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Abstract

Optimization Models for the Integration of Last-mile and Public Transit in a Hybrid Transportation Service

by

Nara Quintela BEGNINI

Recently, many innovative ideas have been proposed to address the evolving challenges of mobility and logistic services. One such idea is to combine the two flows of the last mile of parcel and passenger transportation and integrate them with public transit to achieve higher efficiency.

In this thesis, we design two optimization models to integrate last-mile service and bus lines smoothly. Moreover, passengers and parcels are carried in buses and the last mile vehicles, combining their flows in a hybrid service. Thus, we describe an integrated and hybrid transportation service. The main goal is to analyze such a service regarding cost savings and customer satisfaction. Upon solution, the models find routes for delivery vehicles while synchronizing them to the bus timetable.

The first model is a multiobjective delivery problem that minimizes the passengers' travel time and then the vehicles' drive time. This model is used to compare the performance of such a system against non and partially-integrated services, and we conclude that significant savings in drive time can be achieved.

The second model, also a multiobjective problem, expands the first to include more realistic aspects, such as a heterogeneous fleet, customer pickup and respective priorities. Using three objective functions, we show how to optimize service costs, request total travel time, and request arrival time. The analysis performed in this phase compares the two models that optimize the customers' perspective to determine which yield routes are more convenient for the prioritized requests. Additionally, by including budget constraints, it is possible to visualize the improvement in route quality against the allocated budget.

According to our case study, we conclude that significant savings in drive time can be achieved by implementing the proposed approach and that the integration of modals may be a promising solution to support mobility and logistic services, especially in rural areas. Our models can be used as a tool in a decision framework to assess each particular situation and to assist decision-makers with the appropriate budget allocation, fleet assignment, and customer satisfaction.

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I am deeply grateful to the Japanese society and its government, especially the ministry Monbukagakusho (MEXT), for their support of initiatives such as the scholarship that enabled me to live and study in Japan for five years and funded my research at Osaka University.

I will try to put it into words: I am grateful for the support of my family, my mother Ivanete, my father Rene, and my sister Elis. But, if I did anything right until here, they already feel that my gratitude is ineffable. They have always been there for me and their support has been exceptional. I feel incredibly fortunate to have them in my life. Special thanks to Elis, who did not care at all about time zones and stayed with me in the most critical times during the writing of this thesis.

Finally, this acknowledgments session has a fourth paragraph, in which I try to convey all the love and admiration I feel for all these people. Here is where all the personal growth is, the most impactful side of the last five years. Thank you, Anna, the roomie, who since day 0 has been with me in this journey and is the truly enabler of all my growth in Japan. Thank you, Kako, the golden retriever, who showed me a fulfilling way to live life, love people, and how to survive a PhD. You helped me destroy so many toxic beliefs I had been dragging. And thank you, John, the excellent museum and hiking partner, who knows the best restaurants to eat, drink, and forget the torments of the third year. Because of you two, I will forever cherish our memories in PhDicks. Again? Lastly, but not least, despite the distance, the people in the Crew has always been so supportive and united that I feel very grateful, and proud, for being part of such an amazing group of friends.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Research Context

There is a potential for higher efficiency in the last mile of parcel and passenger transportation that can be realized by the combination of these two flows and further optimized by regarding their respective characteristics. The last mile is defined as the last leg of each transport movement, a term suitable for both passengers and freight transport (Nocera et al., 2021), and more generally, it is the movement from a hub to a final destination (Demir et al., 2022). In the context of delivery, it is an umbrella term that covers a range of shipment services, such as food shopping, ready to eat meals, courier services, among others (Allen et al., 2018; Boysen et al., 2021), as well as mobility services.

The other phases of transportation can be labeled first mile and long distance to imply, respectively, the link from origin to a hub, and the link between hubs. These definitions are not absolute, and even the last mile's limit is not so clear; for example, a bus trip, usually put under the label of long distance, might be the last mile in some cases. The first and last miles are usually considerably shorter geographically than the long-distance leg. However, they require a level of customization and flexibility that renders those operations a very complex task and often hinders economies of scale because, in contrast to long distance, passengers or freight cannot be bundled together in trains or containers, with common origin and destination.

Adding to the complexity, last mile operations have to function under existing and evolving challenges that span from demographic to technological trends. Population growth worldwide will certainly affect the volume of e-commerce sales and people's movement. An aging workforce, and actually any worker striving for a healthy workplace, will certainly demand changes in occupational conditions. Customers are offered options of faster delivery (e.g., same day or 2-hour delivery) or at the desired time window. Cost reduction must go beyond operational costs, such as vehicle movement, and also consider how to deal with traffic jams and absent customers in home deliveries. The recent shareconomy has widened the field of opportunities for efficiency with the concepts of consumers collaborating in the usage of products or services, and business collaborating with competitors in the usage of infrastructure and also services. Most importantly, increased people and freight movement cause negative impacts on the natural and social environment: pollutant emissions, noise, congestion, accidents, and land use (Demir et al., 2022; Savelsbergh & Van Woensel, 2016). Thus, attaining environmental, social, and economic sustainability is probably the final challenge of last mile services in its role to promote higher life quality.

