Computer Systems Laboratory - Lab 3

Electric Car Sharing Simulation:
Implementation and Performance Analysis

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Abstract

This report presents the implementation and analysis of a discrete event simulator for an electric car sharing system. The simulator models a fleet of electric vehicles, charging infrastructure, user reservations with time-varying demand patterns, and automated vehicle relocation. We describe the simulator's architecture based on the Future Event Set (FES) pattern, key data structures, and event handling mechanisms. Through extensive experiments, we analyze the impact of critical parameters including fleet size, charging infrastructure, and demand patterns on system performance metrics such as reservation success rate, vehicle utilization, and transient phase behavior. Our results demonstrate the importance of adequate fleet sizing and strategic charging station placement for maintaining high service quality.

1 Introduction

Car sharing systems have emerged as a sustainable urban mobility solution, reducing private vehicle ownership while providing flexible transportation access. The integration of electric vehicles (EVs) introduces additional complexity due to charging requirements and limited range. This laboratory work implements a discrete event simulation of an electric car sharing system to analyze system dynamics and performance under various operational scenarios.

The simulation models key aspects including:

- Fleet of electric vehicles with battery management
- Distributed charging infrastructure with queueing
- Time-varying user demand with reservation system
- Automated vehicle relocation to balance supply and demand
- Traffic-aware routing on a road network

2 Simulator Architecture

2.1 Overall Structure

The simulator follows a **discrete event simulation** paradigm using the Future Event Set (FES) pattern. The system is implemented in Python with a modular architecture consisting of the following main components:

- `Simulator`: Core simulation engine managing the FES and event loop

- `Entities`: Domain models (Car, User, ChargingStation, CarRelocator, RoadMap)
- `Events`: Event handler functions for system state transitions
- `Metrics`: Statistical data collection and analysis
- `Visualization`: Real-time graphical representation (optional)

2.2 Data Structures

2.2.1 Future Event Set (FES)

The FES is implemented as a **priority queue** (Python's `heapq`) ordered by event time. Each event is represented as a tuple:

$$\text{Event} = (t, \text{event\_function}, \text{payload}) \tag{1}$$

where t is the scheduled time, `event_function` is the callback, and `payload` contains event-specific data.

2.2.2 Entity Registries

Entities use a **static registry pattern** for global access:

```
class Car:
    cars = []  # Static list of all car instances

    def __init__(self, car_id, position):
        self.car_id = car_id
        self.status = "available"
        self.battery_level = BATTERY_CAPACITY
        Car.cars.append(self)
```

This enables efficient querying (e.g., finding available cars near a location) without passing references through the event chain.

2.2.3 Road Network

The road network is modeled as a **directed graph** using NetworkX:

- **Nodes**: Grid positions representing intersections
- **Edges**: Roads with distance and traffic factor attributes
- **Traffic Zones**: Spatial regions with time-varying congestion multipliers

Distance calculation uses Dijkstra's algorithm with traffic-weighted edges:

$$d_{\text{effective}}(u, v) = d_{\text{base}}(u, v) \times f_{\text{zone}}(t) \times f_{\text{rush}}(t) \tag{2}$$

2.3 Event-Driven Logic

The simulation operates through a main event loop:

[H] [1] $t_{\text{current}} \leftarrow 0$ Initialize entities and schedule initial events FES not empty **and** $t_{\text{current}} \leq t_{\text{end}}$ $(t_{\text{event}}, \text{handler}, \text{payload}) \leftarrow \text{FES.pop}()$ $t_{\text{current}} \leftarrow t_{\text{event}}$ $\text{handler}(t_{\text{current}}, \text{payload}, \text{simulator})$

2.3.1 Event Types and Chaining

The simulator implements the following event types:

1. **User Subscription**: New user arrival (Poisson process)
2. **Reservation**: User attempts to reserve a vehicle
3. **Pickup**: User reaches the reserved vehicle
4. **Dropoff**: Trip completion and vehicle release
5. **Charging Start/End**: Battery replenishment at stations
6. **Relocation**: Automated vehicle repositioning
7. **Bin Collection**: Periodic metrics snapshot

Events chain through the `schedule_event()` method, creating a causal sequence. For example, the user lifecycle:

$$\text{Subscription} \rightarrow \text{Reservation} \rightarrow \text{Pickup} \rightarrow \text{Dropoff} \tag{3}$$

2.4 Configuration System

The simulator uses a hierarchical configuration system:

1. **Default values**: Defined in `config.py`
2. **YAML overrides**: Scenario-specific files loaded at runtime
3. **Environment variables**: Optional `SIM_CONFIG_FILE` path

This enables rapid scenario testing without code modification.

