PARA-FLOW: An Event-Based Framework for Modeling Accessible Multi-Modal Urban Mobility

Fernanda Ventorim
Dept. of Computer Science, UC Irvine
Irvine, CA, USA
f.ventorim@uci.edu

Andrew Chio
Dept. of Computer Science, UC Irvine
Irvine, CA, USA
achio@uci.edu

Ruben Vescovo
Intl. Research Inst. of Disaster Science,
Tohoku University, Japan
vescovo.ruben.b7@tohoku.ac.jp

Erick Mas
Intl. Research Inst. of Disaster Science,
Tohoku University, Japan
mas@tohoku.ac.jp

Shunichi Koshimura
Intl. Research Inst. of Disaster Science,
Tohoku University, Japan
koshimura@tohoku.ac.jp

Nalini Venkatasubramanian
Dept. of Computer Science, UC Irvine
Irvine, CA, USA
nalini@uci.edu

Abstract

Urban mobility models support transportation planning, accessibility assessment, and emergency preparedness, yet many assume homogeneous agents and unconstrained routing. We present PARA-FLOW, an event-based framework for accessible multi-modal urban mobility under routine and disrupted conditions. PARA-FLOW separates behavioral intent from trajectory generation through two stages: *Behavioral Event Generation (BEG)*, which generates daily mobility schedules for heterogeneous agents based on demographic attributes, disability profiles, and contextual conditions, and *Network Trajectory Generation (NTG)*, which realizes accessibility- and topology-constrained trajectories. Evaluation using census-derived data for approximately 307,000 people with disabilities in Orange County, California, shows that PARA-FLOW generates topologically feasible routes consistent with agents' transport preferences and disability profiles. Under infrastructure degradation, it quantifies accessibility losses, with average shelter travel times increasing from 25.1 to 92.8 minutes and 157 individuals losing shelter access. Together, these results demonstrate scalable, accessibility-constrained urban mobility modeling.

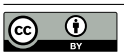
CCS Concepts

• **Information systems** → **Geographic information systems**; • **Computing methodologies** → *Simulation evaluation*; • **Applied computing** → Transportation.

Keywords

Event-based mobility modeling, Accessibility-aware routing, Multi-modal transportation networks, Urban spatial computing

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1 Introduction

Mobility systems are fundamental to daily life, enabling access to healthcare, employment, education, and social participation. However, these systems are typically designed and modeled under assumptions of homogeneous mobility capabilities [1, 18, 38]. These assumptions overlook the needs of more than one billion people worldwide, approximately 16% of the global population [44], who live with disability, given that over one in four adults in the United States report a disability [5]. For those people, mobility is shaped by additional constraints, including diminished motor ability, reliance on assistive devices, dependence on caregivers, limited access to private vehicles, and varying compatibility with public transportation modes. These factors can substantially affect access to essential services and may become even more consequential during evacuations and other emergencies. Together, demographic, socio-economic, and infrastructural factors produce heterogeneous mobility outcomes that are not captured by existing models [16, 32]. Existing work on urban mobility modeling can be broadly categorized into (i) data-driven mobility modeling and trajectory generation approaches, and (ii) constraint-based mobility frameworks.

Data-driven mobility modeling and trajectory generation approaches, e.g., traffic simulations, routing frameworks, and agent-based systems, often rely on population averages and simplified behavioral assumptions [2, 40, 48]. Although these models have advanced evacuation and traffic simulation research, they do not typically consider accessibility constraints and underrepresent the complexity of multi-modal transportation chains. Recent advances in generative trajectory modeling have improved the ability to learn complex mobility distributions, but do not explicitly incorporate accessibility or feasibility conditions and remain primarily unconstrained [24, 28, 43, 45–47, 50]. Thus, such frameworks struggle to quantify accessibility disparities or evaluate infrastructure design choices under heterogeneous mobility capabilities.

Constraint-based mobility frameworks take a complementary perspective by explicitly modeling the physical and infrastructural conditions that drive movement feasibility [7, 8]. Prior work in accessible routing, disability-aware transportation, and mobility accessibility analysis has shown the importance of representing factors such as sidewalk quality, wheelchair accessibility, transportation availability, and service dependencies when modeling mobility behavior [3, 4, 26]. These approaches provide fine-grained

representations of mobility constraints and can identify accessibility barriers within transportation networks. However, they typically operate at the routing level and do not model how activities, destinations, and transportation choices emerge over time.

A parallel body of work has examined mobility under disruptions, including evacuation planning, transportation resilience, and infrastructure degradation scenarios [20, 29, 41]. These studies emphasize the interaction between human behavior, transportation systems, and hazard dynamics, highlighting the importance of accounting for changing network conditions during extreme events. However, resilience-focused mobility models generally rely on population-averaged assumptions and rarely incorporate disability constraints.

Across these research directions, a common limitation is the lack of integration between behavioral decision-making and transportation feasibility. Mobility behavior is inherently time-dependent: individuals make context-aware decisions about activities, departure times, destinations, and transportation modes, while realized movement remains constrained by network topology, modal availability, and accessibility requirements. Many existing trajectory-generation approaches model movement as sequences of spatial locations derived from historical traces [11, 12, 24, 43, 50], without explicitly representing the behavioral processes that give rise to those trajectories. Furthermore, existing datasets and models are often mono-modal and cannot capture the mode transitions, assistance dependencies, and accessibility constraints experienced by individuals with disabilities. These limitations hinder the generation of realistic, accessibility-aware mobility trajectories across both routine and disrupted urban conditions.

To address these challenges, we introduce PARA-FLOW, an event-based computational framework for modeling accessible multi-modal urban mobility. The name PARA-FLOW reflects the framework's emphasis on modeling population mobility flows while accounting for paratransit and disability-specific transportation requirements. The primary task addressed by PARA-FLOW is the generation of individual-level multimodal mobility trajectories that account for accessibility, where mobility patterns emerge from the interaction between behavioral decision-making and transportation feasibility. Individuals first decide when, where, and how they intend to travel based on their demographic characteristics, accessibility needs, and environmental context. These decisions must then be realized within a transportation system that imposes topological, modal, and accessibility constraints. PARA-FLOW separates these two processes, enabling the generation of mobility patterns that are behaviorally informed and spatially feasible. This design provides a scalable framework for analyzing accessibility disparities and mobility outcomes across diverse populations, transportation systems, and environmental conditions. Our key contributions include:

- A formulation for the *accessible trajectory generation problem* that aims to construct human trajectories considering the diverse characteristics and mobility needs of people;
- **PARA-FLOW**, a disability-aware and multi-modal urban mobility framework that represents heterogeneous accessibility needs and transportation constraints, enabling the generation of realistic and feasible mobility trajectories for diverse populations;
- An event-based representation of mobility behavior that incorporates demographic characteristics, disability profiles, accessibility requirements, modal compatibility, and environmental conditions to generate empirically grounded and accessibility-aware behaviors, as well as transportation-feasible mobility trajectories;
- A large-scale evaluation involving 307,000 individuals with disabilities in Orange County, California, demonstrating the realism and feasibility of the generated trajectories, together with scenario-based analyses that quantify accessibility losses and mobility impacts under large-scale infrastructure disruptions.