To cope with these evolving challenges, there have been some suggestions to improve current services and to implement innovative solutions. Currently established services, especially in big cities, include the traditional delivery van or cargo bikes, guided by a human, and self-service pick-up in specific locations. Innovative solutions, promoted by technological advances such as IoT, big data and automation, are being prototyped across the world: micro depot, mobile depot, parcel locker, trunk delivery, parcel shop, unmanned aerial vehicle (drones), delivery robot, crowd shipping (Boysen et al., 2021, p. 6), among others. However, even those solutions also bring new challenges, such as how to implement and optimize them.

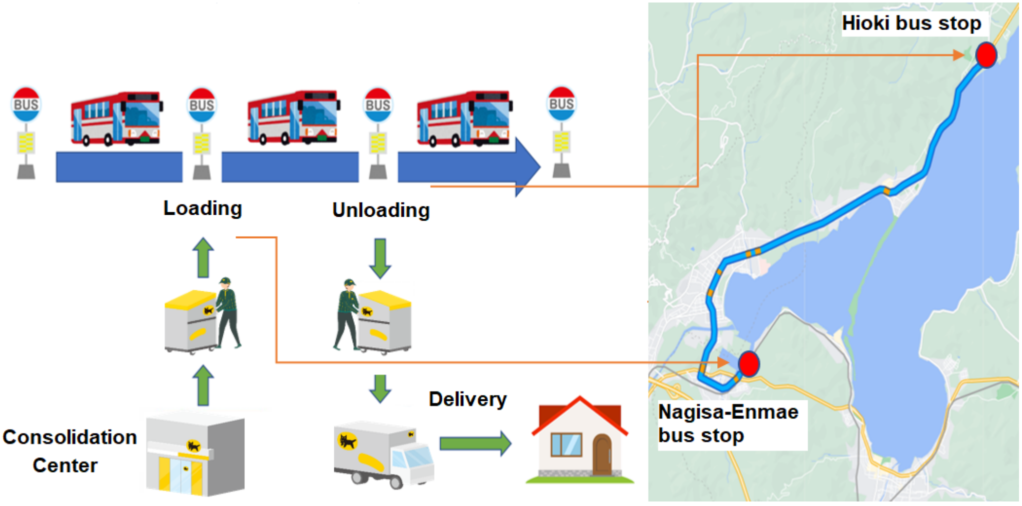
Notably, most works that suggest innovative solutions for mobility and logistics challenges mention the combination of public and freight transportation. The main argument supporting this idea is that, especially in cities, since there is already an overlap in their usage of transport infrastructure, e.g., roads and vehicles, instead of competing for it, sharing these resources might bring an array of benefits. There are many ways in which this combination can occur, but the most commonly proposed approach is by sharing vehicles, either from public transit, such as buses and subways, or private, such as taxis. Taxis could deliver or pick up small parcels in their idle time. Subways could transport goods to the city center, avoiding traffic congestion, provided a dedicated staff and pathway for the goods inside the stations. Buses could do something similar, but with different requirements, such as synchronization with a fleet of last mile delivery vehicles.

The possible benefits of this concept are exploiting the idle capacity of resources, or even reducing this capacity while keeping the same quality of service, as "the same transportation needs can be met with fewer vehicles and drivers" (Ghilas et al., 2013). So, all the benefits of a smaller but efficient fleet are theoretically achievable. Moreover, extending the bus services to include freight transportation would enable logistic operators to load the buses with packages, helping to partially relieve the financial burden of subsidies on bus lines. By transporting the boxes, bus companies might increase their revenue and, on the other hand, logistic operators could cut down on the number of truck trips while also making better use of unused space within the buses.

There are a few existing examples of such services, that combine the flows of people and freight. Two attempts in the Netherlands are the Amsterdam Cargo Tram and Cargo Hitching. The idea in the first one was to use the passenger's

(A) DHL packages are loaded onto the tram at Schwerin, German. Source: DHL, (Tautonline, 2022)

(B) A delivery driver loading cargo into a remodeled cargo space inside the bus. Source: Yamato Transport (Yamato-Holdings, 2018)



(C) Flow of the planned hybrid service by Yamato Transport. Source: Yamato Transport (Yamato-Holdings, 2022)

FIGURE 1.1: Examples of existing hybrid services in Germany, by DHL, and in Japan, by Yamato Transports

track network inside the city center, during the night time without influencing usual tram schedules. Unfortunally it did not reach full implementation due to the lack of fundings (Arvidsson & Browne, 2013). In German, a recent initiative by DHL is attempting a similar system, also using the tramway (Tautonline, 2022), as in Figure 1.1a. The second one is a pilot project, tested in a small village, and its concept includes "cargo that hitches a ride on a vehicle transporting persons, or persons hitching a ride on a vehicle transporting cargo" (Van Duin et al., 2019). In Japan, Yamato Transport has recently joined in partnerships with Kanetsu Transportation (Yamato-Holdings, 2018), Nishi Tokyo Bus (Yamato-Holdings, 2020), and Tango

Kairiku Transportation (Yamato-Holdings, 2022). Small containers with parcels are loaded into the bus (Figure 1.1b) and retrieved in another bus stop (Figure 1.1c). It is expected that the joint services reduces truck's driving distance and CO2 emissions, reducing also environmental impact.

