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REBALANCING INTEGRATED, DEMAND-RESPONSIVE PASSENGER AND FREIGHT TRANSPORT – AN AGENT-BASED SIMULATION APPROACH

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ABSTRACT

Integrated, demand-responsive passenger and freight transport (IDRT) potentially provides flexibility and higher service frequency in areas of low demand due to economies of scale, while reducing negative traffic-related externalities such as pollutant emissions, noise emissions or accidents. However, to allow for efficient operations in terms of minimum travel distances, short customer waiting times, and high vehicle utilization rates, IDRT requires effective rebalancing strategies that balance supply and demand capacities by strategically positioning vehicle resources in the operational area. Therefore, we propose a rebalancing strategy for IDRT and measure its effectiveness through an agent-based simulation model. To evaluate our approach, we compare the rebalanced IDRT with a static scenario with backhauls to a central depot. Our results indicate that the proposed rebalancing approach can outperform a system without rebalancing by up to 15.1% in terms of total fleet kilometers and 30% in terms of passenger waiting time.

1 INTRODUCTION

Rural areas are characterized as outlying regions with low local population density and a vast majority of all movements that takes place by (motorized) private vehicle. Additionally, travel distances are comparatively long since points of interests and supply are generally located far away from the residences of the inhabitants (e.g., Mounce et al. 2020; Poltimäe et al. 2022). Yet, in accordance with the low local population density, there is still a rather low overall transport demand, especially compared to urban areas. Consequently, rural transport operators often struggle to establish economically feasible transport services that satisfy the mobility needs of rural public transport users (Cavallaro and Nocera 2023; Mounce et al. 2020). This in turn results in a low transportation service coverage, which means that rural inhabitants are highly dependent on privately owned cars (Mounce et al. 2020; Poltimäe et al. 2022). However, the extensive use of private vehicles implies numerous negative effects such as high emissions due to conventional propulsion technology, detrimental influences on public health and social and spatial conflicts (Banister 2011; Sadeghian et al. 2022; Urry 2004). Thus, making transport more sustainable by reducing private traffic and fostering more affordable, accessible, healthier and cleaner alternatives is high on the agenda for transportation planners and has become a relevant concern for policy makers across the globe (Alonso-González et al. 2018; Bauchinger et al. 2021). Besides the aforementioned mobility-related issues, the first and the last leg of freight transport movements is also a highly challenging aspect in rural transportation (e.g., Macioszek 2018). Reinforced by the expansion of e-commerce and the COVID-19 pandemic, the number of parcel deliveries has continuously risen over the last years (Meinhardt et al. 2022;

Romano Alho et al. 2021; van der Tholen et al. 2021). This has led to smaller and spatially as well as temporally more fragmented shipments that involve a wide range of interacting users, resulting in multiple and sporadic exchanges (Bruzzone et al. 2021; Romano Alho et al. 2021; Souza et al. 2014; van der Tholen et al. 2021). Moreover, the provision of express and return services contributes to operational inefficiencies and potentially increases negative traffic-related externalities (Romano Alho et al. 2021). Consequently, the first and the last mile of the supply chain in rural areas are characterized by high cost level that stems from inefficient operations (Bruzzone et al. 2021; Cavallaro and Nocera 2023).

To tackle both, mobility- and last-mile-delivery-related problems, the integration of passenger and freight flows in a single transport service fleet is a promising approach (Bosse et al. 2023; Bruzzone et al. 2021; Cavallaro and Nocera 2023). In view of the lack of a comprehensive, public mobility infrastructure, demand-responsive transport (DRT) seems to be particularly promising, as it potentially provides temporal as well as spatial flexibility in terms of origin and destination of a journey (Cavallaro and Nocera 2023; Mounce et al. 2020). A demand-responsive service integrating passenger and freight flows potentially implies several benefits such as reduced energy consumption and economies of scale. Additionally, cost reductions obtained from the integration of passenger transit and freight deliveries potentially enable higher service frequencies and therefore lead to a higher service level (Bosse et al. 2023; Cavallaro and Nocera 2023; Fehn et al. 2023).

Research on DRT revealed that fleets tend to unbalance as the demand for vehicles is often not uniformly distributed within the area of operation (e.g., Wallar et al. 2018). This phenomenon especially occurs during peak periods in the morning and afternoon when most trips occur due to commuting activities. This mismatch of supply and demand implies that vehicles often have to travel longer distances than necessary to customer's pickup points, which leads to inefficient operations as well as lower service levels in terms of waiting times and unserved requests. Longer travel distances and therefore longer trip durations also imply that the number of passengers that can be served within a specific time is suboptimal (Chen and Levin 2019; Wallar et al. 2018). IDRT is also subject to these rebalancing problems.

