Simulating Car-Sharing Demand: A Data-Driven Approach Using Probability Distributions

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Abstract

Car-sharing services face challenges in balancing fleet availability due to fluctuating demand. This paper simulates car-sharing demand using probability distributions, incorporating factors like daily and weekly patterns, seasonal trends, and external influences such as weather and public holidays. Model training considers convergence speed since it dictates how quickly algorithms arrive at solutions, which affects deployment time and computational resources. Using numerical analytical techniques and optimization frameworks, this research looks at how optimization is controlled in the dynamic field of machine learning. The simulation provides a flexible framework for demand analysis, aiding in more efficient fleet management and forecasting.

Keywords

Carsharing demand, simulation, fleet management, time series, artificial dataset

1. Introduction

Car-sharing has become a crucial solution to urban mobility challenges, providing efficient resource utilization and access to transportation. However, operators face fleet imbalance, where the supply of cars does not align with fluctuating demand. Accurate demand prediction is essential for addressing this issue, but there is often insufficient data available for car-sharing services, using time series simulation tools [10] for assessing the effects of variable renewable energy generation on power and energy systems.

To overcome this limitation, this paper focuses on simulating car-sharing demand [1] by developing a time series based on observed patterns. The simulation incorporates various influencing factors such as time of day, day of the week, weather conditions, public holidays, and fleet size [2]. Very important things are those reviews of vegetation phenological metrics extraction using time-series. By generating simulated data, optimization [10] and simulation [11] of carsharing, forecasting the carsharing service demand using multivariable models [12] this work aims to provide a foundation for better demand forecasting and effective fleet management.

2. Background

2.1. Time series

A time series consists of sequential observations recorded at uniform time intervals. These records —whether measurements, counts, or other numerical data—are arranged in order of occurrence. Examples include weather readings, financial market data, and heartbeat signals. The proliferation

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of sensors and tracking systems has led to a surge in sequential data collection, making time series data both widespread and vital. Such data helps in discovering causal relationships, identifying trends and even prediction of next values in many applications such as, but not limited to, medicine, weather-forecast, and economy deciding equivalences [3] among conjunctive aggregate queries. Along with this, time series analysis in the area of data mining aims to extract order pattern in data [4], a lot of interest has been around discovering trends from data which can describe what has happened in the past and what can occur in the future hence guiding towards carsharing revolution [12] giving a vital importance to time series.[1] *6th International Conference RTA-CSIT on 22-24 MAY 2025 in Tirana, Albania.*

2.2. Data simulation

Data simulation is the process with which synthetic datasets are generated that resemble the statistical properties and trends of real data. For instance, simulating visitors to a restaurant may create a bimodal distribution that reflects lunch and dinner hours. This method is commonly used in statistics, economics, finance, social sciences and engineering, to test a model or hypothesis before using it on real data [7]. Sadly, though simulation is critical, we have little formal and comprehensive guidance on how to simulate data, and it is not often offered as a course on its own. This is particularly relevant for time series data, where differences in the timing of observations make direct comparisons challenging. Simulation methods [8] are typically divided into two types: parametric, which rely on predefined mathematical models [9], and non-parametric, which generate data based on observed patterns. The simulation approach in this paper falls into the latter category. While both data simulation and forecasting require forming hypotheses about system dynamics, simulation uniquely accommodates qualitative data, scalable scenario testing, and a more exploratory creative process during its early stages.