The Cargo Hitching project and Yamato's service are the closest to the one investigated in this thesis, expressing the aspect "hybrid" that we want to model. However, they are still limited to the bus, or tram, network, and we propose to combine people and freight also in the last-mile, or in the delivery route illustrated in Figure 1.1c.

Despite these existing initiatives that solve logistic problems in the real world, there is a lack of data regarding actual usage and volume of such operations.

1.1.1 Defining Hybrid, Mixed, and Integrated

In the literature relevant to our work, the terms *integration*, *mixed*, *hybrid*, and even *sharing* are often used interchangeably. Since their meaning and scope are not always explicit, much less standardized by the research community, we need to clarify them in this work.

In some works, sharing means the simultaneous usage of vehicles by many types of customers or, in services where the vehicle is traditionally used by a single customer, their usage by multiple customers of the same type. Shared transportation usually implies the concept of Shared Mobility, which Mourad et al. (2019) classified in two main categories, *People sharing rides*, and *People and goods sharing rides*. In our case, the customers are passengers in the vehicles and people waiting to receive a parcel being carried by the vehicle. So, we investigate a service that combines the two flows, therefore, our work is best inserted into the second category presented above, and we use mixed transportation as an alternative label, instead of Mourad's long one, effectively not using the term sharing.

Regarding hybrid transport, we define it as a transportation service that includes change of transportation mode from on-demand services to public transit, or vice-versa. The literature investigated in Chapter 2 often uses the term integration to describe this same feature, especially in passenger transportation, while the equivalent for freight would be intermodal (Arvidsson et al., 2016). The term co-modality has also been used (Ronald et al., 2016). In this work, we use both term interchangeably.

So, in our scope, a hybrid, or integrated, transportation service is one that coordinates public transit and on-demand last mile transport. Operational decisions for the on-demand part depend on the characteristics of the public transit part, aiming for a smooth transition for the passengers and an efficient one for customers waiting for the freight.

1.2 Overview and Contributions

In this research, we consider a transportation service that integrates bus lines to the last mile, in order to achieve a smooth coordination between these two levels. Moreover, the proposed service also utilizes the same vehicles to transport people and parcels, in a mixed, or hybrid, service. Carrying both types of cargos in the same vehicles adds to the model the requirement of treating parcels and passengers differently, which is implemented by assigning different priorities to each request. We propose an optimization model to minimize costs related to vehicle routing, while maximizing customer satisfaction, which we define as respecting their priorities, based on their perceived value of time.

This thesis is structured in the order of our investigation about the topic, in which we try to answer the following research questions.

Research Question 1 – What problems arise at the operational level of mixed and integrated transportation systems, and how can they be modeled and optimized?

Research Question 2 – How to model a transportation service that coordinates fixed bus lines and last-mile on-demand transport for people and freight?

Research Question 3 – How to design a model that distinguish people and freight, reducing the inconvenience for the former?

Chapter 2: Literature Review

We review a selection of the relevant studies with a focus on modeling and solving hybrid services, essentially tackling the first research question. From this investigation, we identify two areas of application: one being services aimed at transporting passengers; and the other being services aimed at delivering packages in the last-mile. We highlight the research gap as the lack of studies aimed at transporting passengers and parcels simultaneously in the public transit and in the last-mile.

Chapter 3: Design and Analysis of a Hybrid and Mixed Delivery Service

This chapter is based on our published paper "Analysis of last-mile operations for mobility and logistics in rural areas", and it essentially focus on answering the second research question. We start the chapter with a summary of its contributions in Section 3.1. Then, Section 3.2 proceeds to discuss the motivation behind proposing a mixed and hybrid transportation service to rural areas by investigating the challenges specific to these regions.

We define the specific transportation problem in Section 3.3. The demonstration of the suitability of our proposed idea to rural areas will be done by comparing it to traditional services, which are not hybrid or mixed. We create four scenarios which include our proposed and other conventional approaches. Each scenario is modeled in Section 3.4, starting by the model of our proposed service, followed by the explanation of how to reduce it to model the other three scenarios. All models have a Mixed Integer Programming (MIP) formulation. In Section 3.5, we explain how the instances were generated, based on a real area in the Japanese countryside and using the bus timetable of a bus line that operates in the area. Then, we validate the model and show the performance of an implemetation and solution method using a commercial MIP solver. Finally, in Section 3.6, we bring a case study of three parts. First, the drive time required to perform the transportation service in each scenario is assessed. Then, we show the tradeoff between the operational and passenger perspectives. And lastly, we assess the service once more, limited only to package delivery.

Chapter 4: An extended formulation: Pickup and Delivery with Priority

This subsequent research phase extends model and application from the previous chapter and is motivated by a question derived from putting people and packages together in the same vehicle: "how to properly sequence their delivery?". In other words, our third research question. This aspect received little attention in the previous chapter because we considered only delivery and priority to passengers as absolute. However, a deeper investigation is due to obtaining good routes. A minimal route seems appropriate in the operational sense, but it might not be desirable to the customers. It is important to note that here we do not examine applicability to any specific situation, i.e., rural or urban. Our focus was to extend the model, but we did use instances based on the same geographical are as the previous chapter.

