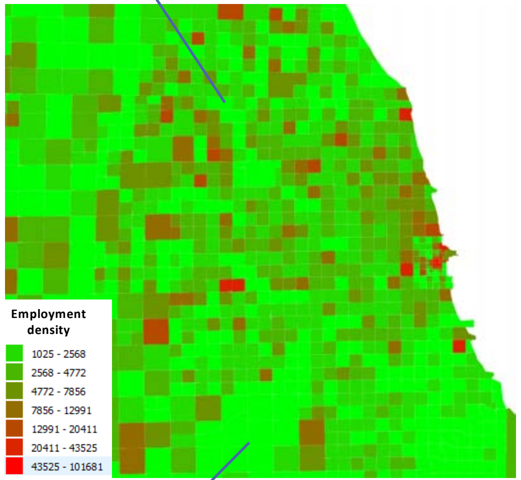
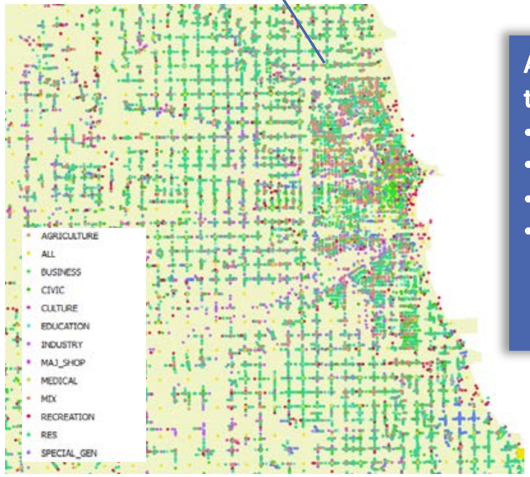
Inputs for Population, Vehicles, and Land Use

Traffic analysis zones:
MPOs (base and forecast):
- Population
- Employment by category
- Housing
- Land use by type (civic, residential, business,…)
- Network skims
- Special generators

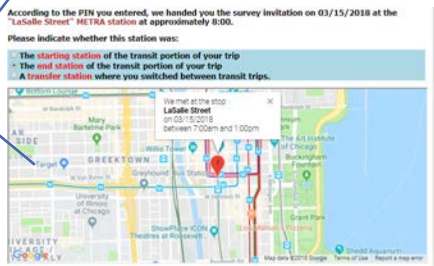


Location / Parcel data
- Land use category
- Size / sq. footage
- Use restrictions
- Parking & access
- Forecasts



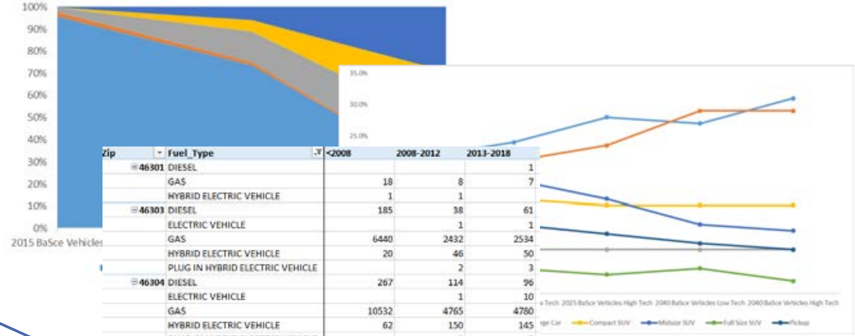
HH Surveys (GPS and diary based)
- Activity engagement
- Routing
- Travel and activity times
- Travel party
- Mode choice
- HH demographics
- Commute patterns

Advanced behavior surveys: Vehicle purchase, travel attitudes, experiences, …
- Stated preference for travel decisions
- New technology purchases
- Experiences / familiarity with new tech
- Travel attitudes and personality factors



Census data (Summary file, ACS…):
- Marginal population distributions
- Population microdata
- Economic census
- Forecasts (UrbanSim)

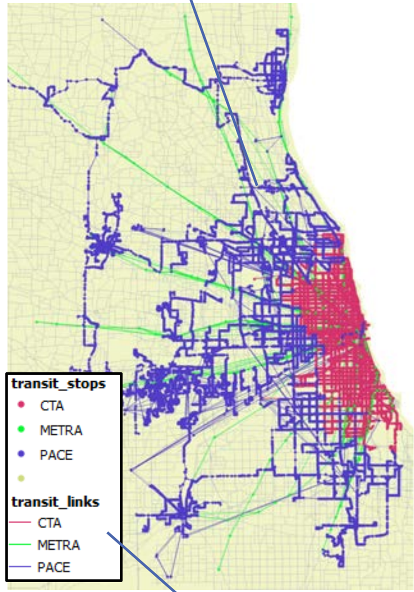
Vehicle distributions
- Segment by powertrain by technology
- Detailed location data (zip code, TAZ,…)
- Advanced technology adoption
- Forecasts by detailed demographics