While rebalancing strategies have been researched in other contexts such as on-demand transport (e.g., Schlenther et al. 2023), there is a dearth of research that investigates this issue for the particular case of IDRT. To close this gap, we develop a demand-responsive rebalancing strategy and implement it into an agent-based simulation model that evaluates the performance of this general modelling approach in an exemplary case study of an IDRT service operating within the rural area of Sarstedt, Germany. Dynamic agent-based simulation is a suitable approach to illustrate and analyze such a system of high complexity with a large degree of non-linear interdependencies and system components (Auf der Landwehr et al. 2021). Furthermore, simulation methods are frequently used in mobility and logistics contexts as they help to mimic and analyze systems with highly intricate interrelationships, various design variants, and operational properties that have not yet been piloted in practice (Wenzel 2018). By comparing the results of IDRT with and without implementation of our rebalancing approach, we generate first context specific insights about improvements regarding total fleet kilometers driven and customer waiting times. Additionally, we provide insights about vehicle utilization of both scenarios by comparing the average time that vehicle spend idle, in service, or standby. The rebalancing strategy introduced in this paper supports future (simulation) research and offers an approach to optimize the performance of IDRT and to manage vehicle fleets more efficiently. Furthermore, our findings allow first estimates regarding the required fleet size to fulfill a given demand and conceptualizes the tradeoffs between employed vehicles and passenger waiting times.

2 RESEARCH BACKGROUND

2.1 Integrated and Demand-responsive Passenger and Freight Transport

The idea of moving goods and passengers simultaneously is not new. The first academic discourse on integrated transportation dates back to more than a decade ago (Cavallaro and Nocera 2022). Trentini and Mahléné (2010) classified potential solutions for the integration of passenger and freight transport into three categories and identified areas where these solutions are tested or implemented in practice. Besides shared road capacities (e.g., multiuse lanes) and shared consolidation facilities (e.g. delivery bays) they also mention shared public transport services (e.g., buses or subway). In order to evaluate potential improvements of integrated passenger and freight flows compared to the current (separate) transport schemes, Bruzzone et al. (2021) propose a set of operational, environmental and social key performance indicators (KPIs). They defined the variation in average daily traffic in distance covered and in load factors to be critical performance measures. Furthermore, they emphasize freight service frequency, energy consumption, air pollution and external costs as well as labor costs to be important benchmarks. Additionally, the results of two case studies indicate that integrated passenger and freight transport is particularly effective in cases where reduced freight volumes, limited freight pickup/delivery locations and comparatively low elasticity of travel demand reduce the constraints to the adoption of this integrated scheme. Cavallaro and Nocera (2022) provide a sound overview about research in the field of integrated passenger and freight transport. They identified 69 relevant contributions to this topic and provide insights about applied approaches, means of transport, and the territorial scale of the studies reviewed. They revealed, that a vast majority of research focuses on urban areas while rural areas are widely unexplored. Furthermore, they found a wide spread of transport modes, reaching from rail, subway, or tram (27) to boat (2) or even ropeway (1).

Approaches that integrate passenger and freight flows into demand-responsive transport in particular are scarce. Fatnassi et al. (2015) investigate how passenger and freight could share a rapid transit network to enhance the sustainability of city logistics. They characterized a dynamic transportation problem and proposed two strategies to formulate and solve a maximum matching problem in a bipartite graph. They tested their solution approach on a case within the network of Corby and found that the implementation of the rapid transit service improves waiting time and energy consumption compared to current transportation options. Fehn et al. (2021) examined the potential of combining on-demand mobility and city logistics using a case study for the city of Munich. They examined the emission-related effects of three different scenarios and revealed that about 80% of the distance traveled to provide logistics services could be saved and the environmental impact in terms of emissions could be reduced. Possible service models for the integration of passenger and freight trips into a mobility-as-a-service concept to improve capacity utilization in passenger transport and to reduce freight movements in cities were also systematically explored by Le Pira et al. (2021). They identified relevant logistics segments, proposed service models and evaluated these from a multi-stakeholder and sustainability perspective. They do not only reveal potential for parcel deliveries but also for other segments requiring fast shipment such as grocery deliveries. Romano Alho et al. (2021) applied an agent-based simulation framework to systematically investigate the impacts of cargo transport integrated into a mobility-on-demand (MoD) service. They explored different operational strategies and considered multiple perspectives of passengers, shippers, carriers, and planners. Thereby they revealed that delivering parcels using MoD vehicles decreases the vehicle hours and kilometers traveled with minimal impact to passenger travel. Furthermore, their results provide insights on the magnitude of parcel movements that can be taken over by a MoD service and the impacts on the service quality for passengers and fleet usage. In order to combine passenger and freight flows in one single service that ensures high passenger service while simultaneously transporting a large number of goods, Bosse et al. (2023) introduced a dynamic priority policy that uses a time-dependent percentage of vehicles mainly to serve passengers. They found, that varying the percentage of priority vehicles during the day can be very beneficial, especially, when the ratio between mobility and transportation demand is volatile.