This chapter also starts by listing the contributions in it, with Section 4.1. Proceeding to the motivation behind the extension of our model in Section 4.2, aiming at capturing more realistic aspects, such as heterogenous fleet, improving the prioritization scheme, and including the pick-up of requests. Section 4.3 formally describes the problem and its new requirements. In Section 4.4, the model is extensively described, focusing on how we model the bus network to handle more than one physical bus line and how to join it with the vehicles movement network. The MIP formulation is introduced. Three deriving models are presented, where their difference is the objective function; they use roughly the same sets of constraints. Proceeding to Section 4.5, we explain the instances used to validate our models; how we performed its validation; the performance of our solution approach, using a commercial MIP solver; and finally the analysis of the impact of allocating three options of budget on the quality of obtained routes, as measured by a tailored metric.

Chapter 5: Concluding Remarks

The final chapter concludes the thesis summarizing its contents and key findings. Additionally, a list of interesting research directions is discussed. The idea investigated in this thesis is innovative and it requires contributions from many research fields. From the mathematical optimization field, we highlight the necessity of efficient algorithms to tackle realistic problems and support long-term strategic decisions.

Chapter 2

Literature Review

The integration of different modals, or transportation modes, in the context of logistics and also mobility is a concept that impacts many areas, from policy making to operational decisions. The same is true to the hybridization of modes, that is, combining people and parcels in the same transportation network. In this review, we concentrate on existing works that address optimization models related to integrated services for people and parcel in the first or the last mile. The focus is also aimed at works that include hybrid services, as we have defined. We are interested in contributions to modeling and determining the routing, assignment, scheduling, and synchronization of vehicles to meet transportation requests, that is, operational decisions. Additionally, in order to investigate how requests are prioritized, we review the prioritization and customer satisfaction in routing problems, mentioning works unrelated to mixed or integrated transport.

2.1 The last-mile and public transit

Last mile problems with common capacity and time constraints are usually modeled as a vehicle routing problem (VRP), where the main concern is distributing goods from a depot to the customers. The VRP is one of the most studied optimization problems. Its applications are extensive, and, just in the transportation field, variants are constantly emerging to capture realistic features. We refer to Vidal et al. (2020) for a recent survey on these.

To achieve a smooth and efficient system, it is necessary to consider route optimization and synchronization between modes. Optimization problems related to routing include the VRP. By adding layers of complexity, such as picking up and delivering cargo along the routes, it yields the Pickup and Delivery Problem (PDP), which in turn, if more attention to human cargo is required, is labeled as the Dial-a-Ride Problem (DARP). All three problems (VRP, PDP, and DARP) contribute with useful insights to develop a model for a mixed and integrated transportation problem. Especially for the mixed aspect, in which people and packages travel together, people have different requirements and perceive the travel experience differently than packages. For this reason, a crucial topic to a successful mixed service is how to model a distinction between people and packages. Otherwise, for all abstraction purposes, the model would see them simply as generic cargo.

In the PDP and DARP research body, the models include a measurement of customer satisfaction. This satisfaction is usually expressed as a function of a time parameter in the model, such as compliance to time windows, or traveling and waiting times as short as possible. A mixed transport model could prioritize the satisfaction of passengers, and in this way make the distinction between the requests. Another method, inspired in the VRP literature, is by directly prioritizing requests, by making a group of requests be visited before another group. This is the approach preferred in Li et al. (2014) and Beirigo et al. (2018), which try to make the parcel transport as "invisible" as possible to the passengers, letting it minimally affect their journey.

2.1.1 Freight-aimed integrated services

The authors of Ghilas et al. (2013) have heavily contributed to the literature of mixed and integrated transportation. They started by proposing an arc-based mixed-integer programming formulation of a problem that required pickup and delivery of two types of requests (parcels and passengers) under the opportunity of including in their trip a transfer to scheduled lines (such as bus or train), used by the general public. The goal was to generate the routes and the schedule of the delivery vehicles. They utilized a commercial solver on small instances to compare the benefits of the proposed system to a non-integrated one and observed that it is possible to gain significant savings, both in terms of monetary cost and CO2 emissions, as well as in fleet size, i.e., fewer vehicles are required. Passengers are distinguished from packages, in terms of modeling, by imposing a maximum trip time for passenger-type requests. In subsequent works, their focus seems to have shifted, from parcel and passenger transport, to exclusively parcels. In Ghilas et al. (2016b), they formulated the Pick-up and Delivery Problem with Time Windows and Scheduled Lines (PDPTW-SL), also contributing with families of valid inequalities for this problem. They compared the proposed system's operational costs to those of the conventional PDPTW, as well as its performance under various network parameters, such as frequency and number of scheduled lines, and tighter or wider time windows. Then, in Ghilas et al. (2016a), the goal was the development of an adaptive large neighborhood search (ALNS) heuristic tool to solve medium-sized instances, of up to 100 requests and three scheduled lines. Inside the ALNS framework for routing problems, they proposed operators and procedures exclusive for the PDPTW-SL. Finally, in Ghilas et al. (2018), an exact method based on a set partitioning formulation and a branch-and-price algorithm was proposed for the PDPTW-SL, to solve instances of up to 50 requests.

The application of autonomous last mile robots was studied in Mourad et al.