Zip	Fuel_Type	<2008	2008-2012	2013-2018
46301	DIESEL			1
	GAS	18	8	7
	HYBRID ELECTRIC VEHICLE	1	1	
46303	DIESEL	185	38	61
	ELECTRIC VEHICLE		1	1
	GAS	6440	2432	2534
	HYBRID ELECTRIC VEHICLE	20	46	50
	PLUG IN HYBRID ELECTRIC VEHICLE		2	3
46304	DIESEL	267	114	96
	ELECTRIC VEHICLE		1	10
	GAS	10532	4765	4780
	HYBRID ELECTRIC VEHICLE	62	150	145
	PLUG IN HYBRID ELECTRIC VEHICLE		3	8
46307	DIESEL	517	188	245
	ELECTRIC VEHICLE	6	3	11
	GAS	23808	12063	12846
	HYBRID ELECTRIC VEHICLE	103	262	282
	PLUG IN HYBRID ELECTRIC VEHICLE		7	28
46311	DIESEL	142	56	65
	ELECTRIC VEHICLE		1	3
	GAS	7684	4085	4502
	HYBRID ELECTRIC VEHICLE	39	102	99
	PLUG IN HYBRID ELECTRIC VEHICLE		1	7

Detailed Inputs for Network and Mode Choice Modeling

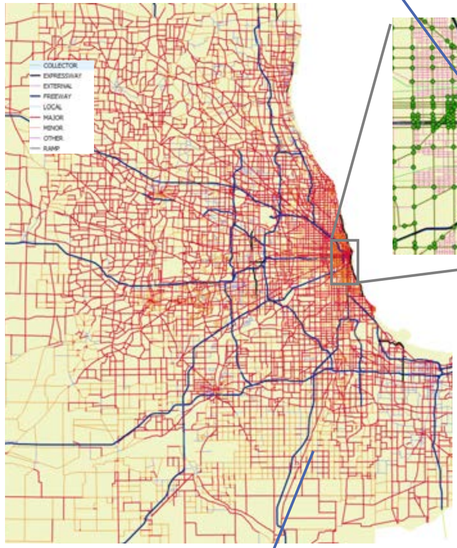
Transit network data:
GTFS (static & real time), agencies:
- Services
- Stop locations
- Schedule and fares
- Vehicles



Transit Data: Agencies, MPO
- Automated passenger counts
- Fare card data
- AVL data
- On-board surveys

Stop	AVG ON	AVG OFF	AVG ACTIVITY
Rosemont CTA Station	3,832.6	2,793.9	6,626.5
95th/Dan Ryan CTA Station	3,446.7	2,818.8	6,265.5
Forest Park Transit Center/CTA Blue Line	3,136.7	2,516.6	5,653.2
Harvey Transportation Center	2,698.0	2,534.3	5,232.2
Midway CTA Station	1,824.7	1,516.0	3,340.7
Elgin Terminal/Elgin Transportation Cente	1,400.1	969.7	2,369.8
Jefferson Park CTA Station	1,576.4	1,222.8	2,799.2

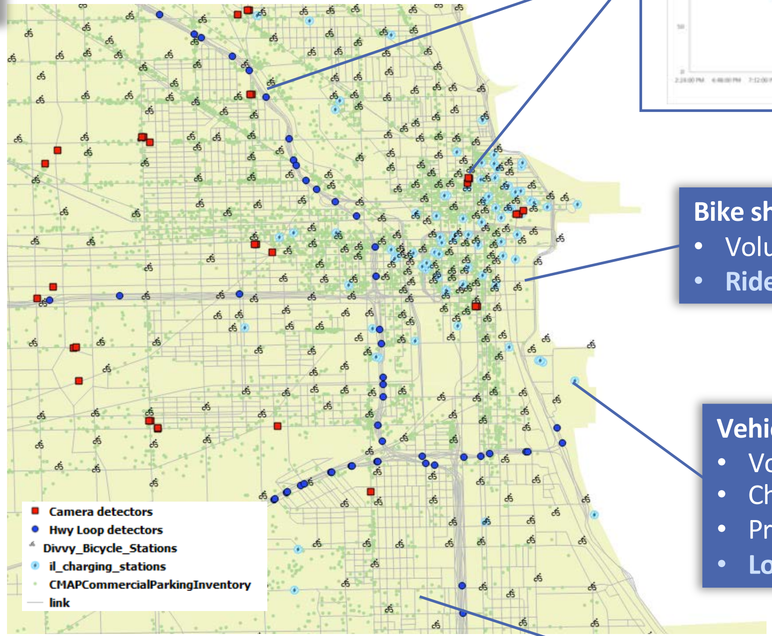
Traffic controls:
DOTs, MPOs
- Signal (timing, phasing, actuation, coordination)
- Stop/yield signs
- Variable Message signs
- Variable lanes
- Tolls
- Pedestrian movements



Road network information: MPOs, DOT, Open sources
- Facility type
- Lanes, speeds, capacities
- Pocket lane locations
- Connectivity
- Use restrictions
- Bike / walk facilities

Taxi and TNC data
- Pickup / drop-off
- Fares & surge pricing
- Wait times
- Vehicles
- Driver surveys
- Passenger info

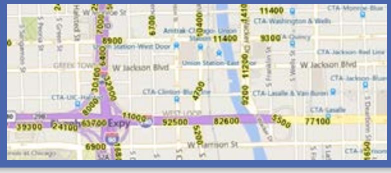
Red light / speed cameras
Hwy / arterial detectors



Bike share:
- Volume
- **Ridership**

Vehicle charging
- Volume / capacity
- Charging events
- Profile
- **Location (EVI-PRO)**

Traffic counts: State DOT, traffic studies, permanent counters, etc.



