Modeling and Optimizing Shared Autonomous Vehicle Fleets for Long-Distance Intercity Travel

Eva Payet*[1] and Francesco Ciari[2]

[1]Intern, Civil Engineering, Polytechnique Montreal, Canada
[2]Professor, Civil Engineering, Polytechnique Montreal, Canada

Short summary

This study examines the optimal fleet sizing of shared autonomous vehicles (SAVs) considering long-distance intercity travel. A network of cities is modeled, with each city characterized by its population, attractiveness, and location. In each city, a fleet covering 10% of the population serves daily intra-city needs. However, intercity movements, reaching up to 20% of the population during peak periods, create additional demand, requiring a reevaluation of fleet size for both local and intercity needs. The methodology uses daily simulations over 30 days, with statistical distributions modeling departures and returns, and dynamic equations adjusting fleet size. Results show that interconnecting more cities increases fleet requirements to 13% of the population nationwide. Extending the network to include additional destinations of similar size and attractiveness stabilizes fleet needs at around 12%, highlighting the importance of large-scale integration.
Keywords : Fleet Optimization, Long-Distance Travel, Multi-City Systems, Shared Autonomous Vehicles

1 Introduction

Shared autonomous vehicles (SAVs) represent a significant innovation in transportation, offering potential solutions to address environmental and economic challenges. These systems have been widely studied in urban settings for their potential ability to optimize mobility, reduce congestion, and improve sustainability (Vosooghi et al., 2019). However, their effectiveness depends on accurate fleet sizing to meet user demand while minimizing operational costs, a complex task that becomes even more challenging during periods when long-distance multi-day travel (week-end, holidays) is frequent, and population movement is significant. Existing research has demonstrated that, in urban areas, a fleet equivalent to 10-12% of the population is sufficient to meet daily transportation needs (B. Qu et al., 2022). Unlike short intra-city trips, which allow one vehicle to serve approximately 10 passengers daily, long-distance interurban trips reduce vehicle efficiency to about two passengers per vehicle. Consequently, intercity travel, which involves up to 20% of a city's population, increases system demand and requires innovative approaches to fleet management. The present study builds upon previous work modeling dynamic flows between two cities during high-demand periods. We analyze several scenarios based on sociodemographic and geographic assumptions, using an aggregated model with daily resolution. The Gumbel distribution, applied to mobile data from Call Detail Records (CDR) (Ciari et al., 2019), is used to model daily departure and arrival rates, reflecting typical intercity long distance travel patterns.
This study contributes to the literature by providing a generalized, multi-city framework for optimal SAV fleet sizing during periods of high interurban mobility, to support their large-scale adoption.

2 Methodology

Global assumptions

Each city i is defined by its initial population, its attractiveness determined by the number of beds rented between July and August 2024 in Canada (Survey on the use of accommodation facilities) and its geographical coordinates (x, y). The proportion of the 10% of vehicles available solely for daily life must be respected at all times. It is assumed that inter-city travel represents 30% of the

total population of each city over the period, in order to accentuate the flows. The simulation is run over 30 days. Departures follow a normal distribution with a peak on the 10th day, while returns follow a gumbel distribution with a peak on the 15th day. These distributions are identical for all cities, and are discretized to calculate daily departure and return rates. Population conservation is ensured : all residents who have left return before the end of the holiday period. The sending rate from one city to another is constant throughout the simulation, regardless of the day : if 70% of the inhabitants of city A leave for a trip and go to city B on day one, this proportion is valid for each day until the end of the simulation. No night-time activity is simulated, fleet adjustments are made at the end of the day.
Optimal fleet sizing is achieved when the available fleet, after daily vehicle allocation, is zero. This means that there is neither a surplus nor a deficit. This criteria may include margins for maintenance or other specific needs.