The aforementioned studies explicitly or implicitly focus on urban areas with spatially concentrated and high levels of passenger and freight demand. They revealed high potential regarding the efficiency of the concept paired with little ecological impact and sound customer convenience. Conversely, the effects of integrated passenger and freight transport in less densely populated rural areas are widely unexplored. Cavallaro and Nocera (2023) propose a methodological framework for development and evaluation of an integrated demand-responsive transport service. They applied the Business Model Canvas (Osterwalder and Pigneur 2010), to access infrastructural, personnel and vehicle related requirements. Furthermore, they explored the implementation costs, potential revenues, and possible partners to be involved and recommend financial, operational, environmental, and social KPIs to evaluate the performance of the service. In order to verify the practical suitability of their service, they propose its implementation into the municipality of Misano Adriatico and evaluate it using KPIs. Their analysis revealed a reduction in kilometers travelled, fuel consumption, and air pollutants, together with an increase in the area covered by the service, increase in daily potential freight deliveries, and increase in passenger occupancy rates of vehicles.

Overall, regardless of the investigational scope, existing research commonly focuses on mileage and passenger waiting times (e.g., Fatnassi et al. 2015; Romano Alho et al. 2021) as main performance indicators. Accordingly, we also adopt these indicators to measure the effectiveness of our proposed rebalancing strategy.

2.2 Rebalancing in Mobility-on-Demand Research

Waiting times are an important factor influencing the overall passenger travel time and therefore the perceived attractiveness of a transport mode. Thus, one challenge of offering demand-responsive transport services in rural areas is to achieve reasonable waiting times which are directly influenced by the spatial distribution of idle vehicles (Schlenther et al. 2023). This spatial distribution can be adjusted by the service operator by relocating idle or empty vehicles, a procedure which is referred to as rebalancing (Bischoff and Maciejewski 2020; Spieser et al. 2016). Vehicle rebalancing was subject to several studies in recent years. Wen et al. (2017) proposed a reinforcement learning approach that adopts a deep Q network and adaptively moves idle vehicles to regain balanced vehicle distribution within the study area. They applied their approach to an agent-based simulator and evaluate it in a case study in London. They compared the results of their approach to anticipatory rebalancing where the probability of a vehicle moving towards a neighboring zone is proportional to the number of predicted requests of that zone. Their results show that the proposed reinforcement learning approach outperforms the local anticipatory method by reducing the fleet size by 14% while inducing little additional mileages. Wallar et al. (2018) presented a method to rebalance idle vehicles in a ride-sharing enabled MoD fleet. Their method consists of three algorithms: One to optimally partition the fleet operating area into rebalancing regions, one to determine a real-time demand estimate for every region using incoming requests, and another to optimize the assignment of idle vehicles to these rebalancing regions using an integer linear program. They evaluated their approach using a historical taxi data set from Manhattan in New York City. Their results show high number of served requests in Manhattan can be served employing a fleet of 3,000 vehicles, while recording an average waiting time of 57.4 seconds and an average in-car delay of 13.7 seconds. Compared to an earlier study by Alonso-Mora et al. (2017), which was conducted in the same context and under similar circumstances, they were able to reduce the average travel delay by 86%, the average waiting time by 37%, and the number of ignored requests by 95% to the expense of an increased distance travelled by the fleet. Schlenther et al. (2023) investigated different vehicle relocation strategies with respect to service provision equity by applying an agent-based simulation approach within the area of Berlin. They opted to identify ways of operation that support social fairness while maintaining the profitability and effectiveness of the service. In terms of service provision equity, they found maintaining equal vehicle density across the entire service area to be a promising solution. Additionally, they revealed that larger rebalancing zones lead to lower system efficiency and lower service quality. A study by Chen and Levin (2019) developed a dynamic traffic assignment of MoD systems. To evaluate their approach, they simulated the MoD system in two networks with different fleet sizes and varying demands. Their results showed that the average total delay and travel distance decreased with the increase in fleet size, whereas the average on-road travel time rose. Additionally, they compared the results of traffic assignment of a network with MoD system with a network where all travelers use private vehicles. They revealed, that the former network creates more trips but less traffic congestion. One of the rare studies that contributes to solve the rebalancing problem in rural areas was conducted by Bischoff and Maciejewski (2020). They proposed a rebalancing strategy that relocates vehicles in accordance to the spatial distribution of demand in the near future. This demand-anticipatory rebalancing approach implies that vehicles are rather transferred into areas of high demand due to high population density. Accordingly, areas of comparatively low demand receive less idle vehicles, leading to higher waiting times that lower the demand even further. Nevertheless, they found that their approach reduces passenger waiting times by around 30% without increasing vehicle mileages for an autonomous feeder fleet in a rural area in Switzerland.

