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Proactive empty vehicle rebalancing for Demand Responsive Transport services

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Abstract

Worldwide, ridesharing business is steadily growing and has started to receive attention also by public transport operators. With future fleets of Autonomous Vehicles, new business models connecting schedule-based public transport and feeder fleets might become a feasible transport mode. However, such fleets require a good management to warrant a high level of service. One of the key aspects of this is proactive vehicle rebalancing based on the expected demand for trips. In this paper we model vehicle rebalancing as the Dynamic Transportation Problem. Results suggest that waiting times can be cut by around 30 % without increasing the overall vehicle miles travelled for a feeder fleet in rural Switzerland.

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1. Introduction

With the help of mobile communication technology, ridesharing operators, or Transportation Network companies (TNCs), have managed to re-design the way how vehicles are dispatched to passengers. In conjunction with a demand-based pricing, this has led to an increased demand for such services in urban areas. In several cities, TNCs are one of the drivers of increased traffic congestion [10]. More recently, the idea of dynamically pooling several passengers into a single vehicle has come up. Pooling might be beneficial for both passengers, who gain from lower prices, and operators, who incur lower operating costs per trip. Also, pooling may reduce the overall vehicle miles travelled and thus help to reduce congestion. That is, if trips would otherwise have been made by private car or non-pooled services.

Outside urban areas, ridesharing may be seen as a replacement or supplement for conventional public transport, especially in areas with an overall low passenger demand. Often, such services are called demand responsive transport

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(DRT). First- and last mile feeder services to and from railway stations could possibly even help to stimulate the demand for railway trips compared to infrequent standard bus services. Especially in the context of automated vehicles (AVs), using smaller DRT vehicles may also become financially attractive. However, using ridesharing as feeder services is complex: Demand for trips is not evenly spread. During certain times, demand for travel towards a station is higher than from there, and vice versa. Thus, a profound fleet control planning and a proactive rebalancing of empty vehicles is required to maintain a high level of service. In this paper, a rebalancing algorithm for a DRT service is introduced and implemented inside an agent-based transport simulation. As a use case, a simulation scenario in a rural area in Switzerland is evaluated. This holistic approach provides a detailed overview of the possible impact of DRT services and fleet rebalancing.

Several recent papers deal with simulation scenarios of (automated) ridesharing and DRT operators. Many of them focus on the possible demand reactions to fleets. Hoerl et al. have evaluated different strategies for both vehicle dispatch and rebalancing in an urban setup [5], however, no pooling of passengers was considered. Reck and Axhausen [9] have evaluated several intermodal ridesharing and public transport offers around the globe, concluding that in most areas the transfer time that occurs from changing from DRT to public transport is often too high to be considered worthwhile by passengers, even if there is an incentive for intermodal trips. Previous simulation studies on intermodal trips suggest that their operations should mainly be considered in regions with low population density, otherwise classic schedule-based public transport is likely to be more efficient [8].

2. Methodology

The simulation platform used in this study is MATSim [1]. Over the last years, a set of MATSim extensions have been developed in order to realistically simulate Dynamic Vehicle Routing Problems (DVRP), such as dispatch of taxis and DRT vehicles. The DRT extension, which has first been introduced in a shared-taxi context for the city of Berlin [4], is based on immediate requests for pooled vehicles, where each passenger is willing to accept a certain detour. The maximum allowable travel time, including the initial waiting time for the vehicle, is calculated as:

$$t_{max} = \alpha \cdot t_{direct} + \beta,$$

where:

- t_{direct} – direct travel time,
- $\alpha \geq 1$ and $\beta \geq 0$.

The actual vehicle dispatch is based on an insertion heuristic, where for each new incoming request all feasible insertion points are assessed and the best one (for a given objective function) is chosen. The feasibility of insertion is checked against the following constraints: vehicle capacity, vehicle availability (time window), maximum wait time and travel time (for both the new request and all other uncompleted requests). By default, if no feasible insertion exists, the request gets rejected. A detailed mathematical formulation of the problem and the insertion heuristic can be found in [4].

The insertion heuristic has proved to provide meaningful and efficient solutions reasonably fast. The extension is used in several research studies around the globe [2, 8, 3, 6]. The DRT module has several extension points that include the functionality of sending vehicles back to depots, simulating electric vehicles [12] or relocating empty vehicles. The implementation of the last is the focus of this paper.