(2021). The task was routing a fleet of autonomous pick-up and delivery robots which could ride public transit. Whether there is space available so the robots can ride it depends on how crowded the public line is, which is discovered upon arrival at the station. The proposed model was based on the one proposed by Ghilas et al. (2016b), with extensions to consider the stochastic nature of passenger demand on public lines. Their solution method is sample average approximation (SAA) combined with an ALNS heuristic, and it was used to evaluate the impacts of different public line capacities and frequencies in the performance of the autonomous delivery service.

For the task of delivering goods, assumed to be consolidated in a distribution center, hence no pickup is necessary, to a congested city center, Trentini et al. (2012) proposed a two-tier system where in the first tier a public bus line connects the distribution center to bus stops, then, in the second tier, city freighters carry out the last-mile transport, named Mixed Urban Transportation Problem (MUTP). They introduced a MIP model for the MUTP, and a metaheuristic algorithm to generate a plan deciding which container should be loaded with which packages, which bus should be loaded with which container, and the city freighter delivery routes. In a following publication, Masson et al. (2017) studied the MUTP and its feasibility subproblem, further detailing the algorithm used to solve them. In a case study, they assessed the impact of the two-tier system on the number of city freighters required and their utilization, comparing it to a single-tier model in which trucks deliver straight from the distribution center.

Pimentel and Alvelos (2018) did not address vehicle routing, instead proposed parcel assignment to the bus stops. They assumed that assignments are valid when the customer location can be reached within the agreed-upon service time. A MIP model is proposed to optimize the freight load balance and synchronization while respecting customers' time windows and minimizing service time.

Azcuy et al. (2021) focused on the tactical problem of deciding where to place transfer stations in a two-tier system while considering operational decisions in the last-mile tier. They derived equations for the expected travel distance from the transfer station to customers' destination on circular and linear transit networks. Also, they proposed a MIP model for minimizing the expected travel distance across different demand scenarios and solved it using an ALNS metaheuristics. The obtained results agreed with the derived equations. They also presented a sensitivity analysis on the instance parameters such as capacity of last-mile vehicles, depot location, customers' clustering and density, and deadlines.

2.1.2 People-aimed integrated services

Aldaihani and Dessouky (2003) was one of the early studies on integrating curb-to-curb services and fixed-route bus lines. They referred to the problem as a hybrid routing problem and looked specifically at finding routes for paratransit vehicles such that total distance traveled, and passengers' total travel time are minimized. They focused on implementing a solution framework with tabu search heuristics to generate and improve feasible routes.

Häll et al. (2009) introduced the Integrated DARP (IDARP), which they defined as the problem of obtaining optimal routes and schedules for vehicles in a dial-a-ride service where the passengers can transfer to a fixed-route service, if necessary. Valid inequalities to strengthen the proposed MIP model were presented. However, they assumed that the fixed route service had a high frequency, so they did not include constraints to model timetables.

Incorporating such realistic constraints, Posada et al. (2017) extended the IDARP to add features such as heterogeneous fleet, and flexible start and end points for the requests, yielding the IDARP with timetables (IDARP-TT). They developed two models for the IDARP-TT and made theoretical comparisons on the growth rate of the number of variables in each model. Thereafter, seeking to evaluate the performance of an IDARP in a real case study of a rural area in Sweden, Posada and Häll (2020) developed an ALNS metaheuristic with an operator specific to the IDARP. Their instance size ranged from 97 to 145 requests, among which only a few trips ended up including a fixed service, which increased passenger travel time by 5 minutes and decreased distance traveled by the vehicles by 16%, on average. Their results demonstrated the potential of integrated passenger transportation.

Molenbruch et al. (2021) also provided an evaluation method for integrated mobility systems in the context of dial-a-ride services and regular public transport. Their problem assumes a heterogeneous set of passengers with different mobility constraints, such as wheelchair users, as well as a heterogeneous fleet of paratransit vehicles. This fleet's total drive distance must be minimized, and public transit need not be used in the passengers' trips. To solve the problem, they developed a metaheuristic procedure based on a large neighborhood search (LNS) method. Their extensive analysis of the benefits of the proposed system covered, for example, the effects of different operational characteristics, such as frequency and speed of the public transit services, and demand-related parameters, such as maximum travel time, number of users, and share of long-distance trips.

Stiglic et al. (2018) studies the potential benefits of having a ride-sharing service as a feeder for public transit, as an alternative for areas where extending the public transit line is not economically viable, such as suburban and rural areas. They focus on matching drivers and riders heading for the same public transit stations and present a heuristic to optimally create single or multi-modal ride-share matches.

