

Are Modular Transport Units the Answer for Tomorrow's Cities?

Matthias Prandstetter, Ulrike Ritzinger, Jürgen Zajicek, Christian Ecker

(Dr. Matthias Prandstetter, AIT Austrian Institute of Technology, Giefinggasse 4, 1210 Vienna, matthias.prandstetter@ait.ac.at)

(Dr. Ulrike Ritzinger, AIT Austrian Institute of Technology, Giefinggasse 4, 1210 Vienna, ulrike.ritzinger@ait.ac.at)

(DI Jürgen Zajicek, AIT Austrian Institute of Technology, Giefinggasse 4, 1210 Vienna, juergen.zajicek@ait.ac.at)

(Mag. Christian Ecker, AIT Austrian Institute of Technology, Giefinggasse 4, 1210 Vienna, christian.ecker@ait.ac.at)

1 ABSTRACT

The transformation in mobility is driven by electrification and automation. This paper examines a shared mobility system that utilizes small, driverless pods for transporting passengers and goods, assessing its efficiency, economic feasibility, and environmental impact.

We model the assignment of vehicles to trips as a Single Load Pickup and Delivery Problem with Time Windows (SLPDPTW) and present an Integer Linear Programming (ILP) formulation. Additionally, a heuristic approach is proposed to optimize trip assignments and the benefit of slipstreaming. We conduct computational experiments based on case studies from Austria to simulate various levels of adoption.

The results indicate that there could be a reduction of up to 75% in the number of vehicles required. However, increased mileage can offset some of these benefits. While slipstreaming improves efficiency, the energy savings it provides remain uncertain. The economic viability of this system depends on reducing the per-kilometer costs of the pod, which may be achievable with advancements in technology. Automated shared mobility presents significant promise but also encounters challenges related to sustainability and cost-effectiveness. Future research should explore larger vehicles, improved routing, and market developments.

Keywords: combinatorial optimisation, fleet size and mix, automated shared fleets, planning, mobility

2 INTRODUCTION

After multiple years or even decades of almost no paradigm change in mobility, we might face a disruptive evolution in mobility culture. Two main developments contribute to this effect: electrification and automation. The breakthrough in electrification is based on developments related to chemistry and physics, i.e., increasing energy density in batteries facilitating long-range electric vehicles. Automation is closely related to developments in new and advanced sensors and the ability to process and analyze the obtained data. Ironically, the automation of the automobile might finally come to completion. According to the Oxford English Dictionary automobile refers to self-moving [1]. Current technological developments raise hopes that self-driving cars will soon be the majority on our roads. Almost all modern cars are already equipped with some kind of driver-assisting technology, which ranges from parking assistants over lane keeping assist systems and cooperative adaptive cruise control to systems supporting overtaking [6]. However, such systems are designed to be assistants. That is, the driver of the car still has to be the driver. He has to be aware of the traffic situation all the time and needs to be able to intervene at any time. In many countries, regulations are even more strict. For example, in Austria, it is required that the driver has to have at least one hand on the steering wheel all the time [7]. However, exceptions exist according to the “Automatisiertes Fahren Verordnung” [8], enabling automated mobility in exceptional cases for testing and development.

In Phoenix, San Francisco, and Los Angeles (all USA), robotaxis are already serving customers regularly [2]. In Hamburg, it is planned to introduce a fleet of 10,000 “autonomous” electric shuttles. However, please note that one has to be careful when using the word autonomous in conjunction with vehicles. Usually, it is referred to as automated mobility. I.e., vehicles that can drive along a pre-defined path according to a set of learned rules. However, no autonomous decisions can be taken in case of (major) disruptions like unforeseen roadwork or even obstacles like broken-down vehicles. One strategy to overcome this is to allow for remote control of the vehicles in case of disruptions [4]. The benefits are evident as the number of personnel needed for vehicle operations can be significantly reduced. However, there are even ideas to at least introduce AI-based methods for supporting the human tele-operators [5].

Another trend that is already state-of-the-art in mobility is car-sharing. The basic principle of car-sharing is that cars are available (either at dedicated stations or free-floating), can be picked up by customers, used for one (or more trips), and then are returned (either at dedicated stations or free-floating) such that the next

customer can use the car. In fact, car-sharing is an extended version of car rental with way fewer bureaucratic hurdles during pick-up and return. Nevertheless, authentication during pick-up and one-time registration is still necessary.

2.1 Concepts for Automated Shared Vehicles

When combining the concepts of car-sharing and automated mobility, two possible options can be followed: First, a more evolutionary approach would be that the basic car-sharing concept is applied, which comprises of users walking to the shared cars, picking them up, and returning them at specific locations. In combination with automated mobility, the driving process would be automated. I.e., the user is only passenger and not driver.