Parking inventory
- Type and ownership
- **Fees**
- **Volume and capacity**

Behavior Models Example: Activity Time-of-day and Duration Choice Models Allow Travelers to Respond to Changing Traffic Conditions and Opportunities

- Model jointly estimated for start time and duration
- Significant copula parameters: joint model valid
- Implemented as a parameterized choice
- Sensitive to key scenario parameters – i.e. **travel times** and **variability**, activity pressure, etc.

↑ Travel time ↓ TOD choice

↑ Variability ↓ TOD choice for morning and afternoon

↑ morning ttime ↓ TOD choice for afternoon and morning off-peak

↑ Scheduled afternoon activities
↓ Afternoon TOD choice

↑ Scheduled activities in afternoon
↑ Morning TOD choice

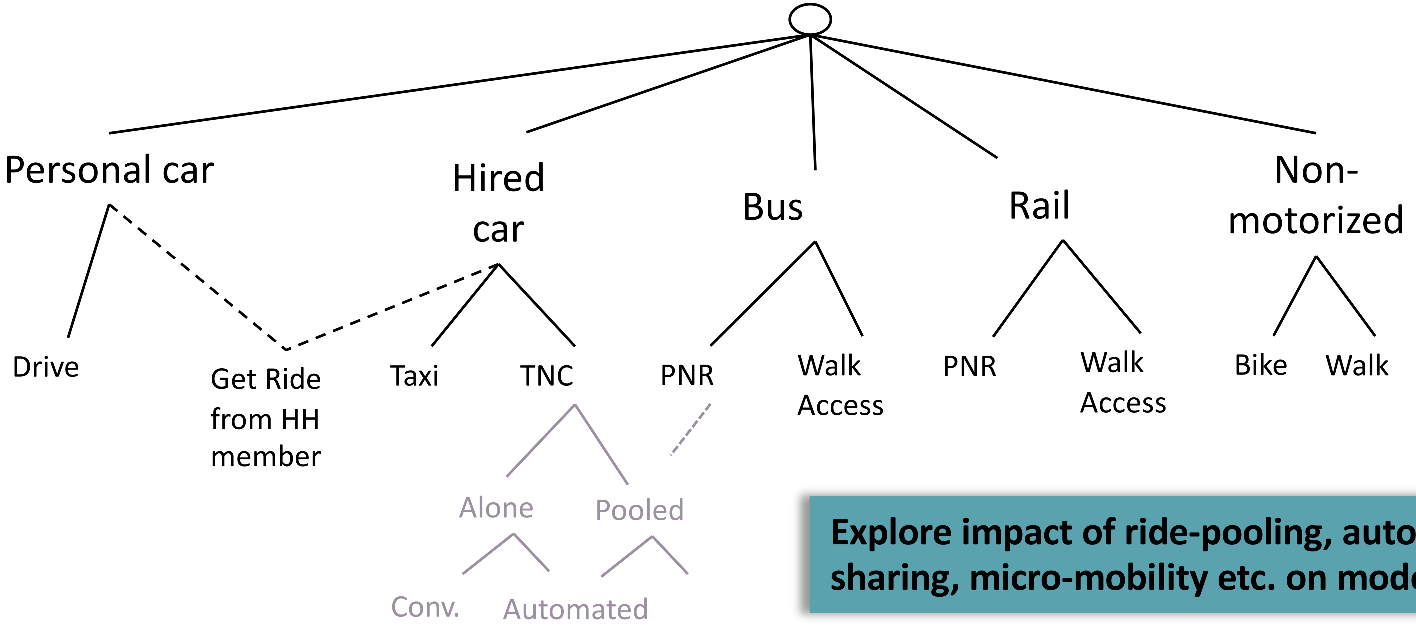
↑ Afternoon variability
↑ All other TOD choice

Start time Alternative	Direct Elasticity			Cross Alternatives	Cross Elasticity		
	Occupancy	TT	TTV		Occupancy	TT	TTV
Morning peak-hour	-	-9.56	-	Morning off-peak	-	-0.17	-
				Afternoon off-peak	-	0.15	-
				Afternoon peak hour	-	-1.82	
				Evening	-	0.35	-
				Night time	-	0.34	-
Morning off-peak	-	-3.63	-1.02	Morning peak hour	-	1.87	0.14
				Afternoon off-peak	-	1.98	0.14
				Afternoon peak hour	-	1.74	0.14
				Evening	-	2.04	0.13
				Night time	-	2.03	0.13
Afternoon off-peak	-2.17	-8.99	-	Morning peak hour	1.01	-0.05	-
				Morning off-peak	0.72	0.24	-
				Afternoon peak hour	0.25	-0.27	-
				Evening	0.08	0.53	-
				Night time	0.11	0.53	-
Afternoon peak-hour	-1.03	-6.59	-1.26	Morning peak hour	0.71	1.08	0.15
				Morning off-peak	0.07	0.45	0.22
				Afternoon off-peak	0.69	0.54	0.22
				Evening	0.23	0.10	0.23
				Night time	0.01	-0.22	0.14
Evening	-	-3.78	-	Morning peak hour	-	1.16	-
				Morning off-peak	-	0.27	-
				Afternoon off-peak	-	-0.38	-
				Afternoon peak hour	-	0.32	-
				Night time	-	-0.06	-