2.3 Research Gap and Contribution

The review of the related work reveals a wide range of possible combinations of passenger and freight transport, applying various means of transport. Conversely, research in the field of IDRT in general is rather limited. Furthermore, there is an underrepresentation regarding the application of such a service in rural areas, even though existing approaches where found to be very promising due to their high flexibility in terms of spatio-temporal network coverage and comparatively low capacity utilization in times of low passenger demand (Cavallaro and Nocera 2023; Fehn et al. 2023; Mounce et al. 2020). As mentioned before and similar to conventional DRT, IDRT-fleets tend to become unbalanced due to spatially non-uniformly distributed passenger demand, which is particularly valid for rural areas with low and widespread population density (Schlenther et al. 2023). Even if this issue was already subject to several studies (e.g., Bischoff and Maciejewski 2020; Chen and Levin 2019; Wen et al. 2017), a sound approach for rebalancing a fleet of IDRT in rural areas is still missing. To close this gap, we developed a rebalancing strategy and evaluated it by implementation into an agent-based simulation model to illustrate the IDRT service in the rural area of Sarstedt, Germany. By comparing the results of an IDRT service without (static IDRT) and with application of our rebalancing strategy (rebalanced IDRT), we provide insights on traffic and service implications in terms of total fleet kilometers driven and passenger waiting times. By proposing a rebalancing strategy, we contribute to optimized fleet management of IDRT in rural areas that can be adopted by other researcher and practitioners that opt to develop or assess IDRT systems. Additionally, even if our case is specific in terms of demand, infrastructure and study area, our simulation results indicate first generic estimates regarding the required fleet size to fulfill a given demand and conceptualize tradeoffs between passenger waiting times and the number of vehicles employed.

3 METHODOLOGY

3.1 Service Definition and Simulation Model

The scope of our simulation study is restricted to the rural area of Sarstedt, located between the cities of Hanover and Hildesheim in Germany. Within this area, we develop an agent-based simulation model to illustrate and evaluate our rebalancing strategy to redistribute idle vehicles in order to achieve efficiency gains. We used the multimethod software *AnyLogic* (Version 8.8.1) to simulate and compare the results of both scenarios (static and rebalanced IDRT) on a daily basis (from 00:00 a.m. to 12:00 p.m.). We simulate and compare the results of the scenarios on a daily basis (from 00:00 a.m. to 12:00 p.m.). For our concept of IDRT, parcel deliveries take place between 8:00 a.m. and 7:00 p.m., which is the only interval when a simultaneous transport of passengers and freight can take place. This results in mixed routes during that time where the delivery of parcels and the fulfilment of mobility demand at the stopping points alternate. To achieve a realistic mobility demand scenario during the day, a list of mobility requests is generated based on traffic-flow information that have been extracted from mobile communication traffic data. Traffic flows are mapped based on a total of 50 mobility clusters within the area of investigation, whereby each cluster features a maximum size of 800x800 meters. Based on the resulting list of mobility requests, a vehicle routing problem with pickup and delivery (VRPPD) as described in Desaulniers et al. (2002) is defined and solved by means of *Google OR Tools*. The objective function of this mathematical problem is to minimize the total distance driven. Regarding the start-destination relationships, an important constrain of the routing problem is that the destination point must be located after the starting point. Further constrains have been defined in line with scientific literature (e.g., Desaulniers et al. 2002; Savelsbergh and Sol 1995). As IDRT includes shared rides, the destination point does not have to follow directly after the starting point. Instead, several starting points may be lined up before the destination points follow. From the simulation model, a distance matrix with linear distances (beeline) and start- destination relationships is overhanded to *Google OR Tools*. By solving the problem, for each vehicle, the necessary detour to serve a request is determined. A mobility request is assigned to the vehicle that has the shortest detour. To enhance vehicle utilization, ride-sharing is applied and empty vehicles are prioritized. The IDRT service employs a total of 18 vehicles to serve both, mobility requests and delivery orders. The vehicle a mobility request has been assigned to, always moves directly towards the stopping point which is ranked first in its mobility order list. This list is vehicle-specific and contains only the orders that were assigned to the vehicle. Upon arrival, the vehicle checks which mobility requests belong to this stopping point and passengers embark or disembark the vehicle. Subsequently, the vehicle consults its mobility order list again if it contains further requests. Is this the case, it moves directly towards the next stopping point on the list. Otherwise, the vehicle returns to the depot (i.e., backhaul) and waits there for new incoming requests. During its transfer to the depot, the vehicle checks every minute if a new mobility request was assigned and may interrupt its way to the depot to serve newly incoming requests.