Second, and (technologically) more advanced, the pickup and return process is transferred to the car. I.e., a car-sharing user calls a car that picks up the user. When returning the car, the user gets off the car and does not further care where and how the car is parked. Instead, the car automatically searches a parking lot. Obviously, the second approach corresponds to a classical taxi service without taxi drivers.

2.2 Contributions of this Paper

In this paper, we focus on the assessment of the second option for combination of automated mobility and car-sharing, i.e., the driver-less taxi service. However, the following assumptions are made. We assume that

- the used vehicles, called pods in the further context, provide space for at most two persons or one pallet of goods.
- the pods can be virtually connected while driving. I.e., they can build convoys. Pods can enter or leave convoys at any time without significantly interrupting the movement of the other pods in the convoy.
- pods can be used for both passenger and freight transport. It is not possible for goods and people to be transported in a pod at the same time. However, a person can be transported first and immediately afterwards a pallet can be transported (and vice versa).
- a significant number of passengers and good transports are shifted from conventional vehicles towards pods.

We assess the impacts of this change in mobility behavior concerning to the number of vehicles needed, the economic viability, and the environmental impact. This is done via optimizing the assignment of pods to trip demand. The underlying ILP model and a basic heuristic for solving large-sized instances are presented. Based on computational experiments conducted for three potential application areas, conclusions are drawn.

2.3 Related Works

According to the ITF (International Transport Forum) [11], it is assumed that an autonomous (shared) fleet can reduce the number of needed vehicles by 90%. However, this study does not consider concurrent trips, as this work does. In [17], the authors assume that one car-sharing vehicle might replace 5 to 20 unshared vehicles.

In [9], Alessandrini et al. investigate the potential for shared automated fleets in the urban context. While the results are quite promising with respect to the expected number of saved lives, reductions in fuel consumption, etc., they envisage a share of 50% of automated cars in approx. 2050 and 100% in 2070. However, their assessments are based on estimations, while this work focuses on applying an optimized vehicle-to-trip assignment.

In [12], the authors address a real-world scheduling problem of automated shuttles. The underlying problem addressed is a dynamic pick-up and delivery problem which needs to be solved with a fleet of automated vehicles. The given problem is tackled with a large neighborhood search-based approach. Challenging is the fact that vehicles on the road might influence each other as maneuvers like overtaking are not possible for the chosen automated fleet.

Related but not directly significant for this work, the authors of [10] evaluate an average occupation rate of 1.3 persons per car in Austria. It has to be kept in mind, that autonomous vehicles will significantly reduce

this number, mainly if they are employed as envisioned in this work where (empty) cars are called to pick up customers.

3 PROBLEM FORMULATION

In this work, the given road network is a directed graph $G = (V, A)$, which consists of a set of nodes $N = \{0, \dots, n\}$ and a set of arcs A , representing the road segments between a pair of nodes $a_{\{i,j\}} \in A$ and $i, j \in N$. Each arc $a_{\{i,j\}} \in A$ has travel costs $c_{\{i,j\}}$ assigned. Furthermore, we consider a set of trip demands D , which represents the commuting distances from a given origin to a given destination. Thus, each trip demand $d \in D$ consists of an origin and destination node pair $\{r_d, s_d\}$, with $r_d, s_d \in N$, having a maximum load of two. The set of all origin and destination nodes is defined as $R \subseteq N$. Additionally, the earliest start time for the demand at the origin is available by e_{r_d} , and the latest end time at the destination is given by l_{s_d} . Since all trip demands must be completed without combining them with other trips, we model the problem as a *single load pickup and delivery problem with time windows (SLPDPTW)* [20]. There, all load from the origin must be transported directly to its destination, which causes empty moves between the destination and the origin of the next trip demand. For directly arriving at the destination, the shortest cost path between each pair of nodes $\{i, j\} \in R$ is computed as $d_{i,j}$. Furthermore, there is a set of pods P available to serve the given number of trip demands. Each pod $p \in P$ has a maximum capacity of two units. However, the capacity constraint can be neglected in this work, since demand combination is not allowed. Although this is not allowed, pods must not take the shortest path from the origin to the destination. This allows pods to take alternative paths. To prevent excessive deviation from the shortest path, a maximum allowed detour \bar{T} is defined, which must not be exceeded.