Flexible, endogenous timing of all activities in the model, that is responsive to network conditions, captures realistic choice behavior…

Behavioral Models Example: Mode Choice Specification to Capture Multi-modal Decisions and New Mobility Options

- Updated ADAPTS/POLARIS mode choice model to include TNC:
  - Leveraged benefits of large household travel survey
  - Combined with smaller, choice-based sample
- Identified and addressed differences between survey datasets
- Constructed full multi-modal options using POLARIS router
- **(Cross)-Nested choice structure allows significant flexibility in modal substitution patterns**



- Key model results:
  Waiting more burdensome than traveling
  Taxi has high value, followed by drive
  Rail has low value due to significant in-vehicle multi-tasking

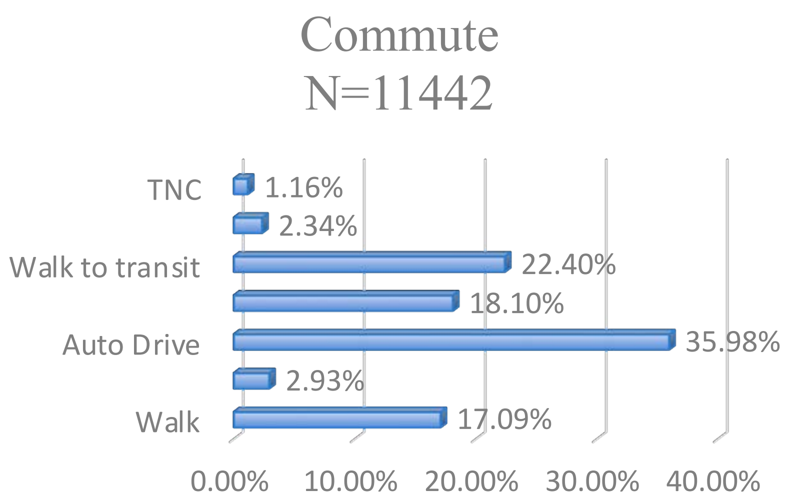
Mode	travel component	VOT by HH Income ($) 5000	30000	75000	120000
Drive	time in motion	$15.36	$18.59	$20.24	$21.09
Drive	parking "vot"	$66.66	$80.68	$87.85	$91.53
Taxi	time in motion	$59.37	$71.86	$78.25	$81.53
RailDrv	IVTT + Ac/Eg	$3.27	$3.96	$4.31	$4.49
RailDrv	Waiting time	$5.04	$6.10	$6.64	$6.92
RailWlk	IVTT + Ac/Eg	$2.53	$3.06	$3.33	$3.47
RailWlk	Waiting time	$3.99	$4.83	$5.26	$5.48
XitDrv	total time (IV,Ac/Eg,Wait)	$1.70	$2.06	$2.25	$2.34
XitWlk	IVTT + Ac/Eg	$11.04	$13.36	$14.55	$15.16
XitWlk	Waiting time	$9.16	$11.08	$12.07	$12.57

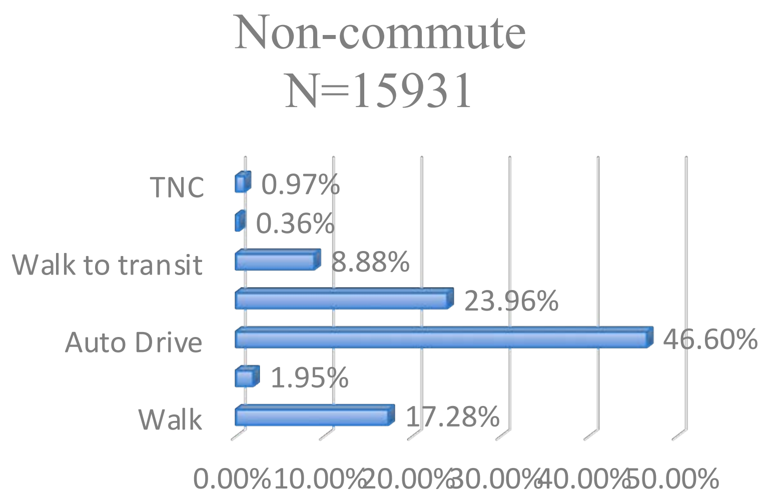
TNC / auto access to transit

Explore impact of ride-pooling, automation, vehicle sharing, micro-mobility etc. on mode choice

