DRIve **F**leet **T**ool - A Mesoscopic Traffic Simulator

Technical report

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Abstract

This report presents DRIFT (DRIve Fleet Tool), a mesoscopic traffic simulator designed to balance the fidelity of microscopic modeling with the scalability of macroscopic approaches. DRIFT represents individual vehicles as discrete agents with unique trajectories and behavioral profiles, while simultaneously capturing aggregate traffic dynamics at the network level. Its modeling framework integrates congestion dynamics via the Bureau of Public Roads (BPR) function, dynamic capacity management, and multiple demand generation models including random, activity-based, zone-based, gravity, and hub-and-spoke. The simulator supports realistic temporal demand patterns, continuous-time resolution, and multi-day simulation horizons. DRIFT provides real-time visualization and comprehensive input/output support for integration with transportation datasets.

1 Introduction

Traffic simulation is a key tool for analyzing, predicting, and optimizing mobility systems. Existing approaches are typically divided between macroscopic models, which emphasize aggregate flow dynamics, and microscopic models, which track vehicles individually at high computational cost. Mesoscopic models offer a middle ground, retaining agent-level detail while enabling efficient large-scale simulation.

DRIFT (DRIve Fleet Tool) is developed to address this balance by providing a modular and extensible mesoscopic framework. At its core, DRIFT combines individual agent tracking with link-based flow management, allowing the study of congestion, demand patterns, and network utilization. The simulator includes configurable source–target selection models, customable temporal demand generation model, and dynamic congestion management. To support practical use, DRIFT integrates interactive visualization, real-time analytics, and flexible data exchange with widely used formats such as OpenStreetMap, GraphML, and CSV.

By design, DRIFT primarily targets transportation scientists by providing a flexible and extensible environment to study mobility dynamics. The remainder of this document details the characteristics of the proposed tool, including simulation granularity, modeling capabilities, source–target selection models, visualization features, and input/output mechanisms.

2 Simulation Granularity

2.1 Mesoscopic Modeling Approach

DRIFT uses an *agent-based mesoscopic* simulation framework that provides the flexibility of individual-traveler modeling with the efficiency of link-level flow updates. Each vehicle is represented as an autonomous agent with a unique ID and type and maintains its own planned route, schedule, and travel history [JK14]. This design aligns with the agent-based transport simulation literature, which emphasizes capturing traveler behavior at the micro level (distinct agents) while operating at an aggregate flow scale [JK14, Ype07]. In practice, DRIFT computes traffic flow at the link (edge) level using standard volume-delay function that depend on aggregate link demand and capacity. In other words, each link has a capacity and supply.

Temporal granularity refers to the resolution at which time is represented in a simulation. In traffic modeling, this choice strongly influences the level of detail, computational cost, and the types of phenomena that can be captured. Fine-grained temporal resolutions allow detailed representations of driver behavior and congestion dynamics, while coarser resolutions enable faster execution at the cost of reduced microscopic accuracy. In DRIFT, time progresses in configurable discrete increments. By default, the simulator advances in one-second steps, although larger increments may be selected when computational efficiency is prioritized [HNA16a]. Beyond fixed step sizes, DRIFT supports real-time multipliers of up to 1000× and simulation horizons extending up to 48 hours. This makes it possible to investigate daily and multi-day traffic dynamics while maintaining control over execution speed. Demand is generated according to configurable 24-hour probability distributions, incorporating peak-hour intensities and activity-specific patterns. This structure allows for the analysis of diurnal demand cycles and congestion phenomena without the full computational overhead of a trajectory-level microscopic model. The temporal design of DRIFT follows the same general principle as other well-established simulation frameworks. MATSim, for example, advances time in one-second increments using a queue-based traffic flow model [HNA16a]. TRANSIMS employs a cellular automaton microsimulator, in which the network is updated at each discrete time step [NB01]. SUMO also operates as a time-discrete simulator, with a configurable step length that defaults to one second [BBEK11, LBBW+18b]. By adopting a similar yet flexible approach, DRIFT ensures comparability with existing platforms while extending their capabilities through configurable horizons and high-speed real-time multipliers.