TABLE 2.1: Summary of the reviewed literature

Study	Request Types	Hybrid	Segment Mixed	Priority	Pickup	Delivery
Ghilas et al. (2013)	P, F	✓	PT, LM		✓	✓
Ghilas et al. (2018), Ghilas et al. (2016b), Ghilas et al. (2016a), Ghilas et al. (2016c), Mourad et al. (2021)	F	✓	PT		✓	✓
Trentini et al. (2012), Masson et al. (2017), Pimentel and Alvelos (2018), Azcuy et al. (2021)	F	✓	PT			✓
Aldaihani and Dessouky (2003), Häll et al. (2009), Posada et al. (2017), Posada and Häll (2020), Molenbruch et al. (2021), Stiglic et al. (2018),	P	✓			✓	✓
Beirigo et al. (2018), Li et al. (2014)	P, F		LM	✓	✓	✓
This thesis	P, F	✓	PT, LM	✓	✓	✓

P: Passenger
F: Freight
PT: Public Transit
LM: Last mile

2.2 Research Gap

Based on this literature review, we identified two growing research fields with relatively recent contributions. Those fields are: hybrid, or integrated, transportation services, where passengers or cargo are allowed to transfer from public transit to on-demand vehicles; and mixed transportation services, passengers and cargo traveling together in the two modes mentioned.

Table 2.1 summarizes the literature investigated and draws a landscape of this field. In the table, the column Request Types refer to the type of requests considered in the study, passenger or freight. This criteria informs about the considerations regarding the requests needs that are potentially transferred to the model, such as a limit on the riding time, usually considered for passengers. Additionally, this column also informs about the intended application of the model. The next column, Hybrid, indicates if the model is considered hybrid according to our definition. In the table, all studies are, regardless of that being explicitly stated in the study itself. The column Segment Mixed indicates where parcels and passengers are transported together, in the public transit level or in the last-mile level. Since the public transit level always transport passengers, this column is not applicable to studies that have only passenger request type.

It is possible to note that the overlap of both types of service is mentioned in only one work, by Ghilas et al., 2013, and the authors did not pursue the same problem in subsequent works. Moreover, in their study, passengers are distinguished from packages by adding constraints imposing a maximum travel time for passengers, while being less restrictive for packages. For this reason, we consider they dealt with the matter of priority among requests, but their method to do so is different than ours. We assign individual priorities to each request, also allowing flexibility in the prioritization. It is possible that a parcel has higher priority than a passenger, in case it is refrigerated, for example.

We believe there is more to explore and suggest in this matter, such as how passengers would be affected and methods to make the shared ride as convenient as possible for all stakeholders (passengers, delivery customers, and transport companies). This gap in the literature is one of the main motivations for this research.

Chapter 3

Design and Analysis of a Hybrid and Mixed Delivery Service

3.1 Chapter Contributions

- The hybrid passenger and cargo last-mile delivery problem integrated with public transit is introduced. The problem consists of optimizing the routes of delivery vans such that they are synchronized with the buses schedule.
- An MIP formulation for the problem is proposed, considering passenger convenience and that it is inserted into a rural environment.
- The developed model is evaluated using instances based on a real bus line in the Japanese countryside. The instances are published, as well as a method to generate new ones, based on publically available information of bus timetables.
- A case study is performed to compare the performance of mixed and integrated service to alternative formats, such as non-mixed and non-integrated ones. The findings suggest that the proposed approach might be particularly effective in rural settings.

3.2 Motivation

As explored in the introduction of this thesis, there is a wide array of mobility and logistic challenges that affect urban areas as well as rural areas. Our proposal of integrating public transit and last-mile services seems suitable to tackle the challenges existing in some rural areas where bus lines suffer from financial sustainability and citizens lack transportation and parcel services. Rural residents face different mobility challenges than their urban counterparts. This population will see a decrease in their numbers (Ritchie & Roser, 2018), and at the same time an increased share of elderly people, especially in developed countries (ITF, 2021). Together, these two elements lower the demand for mobility services and the availability of drivers and other staff members. The World Economic Forum (WEF, 2020) identifies Japan as a prominent case of this issue, which is also evident in certain regions and is projected to worsen year.

On the supply side, a reduced staff makes it challenging to provide flexibility against disruptions, and the impacts might be meaningful. To illustrate, one late bus may affect a user's entire day's plan, leaving them with no other alternatives. Seniors largely rely on public transportation, taxis, and specialized on-demand services, as well as other users who have limited mobility or cannot drive. As a result, these individual's life quality is strongly affected by the quality of transportation services.

Bus lines serve as the primary mode of public transportation in regions without railways, hence one important aspect is also the quality and availability of the bus service. Unfortunately, from a free-market viewpoint, the majority of bus routes are not economically viable (low demand being a primary reason). As a result, the public sector must support those areas, bearing the financial burden of maintaining those routes. Often, however, the frequency of the services is reduced. According to ITF (2021), this is the result of long-standing deficiencies brought on by a lack of emphasis in terms of policy, funding, institutional capacity, service supply, planning, and research, especially when rural projects are contrasted with urban ones.

A partial solution to reduce the burden of subsidies on bus lines is to extend their services to include freight transportation, allowing logistic operators to load the buses with boxes, which would be unloaded at bus stops later on the bus route, as illustrated in Figure 1.1c. In this manner, logistic operators could reduce truck trips, and bus companies may earn extra revenue from carrying the boxes while using idle space inside their buses and increasing their usage.

The motivation of this phase of the research was to support rural transit by developing a people- and freight-carrying service that incorporates bus lines and last-mile on-demand transportation. The major objectives were to model this type of service and demonstrate its benefits over services with different levels of cargo mixing and integration. The suggested model is considered to be helpful for determining feasibility in pre-implementation studies as well as for managing synchronization and routing issues after implementation.