Data

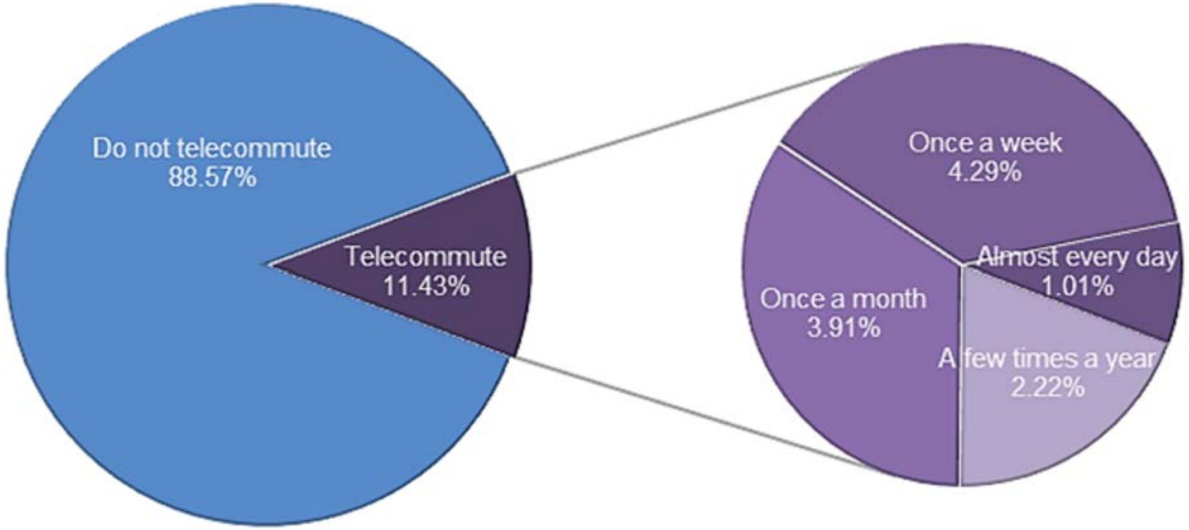
- Chicago Metropolitan Agency for Planning (CMAP) Travel Tracker Survey conducted on 2018-19.
  - Including approximately 14,000 households' activity and travel records for 24 hours.
- Google Maps Direction API including travel time for Transit, Walk and Bike modes
- POLARIS simulated data including travel time and costs for Auto and park & ride modes.





Telecommuting Model Development

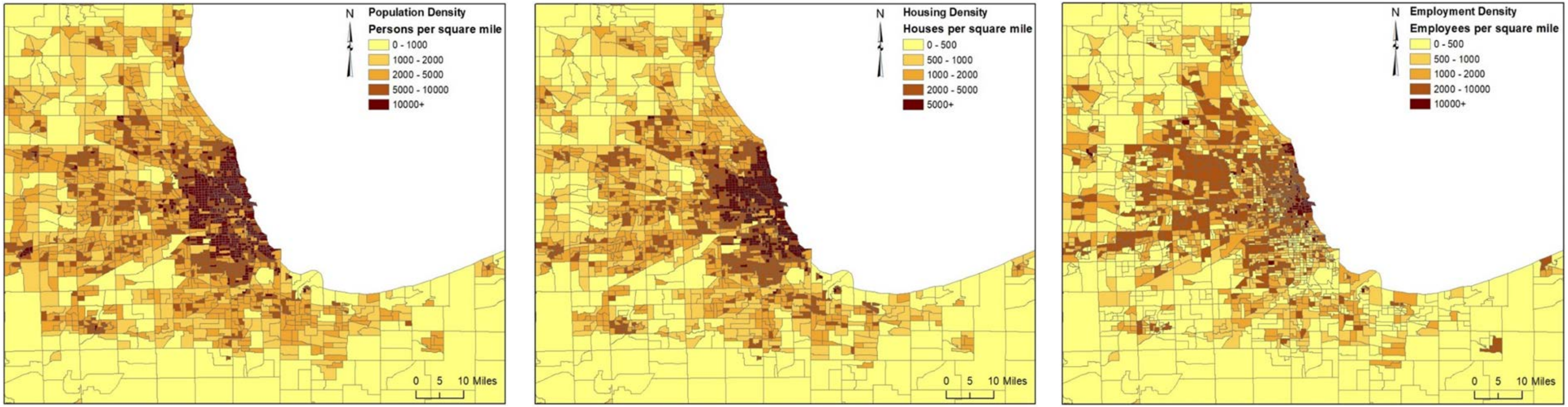
- Data source
  - Travel Tracker Survey conducted by the Chicago Metropolitan Agency for Planning (CMAP)
  - Includes complete travel information of 10,500 households who were asked to report their travel diary for one or two randomly assigned days
  - Information collected
    - Socio demographics (e.g., age, gender, income, etc.)
    - Household features (e.g., number of vehicles, residential location, etc.)
    - Trip-related characteristics (mode, time-of-day, trip duration, etc.)
    - Activity-related features (e.g., activity type and duration, location, etc.)



Distribution of telecommuting frequency in the sample

Telecommuting Model Development

- A set of land-use and built-environment measures is calculated at the level of census tracts based on the available information about individuals' residential and work locations.
- A Zero-inflated hierarchical ordered probit model with correlated errors estimated telecommuting adoption and frequency.