Inter-city attractiveness

The attractiveness of a city k for another i combines its intrinsic score (score_k) which depends on the number of rooms rented in the city i over the period from July to August and the distance separating them ($\text{distance}(i,k)$), according to :

$$A_{i,k} = \begin{cases} \frac{\text{score}_k}{\text{distance}(i,k)^\alpha} & \text{if } i \neq k, \\ 0 & \text{if } i = k. \end{cases}$$

where α controls the impact of distance. In this study, the intrinsic attractiveness of cities has a greater influence than the distance between them, with a parameter $\alpha = 0.5$ but depending on the actual data, different values could be considered to adjust the parameter.
These attractivities are normalised in a matrix A $(n \times n)$, ensuring that each row sums to 1.
We define relative attractiveness as the sum of incoming visitors to the city, calculated from the attractiveness matrix. When it is divided by the resident population leaving the city, we obtain the load ratio, a key indicator for assessing the pressure exerted on a city in terms of mobility :

$$\text{Load Ratio} = \frac{\text{Total number of incoming visitors}}{\text{Total number of residents leaving the city}}$$

Daily fleet sizing

It is assumed that the fleet required to meet the population's transport needs must be available every morning, although departures may occur at any time during the day. To guarantee sufficient availability, vehicles returning to the city will be added to the available fleet only at the end of each day. In this way, the population's daily needs are covered without depending on vehicles returning during the day. For each town i, the fleet required in the morning depends on : the number of residents going on holiday to other towns k, travelers on holiday in town i returning home, and the total number of residents and vacationers staying in town i that day. The number of vehicles required each morning is calculated using the formula :

$$\text{morning needed fleet} = \text{morning departure fleet} + \text{daily fleet},$$

where :

- morning departure fleet covers long-distance departures,
- daily fleet meets the intra-urban needs of the remaining residents.

The fleet required is then adjusted to cover any deficit (δ) detected on a daily basis :

$$\delta_{\text{morning needs}} = \text{morning available fleet} - \text{morning needed fleet}.$$

The fleet is adjusted by adding the missing vehicles from the first day of the simulation, until the day before day d, when a deficit is observed. These vehicles added to each negative delta, although dormant before they are actually needed, serve to determine the optimal fleet required on the first day of simulation. The scenario continues with this adjustment, which will be checked for each new day so that morning_available_fleet reaches the number of vehicles used on each day.
At the end of the day, the available fleet is recalculated, taking into account intercity arrivals (arrival from cities) and the return of locals (arrival back) who bring vehicles with them :

$$\text{transfert} = -\text{morning departure fleet} + \text{arrival from cities} + \text{arrival back}.$$

This transfer is added to the fleet available for the following morning. The next morning, the available fleet is checked against the fleet required for the day. If a deficit is observed, adjustments are applied to make-up the shortfall in vehicles as described above. Although this approach is simplified and does not perfectly reflect reality, it allows the daily vehicle requirements for journeys between cities to be modelled and the optimum fleet needed to meet daily variations in demand to be estimated.

3 Results and discussion

We consider a scenario involving 14 destinations, with their geographical coordinates in figure 1. The arrival of international travelers is not taken into account, only the population of the cities is considered. It is assumed, that the population leaving each city corresponds to 30% percent of the initial population.

At the end of the process, the initial optimal fleet is calculated for each city. Its evolution throughout the simulation is shown in figure 2. This figure indicates a critical day for each city, corresponding either to a minimum or a maximum number of vehicles required. This critical day reflects fluctuations in requirements as a function of inter-city travel. The load ratio for each city is also shown in the figure (top right). A ratio greater than 1 means that the city receives more visitors than it sends residents, resulting in a concave curve in the evolution of its fleet. Conversely, a ratio of less than 1 indicates that the city is sending out more residents than it is receiving visitors, producing a convex curve.