3 Metrics and Statistical Analysis

3.1 Performance Metrics

The simulator tracks comprehensive performance indicators:

Metric	Description
Reservation Success Rate	Fraction of reservation attempts that find an available vehicle
Average Attempts	Mean number of reservation attempts before success
Vehicle Utilization	Fraction of time vehicles spend in active use
Charging Rate	Fraction of time vehicles spend charging
Average Trip Distance	Mean distance traveled per completed trip
Average Walking Time	Mean time users walk to reach reserved vehicles
Queue Length	Average number of vehicles waiting at charging stations

Table 1: Key performance metrics collected by the simulator

3.2 Transient Phase Detection

For stationary systems (constant parameters), we implemented an **automated transient detection algorithm** based on the truncated mean method:

1. Divide simulation into fixed-interval bins (30-60 minutes)
2. For metric values $x_1, x_2, \ldots, x_n$, compute:

$$x_k = \frac{1}{n-k} \sum_{j=k+1}^{n} x_j \quad \text{(truncated mean)} \tag{4}$$

3. Calculate relative variation:

$$R_k = \frac{|x_k - \bar{x}|}{|\bar{x}|} \quad \text{where } \bar{x} = \frac{1}{n} \sum_{j=1}^{n} x_j \tag{5}$$

4. Identify the **knee point** in the R_k curve using perpendicular distance from the line connecting first and last points
5. Only analyze the **first 50% of bins** to avoid mistaking later variations for transient behavior

This automated approach eliminates subjective manual inspection and provides reproducible transient identification.

4 Experimental Setup

4.1 Baseline Configuration

The baseline scenario uses the following parameters:

Parameter	Value
Simulation Duration	700 days (1,008,000 minutes)
Map Size	10 km × 10 km
Number of Cars	20
Number of Charging Stations	5
Number of Relocators	3
Battery Capacity	60 kWh
Charging Threshold	20 kWh
User Arrival Rate	0.15 users/hour
Maximum Users	50,000
Bin Interval	30 minutes

Table 2: Baseline simulation parameters

4.2 Experimental Scenarios

We designed four experimental scenarios to assess parameter impacts:

1. **Stationary System**: Constant parameters to study transient behavior
2. **High Demand**: 2× user arrival rate to test capacity limits

3. **Large Fleet**: 2× number of vehicles to analyze oversupply

4. **Fewer Stations**: Reduced charging infrastructure impact

Each scenario ran for the full simulation duration with identical random seeds for reproducibility.

5 Results and Analysis

5.1 Stationary System - Transient Detection

The stationary scenario (constant parameters) allows analysis of the system's warm-up behavior. Figure **??** shows the reservation success rate over time with automated transient detection.