The SLPDPTW formulated in this work aims to serve all trips with the minimum number of pods while considering the time constraints, such as earliest start time, latest end time, and maximum allowed detour. The second objective is to maximize the positive effects of slipstreaming while operating the pods. In a conventional traffic system with conventional vehicles, a minimum distance must be maintained between vehicles for safety reasons. However, for the pods considered in this work, it is feasible to form convoys in which two or more pods can benefit from slipstreaming, thus reducing energy consumption. This is possible because it is assumed that the pods can communicate with each other, cf. [14]. Therefore, the overall goal is to minimize the number of pods (to reduce costs) while simultaneously maximizing the formation of convoys (to enhance energy efficiency). Since defining a convoy in this dynamic environment can be complex, we opted to maximize the slipstream kilometers of all vehicles. Note, that if only one vehicle is in a convoy, no slipstream kilometers are counted. However, every vehicle from the second onward in a convoy benefits from the slipstream effect, allowing for straightforward computation of slipstream kilometers.

$$\begin{aligned}
 x_{pd} &= \begin{cases} 1 & \text{if pod } p \text{ fulfills demand } d \\ 0 & \text{otherwise} \end{cases} & \forall p \in P, d \in D \\
 b_p &= \begin{cases} 1 & \text{if pod } p \text{ is used at least once} \\ 0 & \text{otherwise} \end{cases} & \forall p \in P \\
 y_{pd}^{ta} &= \begin{cases} 1 & \text{if pod } p \text{ enters arc } a \text{ at time } t \text{ to fulfill demand } d \\ 0 & \text{otherwise} \end{cases} & \forall p \in P, a \in A, d \in D, t \in T \\
 z_{pq}^{ta} &= \begin{cases} 1 & \text{if pods } p \text{ and } q \text{ are entering arc } a \text{ at time } t \\ 0 & \text{otherwise} \end{cases} & \forall p, q \in P, p < q, a \in A, t \in T
 \end{aligned}$$

Figure 1: Variables used in the ILP model.

$$\begin{aligned}
 & \min \sum_{p \in P} b_p - \sum_{p \in P} \sum_{q \in P} \sum_{a_{ij} \in A} \sum_{t \in T} z_{pq}^{ta_{ij}} & (1) \\
 & \text{subject to } \sum_{p \in P} x_{pd} = 1, & \forall d \in D & (2) \\
 & \quad b_p \geq x_{pd}, & \forall p \in P, d \in D & (3) \\
 & \quad b_p \leq b_{p-1}, & \forall p \in P \setminus \{1\} & (4) \\
 & \quad \sum_{t \in T} y_{pd}^{ta_{ij}} \leq x_{pd}, & \forall p \in P, d \in D, a_{ij} \in A, i, j \in N & (5) \\
 & \quad \sum_{\substack{a_{ij} \in A \\ i, j \in N}} y_{pd}^{ta_{ij}} \leq x_{pd}, & \forall p \in P, d \in D, t \in T & (6) \\
 & \quad \sum_{p \in P} \sum_{t \in T} y_{pd}^{ta_{ij}} \leq 1, & \forall a_{ij} \in A, i, j \in N, d \in D & (7) \\
 & \quad \sum_{a_{ij} \in A} \sum_{d \in D} y_{pd}^{ta_{ij}} \leq 1, & \forall p \in P, t \in T & (8) \\
 & \quad \sum_{p \in P} \sum_{t \in T} \sum_{\substack{a_{ik} \in A \\ k \in N \setminus \{i\}}} y_{pd}^{ta_{ik}} = 1, & \forall i = r_d \in R, d \in D & (9) \\
 & \quad \sum_{p \in P} \sum_{t \in T} \sum_{\substack{a_{kj} \in A \\ k \in N \setminus \{j\}}} y_{pd}^{ta_{kj}} = 1, & \forall j = s_d \in R, d \in D & (10) \\
 & \quad 1 - \sum_{d' \in D} \sum_{t' \in T} y_{pd'}^{t'a_{ij}} \geq y_{pd}^{ta_{ij}} & \forall p \in P, t \in T, d \in D, d \neq d', & \\
 & \quad \sum_{p \in P} \sum_{i \in N \setminus \{s_d\}} y_{pd}^{t'a_{ik}} \geq y_{pd}^{ta_{kj}} & \forall p \in P, t \in T, d \in D, a_{kj} \in A, & \\
 & \quad \quad \quad k \in N \setminus \{r_d, s_d\}, j \in N \setminus \{r_d\}, & & \\
 & \quad \quad \quad t' = t - c_{a_{ik}}, t' \geq 0 & (11) \\
 & \quad \sum_{p \in P} \sum_{t \in T} \sum_{\substack{a_{ki} \in A \\ k \in N \setminus \{i\}}} y_{pd}^{ta_{ki}} = 0, & \forall i = r_d \in R, d \in D & (12) \\
 & \quad \sum_{p \in P} \sum_{t \in T} \sum_{\substack{a_{jk} \in A \\ k \in N \setminus \{j\}}} y_{pd}^{ta_{jk}} = 0, & \forall j = s_d \in R, d \in D & (13) \\
 & \quad 1 - \sum_{d' \in D} \sum_{k \in N} \sum_{t'} y_{pd'}^{t'a_{ksd'}} \geq y_{pd}^{ta_{r_dk}} & \forall p \in P, t \in T, a_{r_dk} \in A, & \\
 & \quad \quad \quad k \in N \setminus \{r_d\}, d \in D, d \neq d', & & \\
 & \quad \quad \quad t' = \max(0, t - (\hat{c}_{s_d'r_d} + c_{ks_d'})) & (14) \\
 & \quad \sum_{d \in D} y_{pd}^{ta} + \sum_{d \in D} y_{qd}^{ta} - 1 \leq z_{pq}^{ta} & \forall p, q \in P, p < q, a \in A, t \in T & (15) \\
 & \quad \quad \quad \sum_{q \in P} z_{pq}^{ta} \leq \sum_{d \in D} y_{pd}^{ta} & \forall p \in P, p < q, a \in A, t \in T & (16) \\
 & \quad \quad \quad \sum_{p \in P} z_{pq}^{ta} \leq \sum_{d \in D} y_{qd}^{ta} & \forall q \in P, p < q, a \in A, t \in T & (17) \\
 & \quad \sum_{p \in P} \sum_{t \in T} \sum_{a_{ik} \in A} t \cdot y_{pd}^{ta_{ik}} = f_d & \forall d \in D, i = r_d \in R, k \in N \setminus \{r_d\} & (18) \\
 & \quad \sum_{p \in P} \sum_{a_{kj} \in A} \sum_{t=0}^{\hat{T}} (t + c_{kj}) \cdot y_{pd}^{ta_{kj}} = g_d & \forall d \in D, j = s_d \in R, k \in N \setminus \{s_d\}, & \\
 & \quad \quad \quad t \in T, \hat{T} = l_{s_d} - c_{a_{kj}} & (19) \\
 & \quad \quad \quad f_d \geq e_{r_d} & \forall d \in D, k \in N \setminus \{r_d\} & (20) \\
 & \quad \quad \quad g_d \leq l_{s_d} & \forall d \in D, k \in N \setminus \{s_d\} & (21) \\
 & \quad \quad \quad \hat{c}_{r_d s_d} \leq (g_d - f_d) \leq \hat{T} & \forall d \in D & (22) \\
 & \quad \quad \quad & & (23)
 \end{aligned}$$