In fact, at the present stage, the model developed can abstract both urban and rural environments, but further analysis for urban areas would possibly require large-scale solution approaches, which were not the current focus. While the transportation service proposed in this study can be generalized to any region, the areas we had in mind when defining the problem statement were rural areas.

3.3 Problem Statement

A transportation service provider must attend to numerous requests during the course of a day. Requests might be either passenger or shipment. When someone requests a ride to a location in the rural community, they are making a passenger request. A parcel request is a request for a parcel delivery in the rural community (a household or business). In contrast to shipments, where just a destination is reported, passengers must specify both their intended destination and departure time.

According to a usual movement pattern in rural areas, we assume that users are starting out in a major town that serves as a local service center and are moving toward surrounding villages. The town acts as the population's major hub for essential services, and bus service is available, although on a relatively small scale. For packages, the origin is a warehouse or distribution center; for passengers, it is a public bus terminal or the hub of the points of interest in the region.

The desired solution is one that outputs routes and schedules for the delivery vehicles, transporting each request to its desired location. A fleet of delivery vehicles is available to the service provider, and from now on we will use the term van to refer to a last mile delivery vehicle.

As a result, the problem tackled has an operational nature. Also, the solution coordinates vans with public buses to provide an integrated, or hybrid, transportation service. Such a service handles the demand for personal mobility and parcel logistics originating from a town hub and going to a remote village or community. It is also regarded as a mixed transportation system because people and packages share resources both on fixed bus routes and in the last mile. We assume a static and deterministic setting in which all necessary details, such as the requests, travel times, and destinations, are known in advance for the duration of the planning horizon.

According to our suggested model, after boarding the bus at the planned departure time, the passenger will get out at a bus stop selected in the solution, where a delivery van will be waiting to pick them up and take them to their desired location. The model only addresses passenger delivery in the village. Additionally, we assume that the passenger selects their own departure time because it is based on their schedule in the town center. So, to clarify, we do not consider time windows in our model. Another assumption is that passengers can go to the bus stop where they will board the bus, but do not wish to go to their destination: it is far from the bus stop, or they might be carrying groceries.

The warehouse is, without loss of generality, one stop on the bus route, where parcels begin their journeys after being brought there by several courier companies. Thus the warehouse can also be called, in logistic terms, a consolidation center. The items must be sorted and loaded into the bus by the warehouse staff. When packages arrive at their assigned bus stops, they must be transferred to the vans because there are no other storage facilities along the bus route; that is another reason for the synchronization between buses and vans.

A van is waiting at the bus stop to pick up people and packages for the last mile in their journey. The fleet is uniform and assumed to be prepared to safely carry both passengers and cargo. Buses also have compartments designed to hold packages. It requires some time to transfer packages and people from the bus to the vans. This step must be taken into consideration because it impacts the van's timetable and affects subsequent deliveries. Likewise, upon arrival at the destination, the time required to drop off the passenger and complete a parcel delivery is also taken into account, involving carrying the package to the door and passing it to the customer.

Figure 3.1 depicts a bus line that travels from a town to a distant village, as an illustration of the proposed method. In this scenario, there are two vans, one parcel, and two passengers. Assume that passengers 1 and 2 use the bus at different times during the day, such as in the morning and in the afternoon. We can find, as a a feasible solution, that passenger 1 and the package can transfer at Bus Stop B, where a van is waiting. The van transports them to their destinations and then picks up passenger 2 at Bus Stop A. The second van is not used.

When solving this problem, the following questions must be answered:

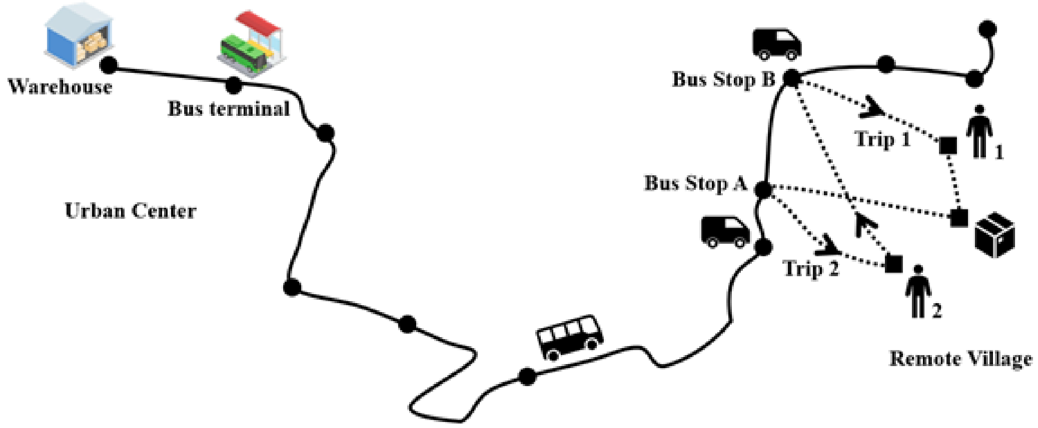


FIGURE 3.1: Example of the proposed mixed and integrated transportation service. The dotted lines represent the routes of vans. The solid line is the fixed bus route.