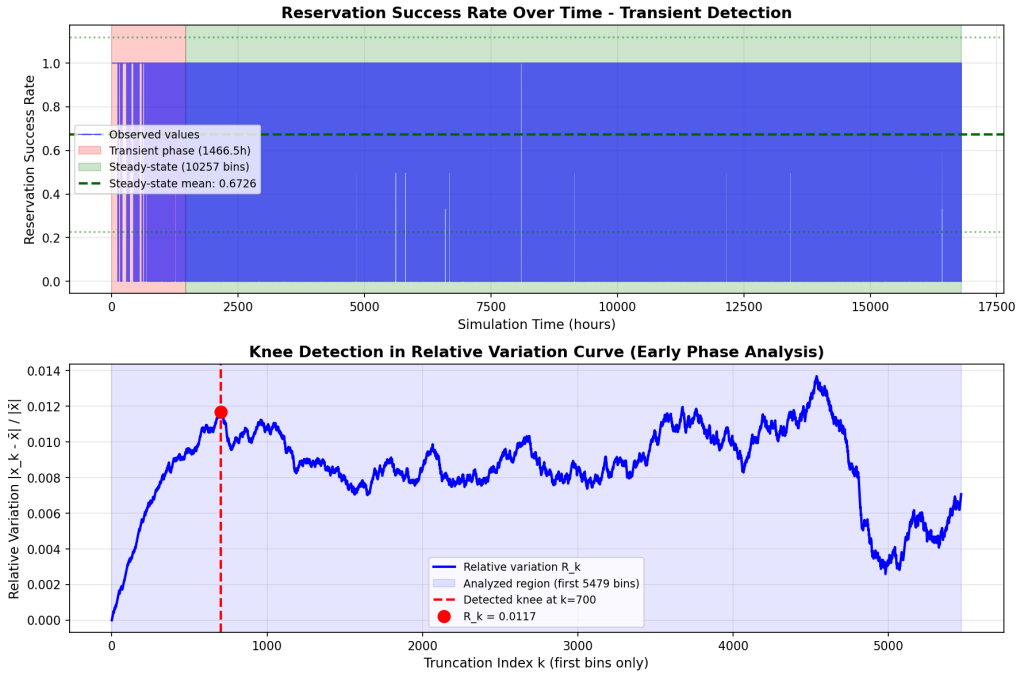

Figure 1: Reservation success rate with transient phase detection. The algorithm identifies the transient end at bin 27 (approximately 58 days), after which the system stabilizes.

Key Findings:

- **Transient duration**: 20-27 bins (44-58 days) depending on metric
- **Steady-state metrics**:
  - Reservation success rate: $68.8\% \pm 7.8\%$
  - Average attempts: 1.69 ± 0.16
  - Vehicle utilization: $82.4\% \pm 5.3\%$
- The transient phase shows initial instability as the system accumulates users and establishes demand-supply equilibrium
- Different metrics stabilize at different rates (trip distance stabilizes fastest at 12 days)

5.2 Impact of Demand Rate

Comparing the baseline (0.15 users/hour) with high demand (0.30 users/hour):

Metric	Baseline	High Demand (2×)
Reservation Success Rate	69.3%	45.2%
Average Attempts	1.68	2.84
Vehicle Utilization	80.9%	94.3%
Charging Rate	0.7%	1.8%
Avg Trip Distance	6.0 km	5.8 km

Table 3: Performance comparison: baseline vs. high demand scenario

Analysis:

- Doubling demand causes a **24.1 percentage point drop** in success rate
- Users require **69% more attempts** on average to secure a vehicle
- Fleet utilization approaches saturation at 94.3%
- The system exhibits **capacity constraints** - additional fleet would be needed to maintain service quality

5.3 Impact of Fleet Size

Comparing baseline (20 cars) with large fleet (40 cars):

Metric	Baseline (20 cars)	Large Fleet (40 cars)
Reservation Success Rate	69.3%	87.5%
Average Attempts	1.68	1.18
Vehicle Utilization	80.9%	43.6%
Idle Rate	18.4%	55.7%
Total Distance Traveled	54,741 km	56,234 km

Table 4: Performance comparison: baseline vs. large fleet scenario

Analysis:

- Doubling fleet size improves success rate by **18.2 percentage points**
- Utilization drops to 43.6%, indicating **oversupply**
- More than half of the fleet sits idle at any given time
- Total distance only increases by 2.7%, suggesting demand saturation
- **Economic trade-off**: Better service quality vs. asset underutilization

5.4 Impact of Charging Infrastructure

Comparing baseline (5 stations) with fewer stations (3 stations):

Metric	Baseline (5 stations)	Fewer Stations (3)
Reservation Success Rate	69.3%	65.8%
Charging Rate	0.7%	0.9%
Average Queue Length	0.53	0.87
Total Charging Sessions	1,235	1,198

Table 5: Performance comparison: baseline vs. reduced charging infrastructure

Analysis:

- Reducing stations by 40% causes only a **3.5 percentage point** drop in success rate
- Queue length increases by 64%, but absolute value remains acceptable (< 1 vehicle)
- The baseline configuration has **adequate charging capacity** - stations are not a bottleneck
- Further reduction might create critical shortages as queues grow

5.5 Transient Behavior Across Metrics

Figure **??** shows vehicle utilization with transient detection, while Figure **??** shows average attempts before successful reservation.