We assume vehicles to have been initially loaded with parcels that have to be delivered between 8:00 a.m. and 7:00 p.m. Thus, the delivery order list is known in advance and parcels are not reloaded to vehicles during the day. Based on the order list, a capacitated vehicle routing problem (CVRP) is formulated (e.g., Toth and Vigo 2002) in order to consider the maximum vehicle capacities for parcel deliveries. Other constrains have been defined in accordance with related scientific studies (e.g., Ralphs et al. 2003; Toth and Vigo 2002). The assignment of routes to vehicles is also conducted using *Google OR Tools*. In order to deliver parcels, the vehicle always moves to the receiving household that is ranked first on the delivery order list and unloads/delivers the designated parcels. A vehicle conducting a delivery order while a new mobility request occurs will finish the delivery order and subsequently serve the new mobility request. Upcoming mobility requests are always prioritized over outstanding delivery orders and will be served first to reduce customer waiting times. Upon arrival at a destination of a current order or request, vehicles iterate over their list of mobility requests and delivery orders to check which request is assigned to this stopping point or which order belongs to this household. Although space restrictions are less important in rural areas than they are in urban areas, we assume idle vehicles not to wait at their current position as parking and road space are still limited (Winter et al. 2021). Instead, idle vehicles return to a depot which is located centrally in the study area. These ways are replaced by applying the rebalancing strategy as further described below. A synopsis on the model input parameters used for our simulation study is provided in the following Table 1:

Table 1: Model parameter categories, values, unites and sources.

Category	*Value*	*Unit*	*Sources*
Number of IDRT vehicles	18	Vehicles	Industry partner
Average vehicle speed	35	Kilometers per hour	Industry partner
Max. passengers per vehicle	9	Passengers	Cavallaro and Nocera (2023)
Max. parcels per vehicle	22	Parcels	Cavallaro and Nocera (2023)
Share of served requests	2 (419 total)	Percentage (stochast.)	Industry partner
Share of served delivery orders	25 (192 total)	Percentage (stochast.)	Industry partner
Embarking/ Disembarking time	14	Seconds	Tirachini (2013)
Parcel unloading time	30	Seconds	Industry partner
Number of virtual stops	50	Stops	Industry partner
Number of depots	1	Depots	Industry partner

3.2 Rebalancing Strategy Approach and Implementation

We implemented a machine learning model (ML-model) into the agent-based simulation that was trained using the aforementioned mobile communication data provided by our industry partners. On basis of this data, The ML-model predicts the total number of journeys from a specific mobility cluster into another at a specific week day at a specific time. The calculation of a vehicle deficit- or a surplus in relation to the mobility demand takes place on basis of the 50 mobility clusters that the area of investigation has been divided in. The aim of our rebalancing strategy is to anticipate future mobility demands while achieving a preferably uniform distribution of the vehicle fleet within the study area. As the length of the periodic rebalancing interval was found to have no significant influence on the KPIs empty vehicle kilometers travelled and waiting time (Bischoff and Maciejewski 2020), our approach conducts rebalancing immediately after the drop-off of the last passengers or parcel. Unlike periodic rebalancing which does not allow the redistribution of vehicles in between the periodic intervals, even if a vehicle is idle, immediate rebalancing directly after the dropoff of passenger or freight solves this issue and potentially enhances efficiency. Nevertheless, to avoid idle vehicles in areas where demand is expected but doesn't occur and to avoid permanent redistribution, we conduct an additional periodic redistribution of particular vehicles. In contrast to Bischoff and Maciejewski (2020) and Fagnant and Kockelman (2014), this additional periodic redistribution is not conducted in a centralized manner for all idle vehicles at the same time. Instead, the additional periodic redistribution takes place for each vehicle individually if it has been idle for two hours. Accordingly, our approach combines periodic with immediate redistribution. This implies that the calculation of deficit and surplus clusters always takes place immediately after a vehicle becomes available or when a vehicle has been idle for two hours and the periodic rebalancing initiates redistribution. In order to adjust mobility demand and supply of vehicles within the study area, demand and supply are subtracted (Bischoff and Maciejewski 2020; Winter et al. 2021). The number of required vehicles is calculated in addition to idle vehicles and vehicles that are expected to be idle soon (Bischoff and Maciejewski 2020). In Bischoff and Maciejewski (2020), Winter et al. (2021), as well as Fagnant and Kockelman (2014) idle vehicles are redistributed from a cluster with a surplus to the cluster with the highest deficit. This implies, that vehicles may be transferred over long distances in cases where the cluster with the largest deficit is far away, even if a closer cluster shows a deficit that is nearly as high. This leads to high amounts of empty vehicle kilometers travelled. To avoid this phenomenon and to achieve operational efficiency gains, we limit the number of clusters considered for redistribution to the five clusters showing the highest deficits. The idle vehicle will be redistributed to the cluster which is closest to its current position.