Figure 2: The constraints of the ILP model.

We formulate the SLPDPTW model as an integer linear program. Therefore, we introduce the variables and the ILP formulation as shown in Figures 1 and 2. The objective is to minimize the total number of used pods and maximize the number of pods using the same arc at the same time (1). Constraint (2) ensures that each trip demand is fulfilled by exactly one pod. Constraint (3) enables pod p if it fulfills at least one demand and (4) allows pod p to be only enabled if pod p-1 is active (symmetry break). Constraint (5) states that for a pod and a trip demand an arc can be used only once over time. Constraint (6) determines that a pod which

fulfills a demand enters an arc exactly once at exact one time. Constraint (7) expresses that each arc is used exactly once for a demand independent of the pod and time), and (8) expresses that each pod is used exactly once at a time, independent of the arc and the demand. Constraint (9) and (10) ensure that there is exactly one outgoing arc at the origin node of a demand and exactly one ingoing arc at the destination node. Constraint (11) ensures that a pod is not used for other demands while traversing an arc. Constraint (12) ensures the consistency of a path between origin and destination node. Constraint (13) and (14) ensure that there is no ingoing arc at the origin node and no outgoing arc at the destination node of a trip demand, because only paths from origin to destination are constructed instead of tours, and (15) ensures that there is enough time (at least the shortest path costs) to get the pod from the destination node to the origin node of the next trip demand. Two pods transporting different demands entering the same arc at the same time is stated in (16), while (17) and (18) force it to zero if this is not the case. Constraint (19) determines the begin time at the origin node and (21) ensures that this is after the given earliest allowed start time. And (20) and (22) determine the begin time at the destination and ensure that this is before the latest allowed end time. Finally, constraint (23) checks if the travel cost from the origin to the destination does not exceed the maximum allowed detour.

4 ALGORITHMIC APPROACH

The solving capability of the implemented ILP approach is quite limited when it comes to the size of the instances. It is not feasible to manage a road network with a large number of trip demands and with a planning horizon of one day while achieving a timely resolution within seconds. Therefore, we have also developed a heuristic algorithm for solving the SLPDPTW.

The heuristic begins by assigning pods to the trip demands. First, it preprocesses the data to calculate the shortest cost path from the origin to the destination for all trip demands. It then sorts the list of trip demands according to their earliest start time. Next, the greedy heuristic generates a starting solution by sequentially assigning the trip demands with the shortest path costs using a first-fit insertion method, while adhering to their earliest start and latest arrival times. If no feasible insertion can be found for a trip demand, it will be assigned to a new pod.