The goal of relocating idle vehicles over the operations area is to ensure that the spatial availability of vehicles follows the spatial distribution of demand in the (near) future. Because moving idle vehicles generates cost, it needs to be performed in an efficient way. One way of solving vehicle rebalancing is by modelling it as a transportation problem, where the cost of moving idle vehicle is minimized. The transportation problem can be efficiently solved in polynomial time using dedicated algorithms. However, there are many decisions to be taken while converting a vehicle rebalancing problem to a transportation problem, such as:

- what is the expected demand for the DRT service?
- what is the target number of vehicles to be available in each zone? (i.e., how to map the demand for the DRT service to the number of DRT vehicles required to provide that service?)
- what vehicles can be considered rebalanceable, i.e., can be sent from the current location to somewhere else?
- what vehicles can be counted as available in each zone, i.e., can serve requests originating from that zone?
- how often should the rebalancing procedure be executed? (e.g., periodically or in response to incoming events, such as a new request submission, vehicle arrival etc.)
- what is the optimal zonal aggregation level

These and similar questions are already hard to answer for non-pooled services (e.g. taxi). Sharing rides makes them even harder. Once they are answered, we can build a transportation problem, where the deficit of vehicles in some zones needs to be satisfied by sending vehicles from the zones with an oversupply of vehicles.

To provide the rebalancing functionality for the DRT vehicles in MATSim, we adapted the DTP (Dynamic Transportation Problem) method proposed in [7] for redistribution of empty Personal Rapid Transit vehicles. The method is available in MATSim as `MinCostFlowRebalancingStrategy` and consists of the following steps:

1. Group *rebalanceable* vehicles by zone. By default, all idle vehicles for which the remaining operations time is not less than the $T_{MIN_SERVICE}$ threshold are considered rebalanceable)
2. Group *soon-idle* vehicles by zone. These are busy vehicles which are expected to become idle soon, like: (1) approaching the last planned stop, (2) being recharged, or (3) being relocating. By default, the following two conditions must be met for a vehicle to be considered soon-idle:
 - the remaining operations time is not less than $T_{MIN_SERVICE}$, same as for an idle vehicle
 - additionally, the vehicle is expected to become idle not later than in a T_{MAX_BUSY} amount of time

Both rebalanceable and soon-idle vehicles are considered *inbound* vehicles in a given zone.

3. Estimate the *target* number of inbound vehicles per each zone. By default, a linear function of the expected demand, which is the number of trips originating from a given zone in the next time interval ($T_{INTERVAL}$) is based on historical runs (like previous iterations). By default, the time interval is set to 1800 seconds. The linear coefficient a models the relation between the number of incoming requests and the target number of inbound vehicles ready to serve them. The b constant is responsible for setting the desired number of extra vehicles. Both parameters strongly depend on the length of the time interval. They also should be relatively low to prevent the rebalancing method from over-reacting which increases empty mileage and reduces availability of vehicles.
4. Calculate the surplus of vehicles δ_i for each zone i :

$$\delta_i = \min(r_i + s_i - t_i, r_i),$$

where:

- r_i – the number of rebalanceable vehicles in zone i ,
- s_i – the number of soon-idle vehicles in zone i ,
- t_i – the target number of inbound vehicles in zone i .

A positive surplus means that there is an oversupply of vehicles in zone i and δ_i vehicles can be redistributed to other zones. A negative surplus means an undersupply of vehicles in zone i and δ_i more vehicles are required to be relocated to this zone.

5. Solve a transportation problem, where zones with surplus are producers and zones with the deficit are consumers of vehicles, in order to obtain (non-negative) inter-zonal flows of rebalanceable vehicles f_{ij} , for each pair of