The rest of this paper is organized as follows. Section 2 reviews related work and identifies limitations in existing mobility models. Section 3 formalizes the accessible mobility problem. Section 4 presents the PARA-FLOW framework, and the details of the event-based modeling architecture and trajectory generation methodology. Section 5 evaluates the framework through a series of experiments, and Section 6 concludes the paper.

2 Mobility Modeling for Diverse Populations

We next discuss prior work in urban mobility modeling, accessibility-aware transportation analysis, and generative trajectory synthesis. To this end, we first present background on mobility representations and data-driven mobility generation approaches, followed by existing methods for modeling constrained and accessibility-aware movement and their limitations in capturing realistic, feasible, and heterogeneous mobility behavior.

2.1 Background and Challenges

Urban mobility is modeled through a range of representations that vary in both abstraction and scale. At the most fine-grained level, movement is captured as continuous trajectories or sequences of spatiotemporal points derived from GPS traces and sensor data [8, 49]. Discrete representations instead encode mobility as transitions between locations, including state-based sequences (e.g., origin–destination pairs or activity states) and visit-based records associated with points of interest [6, 9]. Other approaches aggregate movement into spatial units, such as occupancy grids, flow matrices between regions, or network-level traffic assignments, enabling system-level analysis of demand and congestion. These representations also differ in temporal and population granularity, ranging from high-frequency individual traces to coarse, aggregate flows over time intervals. While each formulation supports different analytical and modeling goals, they collectively shape how mobility is abstracted, learned, and simulated in existing systems.

Within data-driven mobility modeling, extensive work across transportation science and machine learning has focused on representing and predicting mobility patterns. Foundational work in activity-based modeling and trajectory mining [18, 39, 49] established how human mobility can be captured as sequences of spatial–temporal decisions. More recently, deep learning methods (including recurrent and transformer-based architectures) have been widely adopted for trajectory prediction and next-location recommendation, demonstrating strong performance in modeling spatiotemporal dependencies and regularities in human movement [15, 30]. Generative extensions further enable the synthesis of realistic mobility trajectories that mimic observed patterns [24, 28, 43, 50].

Building on this, recent work has explored generative trajectory modeling with stronger sequence modeling capabilities and controllability. Transformer- and LLM-inspired approaches, such as TrajGPT [24], MobTCast [46], GETNext [47], STAR-HiT [45] and Geo-Llama [28], model mobility as a sequence generation problem, leveraging contextual dependencies to produce realistic visit or trajectory sequences. Other approaches focus on controllability and generative flexibility, such as ControlTraj [50], which incorporates user-defined constraints into trajectory generation, and diffusion-based models such as Diff-RNTraj [43], which generate trajectories through iterative denoising processes. These methods improve the realism and diversity of generated trajectories and, in some cases, allow for partial conditioning on spatial or temporal constraints.

Parallel to generative modeling, research on accessibility and constrained mobility has focused on understanding how individuals interact with transportation systems under varying levels of access and support. Prior work in accessibility analysis and transportation equity [3, 17] develops metrics to quantify access to opportunities and infrastructure, while other approaches incorporate constraints into routing and evacuation models [10, 21, 26]. These methods account for feasibility and system-level constraints but are not designed to generate individual-level mobility trajectories, nor do they capture the behavioral processes underlying movement decisions.

2.2 Overview of the PARA-FLOW Approach

Modeling accessible urban mobility requires simultaneously capturing how individuals make mobility decisions and how those decisions are constrained by transportation infrastructure. To address these challenges, we present PARA-FLOW, a modular computational framework for generating accessibility-aware multi-modal mobility trajectories. The key intuition behind PARA-FLOW is to separate behavioral intent from spatial realization through two interconnected models. Given demographic, infrastructural, and environmental inputs, PARA-FLOW first generates event-based mobility schedules that describe what individuals intend to do and then converts these mobility schedules into realistic and feasible trajectories over a transportation network.

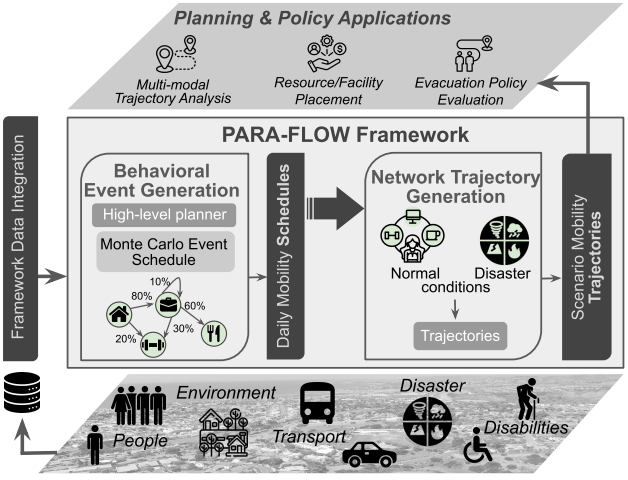


Figure 1: PARA-FLOW architecture

Figure 1 illustrates the PARA-FLOW architecture. An integrated data layer combines demographic, transportation, and environmental information into a shared spatial representation. These inputs are used by the BEG, which employs probabilistic event generation and Monte Carlo sampling to construct time-dependent mobility schedules conditioned on heterogeneous agents. Each mobility schedule is represented as a sequence of semantic events describing activities, destinations, departure times, and transportation choices. The NTG then maps these events onto a multi-modal transportation graph and generates accessibility-aware trajectories subject to modal, infrastructural, and network constraints. Environmental conditions dynamically modify network topology, accessibility, and traversal costs, enabling the framework to represent both routine and disrupted mobility conditions. PARA-FLOW produces a set of time-indexed multi-modal trajectories that capture both behavioral intent and transportation feasibility, supporting analyses of accessibility disparities, mobility dynamics, and infrastructure performance across diverse urban scenarios.

3 Modeling Heterogeneous Human Mobility

This section formalizes the key components for modeling heterogeneous urban mobility, including the transportation network, individuals and their disability-related mobility constraints, and environmental conditions. We capture how demographic and disability characteristics influence mobility behavior and accessibility. This defines how individuals make decisions, interact with transportation infrastructure, and move through urban environments.

3.1 Formal Components

Transportation Network. Urban mobility in a transportation system is composed of locations and their connections. We represent this as a directed graph: $G = (V, E)$, where V is the set of locations that individuals may visit and E is the set of traversable connections between them. Each node $v \in V$ is associated with a spatial coordinate $(long(p), lat(p))$ and a semantic label l describing its function (e.g., home, work, hospital, shelter). Each edge $e \in E$ is defined as $e = (length, K_e, \bar{s})$, where $length$ is a geometric distance, $K_e \subseteq \mathcal{M}$ is the set of transportation modes permitted to traverse the edge, and $\bar{s}$ is the maximum traversable speed on the edge.