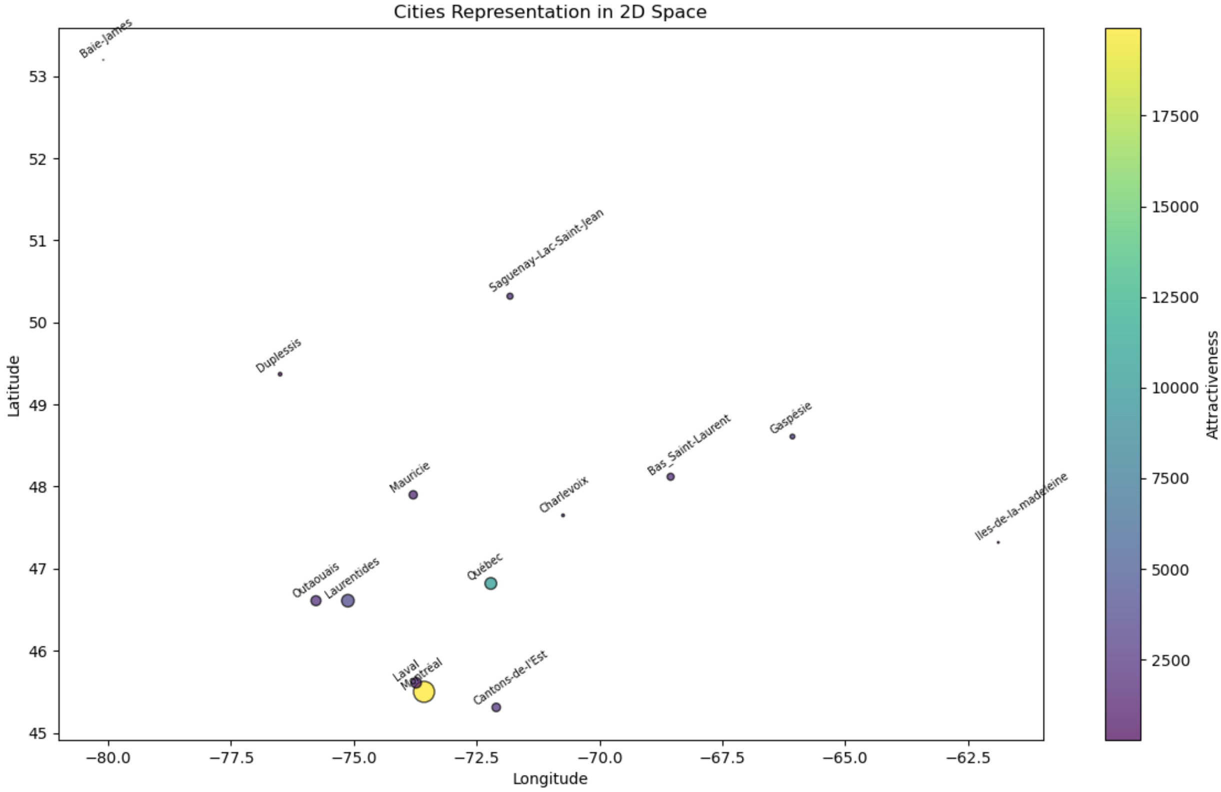

Figure 1 – Cities map representation

This load is linked to the initial optimal fleet calculated :

— A high load (ratio $>$ 1) requires an initial fleet representing around 10% of the city's population. Knowing that this fleet cannot fall below this proportion in our simulation.

— A low load (ratio $<$ 1) implies a significant increase in the initial fleet to compensate for the imbalance.