After establishing the starting solution, it is evaluated in terms of slipstreaming, which involves calculating the total slipstreaming travel costs for all pods and trip demands. We determine for each trip demand when the edges of their respective paths must be entered to maintain a feasible solution. This results in a map that records, for each visited edge, a list of trip demands that traverse that edge, along with a time window indicating possible entry times. The entries in this list serve as potential candidates for slipstreaming. In the subsequent step, the heuristic combines trip demands for slipstreaming if their entry time windows overlap. When overlap occurs, the time windows for all affected entries in the map must be updated. This involves reassessing all edges of the paths for the trip demands, as well as for any other trip demands that are already slipstreaming with them. Once all time windows for edge entry times are updated, the number of slipstreaming pods for all edges can be computed, and this number is then multiplied by the respective travel costs.

The objective is to improve slipstreaming, even if it results in additional travel time. To achieve this, we assess alternative routes for each trip demand, ensuring that these alternatives do not exceed the maximum allowed detour costs. The heuristic method involves ten iterations, during which we randomly select alternative travel paths for all trip demands and verify whether the solution is still feasible within the constraints of the earliest start and latest end times. If a proposed solution is not feasible, we retain the shortest cost path in the solution set. Following this, we evaluate the slipstreaming costs. Ultimately, the solution that maximizes slipstreaming, along with its corresponding paths (whether they are the shortest or alternatives), is returned as the final solution.

5 EXPERIMENTAL SETUP

The computational experiments conducted in this study are based on three showcases taken from Austria: IZ NÖ Süd (an industrial area in the south of Vienna), Vienna Airport region, and the triangle Korneuburg-Flordisdorf-Gerasdorf (a suburban region in the north of Vienna). We used the traffic network, statistics on commuting behaviour [15], and land use information [16] for each of these regions to generate instances mimicing real-world characteristics. Trip demand generation involves determining an origin, a destination,

and a desired departure time for each trip. Within the study area, origins and destinations are randomly selected based on land use patterns [16]. Specifically, commuter trips originate or terminate in residential or commercial zones. For trips that begin or end outside the study area, origins or destinations are designated as access points, which include highway entrances and public transit stations. The distribution of these access points between highway entrances and transit stations is strategically designed to reflect the observed modal split, informed by statistical data [15]. Departure times are also assigned based on statistical distributions [15]. For trips based on freight transports, a similar approach was chosen, although the numbers are based on educated estimations according to experience of the authors and the project partners. We refer to Table 1 to summarize the statistics considered for the further used showcases. Please note that they are named A1, A2, and A3 as they are only based on the areas as mentioned above, but the results are not representative of these areas as some assumptions (e.g., freight transport) need to be made.

Based on these statistics, the following instances have been generated: For each area A1, A2, and A3, we assume that only 5%, 10%, 20%, 30%, and 40% of the people are willing to switch to the proposed pods. For each percentage, 20 instances have been randomly generated (based on the above mentioned statistics) resulting in an overall of 300 instances, which have been solved using the described heuristic approach.

In order to compare the impact of considered pod-based system, two comparisons are made. First, the overall number of pods is compared to the overall number of vehicles needed to satisfy all the trip demands. We consider that all freight trips are done via trucks. As the load unit for freight trips is considered to be pallets, the numbers given in Table 1 need to be divided by 33, i.e., the number of pallets to be loaded on a truck. For the commuters, we need to assume that each individual traveller uses his or her own car. That is, for example, that for A1 20,900 cars are needed to satisfy the trip demands done via car.

The second comparison is on the actual costs associated with the trips. For this purpose, we calculate the costs of the individual trips in the status quo based on the Austrian statutory mileage allowance, which is 0.52€/km.

	area [km ²]	commuters	freight (pallets)	avg.MIT [%]
A1	2.7	22,000	3,800	95
A2	73.0	37,750	9,700	87
A3	70.0	125,330	14,000	88

Table 1: Basic statistical data for the considered showcases. The area corresponds to the overall area in the showcase. Commuters, as well as freight, include inbound and outbound trips per day, and avg.MIT denotes the modal split for motorized individual traffic (MIT).

6 COMPUTATIONAL RESULTS

As described in the previous section, 300 randomly generated instances have been used for our computational experiments. Each of the instances has been solved using the proposed heuristic approach, as the exact model presented is not powerful enough to solve instances of these sizes.

In Figure 3-5 the obtained results are shown. For each showcase, the number of vehicles before the switch and the number of pods afterwards are shown in the left diagram (avg #cars vs. avg #pods). In addition, the relative reduction in the number of vehicles is shown. It can be seen that for the smallest instance (A1) only 56% reduction in cars could be achieved. For the larger instances up to 75% could be achieved. That is, the potential is enormous. At the same time, this number is in line with numbers found in the literature for car-sharing concepts, cf. [17].

In addition, we show on the right side of Figure 3-5 the comparison of the vehicle travel time. The red bar indicates the travel times (of vehicles) in the current situation. Vehicles are used for only one trip before being parked. The grey bar indicates the travel times of the pods. Please note that pods need to travel with the passenger (or goods), they travel empty to the origin of the next trip demand and in addition, might take detours during occupied travel in order to profit from slipstreams. Therefore, the overall travel time of pods is longer. At the same time, slipstream travelling can be done (indicated by the purple bar). This is not possible for individual cars due to safety reasons). The line indicates how much energy consumption (compared to conventional trips) are “allowed” during slipstream travelling such that the pods system does not consume more energy than the conventional system. It can be clearly seen that this allowed energy

consumption significantly raises with the relative share of pod users. However, values are still quite low with a maximum of about 30%.