Modes of Transportation. Urban mobility occurs over a multi-modal transportation system where people may travel using different transportation modes, each with distinct accessibility requirements and operational constraints. Let $\mathcal{M}$ = *Walk, Wheelchair, PrivateVehicle, Paratransit, RegularBus, AccessibleBus, Rideshare, Not-Moving* is the set of available transportation modes. Each transportation mode is associated with a feasible subset of network edges, expressed using a mode-feasibility function:$f(m, G) \rightarrow E_m$, where $E_m \subseteq E$ is a subset of edges that can be traversed using mode m. Each mode $m \in \mathcal{M}$ is associated with a subset of network edges that it can traverse, reflecting differences in infrastructure compatibility, service availability, and accessibility requirements. For example, pedestrian and wheelchair users may rely on sidewalks and accessible pathways, while vehicle-based modes operate on roadway infrastructure. Information about mode availability and infrastructure compatibility can be derived from publicly available transportation datasets, such as OpenStreetMap [37], GTFS transit feeds [19], and accessibility-related infrastructure attributes.

People. Individuals are characterized by their diverse demographics and mobility needs. Let $P = \{P_1, P_2, \ldots, P_n\}$ denote a population of people. We characterize an individual P_j using the tuple $(A_j, D_j, S_j(t))$, where A_j denotes age, D_j is the disability profile, and $S_j(t)$ is the individual's state at a given time t.

Disabilities. Let $D_j = (type_j, MC_j)$ denote a disability profile, where $type_j \in$ *Mobility, Vision, Hearing, Cognitive, MedicalDeviceDependent* denotes a disability category, and $MC_j = (v_j, \mathcal{M}_j, \alpha_j, \beta_j)$ represents the associated mobility constraints. The category *MedicalDeviceDependent* captures individuals whose mobility and activity patterns depend on powered medical equipment or regular access to medical services. Specifically, v_j denotes a speed modifier (e.g., reduced walking speed for individuals with mobility impairments); $\mathcal{M}_j \subseteq \mathcal{M}$ defines the set of feasible transportation modes; α_j encodes accessibility requirements (e.g., wheelchair-accessible infrastructure or accessible transit services); and β_j captures assistance or service dependencies (e.g., caregiver support, paratransit eligibility, or dependence on powered medical equipment). Also, *Cognitive* disabilities may be represented through behavioral constraints affecting feasible activities and assistance requirements. Together, these constraints govern both behavioral decisions and feasible interactions with the transportation network.

State. As individuals move through space and time, their state evolves according to their current location, transportation mode, and intended destination. We capture this through a time-dependent state representation: $S_j(t) = \big(crd_j(t), TrM_j(t), d_j(t)\big)$, where $crd_j(t) \in \mathbb{R}^2$ denotes spatial location, $TrM_j(t) \in \mathcal{M}$ denotes the active transportation mode, and $d_j(t)$ denotes the intended destination.

Environmental Setting. Mobility decisions and transportation availability are influenced by external environmental conditions that evolve over time. Let context variable $C(t)$ represent both routine urban conditions and disruption scenarios. This determines the operational transportation network $G(t)$ and the feasible action space $A_j(t)$ available to each individual over time.

Network Effects. Environmental conditions may alter transportation infrastructure through disruptions, and congestion, etc. We model these effects through the function $G_d(t) = \phi(G_n(t), H(t))$, which maps the baseline transportation network G to a disrupted network under hazard $H(t)$. $\phi_d(\cdot)$ is defined as a composition of operators that modify the network in response to environmental conditions. Hazards may remove edges, $E \leftarrow E \setminus E_H(t)$, representing road closures caused by hazard damage, or debris blockage. They may also remove nodes, $V \leftarrow V \setminus V_H(t)$, corresponding to inaccessible locations such as damaged facilities or closed transit stations. Partial disruptions are captured through edge traversal modifications, which reduce travel speed or increase traversal cost along affected network segments. Formally, $speed(e) \leftarrow speed(e) - \Delta_e(H, t)$, where $\Delta_e(H, t)$ represents hazard-induced increases in traversal difficulty resulting from congestion, reduced roadway capacity or degraded infrastructure conditions. Finally, hazards may modify node attributes, $l_v \leftarrow l_v^H(t)$, reflecting changes in facility availability or functionality. Together, these operators capture infrastructure disruption, partial blockage, and changes in service availability induced by environmental conditions.

Behavioral Effects. Let $A_j(t)$ denote the set of feasible actions for individual P_j at time t. We define: $A_j(t) = \psi(P_j, C(t))$, where $\psi(\cdot)$ filters available actions based on an individual's demographics, disability profile, mobility constraints, and the prevailing environmental conditions. Intuitively, $\psi(\cdot)$ determines which activities, destinations, and transportation options remain feasible under a given context. For example, under disruption, $A_j(t) \subseteq A_j^{base}$, reflecting restricted activities, destination choices, or mobility options.

3.2 Accessible Trajectory Generation

We next formulate the accessible trajectory generation problem by defining the concept of valid trajectories for individuals, and then discuss its intended use in practice.

Definition: Valid Trajectory. For a person $P_j \in P$, let a trajectory τ in network G be an time-ordered sequence of traversed edges $[(e^{(1)}, t^{(1)}), \ldots, (v^m, t^{(m)})]$, where $t^{(i)}$ denotes the time at which P_j begins traversing edge $e^{(i)}$. We consider the trajectory to be *valid* when the next three conditions hold: (i) *Modal feasibility*: the mode of transportation used by p to traverse each edge is permitted on the edge and feasible for the person; (ii) *Speed feasibility*: the time taken to traverse each edge must respect the edge's maximum traversable speed; and (iii) *Continuity*: consecutive edges of the trajectory are connected. These are expressed in Equations (1a)-(1c).

$$TrM_j(e^{(i)}) \in k \cap \mathcal{M}_j, \forall e^{(i)} \in E \tag{1a}$$

$$t^{(i+1)} - t^{(i)} \leq \overline{e}^{(i)}, \forall t \in T \tag{1b}$$

$$e^i = e^{i+1}, \forall i \tag{1c}$$

Problem Statement. Given a transportation network G, a population $P = \{P_1, \ldots, P_n\}$, and environmental conditions $C(t)$, the *accessible trajectory generation problem* produces a set of time-indexed, multi-modal trajectories $X = \{\tau_1, \tau_2, \ldots, \tau_n\}$, where each trajectory τ_j represents the realized movement of individual P_j through space and time. Each trajectory τ_j must be *valid* and satisfy the conditions in Equations (1a)–(1c). Behavioral decisions used to generate τ_j must be selected from the *feasible action* space $A_j(t)$, subject to the individual's disability profile D_j and mobility constraints MC_j.

Studying accessibility-aware trajectory generation is useful to understand how heterogeneous mobility needs interact with multimodal transportation systems under varying environmental conditions. These trajectories provide a foundation for evaluating accessibility, transportation equity, infrastructure utilization, and mobility performance across diverse populations and urban contexts. By generating **realistic and feasible** multi-modal mobility trajectories for individuals, PARA-FLOW enables scenario-based evaluation by quantifying how changes in infrastructure, transportation services, or environmental conditions affect individual mobility.

4 The Two-Stage PARA-FLOW Framework

PARA-FLOW models accessible urban mobility in two stages, as shown in Figure 2. The Behavioral Event Generation (BEG) constructs event-based mobility schedules that capture when, where, and how individuals intend to travel, conditioned on demographic attributes, disability profiles, and environmental context. The Network Trajectory Generation (NTG) then transforms these symbolic mobility schedules into feasible trajectories over a transportation network while accounting for accessibility requirements, modal compatibility, and dynamic network conditions.