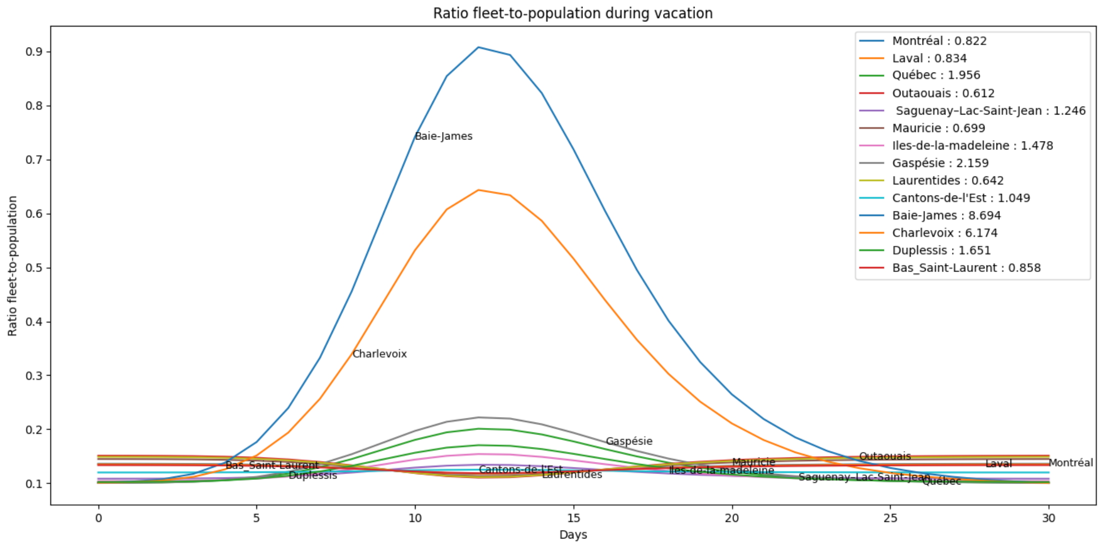

FIGURE 2 – Overcrowding level of each cities

Consider the case of Baie James, a small remote town (1979 inhabitants) with low absolute attractiveness, as shown on the map in Figure 1. Although it attracts practically no vehicles from other towns, it has the highest overload, with a load ratio of over 8. Indeed, because of its small population, even though it attracts very few vehicles in terms of absolute attractiveness, it receives more than it sends.

In contrast, the city of Montreal, which has a very large population (1,900,000) and is very attractive in absolute terms, has a load ratio of 0.6. It sends a lot of vehicles to other destinations (always 30% of the initial population). As a result, Montreal is emptying more than it is filling over the period. It will need a larger initial fleet (13.8% of the population) compared with 10% for Baie James as shown in figure 3 .

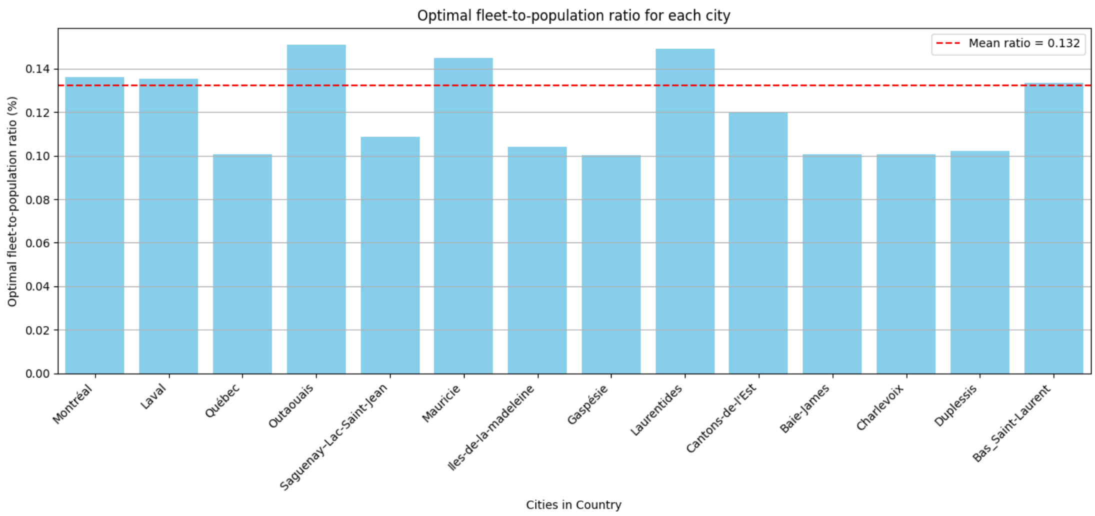

FIGURE 3 – Optimal fleet for each city

Secondly, we generalize our simulation by connecting an increasing number of cities to the 14 existing in this figure 4. We distinguish two cases. Firstly, the addition of cities with a load ratio greater than 1, i.e. cities that fill up, such as Baie James. The other is the addition of cities with load ratios exclusively below 1, i.e. cities that are tending to empty out, such as Montreal. In both cases, we see an increase in fleet size for all cities. Moreover the optimal fleet reaches up to maximum 16% but once the number of interconnected cities exceeds 60, the optimal fleet to be deployed decreases.