Compared to microscopic simulators such as SUMO, which resolve detailed car-following and lane-changing at the vehicle level [LBBW+18a], DRIFT abstracts these dynamics into mesoscopic link-level updates while still retaining agent-specific routing and activity patterns. Unlike purely macroscopic assignment models that operate only on aggregate flows, DRIFT preserves heterogeneity in agent types (e.g. commuters, deliveries, leisure trips) and their corresponding demand models. Its design philosophy is closer to frameworks like MATSim, which emphasize agent-based daily plans [HNA16b], but DRIFT maintains a simplified mesoscopic propagation model to reduce computational overhead. By integrating congestion functions, dynamic demand generation, and multiple source–target selection models, DRIFT provides a flexible platform for transportation scientists to study how behavioral assumptions and network dynamics interact at scale.

3 Modeling Capabilities

DRIFT supports multiple demand-generation models (random, activity-based, zone-based, etc.), congestion modeling, and realistic temporal demand profiles, enabling long-term scenario analysis and real-time updates. For any source-target $(s - t)$ model, users can specify the number of agents in the simulation, with a default value of 300.

3.1 Congestion Modeling

Link travel times in DRIFT are computed using the classical Bureau of Public Roads (BPR) congestion function given in the Equation 1.

$$t = t_0 \left(1 + \alpha \left(\frac{v}{c}\right)^{\beta}\right), \tag{1}$$

where t is the travel time under current conditions, t_0 is the free-flow travel time, v is the current traffic volume on the link, c is the link capacity, and α, β are calibration parameters. This polynomial BPR function was first introduced in the *Traffic Assignment Manual* by the U.S. Bureau of Public Roads [U.S64] and has since become widely used in transportation planning [GAJA23]. In particular, standard practice is to use $\alpha = 0.15$ and $\beta = 4.0$ [GAJA23], values which capture the typically gradual delay at low flow and a sharp increase in travel time as flow approaches capacity.

To capture evolving congestion, DRIFT incorporates dynamic capacity management. Link capacities can be adjusted in real time based on prevailing traffic speeds or external conditions. For example, if traffic speed on a road segment drops due to high density, the effective capacity of that link is reduced and travel times are updated accordingly.

3.2 Temporal Demand Patterns

DRIFT supports realistic temporal demand modeling by allowing users to define hourly probabilities for trip generation over a 24-hour cycle. This enables the reproduction of typical daily mobility patterns, such as pronounced peaks in the morning and evening corresponding to commuting periods, moderate activity around midday, and minimal demand during night hours [FIE14]. Trip departures are generated according to these user-defined distributions, which can be adjusted to explore alternative scenarios or special events. The simulator further supports extended temporal horizons of up to 48 hours, allowing multi-day analyses in which daily demand profiles are repeated. This flexible framework enables researchers to capture time-dependent variations in travel demand while maintaining control over scenario design [OW11a].

3.3 Source-Target $(s-t)$ Models

Source-target $(s-t)$ models generate synthetic travel demand by assigning origins and destinations for trips. This corresponds to the trip distribution step in transportation planning, where a trip table is constructed from origins to destinations [OW11b].

3.3.1 Random Model

All nodes have equal probability of being chosen as origin or destination, leading to a uniform distribution of trips [BCG+09]. The probability of selecting node i as origin and node j as destination is given by Equation 2.

$$p_{ij} = \frac{1}{N^2}, \tag{2}$$

where N is the total number of nodes.