Distribution of derived built-environment factors in Chicago Metropolitan Area

Telecommuting Model Estimation

- Telecommuting adoption and frequency model suggests
  - occupation type also plays an important role in both participation and frequency level.
  - education and income level significantly affect both telecommuting participation and the frequency level.
  - flexibility of work schedule increases the probability of both telecommuting participation and frequency.
  - importance of trip-related and land-use variables on telecommuting choice:
    - travel time and distance to workplace
    - population density
    - employment density

Estimation Results of zero-inflated hierarchical ordered probit model with correlated errors.

Variables	Parameter	t-Stat
Participation equation (Potential of Telecommuting Model):		
Constant	-0.98^{***}	−5.33
Gender: male	0.26^{***}	3.01
Income: low	-0.64^{***}	−5.64
Education: low	-0.67^{***}	−6.03
Trip distance: high	0.22^{*}	1.75
HH worker	0.18^{***}	3.04
Work flexibility	0.89^{***}	6.81
Occupation: transportation	-0.24^{*}	−1.65
Occupation: management	-0.61^{*}	−1.82
Occupation: health	-0.38^{***}	−3.30
Employment density: high	0.34^{***}	3.00
Population density	-0.07^{***}	−3.46
Activity equation (Level of Telecommuting Model):		
Constant	-0.62^{***}	−3.01
Income: med	0.49^{***}	6.03
Age: 35–55	0.20^{***}	3.31
Education: graduate	0.31^{***}	4.48
Trip duration	0.23^{***}	3.06
HH vehicle	0.14^{***}	4.15
Work flexibility	0.82^{***}	8.49
Occupation: government	-0.23^{**}	−2.19
Occupation: communication	0.31^{**}	2.27
Occupation: manufacturing	-0.16^{*}	−1.65
Employment density: low	-0.22^{***}	−3.10
Threshold variables:		
Work duration	0.03^{***}	2.89
Vehicle availability	-0.11^{*}	−1.72
HH vehicle: high	0.26^{***}	3.22
Threshold constants:		
θ_1	-1.60^{***}	−10.86
θ_2	-0.47^{***}	−4.08
θ_3	0.43^{***}	4.64
Correlation coefficient:		
ρ	0.28^{*}	1.91
log-likelihood at convergence	−3206.05	

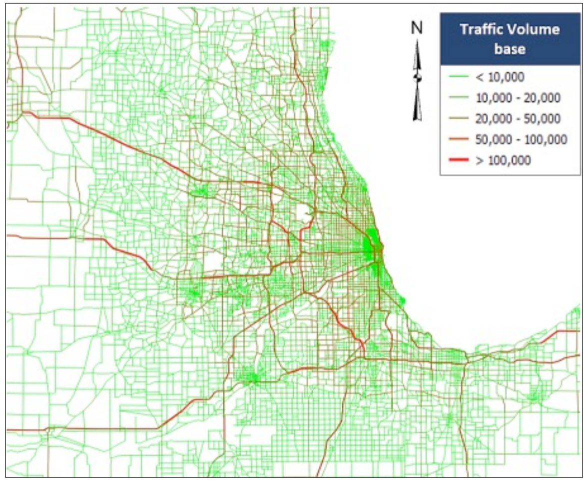
Note: ***, **, * indicate significance at 1%, 5%, and 10% level.

Implementation in POLARIS

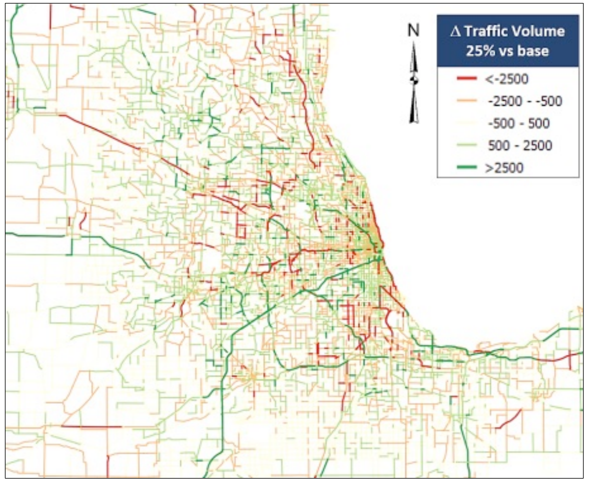
- The results endorse the fact that telecommuting policy has the potential to reduce network congestion and vehicular emissions specifically during rush hours
- As a sustainable transportation policy, Telecommuting can alleviate network congestion by reducing the total daily VMT and VHT by up to 2.4% and 4.15%
- Telecommuting policy also has the potential to reduce GHG and PM2.5 emissions by up to 2.65% and 2.95%