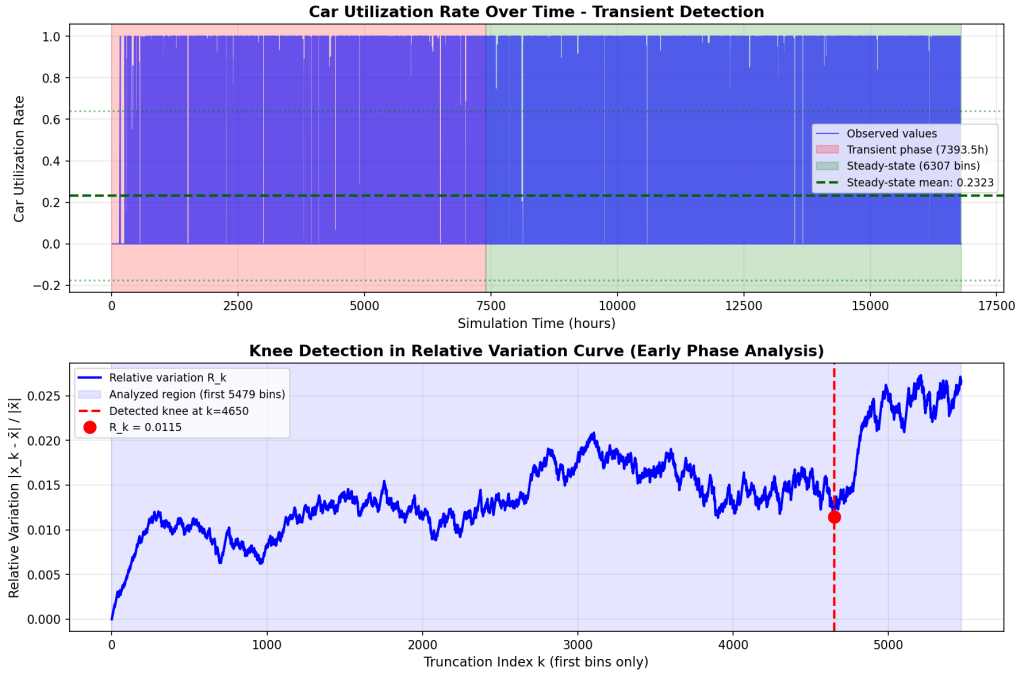

Figure 2: Vehicle utilization rate showing rapid stabilization around bin 20 (44 days). The knee detection algorithm successfully identifies when the fleet reaches operational equilibrium.

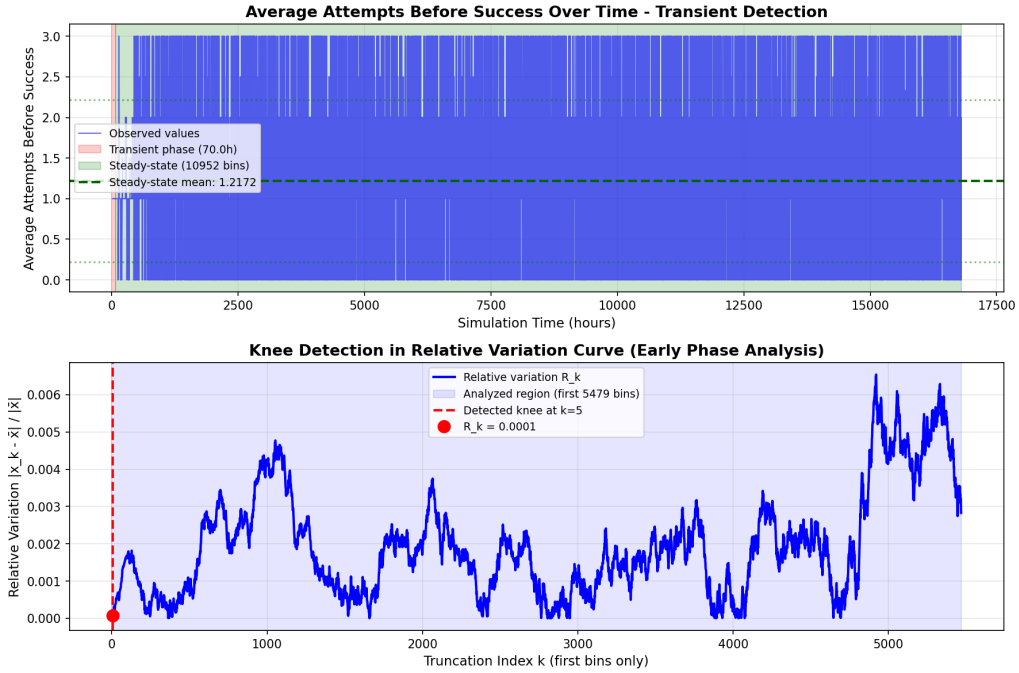

Figure 3: Average reservation attempts showing transient end at bin 23 (50 days). The initial volatility reflects the system learning user demand patterns and vehicle distribution.