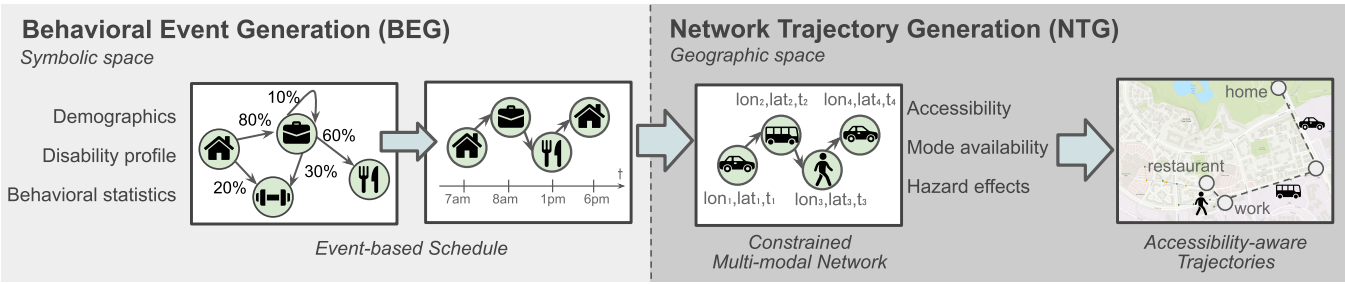


Figure 2: Two-stage PARA-FLOW approach

4.1 Behavioral Event Generation

For each individual P_j, BEG generates a sequence of events $E_j = \{e_1, e_2, \ldots, e_K\}$, where each event $e_i = (o_i, d_i, m_i, t_i, a_i)$ encodes an origin, destination, mode, departure time, and activity. The model operates as a Monte Carlo event scheduler conditioned on demographic attributes, disability profile D_j, and environmental context $C(t)$. Schedules are sampled from activity distributions to introduce stochasticity, producing symbolic mobility events that serve as input to NTG. Algorithm 1 summarizes the process.

Algorithm 1: Behavioral Event Generation (BEG)

Input: Population P, environmental context $C(t)$
Output: Event schedule set $\mathcal{E}$

$\mathcal{E} \leftarrow \emptyset$
foreach $P_j = (A_j, D_j, S_j(t)) \in P$ **do**
  $\mathcal{E}_j \leftarrow \emptyset$; $clock \leftarrow t_0$
  $\rho_j \sim Categorical(\mathcal{R}, w^{D_j})$; // behavioral pattern
  foreach *candidate activity* $a \in \rho_j$ **do**
    $z_a \sim Bernoulli(p_a^{D_j})$; // participation gate
    if $z_a = 1$ **then**
      $\delta_a \sim \max(\delta_{\min}, \Gamma(\gamma_{shape}, \gamma_{scale}))$
      $t_{start} \leftarrow clock$
      $clock \leftarrow clock + \delta_a$
      $e_i \leftarrow (a, t_{start}, \delta_a)$
      $\mathcal{E}_j \leftarrow \mathcal{E}_j \cup \{e_i\}$
  $C(t) \leftarrow \textsc{UpdateContext}(C(t), \mathcal{E}_j)$
  $\mathcal{E} \leftarrow \mathcal{E} \cup \{\mathcal{E}_j\}$
return $\mathcal{E}$

Behavioral parameters are derived from data on time-use and participation at the population-level. For each disability type type$_j \in D$, we construct a profile θ_j by partitioning respondents according to six functional-difficulty indicators: mobility, physical tasks, hearing, vision, remembering, and self-care. The resulting disability subpopulation serves as the calibration target for all behavioral parameters, while the full sample provides reference baselines for comparison. For each activity type $at \in AT$: (i) the daily participation rate $p_a^{D_j}$, defined as the fraction of respondents reporting any time in activity a; (ii) the conditional mean duration $\mu_a^{D_j}$ over respondents with $t_a > 0$; and (iii) the conditional standard deviation $\sigma_a^{D_j}$. This parameterization captures systematic differences in activity participation and time allocation across disability groups.

To structure the temporal ordering of activities, P_j is assigned a behavioral pattern $\rho_j \in R$, where R comprises five behavioral archetypes: *working_full_time*, *working_part_time*, *active_non_worker*, *limited_mobility*, *home_centered*. These archetypes were designed to capture common mobility lifestyles observed in population-level activity surveys and provide a representation of heterogeneity in daily activity participation. These archetypes capture heterogeneity along two dimensions: employment participation and out-of-home activity level, with daily travel time operationalizing the latter. The weights w^{D_j} form a normalized categorical distribution estimated separately for each disability group $\rho_j \sim Categorical(\mathcal{R}, w^{D_j})$ (Alg. 1, line 4), from empirical statistics.

Given pattern ρ_j and profile θ_j, the schedule for individual P_j is generated through a two-stage Monte Carlo procedure applied independently to each candidate activity a in the template (Alg. 1, lines 5–12): *Stage 1 - Participation gate.* A Bernoulli draw determines whether activity a occurs on the diary day: $z_a \sim Bernoulli(p_a^{D_j})$. Structural activities (sleep, personal care, leisure) and activities whose frequency is fully controlled by pattern assignment (work) are exempt from gating to avoid double-stochasticity. And *Stage 2 - Duration sampling.* For activities where $z_a = 1$, duration is sampled from a gamma distribution which accommodates the strict positivity and right-skewed variance human activity durations: $\Gamma(\gamma_{shape}, \gamma_{scale})$. A running clock advances by δ_a after each activity, propagating duration variability forward through the schedule so that downstream start times shift naturally.

After each individual's mobility schedule is generated, $C(t)$ is updated to reflect accumulated demand through three feedback channels (Alg. 1, line 13): (1) *Network congestion:* Each completed trip to destination d at hour h increments a counter $n_{d,h}$, producing a travel time multiplier $\kappa(d, h, C(t)) = 1 + \log(1 + n_{d,h}/\eta_d)$ that inflates base travel time estimates for individuals routing through the same corridor. (2) *Mode availability:* Environmental conditions may alter the availability of transportation modes. Under disruption scenarios, certain modes may become less accessible due to service interruptions, reduced coverage, or infrastructure damage. This effect is captured through a mode-specific availability factor $\omega(m, C(t)) \in [0, 1]$, which modifies mode selection probabilities. (3) *Facility capacity:* Unlike distributed destination categories (grocery stores, restaurants), which have many locations assigned specifically in NTG, hospitals and shelters are genuinely scarce resources. For these, a gate multiplier $\lambda(d, C(t)) \in [\lambda_{\min}, 1]$ scales the participation probability $p_a^{D_j}$ downward as occupancy approaches capacity, primarily relevant under hazard-induced stress, when shelter capacity is finite, and emergency departments are overwhelmed.