Changes in Emissions and Fuel Consumption in Telecommuting Scenarios

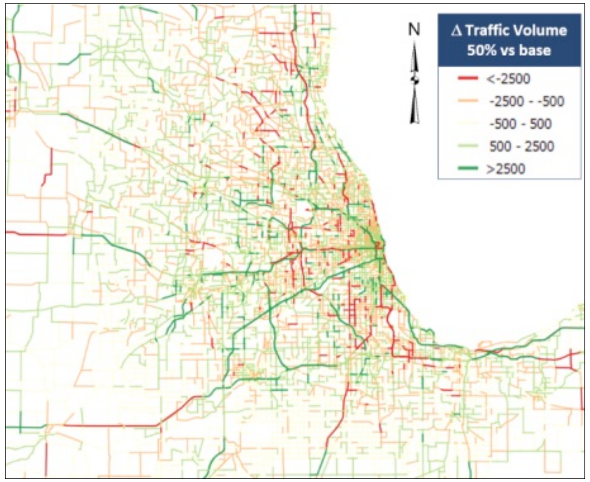
Emissions	Flex–25 vs. base scenario	Flex–50 vs. base scenario
Average Daily GHG (US ton)	-329.5 (-0.3%)	-766.3 (-0.7%)
Average Daily $PM_{2.5}$ (lb)	-164.2 (-0.05%)	-367.5 (-1.1%)
Average Daily Fuel Consumption (Million Gallons)	-0.03 (-0.3%)	-0.08 (-0.8%)



(a) Baseline traffic volumes



(b) changes in network traffic volumes: Flex 25% vs. base



(c) changes in network traffic volumes: Flex 50% vs. base

Long-Distance Travel Overview

- Purpose
  - Critical to understand – what happens when travelers replace their average day trip with long-distance trips
  - Simulation of long-distance travel model is warranted
    - To represent travel demand in a more behaviorally realistic way
    - To provide solutions for the travel demand increment due to airport expansions
- Presents long-distance trip generation model and appropriate behavioral models representing the choice of airport access/egress mode including the high-speed rail
- Implements long-distance travel models within POLARIS and establishes linkages with activity-based models

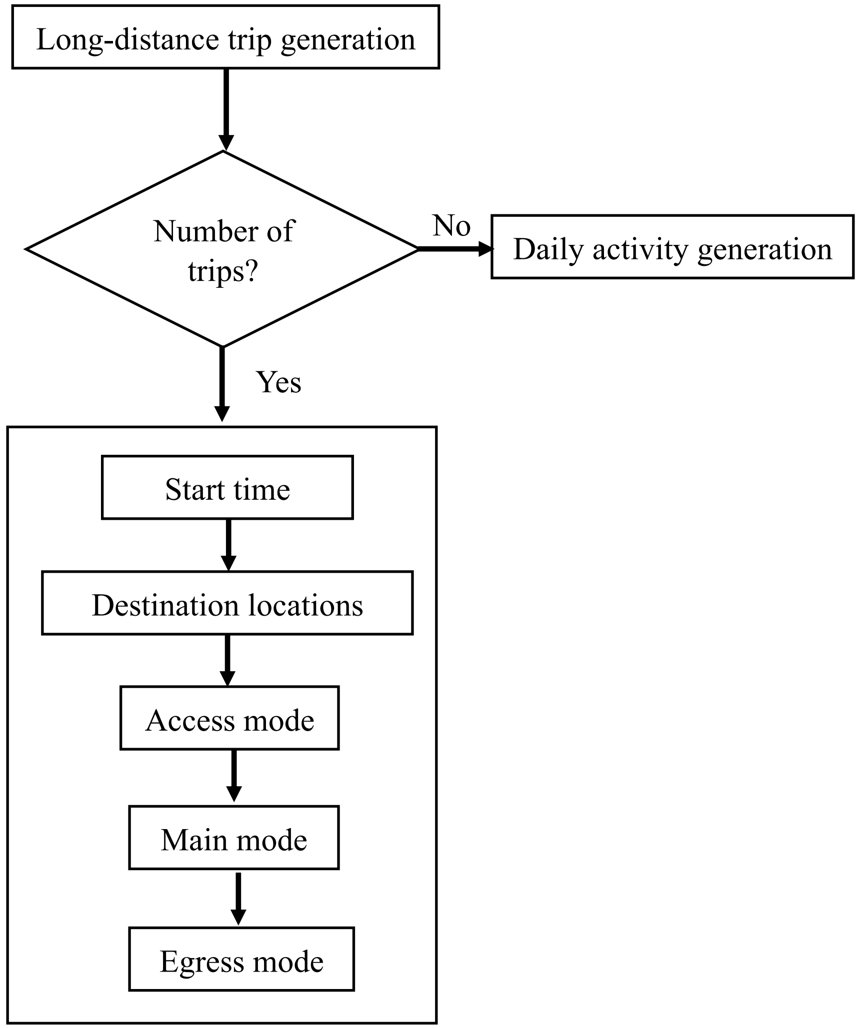
Long-distance Travel Model Development

- Data source
  - Multi-wave survey of long-distance travel behavior for state of Illinois
  - Responses: 1791 households; 2,225 individuals; 3012 long-distance trips
  - Information collected:
    - Socio-demographics and Household features (e.g., housing income, vehicle ownership, etc.)
    - Details about all long-distance trips of the individual within a determined period (e.g., number of long-distance trips, start day and time, main mode of the trip, access/egress mode if applicable, party size, origin and destination, trip purpose, etc.)