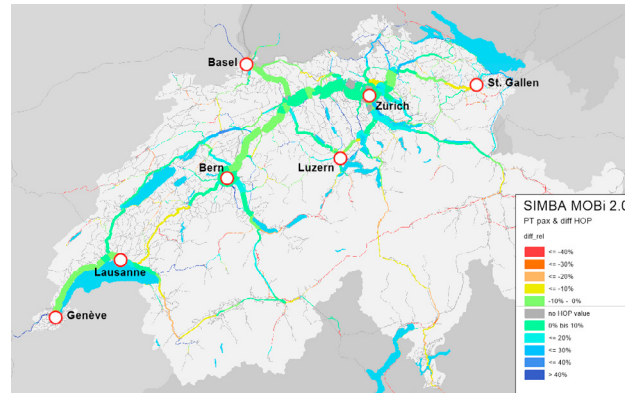


Fig. 1. Comparison of simulated daily rail passenger volumes and real-world counts (*HOP* values)

zones, i and j . The cost c_{ij} of moving a vehicle from zone i to j is, by default, the travel time between centroids of both zones.

- For each pair of zones i, j , choose f_{ij} rebalanceable vehicles in zone i that are closest to the centroid of zone j and dispatch them there.

The above procedure is called periodically with at a t_{reb} interval (by default, $t_{reb} = T_{INTERVAL}$).

3. Simulation Setup

3.1. Simulation model

The simulation model used in this paper is SIMBA MOBi, a multi-modal MATSim based simulation model of Switzerland. The model has been developed by the Swiss Federal Railways (SBB) for the last three years with the focus on accurately depicting passenger transport for the whole country for a typical weekday. The model combines a detailed activity based demand model, named MOBi.Plans, with a typical MATSim setup that has been enriched with special features, such as a parking choice model. Input data is based on a variety of sources, including government data, SBB corporate data and, to some extent, open-data. The model is calibrated against counts both for private and public transport, with a focus on accurately fitting the passenger flow throughout the railway network (cf. to Figure 1) A detailed description of the model can be found in [11]. Depending on the type of application, a 10 %, 25 % and 100 % version of the model can be run. This is a common procedure in MATSim simulations [1].

3.2. Study setup

Ridesharing may be of special interest as a feeder service to and from railway stations in less urbanized areas. As a study case, a sub-scenario was cut out of the existing nationwide model (100 % scale) that only comprises of those agents who perform at least one activity in the canton of Neuchâtel. The area is of rural and mountainous character, with roughly 176 000 people living there. There are two major railway stations, one in Neuchâtel and one in La Chaux-de-Fonds. Using the MATSim intermodal public transport extension¹, a fictive DRT feeder service is allowed to serve passengers within a 4-kilometer radius (beeline distance) around either station. In order to estimate the maximum likely demand for such services, no price is charged to agents in excess of the rail ticket. This results in roughly 11 100 feeder trips. This demand estimate is used as a base for the following rebalancing experiments. On the supply side, there is a total fleet of 100 vehicles, each with a capacity for up to four passengers. The demand is spread

¹ see <https://github.com/SchweizerischeBundesbahnen/matsim-sbb-extensions>

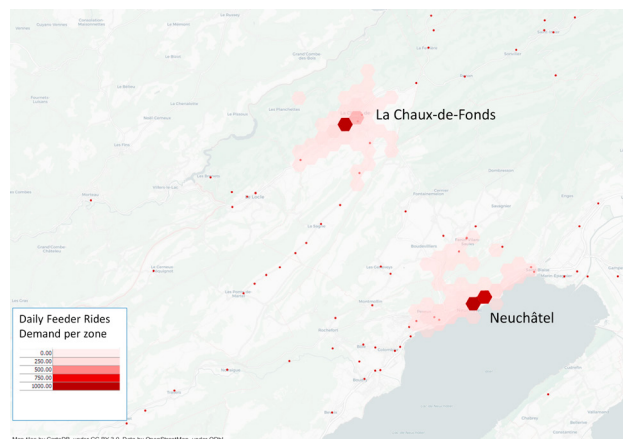


Fig. 2. Daily demand for DRT feeder services around Neuchâtel and La Chaux-de-Fonds train station

within the inhabited area around the two stations (see Figure 2). The demand is not distributed evenly: In Neuchâtel, most requests come from the more densely populated area along the lake shore and less from the mountainous regions.