Together, these channels ensure that individual scheduling decisions accumulate into emergent population-level constraints that

realistically restrict $A_j(t)$ for later agents. Under disruption $H(t)$, all three effects amplify simultaneously: affected destinations become unreachable ($\lambda = 0$), congestion multipliers grow, and mode availability degrades as demand concentrates on fewer services.

4.2 Network Trajectory Generation

This model maps the symbolic event sequences produced by BEG onto a transportation graph, generating spatially and temporally feasible trajectories subject to accessibility and modal constraints. The process is summarized in Algorithm 2.

Each destination generated by the BEG is represented as a semantic activity category rather than a specific location. The NTG therefore performs a localization step that maps each semantic destination to a concrete facility in the transportation network (Alg. 2, line 6). Given a destination category d (e.g., hospital, grocery store, community center, or park), the model identifies candidate facilities with matching semantic labels within a search radius r_d (15 km by default) of the individual's home and selects an accessible facility. Destination assignments are cached per individual so that repeated visits to the same destination category correspond to the same facility throughout the day. Home locations are sampled from nodes in the largest weakly connected component of the walk network, ensuring reachable destinations. Distances are computed in a projected metric coordinate system, and facilities represented as building polygons are mapped to their centroid coordinates.

The transportation network is constructed from publicly available road, pedestrian, and accessibility infrastructure data. Mode-specific routing subgraphs are derived by filtering the network according to modal compatibility and individual mobility constraints (Alg. 2, line 8), which are cached and reused across individuals sharing the same mode and disability profile, improving scalability. Combined with destination localization, this produces feasible origin–destination pairs (v_o, v_d) for accessibility-aware routing.

Given a localized (v_o, v_d) and a feasible mode-specific network $G_m(t)$, the NTG computes an accessibility-aware route using A*

Algorithm 2: Network Trajectory Generation (NTG)

Input: Event schedule set $\mathcal{E}$, baseline network $G_n(t)$, hazard process $H(t)$
Output: Trajectory set $\mathcal{T}$

1 $G(t) \leftarrow \phi(G_n(t), H(t))$; $\mathcal{T} \leftarrow \emptyset$
2 **foreach** $\mathcal{E}_j \in \mathcal{E}$ **do**
3 $(A_j, D_j, MC_j) \leftarrow \textsc{Profile}(P, \mathcal{E}_j)$; $\tau_j \leftarrow \emptyset$
4 **foreach** $(e_i, e_{i+1}) \in \mathcal{E}_j$ **do**
5 $(o_i, d_i, t_i) \leftarrow \textsc{ParseEvent}(e_i, e_{i+1})$
6 $(v_o, v_d) \leftarrow \textsc{LocalizePOI}(o_i, d_i, P_j, G(t_i))$
7 $m_i \leftarrow \textsc{AssignMode}(P_j, v_o, v_d, MC_j, C(t_i))$; `// sample mode using localized trip distance`
8 $E_j(t_i) \leftarrow f(m_i, G(t_i))$; `// filter by mode and disability constraints`
9 $\pi_i \leftarrow \textsc{AccessibleRoute}(v_o, v_d, m_i, t_i, E_j(t_i))$
10 **if** $\neg$*Feasible*(π_i, m_i, MC_j) **then**
11 $\pi_i \leftarrow \textsc{FailedTrip}(o_i, d_i, reason)$
12 $\tau_j \leftarrow \tau_j \oplus \pi_i$
13 $\mathcal{T} \leftarrow \mathcal{T} \cup \{\tau_j\}$
14 **return** $\mathcal{T}$

search (Alg. 2, line 9). Edge costs correspond to estimated traversal time derived from network attributes and characteristics of the transportation-mode. By using an accessibility-aware network, the routing process respects modal compatibility, mobility constraints, and time-varying network conditions. The path π_i is appended to the individual's trajectory as the spatial realization of the corresponding mobility event. Following route generation, the resulting trajectory is validated against the individual's constraints (Alg. 2, lines 10–11). Routes that violate those constraints are marked as failed trips. This validation step ensures that all successful trajectories satisfy the constraints defined in Section 3.1.

The output of NTG is a tuple containing origin and destination coordinates, mode, trip distance, estimated travel time, departure and arrival timestamps, disability type, and a trip success flag. At the population level, the collection of origin–destination pairs constitutes a time-indexed multi-modal mobility dataset that captures both the heterogeneity of travel behavior across disability types and the spatial constraints imposed by the transportation network.

5 Experimental Evaluation of PARA-FLOW

Next, we evaluate PARA-FLOW on its ability to generate realistic and feasible mobility behaviors under accessibility, modal, and network constraints. PARA-FLOW can reproduce population-level mobility patterns while generating accessibility-aware trajectories suitable for analyzing routine and disrupted conditions.

5.1 Experimental Setup

Case Study. We evaluate PARA-FLOW using Orange County (OC), California, a large metropolitan region with over 3M residents and a diverse transportation system that includes road networks, pedestrian infrastructure, public transit services, and paratransit operations. OC is home to more than 300K individuals with disabilities, providing a large and heterogeneous population for evaluating accessibility-aware mobility generation. It faces a range of natural hazards (earthquakes, wildfires, and flooding), making it a suitable setting for studying routine and disrupted mobility conditions.

Data Sources. PARA-FLOW integrates multiple public datasets describing transportation infrastructure, population characteristics, and human mobility behavior. Transportation networks, pedestrian infrastructure, transit services, and facility locations are obtained from OpenStreetMap (OSM) [37]. Population demographics and disability characteristics are derived from the U.S. Census and American Community Survey (ACS) [34]. Behavioral parameters are calibrated using the American Time Use Survey (ATUS) [35], which provides diary-based records of daily activity participation and time allocation across activity categories. ATUS activity categories include work, meals, grocery shopping, medical appointments, exercise, and other daily activities. Individual demographic attributes and disability profiles are sampled according to observed population distributions and subsequently used to parameterize behavioral schedules and mobility constraints. Mobility characteristics are evaluated against the National Household Travel Survey (NHTS) [36], which provides information on travel behavior, trip distances, travel times, and transportation mode usage.