3.3.2 Activity-Based Model

Trips are generated based on individual activities and purposes (e.g., work, leisure, shopping), with demand arising from agents' daily schedules rather than zones [BAB96]. Each agent a has its own OD preference pattern, so the probability of a trip from node i to node j for agent a is given by Equation 3.

$$p_{ij}^{(a)} = \frac{w_{ij}^{(a)}}{\sum_{k,l} w_{kl}^{(a)}}, \tag{3}$$

where $w_{ij}^{(a)}$ is a weight reflecting the likelihood of agent a making a trip from i to j.

3.3.3 Zone-Based Model

The network is partitioned into geographic zones, and trips are distributed within and between zones with configurable probabilities [Wei86]. The probability of a trip from node i in zone A to node j in zone B is given by Equation 4.

$$p_{ij} = \frac{p_{AB}}{n_A n_B}, \tag{4}$$

where p_{AB} is the probability of a trip between zones A and B, and n_A, n_B are the number of nodes in zones A and B respectively.

3.3.4 Gravity Model

The Gravity Model is based on the gravitational principle applied to trip distribution, where the number of trips is inversely related to distance and proportional to the size or attraction of the origin and destination locations [Voo56]. The estimated number of trips from zone i to zone j is given by Equation 5.

$$T_{ij} = K \frac{S_i A_j}{d_{ij}^{\beta}}, \tag{5}$$

where K is a constant, S_i is a size variable of the origin, A_j is the attraction of the destination, d_{ij} is the distance between i and j, and β is a distance-decay parameter. The corresponding trip probability is given by Equation 6.

$$p_{ij} = \frac{T_{ij}}{\sum_{k,l} T_{kl}} = \frac{S_i A_j / d_{ij}^{\beta}}{\sum_{k,l} S_k A_l / d_{kl}^{\beta}}. \tag{6}$$

3.3.5 Hub-and-Spoke Model

A subset of high-centrality nodes act as hubs, concentrating flows from peripheral nodes [CC13]. Let H denote the set of hubs. The probability of a trip from peripheral node i to peripheral node j via hub $h \in H$ is given by Equation 7.

$$p_{ij} = \sum_{h \in H} p_{ih} p_{hj}, \tag{7}$$

where p_{ih} is the probability of traveling from i to hub h and p_{hj} the probability of traveling from hub h to j.

4 Visualization and Real-Time Features

4.1 Real-Time Visualization

DRIFT provides comprehensive real-time visualization capabilities through an interactive network display. Users can pan and zoom across the network using mouse controls, enabling detailed exploration of specific areas while maintaining an overview of the entire system. Moving agents are visualized as color-coded entities according to their type, their movement is animated dynamically to reflect their trajectories, and waiting agents are displayed in black. The network topology is rendered with performance-optimized techniques, including automatic level-of-detail adjustments that ensure smooth operation even for large-scale scenarios. In parallel, a live statistics display provides continuous feedback on the current simulation time in a 24-hour format, the elapsed time since the start of the simulation, the number of active moving agents, and the overall network utilization expressed as a percentage. Examples are given in Figures 1 and 2.

4.2 Real-Time Trip Records

During the simulation, the data generated by each agent for every completed trip are stored in a table that updates in real time. Each row of this table corresponds to a single trip and includes the agent identifier, the agent type, the origin and destination nodes, and the departure time expressed in hours, minutes, and seconds. The trip record also contains the total travel distance in meters, the travel time in seconds, and the average speed in kilometers per hour. In addition, the complete path is stored as an ordered list of node identifiers representing the sequence of nodes traversed during the trip. An example is given in Figure 3.

4.3 Real-Time Analytics Dashboard

DRIFT provides a real-time analytics dashboard to monitor simulation performance and network behavior. The dashboard includes seven time-series plots, which track key metrics as the simulation progresses. These plots display the number of moving agents, overall network utilization, average vehicle speed, average trip distance, average trip duration, average number of nodes per trip, and the distribution of agent types over time. All averages are computed based on the data captured since the previous update of the plots. Together, these plots allow users to observe dynamic trends, identify congestion patterns, and assess agent behavior across different network regions. An example is given in Figure 4.