Please note that computational times for the heuristic are up to about two hours for the largest instances which is quite low compared to the observation that these computations are needed just once when planning the introduction of such a system.

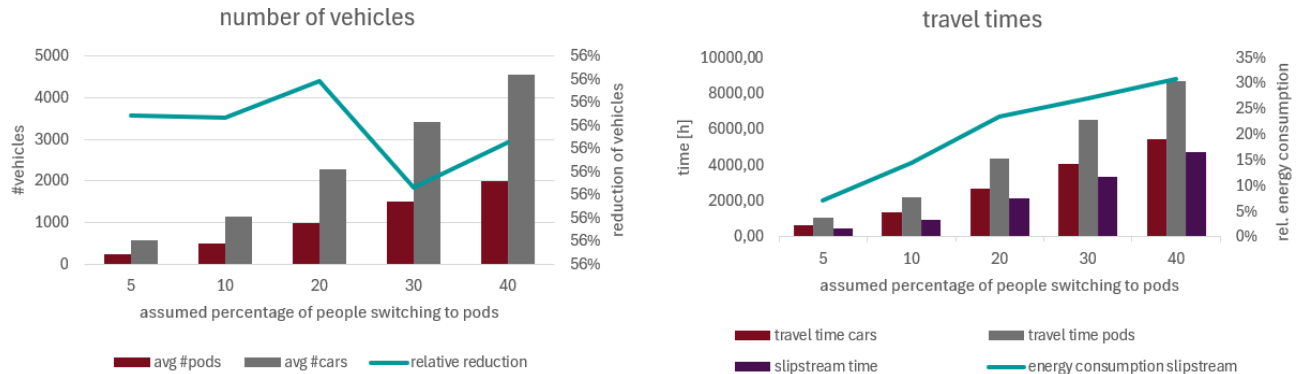


Figure 3: Showcase A1; comparison of the number of vehicles (left); comparison of the travel times (right)

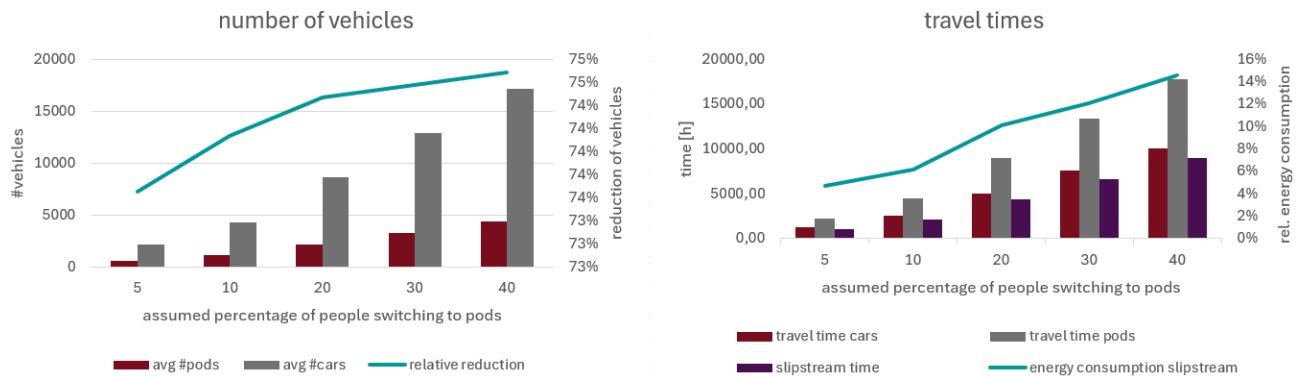


Figure 4: Showcase A2; comparison of the number of vehicles (left); comparison of the travel times (right)