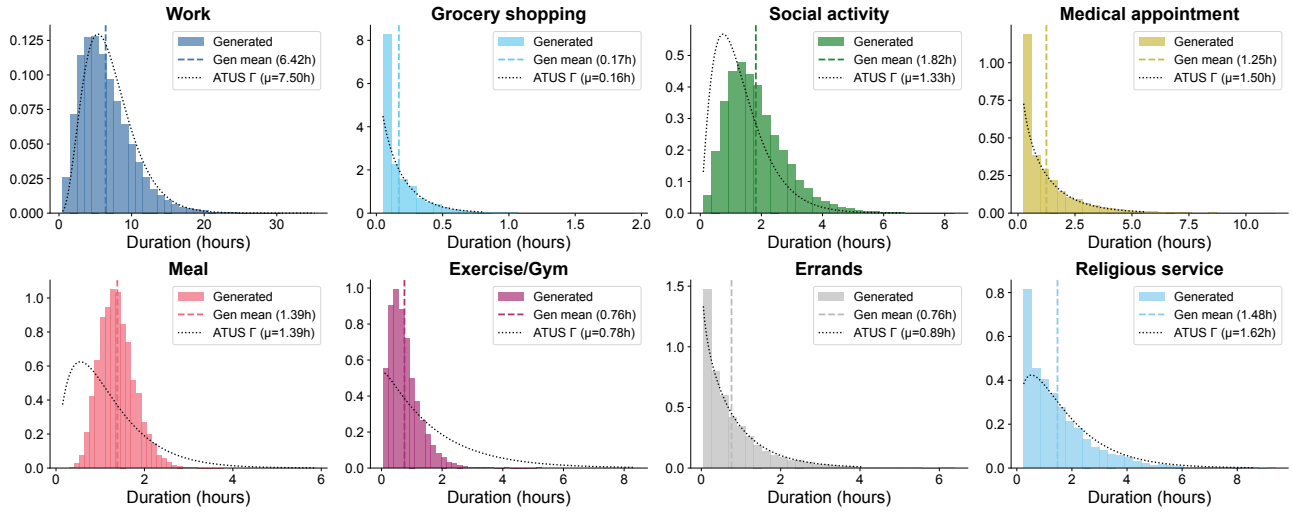


Figure 3: Time allocation per activity

5.2 Baselines and Evaluation Metrics

We evaluate PARA-FLOW along two primary dimensions: **realism** and **feasibility**. Realism measures the extent to which generated mobility behavior reproduces observed activity participation patterns, travel behavior, and transportation usage. Feasibility measures whether generated trajectories satisfy accessibility requirements, transportation-mode constraints, and network connectivity conditions. Together, these dimensions assess whether PARA-FLOW produces mobility trajectories that are both behaviorally representative and operationally valid.

For realism evaluation, generated activity and mobility statistics are compared against reference distributions derived from population behavioral and travel surveys. For feasibility evaluation, we compare PARA-FLOW against three baselines: *RAND*, which samples activities, destinations, and transportation modes uniformly at random; *PROB*, which uses empirical activity and mode probabilities but does not enforce accessibility constraints; and *GREEDY*, which assigns the nearest destination and routes all trips using private vehicles. Experiment-specific metrics and evaluation procedures are described within the corresponding subsections.

In addition to realism and feasibility, we evaluate the **utility** of PARA-FLOW as a decision-support and scenario-analysis tool. These experiments examine how changes in environmental conditions affect accessibility, mobility performance, and infrastructure utilization, demonstrating the framework's ability to support planning and resilience analysis under disrupted conditions.

5.3 Behavioral and Mobility Realism

We first evaluate the realism of the activity patterns and travel behavior generated by PARA-FLOW by comparing simulated mobility against reference distributions derived from population-scale behavioral and travel surveys. Behavioral realism is assessed through activity participation rates and activity duration distributions, while mobility realism is evaluated using transportation mode shares, trip distances, and travel times. Because PARA-FLOW is designed for large-scale population synthesis, we additionally examine the stability of aggregate mobility statistics across many population sizes.

Figure 3 and Figure 4 compares duration distributions and participation rates of activities generated by PARA-FLOW against the disability-conditioned estimates derived from ATUS, respectively. Across all activities, PARA-FLOW achieves a median absolute participation error of 7.4%, indicating close agreement with observed behavioral patterns. Participation estimates for work, exercise, and medical appointments remain within 3% of survey observations. At the same time, larger differences are observed for social activities and errands, which are inherently more discretionary and therefore exhibit greater variability across individuals and disability groups. Overall, the results demonstrate that PARA-FLOW reproduces population-level activity participation patterns while preserving behavioral heterogeneity. The average duration error is 0.27 hours (16 minutes), corresponding to an average percentage error of 12.9%. Meals, exercise, and grocery shopping exhibit the closest agreement with observed durations, while larger deviations occur for work and social activities. These activities typically display substantial variability in real-world behavior, making them more difficult to reproduce precisely through population-level statistical models. Despite these differences, the generated distributions preserve the characteristic long-tailed structure observed in survey data, indicating that PARA-FLOW captures both typical and infrequent activity durations.

Realistic mobility models must also reproduce plausible spatial and temporal patterns of movement. We next examine the network-level distribution of generated trips across transportation modes and

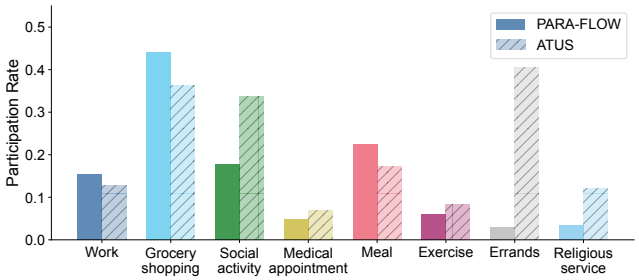


Figure 4: Activity participation rates

time periods. These experiments evaluate whether PARA-FLOW produces coherent mobility flows that reflect expected patterns of urban transportation demand.

Figure 5 shows network utilization patterns grouped by transportation mode. Of the 62,512 generated trips, 14.4% are performed using walking or wheelchair mobility, 26.5% use transit services, and 59.1% rely on private transportation modes. Distinct spatial structures emerge across these groups. Walking and wheelchair trips are centred on local street and pedestrian networks, reflecting the shorter travel distances associated with neighborhood-scale mobility. Transit demand follows a smaller number of high-capacity transportation corridors, while private transportation exhibits the broadest spatial coverage, connecting distant regions of Orange County through the arterial and freeway network. The most heavily utilized corridors coincide with major transportation routes, indicating that PARA-FLOW produces network usage patterns consistent with the underlying transportation infrastructure. Together, these results suggest that the framework generates spatially coherent mobility behavior beyond aggregate statistical matching.

Figure 6 illustrates temporal variation in network utilization throughout the day. Morning travel (6–11h) accounts for 8,197 trips (13.6% of all trips) and is concentrated along a limited set of major commuting corridors. Activity peaks during the afternoon period (12–17h), which contains 29,984 trips (49.8%) and exhibits the widest spatial coverage across the transportation network. Evening travel (18–23h) remains substantial, accounting for 22,038 trips (36.6%), but becomes more spatially dispersed as individuals return home and engage in discretionary activities. The temporal shift from concentrated morning movement to broader afternoon and evening travel patterns is consistent with expected daily urban mobility dynamics, indicating that PARA-FLOW captures both spatial and temporal heterogeneity in population movement.