Our work, and therefore the results presented, has a number of limitations and areas for improvement. For example, the model used simplified assumptions concerning the ratios set between

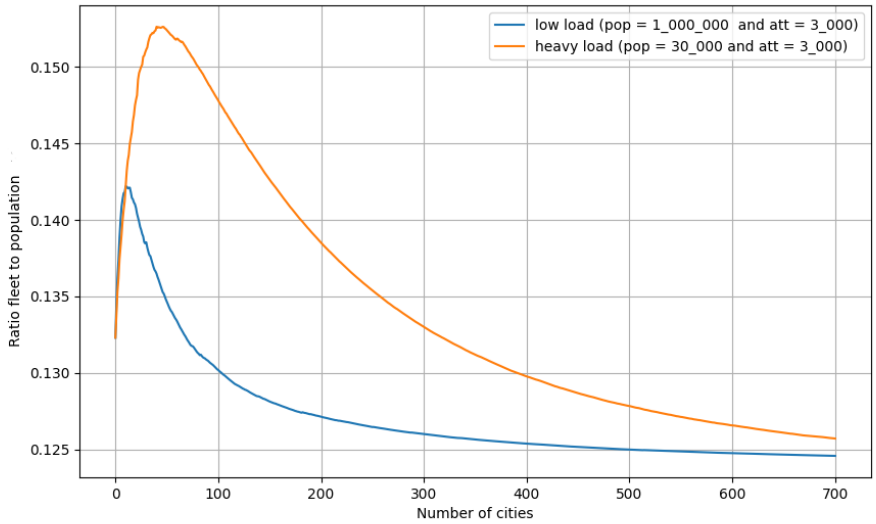

FIGURE 4 – Generalization to 700 cities connected

vehicles and people which will be adjusted in the light of studies showing variations due to demographic changes. The value of 10% of the fleet needed for everyday life comes from studies carried out on urban centers, whereas it could be that smaller centers need proportionally more cars. We are also attributing the same distribution to each city, is if it would follow and intrinsic need. However, it is likely that not all cities will have 30% of the population going for long-distance multi-day travel. Some may retain the majority of their population regardless of the period. We would also need to use real data to reproduce a complete country which would include thousands of interconnected cities. This would enable us to observe more realistic exchanges. It is important to note that these results should only be considered in the case of adding cities with identical load types. This stabilisation at 12% only reflects this behaviour, which is bound to change with real data. We are also aiming to refine our model by moving from a daily resolution to an hourly resolution in order to obtain better information on demand and to consider several modes of transport, including shared autonomous vehicles, buses and micro-mobility options. This expansion will give us valuable information of system's needs during peak and off-peak periods for traveling in and out of the city. In our current model, we haven't considered the maintenance, recharging and unloading times that would impact on the fleet we actually need to deploy to meet users' needs.
This change in methodology will enable us to carry out a more complete study of the size of the fleet during the holidays, allowing us to capture more accurately the dynamic fluctuations in travel demand fluctuations in travel demand that occur during these periods.

4 Conclusions

The results show that intercity travel reduces SAV efficiency compared to urban trips, requiring a higher fleet size. Cities with higher load ratios and then receiving more visitors than they send out require smaller initial fleets, while those with lower ratios need larger fleets to address imbalances. Expanding the network of interconnected cities of similar attractiveness and size one by one, initially increases fleet requirements to a peak of 16% of the population but eventually stabilizes around 12% as the system scales. These findings underlines the importance of dynamic and scalable fleet management strategies to optimize SAV systems and ensure efficient mobility across extensive intercity networks. Compared to studies focusing on intra-city travel only, the difference in terms of fleet size may seem minimal relative to the population (2-6%), but it should be stressed that this is substantial if considered relative to the fleet size (20-60%). The latter may be more important than the former when trying to operationalize the system, because of management and cost concerns. Additionally, adding more detail to the simulation, along the lines suggested by the limitations mentioned above, given they nature, is expected to increase rather than decrease the amount of vehicles needed. From this perspective, the further refinement of the model, and an expansion of the discussion from city-centered to multi-city SAV systems seems even more necessary.

Références

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