3. Simulation Suite

3.1. Initial Simulation phase

Drawing on the analysis conducted by [3] for Car2Go in Vancouver, Canada, the following illustrates the hourly demand:

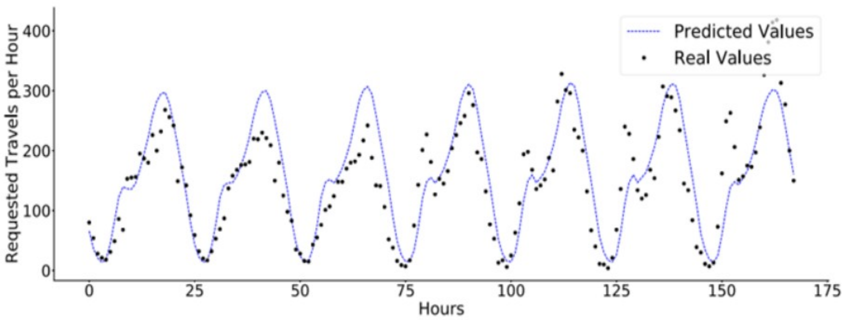

Figure 1: Number of travel requests per hour over one week.

This scenario adopts a free-floating model; however, the simulation here does not distinguish between one-way, round trip, and free-floating services. Instead, its primary objective is to accurately replicate real-world behavior by incorporating all essential parameters for an effective and scalable simulation model [5]. The figure above illustrates the number of travel requests per hour over one week. Noticeable similarities emerge across days, with higher demand on Friday, Saturday, and Sunday—a trend reflecting increased car-sharing usage over the weekend. This consistent daily pattern allows the simulation to focus on modeling hourly demand within a 24-hour period.

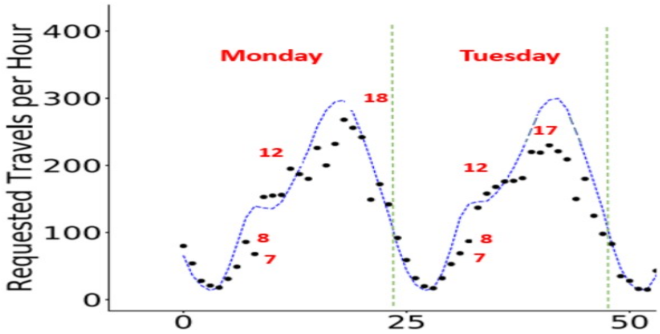

Figure 2: Graphically cosine-like distribution, mathematically

The figure above isolates hourly demand trends for Monday and Tuesday, offering a closer look at daily car sharing usage. Both days display similar patterns, indicating consistent behavior that could impact operational planning and resource allocation [6]. Notably, two clear peaks appear on each day one around 11 or 12 in the late morning/early afternoon, and another at about 5 or 6 in the early evening, corresponding to periods of increased activity such as lunch breaks, errands, and evening commutes in urban settings. Focusing on Monday, the 24-hour demand divides into three segments, with the first segment (from midnight to around 6–7 a.m.) following a cosine-like distribution, mathematically expressed as:

[illegible] (1)

Here, x denotes time, varying from 0 to a multiple of 2π to complete one cycle. By fine-tuning parameters like amplitude (A) and bias (b), the simulation can shape the data as needed. While the cosine function outputs values between -1 and 1, actual hourly demand falls within [0, 100], so careful adjustments align the simulation with real-world (Car2Go) data.

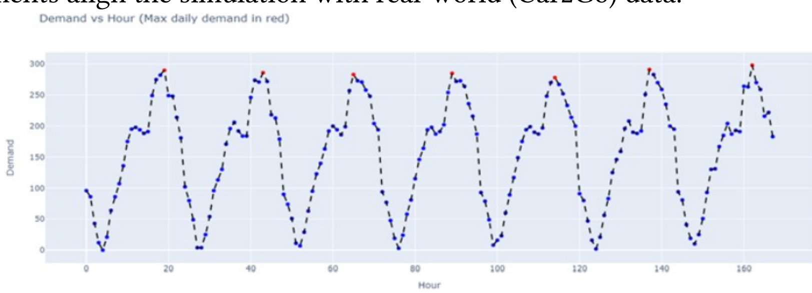

Figure 3: The visual representation throughout daily demand patterns for each day.

Figure 3 illustrates how high numbers per day can create large inequalities and discrepancies, and how this can be used to reduce costs and make car-sharing companies more sustainable.