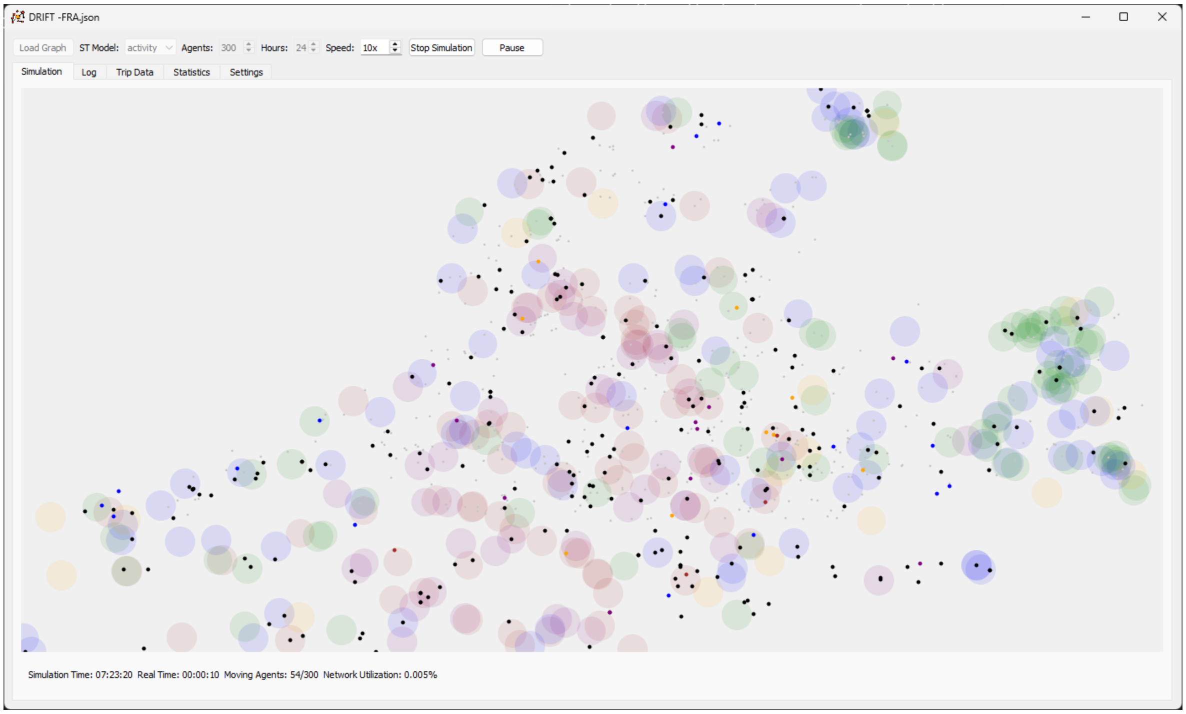

Figure 1: Screenshot - Real-time Network Visualization - Activity $s-t$ model

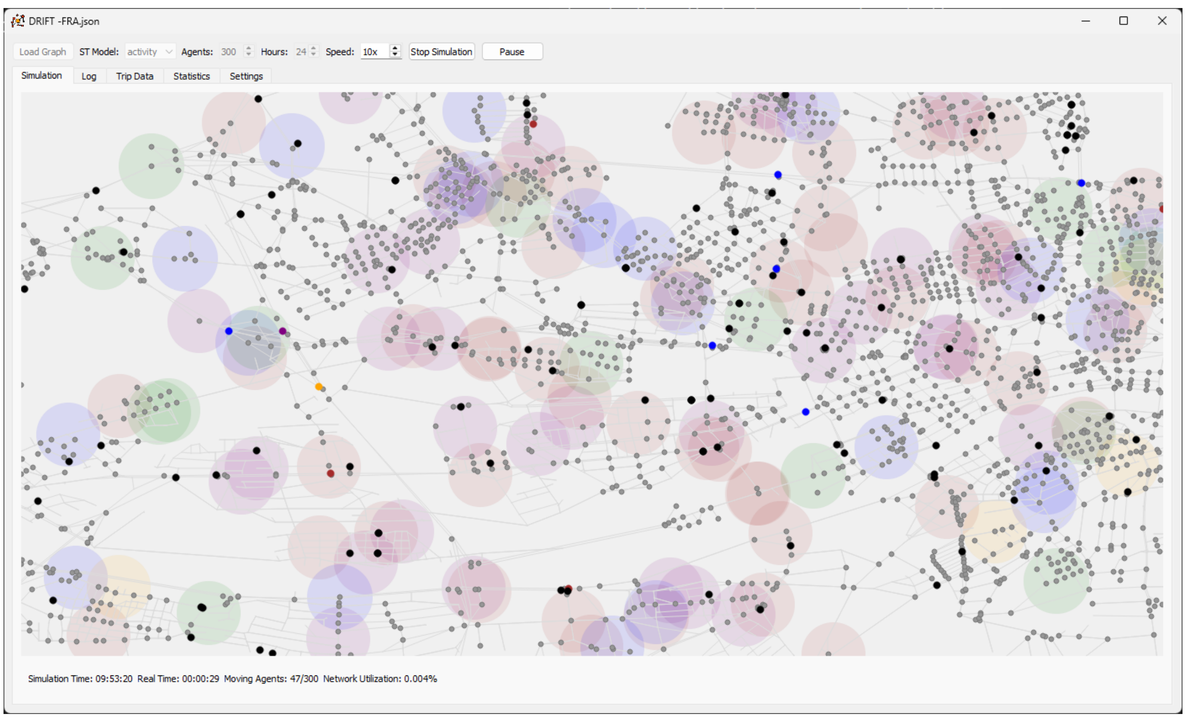

Figure 2: Screenshot - Real-time Network Visualization (zoomed) - Activity $s-t$ model

In addition to the real-time visualizations, the dashboard provides network-level statistics that are computed when the network graph is loaded. These statistics include the total number of nodes and edges, network diameter and density, connectivity measures, and the average clustering coefficient. These metrics offer insight into the structural properties of the network, complementing the temporal analytics obtained from the live time-series plots.