- Long-distance travel models developed (for <u>business trips</u> and <u>non-business</u>)
  - Trip frequency models
  - Start time choice model
  - Access mode choice model
  - Egress mode choice model

Implementation in POLARIS

- At first, long-distance (LD) trip frequency models generate trip decisions and number of trips using zero-inflated negative binomial model
- For trips = 0, activity generation model generates average day trips and its attributes
- No. of long-distance trips ≥ 1 triggers the implementation of other trip attributes
- LD travel module replaces daily activity generation model, and generates long-distance trip attributes
- For each trip,
  - start time model generates time-of-day of the long-distance trip start time using multinomial logit model
  - destination is generated using nested logit model
  - finally, runs mode choice processes using multinomial logit model for access, main and egress modes



Micromobility

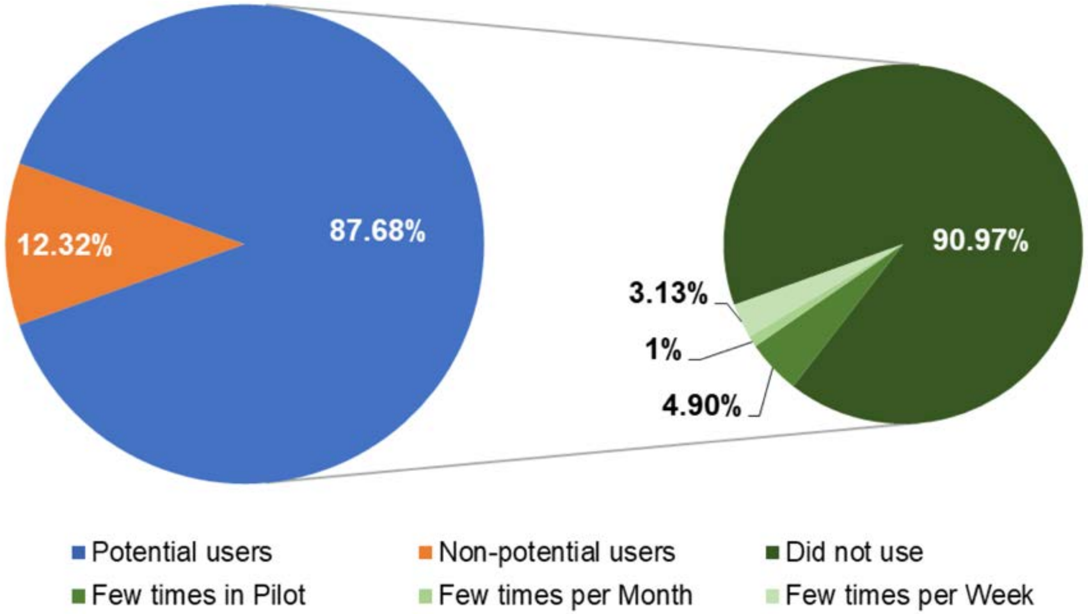
- E-scooters/e-bike/shared-bike provide people more options for short-distance trips
- Supplement transit services by providing more access/egress alternatives
- Carbon-free mobility - contributes to sustainable city development
- Purpose:
  - To better understand the role of shared micromobility in urban mobility
  - To explore how people adopt mcromobility
  - How frequently they use them
- Presents micromobility adoption choice model
- Implements the adoption behavior within POLARIS
- Run operational scenarios to understand the effect of future micromobility usage

Data

- E-Scooter Adoption Model Survey: 603 respondents
- Collected information
    - Demographics
    - E-scooter adoption behavior (frequency of use) based on e-scooter pilot program participation
    - Reasons for e-scooter use
    - Daily travel mode choice (mode and usage frequency)
    - Residential location
- Additional data: EPA Smart Location Database, E-scooter API for trip service characteristics

Model

- Differentiate users
  - Potential users (access to e-scooters but have not used it)
  - Non-users (no access to e-scooters)
  - Four level of usage considered for potential users
    - Do not use
    - Few times during pilot (3 months)
    - Few times per month
    - Few times per week



- Zero-inflated ordered probit model
  - Bi-level approach, dealing with excessive zero counts
  - Jointly investigates intention to adopt e-scooters and associated usage frequency

Scenarios

- 5 operational scenarios of e-scooter deployment were studied in *Bloomington*
- Demand for e-scooters depended on e-scooter availability by time of day
- Since some short auto trips can be replaced by e-scooters, **VMT savings up to 8%** are observed
- Shift away from walk also helps lower overall **PHT up to 11%**

E-scooter fleet size	Trips Made	% ΔVMT	% ΔPHT
Base | 500	11,549	-	-
5x | 2,500	14,166	-2.8%	-4.1%
10x | 5,000	15,382	-4.5%	-5.6%
25x | 12,500	17,030	-5.9%	-8.9%
50x | 25,000	18,343	-8.3%	-11.1%

VMT – Vehicle Miles Traveled
PHT – Person Hours Traveled

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