In order to determine the impact of rebalancing on the system, several simulation experiments are conducted. Firstly, a base case is run without any rebalancing. Secondly, both a and b parameters are varied between 0.1 and 0.9, using a fixed interval for rebalancing $t_{reb} = 60 \text{ minutes}$. Finally, in a third set of simulations, the rebalancing interval t_{reb} is varied between 15 and 90 minutes. In all these simulation runs, the cell size for the rebalancing is set to 5000 meters. The main indicators for the performance of the rebalancing approach are the waiting time per request (both average and the 95th percentile value) and the fleet-wide empty-to-total mileage ratio (e^D).

4. Results

In the reference case without rebalancing, the average waiting time for a vehicle to arrive is 5:47 min, with the 95th percentile being at 15:30 min. Irrespective of the values for a and b set, vehicle waiting can be generally reduced in the scenarios with rebalancing and are generally below 5 minutes. The lowest average waiting time of 4:17 min (and a 95th percentile of 8:59 min) can be reached with a parameter set of $a = 0.8$ and $b = 0.3$. Also, in-vehicle travel times can be slightly decreased with rebalancing enabled. In all cases, including in the reference base case, the average idle mileage rate of vehicles is around 25 %.

In Figure 3 overall travel times, including the in-vehicle travel time, are shown for all scenarios. At train stations, where most of the demand is originating from, waiting times for vehicles can be significantly decreased. At Neuchâtel station, the average waiting time for a vehicle is around 2.5 minutes with vehicle rebalancing. Longer wait times here mostly occur because the fleet is operating at capacity.

In a third set of experiments, the interval t_{reb} in between rebalancing steps is varied between 15 and 90 minutes for the parameter set $a = 0.8$ and $b = 0.3$. In all cases, the rebalancing algorithm behaves very stable: Both passenger waiting times and empty mileage rate of vehicles are on a similar level for all defined intervals and do not widely differ.

5. Conclusion

Estimating the demand of a DRT system is of utter importance for its acceptance: Customers expect a reliable service with low waiting times, especially when departing to and from train stations. Thus, fleet operators need to rebalance their vehicles proactively but not over-actively in order to maximize system throughput and avoid unnecessary empty mileage. The rebalancing heuristics presented in this paper can fulfil these needs in a sufficient way, reducing waiting times in average by over 20 %. For the operator, the cost of rebalancing is rather low: Compared to the reference case, no additional vehicle mileage is generated in the presented example. The case study described in this

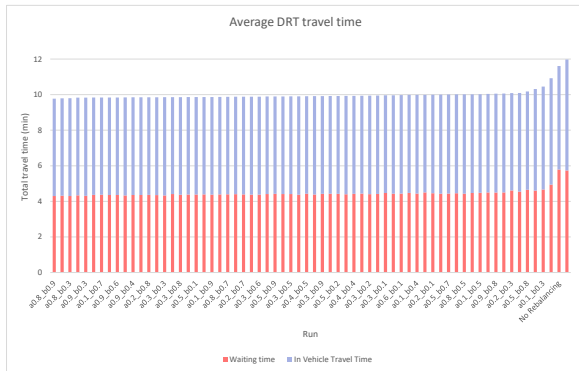


Fig. 3. Travel time statistics for different values of a and b .

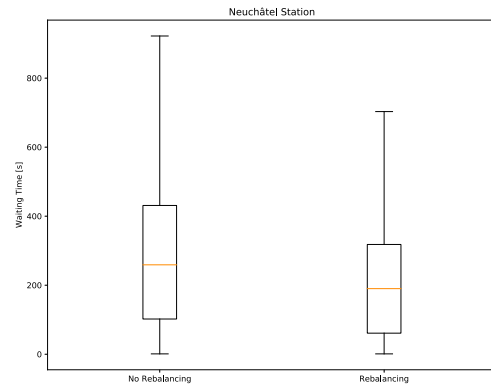


Fig. 4. Waiting time distribution at Neuchâtel train station without rebalancing and with rebalancing ($a = 0.8/b = 0.3$).

paper could be of relevance for future fleets of Shared Autonomous Vehicles serving rural areas. Due to break times and other needs, the situation might be a bit more complex for operations with drivers. In such a case, decentralized depots (or taxi ranks) may be considered as rebalancing spots.

Future work in the area could continue to focus on improving rebalancing strategies while also considering other real-world problems, such as recharging batteries of electric fleet vehicles. Furthermore, the simulation of a realistic scoring and pricing behavior should be focused on.

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