Table 1: Population-scale stability of PARA-FLOW

Population	Mode MAE	Activity MAE	Dist. (km)	Time (min)
1k	2.96	6.47	6.86	9.30
5k	3.07	6.11	7.60	9.13
30k	3.01	6.57	6.54	8.91
100k	2.94	6.59	7.19	8.93
300k	2.87	6.05	6.81	8.43

Table 1 evaluates the stability of PARA-FLOW across population sizes ranging from 1,000 to 300,000 individuals. We measure four aggregate mobility characteristics relevant to accessibility-aware trajectory generation: activity-participation error (relative to ATUS activity rates), mode-share error (relative to NHTS mode distributions), median trip distance, and median travel time. Across all population sizes, these metrics remain highly stable. Activity-participation error varies between 6.0% and 6.6%, while mode-share error remains near 3%. Similarly, median trip distance ranges from 6.5 to 7.6 km and median travel time varies by less than one minute across simulations. These results indicate that PARA-FLOW produces consistent behavioral and mobility statistics as the population

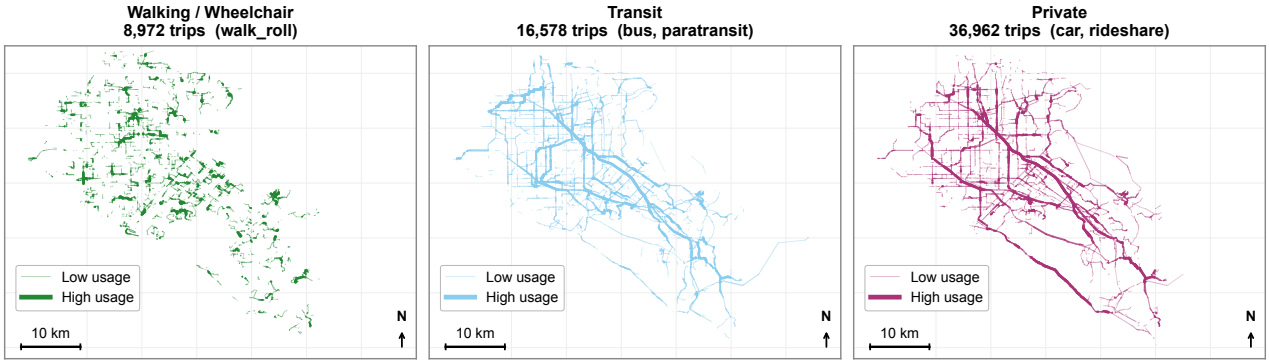


Figure 5: Road network usage density by transportation mode

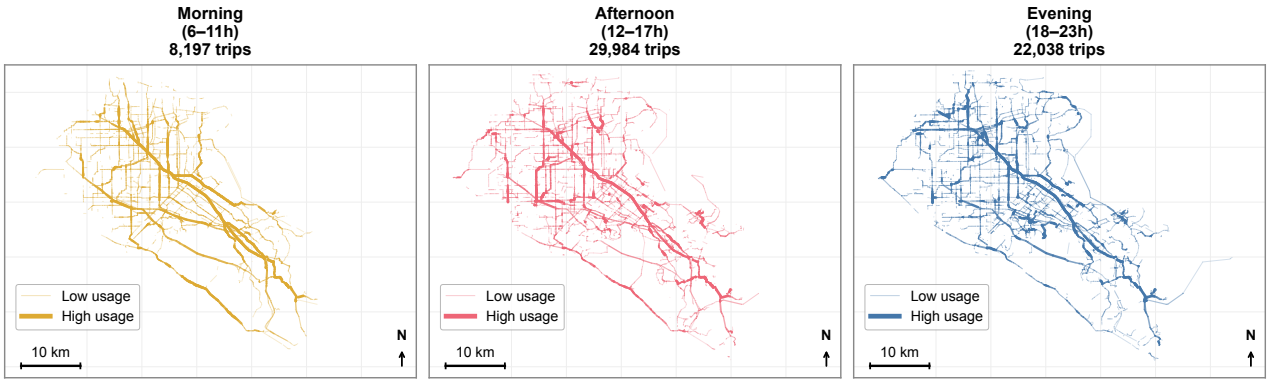


Figure 6: Road network usage density by time of day

size increases. Notably, the 30k-agent configuration yields aggregate mobility characteristics nearly identical to those obtained using the full 300k-agent population, supporting its use in computationally intensive feasibility and disruption experiments. Furthermore, all generated trajectories remained valid across population scales, with no accessibility violations observed.

5.4 Feasibility and Baseline Comparison

Our next experiment evaluates the feasibility of the trajectories generated by PARA-FLOW. A trajectory is considered valid if a feasible route exists in the transportation network and the selected transportation mode satisfies all accessibility and mobility constraints associated with the individual. We compare PARA-FLOW against the three baseline approaches, *RAND*, *PROB*, and *GREEDY*, introduced in Section 5.2, and evaluate their ability to generate valid trajectories while respecting all constraints.

Table 2 shows that PARA-FLOW achieves 100% trajectory validity, compared with 95.7% for GREEDY, 84.5% for PROB, and 75.2% for RAND. Relative to PARA-FLOW, RAND produces nearly one in four infeasible trips, while PROB and GREEDY generate 15.5% and 4.3% infeasible trajectories, respectively. These failures result from assigning destinations and transportation modes without jointly considering accessibility, network connectivity, and disability-specific mobility constraints. Although GREEDY substantially improves feasibility through nearest-destination assignment and unrestricted private-vehicle use, it still generates infeasible trips because accessibility requirements are not explicitly enforced.

Table 2: Comparison of mobility generation methods

	Feasibility	Mobility Characteristics	
Method	Valid (%)	Travel Time (min)*	Dist. (km)*
PARA-FLOW	**100.0**	8.43	6.81
GREEDY	95.7	4.9	1.89
PROB	84.5	20.9	22.54
RAND	75.2	22.5	22.26

* Median values

The mobility characteristics further highlight how different generation strategies influence the resulting trajectories. GREEDY produces the shortest trips, with a median travel distance of 1.89 km and a median travel time of 4.9 minutes, reflecting nearest-destination assignment. While this strategy improves feasibility, it substantially reduces the diversity of destination choices and travel behavior. In contrast, RAND and PROB generate substantially longer trips, with travel distances exceeding 22 km and travel times above 20 minutes, because destinations are selected without considering all constraints. PARA-FLOW produces intermediate travel distances (6.81 km) and travel times (8.43 minutes) while simultaneously maintaining complete trajectory validity. By balancing accessibility constraints with heterogeneous behavioral schedules, PARA-FLOW preserves the diversity of mobility patterns observed in population-level activity and travel surveys, rather than collapsing movement toward nearby destinations or generating unconstrained long-distance travel. These results suggest that accessibility-aware mobility generation requires jointly modeling behavioral decisions, transportation constraints, and network feasibility.

Table 3: Transportation mode shares (%) compared against NHTS dataset

Mode	NHTS	**PARA-FLOW**	PROB	RAND	GREEDY
Walk/ Wheelchair	12.0	**14.4**	0.4	0.7	0.0
Car	48.0	**42.9**	56.0	26.3	100.0
Bus	7.0	**6.9**	7.2	23.6	0.0
Paratransit	13.0	**15.6**	15.4	26.0	0.0
Rideshare	20.0	**20.2**	21.0	23.3	0.0

Feasibility alone does not guarantee realistic mobility behavior. Table 3 compares transportation mode distributions generated by PARA-FLOW against disability-conditioned NHTS benchmarks, which serve as the empirical ground truth for travel behavior in our evaluation. PARA-FLOW closely reproduces the observed mode shares across all transportation modes, with deviations below 3 percentage points for most categories. The strongest agreement is observed for bus usage (6.9% versus 7.0%), rideshare usage (20.2% versus 20.0%), and car travel (42.9% versus 48.0%). The framework also captures substantial walking/wheelchair mobility (14.4%) and paratransit usage (15.6%), reflecting the heterogeneous transportation needs of individuals with disabilities.