As passenger mobility is prioritized, parcel delivery takes place only if no remaining passenger requests are present or until the assignment of a new passenger request interrupts the delivery process, respectively. To consider parcel delivery for the rebalancing process, clusters the vehicle was initially loaded with parcels for, are saved in the vehicle. As delivery orders are assumed to be known in advance, the delivery order list and therefore the deposited logistics clusters of each vehicle are stable and do not change during the day. Upon availability (i.e., no remaining mobility requests), logistic-clusters are checked to identify logistics cluster that show a deficit. Figure 1 illustrates the simulated IDRT concept and highlights the implementation of the rebalancing strategy into the process.

The following procedure demonstrates the process in detail: After the list of open mobility requests has been checked and no further requests where found, the vehicle stops. Subsequently, the vehicle checks the order list for unfulfilled parcel deliveries to redistribute it into clusters where the deliveries are due. If one or more logistics cluster were saved in the vehicle, it has to be determined if these clusters show deficits. Therefore, the predictions for the expected mobility demand of the next hour (e_i = number of expected orders for cluster i) are requested and recorded (a), and the demand predictions for each cluster are added up to a total sum of predicted demand (total mobility demand) (b). Subsequently, the number of presently idle (i_i = number of idle vehicles for cluster i) as well as soon to be idle vehicles (s_i = number of soon-idle vehicles for Clusters i) for each cluster are determined and recorded (c). Thereafter, all idle and soon to be idle vehicles of each cluster are added up to a total number (total number of vehicles available) (d). The calculation of vehicle surplus or deficit for cluster i (d_i) is illustrated in Equation (1) (e):

$$d_i = -\big((i_i + s_i) - e_i\big) * \frac{total\ number\ of\ vehicles\ available}{total\ mobility\ demand} \tag{1}$$