3.2. Incorporating Weather Data into the Simulated Dataset

Weather's impact on car-sharing usage continues to be a topic of debate among experts. While some maintain that weather exerts a minimal influence on demand shifts, Figure 4 from [6] offers a contrasting viewpoint.

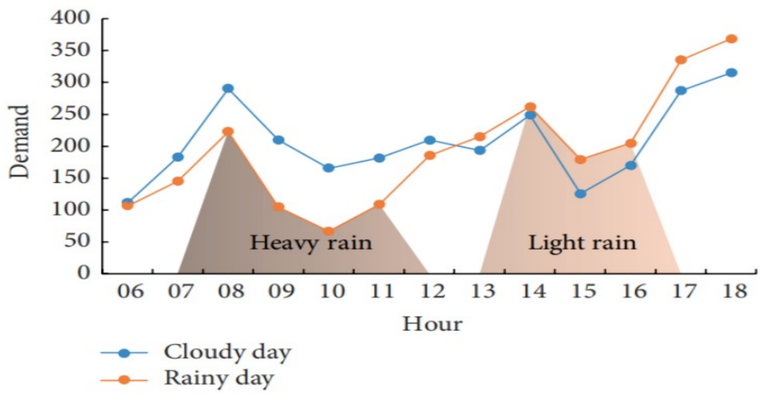

Figure 4: Comparison of the demand for car-sharing services compared to cloudy and rainy days

In the referenced study, researchers systematically compared similar weekdays under different weather conditions to reveal subtle influences on car-sharing usage. Their findings uncovered a complex connection between weather patterns and demand dynamics. Specifically, heavy rain between 6:30 am and 11:30 am was associated with a notable drop in demand compared to overcast conditions, whereas light rain during the afternoon hours (from 1 pm to 5 pm) correlated with a significant rise in demand. Using the insights from [9] small alterations to hourly demand were performed. This simulation was calibrated to reflect these empirical relationships by determining strong correlations between weather conditions and deviations in demand.

3.3. Final Steps of the Simulation

Our simulation is currently designed around a fixed fleet size of ~400 vehicles, which considerably limits the solution space for type of operational scenarios. Therefore, to create a more generic solution, we need to go beyond those limitations and enable variable fleet sizes. A proper scalable simulation should allow the users to configure a fleet that best fits their requirements. This will involve augmenting the model by incorporating fleet size as a time-varying parameter. This central change reengineers the primary mechanics of the simulation, so that hourly demand numbers directly react to the number of available vehicles. So, as the fleet expands/shrink, it will definitively paint a more realistic picture of what is happening in the world (at least in the simulation). The last result simulated dataset will have one additional column for fleet size now, giving a complete picture of what vehicles mean in terms of their market presence, offering a comprehensive view of how vehicle availability influences demand dynamics.

4. Conclusions

The final stage of the simulation has a notably unique feature that noticeably enhances the simulation dynamics: mobility in fleet size, which encourages the simulation to be more realistic according to the operational aspect. The upgrade allows stakeholders to investigate the impact of altering fleet sizes on meeting demand and assist car-sharing companies optimize resource allocation.

We address this gap by developing a scalable, robust simulation model of car-sharing demand, which is contextually tied to real-world parameters like hourly utilization profiles, weather effects, and fleet size constraints. It then uses mathematical models, such as cosine and bimodal distributions, to reflect daily and weekly demand variations in the simulation.

Incorporating the probabilistic perspective gives a better representation of demand fluctuations over longer periods. Moreover, the incorporation of weather data improves each model's realism, accounting for the role of variable weather in the usage of car-sharing. To reflect monthly or annual demand changes in the simulation, we can use mathematical models, such as sine and modal probability distributions or even other models to the next future. These results contribute to the recent literature on demand forecasting, provide guidance for operational planning, and demonstrate how simulation can support decision-making in economic trends, or city-specific mobility policies, to enhance predictive accuracy.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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