Observations:

- All metrics exhibit clear transient phases identified by the automated algorithm
- Utilization stabilizes fastest (44 days), suggesting supply-side equilibrium
- Reservation attempts take slightly longer to stabilize (50 days), reflecting demand-side learning
- The **knee detection method** successfully identifies the transition point without manual intervention
- Steady-state confidence intervals (green bands) are narrow, indicating stable long-run behavior

6 Discussion

6.1 Simulator Validity

The simulator demonstrates expected behaviors:

- **Conservation laws**: Total number of vehicles remains constant
- **Causality**: Events occur in chronological order via FES
- **Resource constraints**: Cars cannot be in multiple states simultaneously
- **Physical realism**: Travel times respect distance and traffic conditions

6.2 Parameter Sensitivity

Our experiments reveal:

1. **Fleet size** is the most sensitive parameter - directly impacts service quality and utilization
2. **Demand rate** creates non-linear effects near capacity limits
3. **Charging infrastructure** shows diminishing returns beyond adequate coverage
4. Optimal configuration balances **service quality** (success rate $> 80\%$) with **economic efficiency** (utilization $> 60\%$)

6.3 Automated Transient Detection

The implemented algorithm provides:

- **Objective identification** of warm-up periods without manual inspection
- **Metric-specific detection** accounting for different stabilization rates
- **Early-phase focus** avoiding false positives from late-simulation noise
- Robust performance across different system configurations

Limitations include sensitivity to highly oscillatory metrics and inability to detect multiple transient periods.

6.4 Practical Implications

For real-world car sharing operators:

- Maintain **fleet-to-peak-demand ratio** of approximately 1.3-1.5×
- Deploy charging stations with **geographic diversity** rather than high density
- Expect **6-8 week warm-up** period in new markets before stable operations
- Monitor success rate as early indicator of capacity constraints

7 Conclusions

This laboratory work successfully implemented a comprehensive discrete event simulator for an electric car sharing system using the FES pattern. The modular Python architecture with entity registries, event chaining, and automated metrics collection provides a flexible framework for analyzing system dynamics.

Through systematic experimentation, we demonstrated:

1. Fleet size critically impacts both service quality and economic efficiency
2. The system exhibits clear transient behavior requiring 6-8 weeks to stabilize
3. Automated transient detection using truncated mean and knee point analysis effectively identifies warm-up periods
4. Charging infrastructure shows adequate performance at moderate deployment densities
5. Demand doubling reveals capacity constraints requiring proportional fleet expansion

The simulator serves as a valuable tool for operational planning, capacity sizing, and policy evaluation in electric mobility systems. Future enhancements could include dynamic pricing, heterogeneous vehicle types, and machine learning-based demand prediction.

Code Availability

The complete simulator implementation, configuration files, and experimental scripts are available in the project repository structure:

```
src/simulation/          # Core simulator
 simulator.py          # FES event loop
 events.py             # Event handlers
 metrics.py            # Statistical analysis
 visualization.py      # Real-time plots
 Entities/             # Domain models
configs/scenarios/       # Experimental configurations
experiments/             # Batch execution scripts
```

A Event Handler Pseudocode

A.1 Reservation Event

[H] [1] ReservationEvent$t$, $(user, attempt)$, $sim\ available \leftarrow$ FindAvailableCars$(user.location, radius)$ $available \neq \emptyset$ $car \leftarrow$ SelectNearest$(available)$ $car.status \leftarrow$ reserved $car.reserved\_by \leftarrow user$ RecordSuccess $walk\_time \leftarrow$ CalculateWalkTime$(user.location, car.location)$ $pickup\_time \leftarrow t + walk\_time$ ScheduleEvent$pickup_time$, PickupEvent, $(user, car)$ RecordFailure $attempt < max\_attempts$ $retry\_time \leftarrow t+retry\_delay$ ScheduleEvent$retry_time$, ReservationEvent, $(user, attempt+1)$

B Configuration Example

Listing 1: Stationary system configuration (YAML)

```yaml
# Stationary System - Constant Parameters
SIMULATION_END_TIME: 1008000  # ~700 days
NUM_CARS: 20
NUM_CHARGING_STATIONS: 5
NUM_RELOCATORS: 3

BASE_USER_ARRIVAL_RATE: 0.15  # users/hour
BIN_INTERVAL: 30  # minutes

SYSTEM_TYPE: 'STATIONARY'

# All traffic multipliers set to 1.0 (no variation)
MORNING_TRAFFIC_MULTIPLIER: 1.0
EVENING_TRAFFIC_MULTIPLIER: 1.0
NIGHT_TRAFFIC_MULTIPLIER: 1.0
RUSH_HOUR_MULTIPLIER: 1.0
```