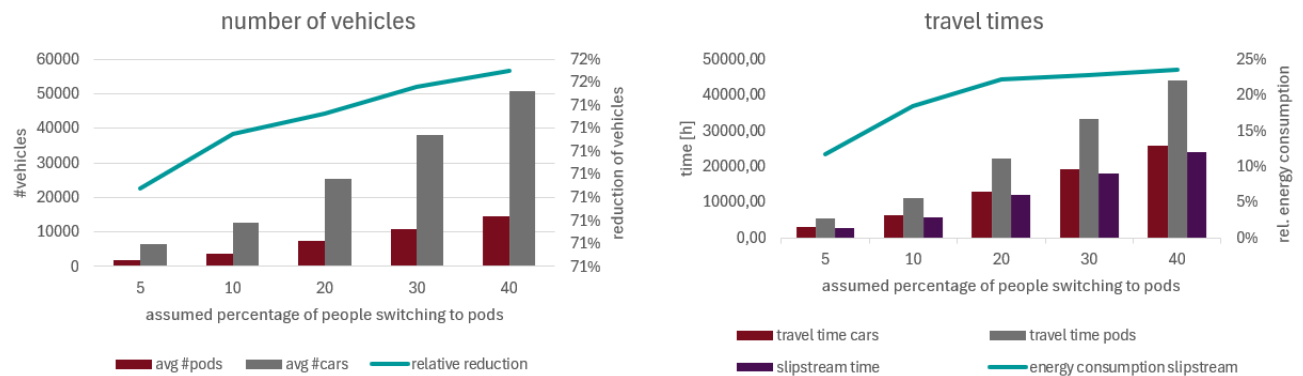


Figure 5: Showcase A3; comparison of the number of vehicles (left); comparison of the travel times (right)

7 ECONOMIC ASSESSMENT

While in Section 6 only traffic related evaluations are done, this section tries to focus on the economic part of the proposed system. A detailed assessment is quite hard, as many different options have to be considered. Therefore, a first estimate is tried within this section.

First, we compute the value for the overall travel costs according to the Austrian statutory mileage allowance, which is currently at 0.52€/km. As can be seen in Table 2, the costs range for the chosen test instances from around €9,000 to €335,000 per day on travel costs.

For the proposed pod-based mobility system, the maximum costs per kilometer such that the system is still economically viable (compared to the status quo) can be computed based on the costs of the current system divided by the distance to be traveled by the pods. As can be easily seen in Table 2, the economic viability of

the system is only given if the per-kilometer costs are far below the currently assumed costs for conventional vehicles.

Therefore, we made a short calculation trying to obtain a range of realistic cost values per kilometer for the operation of the pods. Based on a price list for renting pods [18], we obtained a range of 0.26€/km to 0.38€/km which indicates that operation at the economic break-even point might be realistic but strongly depends on the further development of the pod market.

	% of pod users	costs conventional (per day) [€]	resulting maximum costs per km for pods [€]
A1	5	8,800	0.32
	10	17,600	0.32
	20	35,300	0.32
	30	52,900	0.32
	40	70,500	0.32
A2	5	16,400	0.29
	10	32,800	0.29
	20	65,400	0.29
	30	93,100	0.29
	40	131,000	0.29
A3	5	42,000	0.30
	10	83,800	0.30
	20	167,700	0.30
	30	251,600	0.30
	40	335,300	0.30

Table 2: Estimated costs per day for trips using the conventional traffic system or the introduced pod-based mobility system.

8 SUMMARY AND CONCLUSIONS

Within this work, we proposed the introduction of a car-sharing system incorporating automated vehicles referred to as pods. These pods are considered to be rather small such that at most two persons or one pallet can be loaded. Based on three real-world motivated showcases, we assessed the traffic related as well as the economic impact. It can be easily shown that even when applying an optimized scheduling of vehicles to trip demands, additional mileage (compared to the status quo) needs to be covered by such a system. At the same time, the number of vehicles can be reduced by up to 75%. Further, it could be shown that such a system might benefit from the ability to use slipstream effects. However, due to the additional mileage, the energy consumption of the vehicles in the slipstream should be at most 30% compare to the energy consumption of vehicles not profiting from slipstreams. Although, it is necessary to evaluate whether such values can be achieved for pods, studies for trucks indicate that these values are far below realistic boundaries as for trucks energy savings in platooning are about 30% maximum [19].

The economic assessment revealed that the per-kilometer costs of conventional cars compared to the per-kilometer costs of automated pods can be much higher in order to obtain the same total system costs (related to travel). Based on prices promoted by one pod producer automated cars are much more expensive than conventional ones. Nevertheless, the first estimates show that the necessary cost reduction for per-kilometer prices could be achieved with automated pods. However, it is necessary to perform a further analysis considering costs for parking space and other effects as well. This is left for future work.

To summarize, from the current viewpoint it is very unlikely that a fully automated pod-based mobility system is ecological/traffic-related viable. From an economic point of view, the break-even point might be reached. However, it is necessary to further investigate whether different pods (e.g., larger with more bundling potential) could have a positive effect. In addition, future prices of pods might significantly drop, which could lead to more economic options.

9 ACKNOWLEDGEMENTS

This work received funding from the Austrian Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology (BMK) in the Mobilitätswende programme under grant FO999909875 (project IMAMTU). We acknowledge our project partners Fraunhofer Austria Research GmbH who strongly supported in data collection and data provision. We acknowledge the contribution of Clovis Seragiotto for helping at data processing and implementation of the optimization approaches.