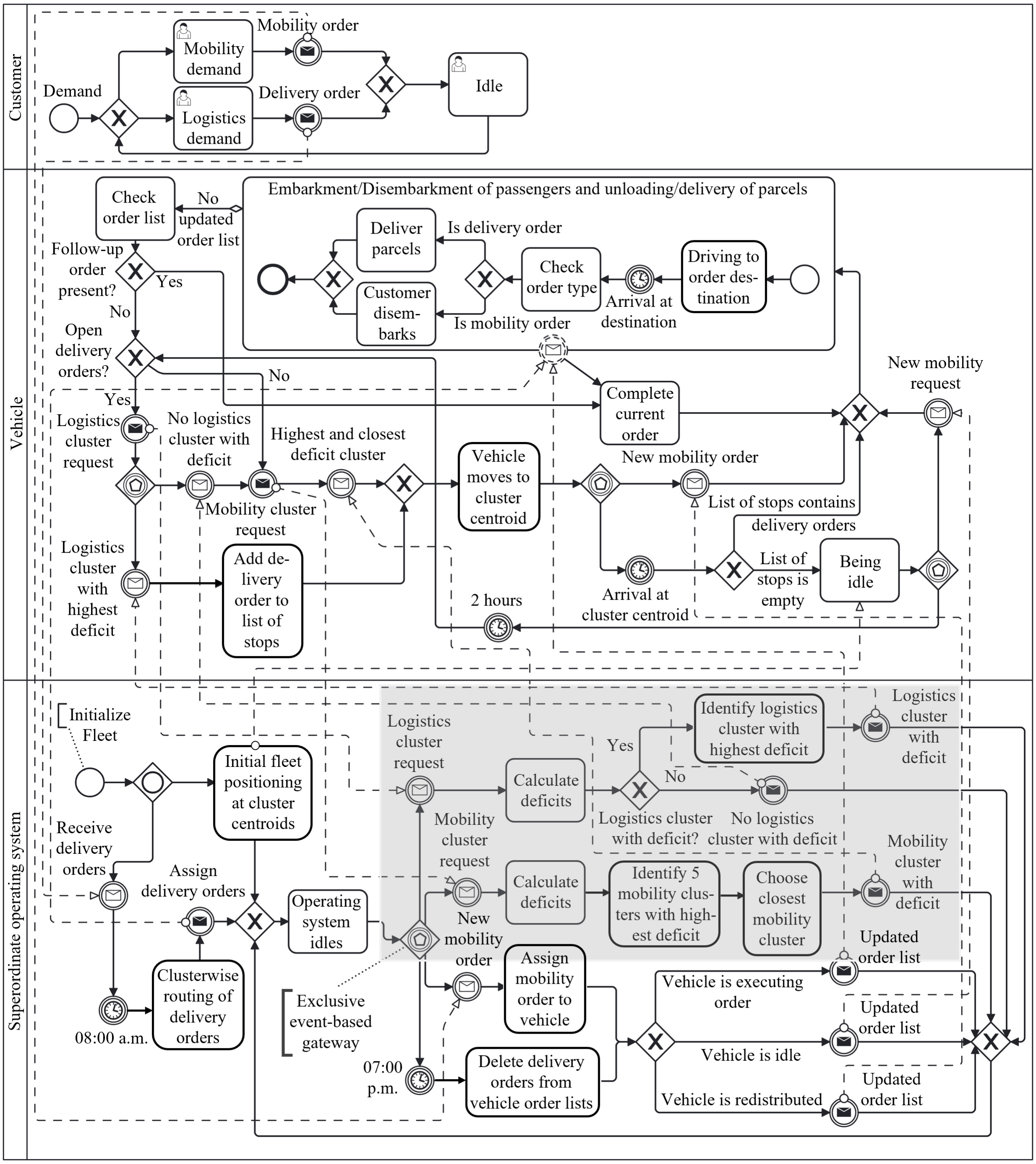

Figure 1: Process model illustrating IDRT and rebalancing strategy implementation.

4 RESULTS

To assess the impact of IDRT and the suggested rebalancing strategy within the rural area of Sarstedt, Germany, the proposed simulation model has been employed for two different simulation experiments. Preliminary tests of our simulation approach showed minimal standard deviation in the obtained target figures as the stochastic input parameters are limited to the share of mobility requests and delivery orders served by the IDRT system. Therefore, we refrained from a Monte Carlo approach and conducted a single simulation run for each scenario to evaluate the individual impacts regarding average total fleet kilometers and average customer waiting times. Furthermore, we evaluate differences between the scenarios in terms of total vehicle times in service, rebalancing or idle. To enhance the usability of our results and to design more realistic scenarios, we chose parameters that were mentioned in recent literature as well as interviews conducted with public mobility and logistics service providers.

Assuming 2% of all mobility request (419 in total) and 25% of all delivery orders (192 in total) to be fulfilled by the IDRT fleet, total fleet kilometers driven of 6,814.73 occur in the case of static IDRT and 5,787.03 in the case of rebalanced IDRT. After implementing our rebalancing strategy, the total vehicle time at service (processing mobility requests and delivery orders) to serve the given demand can be reduced from 8,564.66 minutes in the case of static IDRT to 7,172.83 minutes in the case of rebalanced IDRT. This corresponds to an improvement of 16.3%. Furthermore, the time spend for backhaul of vehicles to the depot or for rebalancing vehicles in accordance to demand predictions is reduced from 2,612.01 to 2,444.11 minutes at the expense of longer standby times of 14,742.25 minutes in the case of static IDRT and 16,301.98 minutes when applying rebalancing (see Figure 2). Accordingly, the time spend for the backhaul or rebalancing respectively can be reduced by 6.4% while the vehicle time standby increases by 10.6%. The average passenger waiting time can be enhanced from 8.67 (static IDRT) to 6.06 minutes after applying the rebalancing approach which corresponds to a reduction of 30% (see Figure 2). The results show that the application of our rebalancing strategy reduces the average kilometers driven per vehicle from 378.6 to 321.5 kilometers or by 15.1%. Thereby, the kilometers driven to serve mobility requests are reduced from 244.75 kilometers in the case of static IDRT to 216.02 kilometers after the application of rebalancing. To serve delivery orders, 24.12 kilometers occur in static and 13.58 in the rebalanced IDRT case. This accounts for a reduction of 11.7% for mobility and 43.7% for delivery purposes. Furthermore, the average vehicle kilometers driven for the backhaul or rebalancing are reduced by 16.2% from 109.72 to 91.90 kilometers (see Figure 3). Furthermore, the share of service kilometers to serve mobility requests and delivery orders per vehicle in relation to the average total vehicle kilometers driven can be slightly improved by 0.4%. As shown in Figure 2 the overall reductions in fleet kilometers and expenditure of time for service and rebalancing are realized at the expense of higher standby times (idle vehicles).