In contrast, the baseline methods achieve feasibility by simplifying or ignoring key aspects of mobility behavior. GREEDY assigns all trips to private vehicles, eliminating the mode-selection and accessibility challenges present in real transportation systems. RAND and PROB generate more diverse transportation patterns but substantially overestimate transit and paratransit usage while underrepresenting walking and wheelchair travel. These results indicate that matching observed transportation behavior requires jointly modeling accessibility constraints, behavioral preferences, and transportation feasibility.

Taken together, the results in Tables 2 and 3 demonstrate that PARA-FLOW achieves complete trajectory feasibility while preserving realistic transportation-mode distributions. No baseline method simultaneously provides accessibility-aware routing, heterogeneous mobility behavior, and full trajectory validity.

5.5 Applying PARA-FLOW in Extreme Events

To demonstrate the practical utility of PARA-FLOW, we evaluate the framework under a large-scale infrastructure disruption scenario. We use the USGS ShakeOut M7.8 Southern California earthquake scenario [42] and model transportation network degradation using HAZUS-derived [14] estimates of road and bridge damage. Mobility trajectories are recomputed on the disrupted network, enabling analysis of accessibility losses, travel-time degradation, infrastructure exposure, and population isolation across disability groups.

For this experiment, we assume that all individuals require evacuation and independently travel to the nearest feasible shelter. This assumption is intended to isolate the effects of transportation-network degradation and accessibility constraints on mobility outcomes. We acknowledge that real evacuation behavior is substantially more complex, with many individuals choosing to shelter in place, delay evacuation, or travel as part of households or social groups [13, 23]. However, our objective is not to model evacuation decision-making itself, but rather to examine how disruptions to

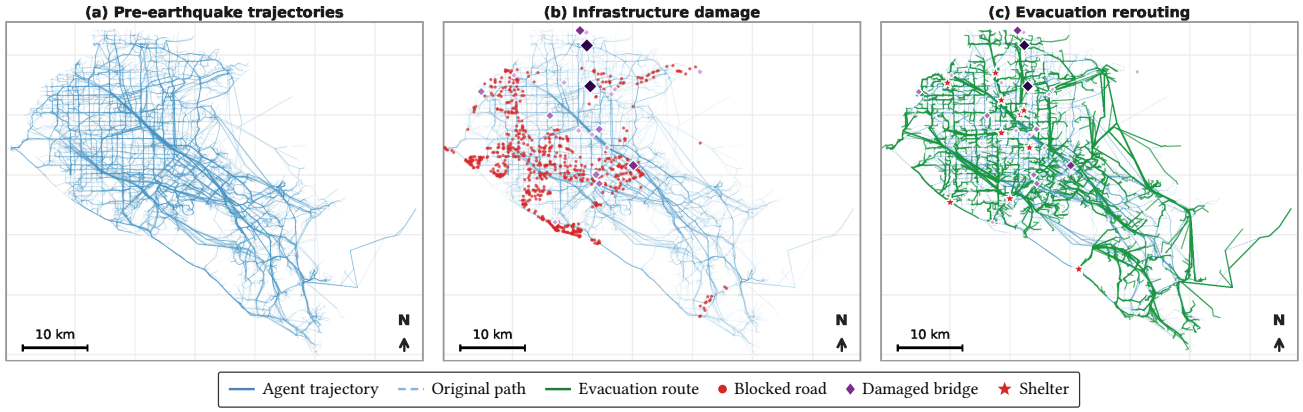


Figure 7: PARA-FLOW evacuation simulation under the ShakeOut M7.8 earthquake scenario. (a) Baseline mobility conditions before disruption. (b) Earthquake-induced infrastructure damage estimated using HAZUS. (c) Evacuation trajectories rerouted to emergency shelters over the degraded transportation network.

transportation infrastructure affect accessibility and mobility feasibility for populations with diverse mobility needs. Consequently, this scenario should be interpreted as a controlled stress test of accessibility and transportation feasibility under severe disruption rather than a predictive model of population evacuation behavior.

Figure 7 summarizes the ShakeOut disruption experiment. The earthquake scenario removes only 2.37% of transportation-network edges, but this localized infrastructure damage produces system-wide mobility consequences. Nearly 60% of post-event trips require rerouting because they encounter blocked or degraded infrastructure, and median travel time to the nearest shelter increases from 8.4 to 33.6 minutes. This shows that even limited topological disruption can substantially alter mobility when travelers depend on constrained sets of feasible routes. The disruption also produces unequal impacts across mobility groups. Mobility-impaired individuals experience the highest exposure, with 64.7% of their trips intersecting damaged infrastructure. Paratransit users show a similar pattern, with 63.0% of trips encountering disrupted network elements. These groups are more vulnerable because they rely on accessible corridors, compatible vehicles, and service availability, leaving fewer viable alternatives when infrastructure is degraded.

Shelter accessibility further illustrates this disparity. Before the earthquake, all simulated individuals could reach at least one emergency shelter. After the disruption, 157 individuals lost access to all shelters, and average travel time to the nearest shelter increased from 25.1 to 92.8 minutes. Thus, although most of the network remains physically connected, accessibility declines sharply for some individuals. This distinction is important for emergency planning: a road network may appear operational in aggregate while still failing to serve travelers with disability-specific mobility constraints.

Overall, the scenario demonstrates how PARA-FLOW can translate infrastructure damage into quantifiable accessibility impacts. Beyond estimating aggregate disruption effects, the framework enables planners to examine how environmental conditions influence accessibility, mobility performance, and infrastructure utilization across different population groups. Such analyses can identify populations at elevated risk of isolation, quantify accessibility losses, evaluate shelter accessibility, and identify critical accessible corridors. Accordingly, the scenario demonstrates PARA-FLOW's capability to quantify accessibility impacts under externally specified disruptions rather than to validate disaster-specific evacuation behavior. These outputs provide a basis for future scenario-based evaluation of interventions such as infrastructure restoration, accessible transit provision, and shelter placement.

6 Conclusion and Future Directions

This paper presents PARA-FLOW, a framework for modeling accessible multi-modal urban mobility. By representing mobility as a sequence of semantic activities that are realized over transportation networks, PARA-FLOW enables the analysis of how demographic characteristics, disability-related constraints, transportation infrastructure, and environmental conditions jointly shape mobility outcomes. Our evaluation demonstrates that the framework produces both behaviorally informed mobility patterns and feasible accessibility-aware trajectories, while supporting the analysis of mobility and accessibility under routine and disrupted conditions. More broadly, PARA-FLOW provides a foundation for studying transportation equity, accessibility disparities, and mobility resilience at population scale. Looking forward, we envision extending the framework across diverse geographic regions and transportation systems, particularly incorporating the techniques in [25] and building on collaboration efforts focused on tsunami preparedness and accessible evacuation planning in Japan [22, 27, 31, 33]. We also plan to deploy PARA-FLOW in planning and tabletop-exercise settings where accessibility-aware mobility forecasts can support operational decision-making. Finally, combining PARA-FLOW with emerging urban foundation models and large-scale mobility datasets may enable richer representations of human behavior and transportation systems, supporting next-generation scenario analysis and resilient infrastructure planning and design.

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