10 REFERENCES

- [1] Oxford English Dictionary: automobile. https://www.oed.com/dictionary/automobile_adj. Last visited Feb 2025.
- [2] Waymo. Website. <https://waymo.com/>. Last visited Feb 2025.
- [3] Connected Automated Driving. Report on Project ALIKE.(2023) <https://www.connectedautomateddriving.eu/blog/project-alike-aims-for-10000-autonomous-electric-shuttles-in-hamburg-by-2030/>. Last visited Feb 2025.
- [4] Lei Kang, Wei Zhao, Bozhao Qi, and Suman Banerjee. 2018. Augmenting Self-Driving with Remote Control: Challenges and Directions. In Proceedings of the 19th International Workshop on Mobile Computing Systems & Applications (HotMobile '18). Association for Computing Machinery, New York, NY, USA, 19–24. <https://doi.org/10.1145/3177102.3177104>
- [5] Cirianni FMM, Comi A, Quattrone A. Mobility Control Centre and Artificial Intelligence for Sustainable Urban Districts. Information. 2023; 14(10):581. <https://doi.org/10.3390/info14100581>
- [6] Duarte SP, Lobo A, Ferreira S, Couto A. Driving as a Service: Promoting a Sustainable Transition to Automated Driving. Sustainability. 2024; 16(7):2809. <https://doi.org/10.3390/su16072809>
- [7] Republik Österreich. Bundesgesetz. Straßenverkehrsordnung. <https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=10011336>. Last visited Feb 2025.
- [8] Republik Österreich. Bundesgesetz. Automatisiertes Fahren Verordnung. <https://www.ris.bka.gv.at/GeltendeFassung.wxe?Abfrage=Bundesnormen&Gesetzesnummer=20009740>. Last visited Feb 2025.
- [9] Adriano Alessandrini, Andrea Campagna, Paolo Delle Site, Francesco Filippi, Luca Persia. Automated Vehicles and the Rethinking of Mobility and Cities, Transportation Research Procedia, Volume 5, 2015, Pages 145-160, ISSN 2352-1465, <https://doi.org/10.1016/j.trpro.2015.01.002>.
- [10] Tomschy, R., Herry, M., Sammer, G., Klementsitz, R., Riegler, S., Follmer, R., Gruschwitz, D., Josef, F., Gensasz, S., Kirnbauer, R., et al.: Österreich unterwegs 2013/2014: Ergebnisbericht zur österreichweiten Mobilitätserhebung. Technical report, Bundesministerium für Verkehr, Innovation und Technologie (2016). https://www.bmk.gv.at/dam/jcr:fbe20298-a4cf-46d9-bbec-01ad771a7fda/oeu_2013-2014_Ergebnisbericht.pdf. Last visited Feb 2025.
- [11] ITF (2015) Urban mobility system upgrade: how shared self-driving cars could change city traffic. International Transport Forum Policy Papers, Bd. 6. OECD-Publishing, Paris
- [12] Ritzinger U., Hu B., Reinthaler M. (2025): On-demand Automated Guided Vehicles in Yard Logistics. In LNCS, Vol.15173. Proceedings of Computer Aided Systems Theory – EUROCAST 202419th International Conference, Revised Selected Papers. Springer. (to appear)
- [13]AIT Austrian Institute of Technology (2024) Project Website IMAMTU. <https://www.ait.ac.at/en/research-topics/transport-optimisation-energy-logistics/projects/imamtu>Last Accessed Feb 2025.
- [14] NExT S.R.L. (2025) Website. <https://www.next-future-mobility.com/> Last Accessed Feb 2025.
- [15] Lammer F., Cik M., Rittler C., Fellendorf M.(2023) Kordonenerhebung Wien 2022.https://www.vor.at/fileadmin/CONTENT/Downloads/KordonenerhebungWien_2022_barr_.pdf
- [16] Land Niederösterreich (2025) Flächenwidmung NÖ.Land Use NÖ <https://atlas.noe.gv.at/atlas/portal/noe-atlas/map/Planung%20und%20Kataster/FI%C3%A4chenwidmung>
- [17] Bondorová, B., & Archer, G. (2017). Does sharing cars really reduce car use?.<https://www.transportenvironment.org/sites/te/files/publications/Does-sharing-cars-really-reduce-car-use-June%202017.pdf> Last Accessed Feb 2025.
- [18] NExT S.R.L. (2023) get-next.com: Public price list No3 Last accessed Sep 2023.
- [19] S. Tsugawa, S. Jeschke and S. E. Shladover, "A Review of Truck Platooning Projects for Energy Savings," in IEEE Transactions on Intelligent Vehicles, vol. 1, no. 1, pp. 68-77, March 2016, doi: 10.1109/TIV.2016.2577499.
- [20] Archetti, C., Speranza, M.G. (2005). Collection of Waste with Single Load Trucks: A Real Case. In: Fleischmann, B., Klose, A. (eds) Distribution Logistics. Lecture Notes in Economics and Mathematical Systems, vol 544. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-17020-1_6