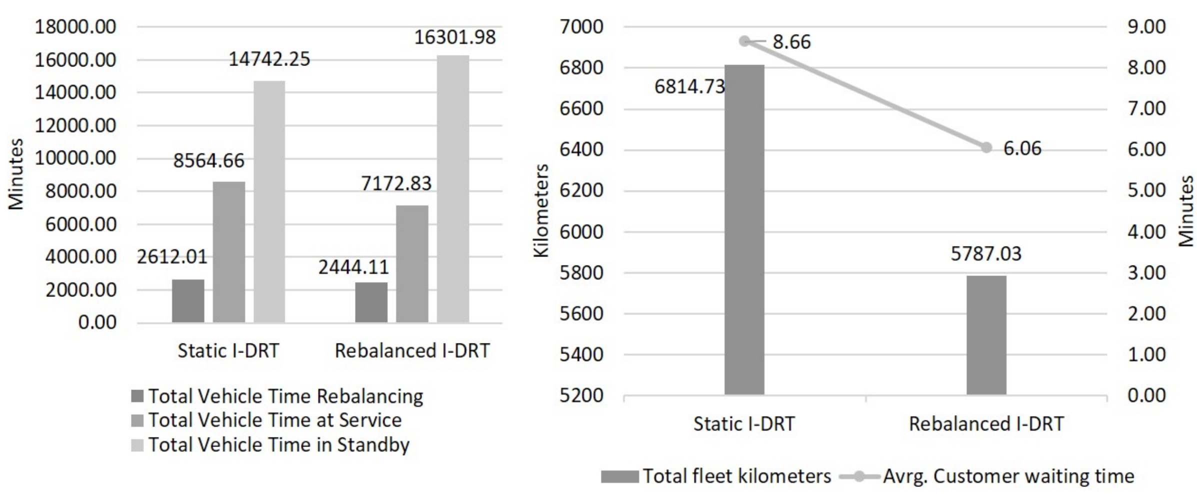

Figure 2: Total expenditure of time per vehicle, total fleet kilometers driven, and average passenger waiting times per scenario.

5 DISCUSSION AND CONCLUSION

Our results show that the proposed IDRT system with application of our rebalancing strategy outperforms the static system in terms of total fleet kilometers driven and average vehicle kilometers driven to serve mobility requests, delivery orders, and for rebalancing or backhaul purposes. Furthermore, the passenger waiting time for the mobility service, which is an important measure for the service quality (Schlenther et al. 2023), can be reduced. Additionally, even if the scenarios where not investigated in terms of different fleet sizes, the revealed overall increase in standby time by about 10% suggests that an IDRT service applying our rebalancing strategy is able to serve a given demand using fewer vehicles compared to static IDRT.

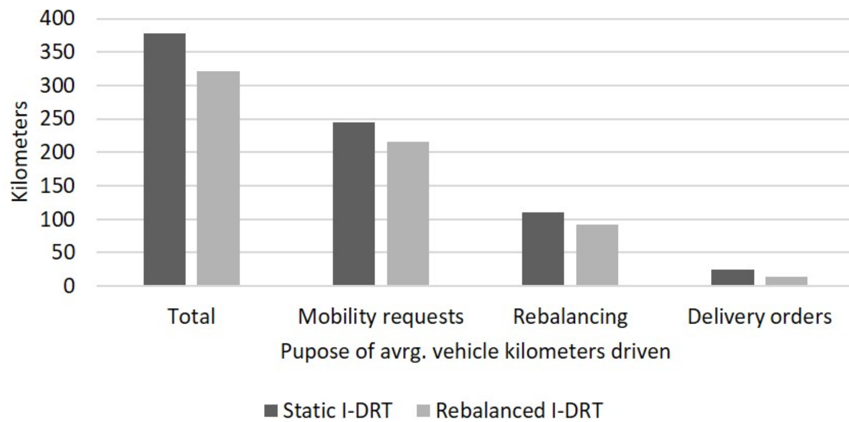

Figure 3: Purposes of average vehicle kilometers driven per scenario.

Our findings are in accordance to Wallar et al. (2018) who found that their rebalancing approach to allow for higher service rates while using less vehicles in the network of Manhattan in New York City. The reduction in passenger waiting time of about 30% realized by our approach is also in line with literature as Wallar et al. (2018) achieved reductions of even 37% in the urban area of Manhattan while Bischoff and Maciejewski (2020) revealed an improvement of 20% in rural Switzerland. Overall, our study emphasizes the high potential of rebalanced IDRT over static IDRT regarding the use of resources, reduction of environmentally harmful emissions and in improving access to mobility services in outlying rural areas.

Nevertheless, to simplify our approach and as we focused on the proposed rebalancing approach, we made several assumptions and excluded a number of aspects from our examination, which may serve as fruitful amendments for future research. We did not consider any environmental factors such as congestion, accidents or other traffic-related disorders. Furthermore, the loading of vehicles in terms of logistics (e.g., with parcels) where not mimicked within our simulation. Instead, we assumed all parcels to be initially loaded to vehicles at the depot. Similarly, we assumed that all recipients are actually encountered for delivery and did not consider varying parcel sizes and their influence on vehicle capacities. Moreover, we did not take into account a detour factor limiting the passenger travel time and detours caused by pooling of different requests. Ultimately, further research is needed to expand our approach to assess the economic feasibility by implementing monetary cost models or the environmental impact by applying models to measure the actual amount of harmful emissions of IDRT. Additionally, to provide broader insights on the performance of different rebalancing strategies, future research may add alternative scenarios to the given setup or transfer the proposed approach to different study areas.

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