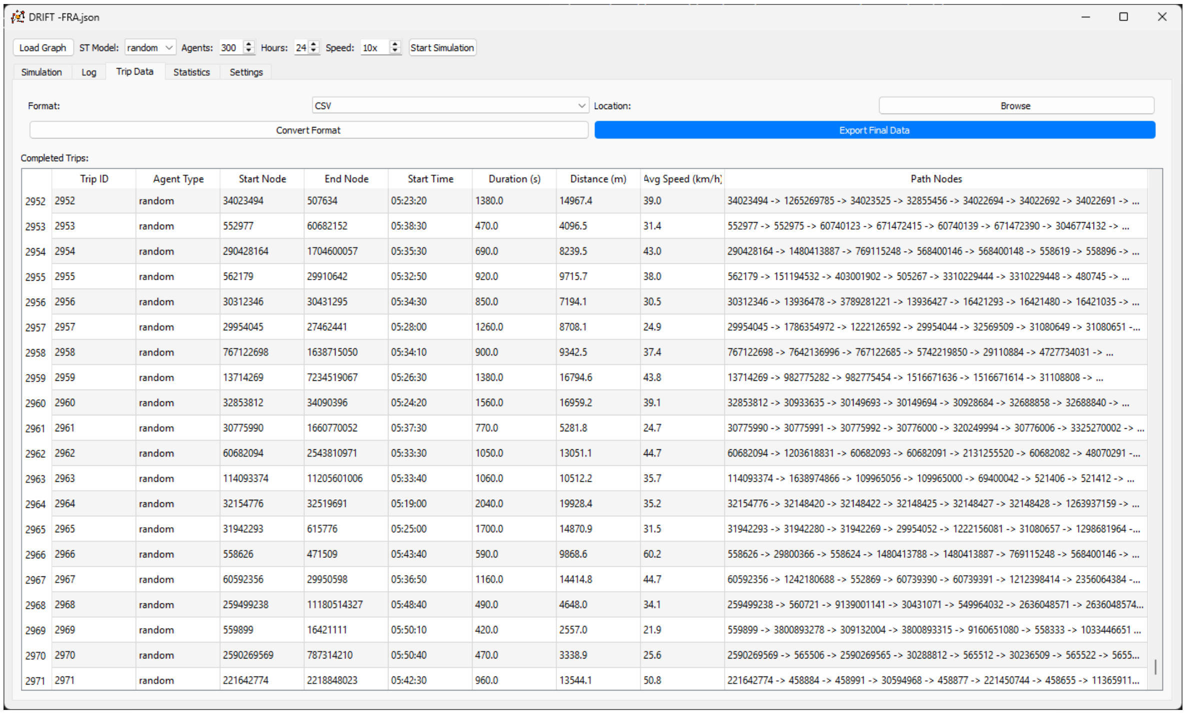

Figure 3: Screenshot - Real-Time Trip Records

Figure 4: Screenshot - Real-Time Analytics Dashboard (focused on plots)

5 Input/Output File Types and Data Exchange

5.1 Supported Input Formats

DRIFT provides extensive support for a variety of graph and network data formats, allowing seamless integration with existing transportation datasets and other simulators. OpenStreetMap (OSM) formats are fully supported, including OSM XML files (`.osm`) and OSM Protocol Buffer Binary files (`.pbf`, `.osm.pbf`), with automatic handling of coordinate systems and node positioning. The simulator also accepts Graph Markup Language (GraphML, `.graphml`) files, which are compatible with NetworkX and preserve all node and edge attributes while supporting both weighted and directed graphs. Additionally, DRIFT can import custom network definitions in JavaScript Object Notation (JSON, `.json`), providing flexible attribute storage in a human-readable and easily editable format. Matrix Market Format (MTX, `.mtx`) is supported for efficient representation of sparse networks, making it suitable for large-scale scenarios and standard academic workflows. Finally, edge lists in Comma-Separated Values (CSV, `.csv`) format are supported, with optional custom delimiters and compatibility with common spreadsheet applications.

5.2 Export Capabilities

DRIFT provides data export functionality to facilitate detailed analysis and reporting. Trip data can be exported in CSV format, containing detailed information for each trip, or in JSON format. In addition, the simulator supports the export of real-time statistics and network analysis data, including time-series information on network utilization, agent movement statistics, and performance metrics. Network topology statistics, connectivity analysis results, and centrality measures can also be exported. Furthermore, all statistical plots can be saved both as CSV files for quantitative analysis and as PNG images for visual documentation.

6 Technical Architecture and Implementation

6.1 Software Framework

DRIFT is implemented using Python frameworks and libraries that provide the foundation for simulation, analysis, and visualization. Core libraries include NetworkX for graph data structures and algorithms, PyQt5 for the graphical user interface, Matplotlib and Seaborn for real-time plotting and visualization, and NumPy and SciPy for efficient numerical computations. Geospatial data are handled using OSMnx, osmread, and GeoPandas, while HDF5 files are supported through h5py for efficient file input/output operations. The simulator also utilizes standard Python modules for threading and concurrency, system utilities, random number generation, date and time handling, mathematical operations, file system interaction, JSON handling, serialization, logging, and data structure management.

The software architecture follows a modular design, with separate modules dedicated to agent management, traffic dynamics, and visualization. $s - t$ selection models are implemented in a plugin-style structure, allowing for flexible integration and experimentation. Simulation parameters are fully configurable, enabling users to adapt the system to various network sizes, agent behaviors, and experimental scenarios.

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