- How do we find minimal routes such that all requests are fulfilled and the van are synchronized with the buses?
- Which parcels should be loaded onto which buses?
- At which bus stop should which passenger disembark, and also which parcels should be taken from the bus there?

The answers to the preceding questions must take into account both the perspectives of the service provider and the passenger. The transportation provider wants to keep operating costs, or the expenses related to vehicle usage, as low as possible while yet ensuring that all requests will be fulfilled within the scheduled time horizon. The passengers want to arrive as soon as possible and in a comfortable manner. The passenger perspective is frequently incorporated into DARP models, as stated by Paquette et al. (2013), by adding constraints or adopting objective functions to regulate the level of service indicators, such as the maximum journey duration, mean waiting time, and the difference between actual and desired arrival times, among other criteria. These interests are conflicting in a mixed system because a longer route that visits a passenger's destination first and then delivers a package is more appealing to the passenger than a shorter route that does these in reverse, being more favourable to the company. Besides that, given that this system is integrated, giving the passengers priority results in routes where the van must travel to bus stops that are typically more convenient for the passengers, instead of economical for the company. Due to this, we use the following objective functions that reflect the aforementioned perspectives: (1) Reduce the total amount of time passengers spend traveling, and (2) Reduce the total amount of time vans spend driving.

The network's design must be taken into consideration when solving a transportation problem. Bus schedule frequency, bus stop placements, the number and capacity of vans, and depot location are only a few design decisions. Due to the fact that they fall beyond the purview of the current investigation, our suggested approach does not attempt to optimize these choices.

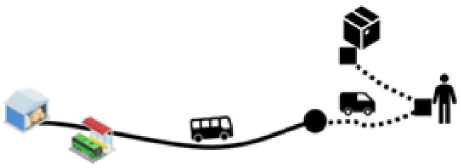
3.3.1 Scenarios for comparison

To show the benefits of our mixed and integrated approach, we compare it to conventional services. In decreasing order of integration and mixing, Table 3.1 summarizes the features of four scenarios, whereas Figure 3.2 illustrates them.

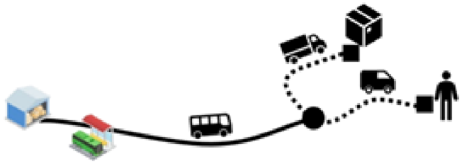
TABLE 3.1: Summary of the four scenarios, highlighting their aspects.

Scenario	**Mixed**	**Hybrid**
A	✓	✓
B	Partially (In bus lines)	✓
C	–	Partially (For passengers)
D	–	–

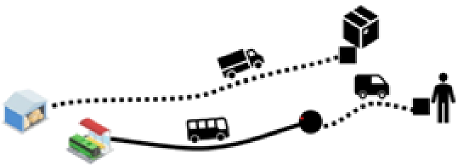
The proposed approach is Scenario A. In Scenario B, the mixed aspect is kept at the level of the public transit system but is dropped from the last mile. In other words, separate last-mile fleets are available to handle parcels and passengers. In Scenario C, people use bus service first, followed by vans, and packages are directly delivered by trucks from the major town. Trucks have a bigger carrying capacity than vans, thus we classify them as a separate sort of vehicle. So, this case is not



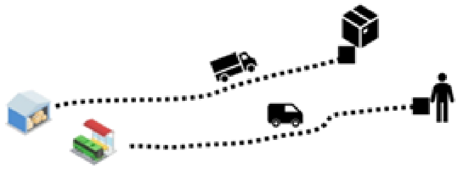
(A) Scenario A



(B) Scenario B



(C) Scenario C



(D) Scenario D

FIGURE 3.2: Illustrations of the four scenarios.

mixed, since passengers and packages are kept apart entirely. For the passengers, however, solutions are still integrated. Lastly, Scenario D describes a scenario in which there are no bus lines and exclusive services fulfill all requests from their point of origin.

3.4 Model Development

In this section, we propose a mixed integer programming formulation for the four scenarios discussed. We begin by introducing notation and description that are specifically focused on Scenario A because it can be described as an extension of the other scenarios. Then, we will explain how to change it to model Scenarios B, C, and D.

We denote by $R = R^c \cup R^p$ the set of all customer requests, where R^c are parcel requests and R^p are passenger requests. Our problem does not consider pick up a passenger or parcel so we let each node $i \in R$ represent the destination of a request. To model bus movement, we let B be the set of buses and S be the set of physical bus stops along the considered bus line. To model the bus timetable, we use set $T = B \times S$, where each node $i \in T$ is visited by a bus at time h_i. An interpretation of this set is that each node represents a point in time and space where passengers and parcels can transfer from a bus to a van. Observe that we did not consider bus capacity for parcels or passengers because, since this study is focused on rural areas, we assume low demand, below any level that would affect operations and the feasibility of solutions. Since passengers decide which bus they will ride, the transfer nodes available for them are those on their bus timetable. For this reason, set $T^p(r) \subset T, \forall r \in R^p$ contains the transfer nodes that passenger r may use.

The last-mile vehicles vary according to the scenario, either a truck or a van, but the fleet is considered to be homogeneous, with a capacity of q_c units of parcels and a capacity of q_p people. Set O contains the location of the initial depot of each vehicle in the fleet and set O^f contains their final depot. Initial and final depots can be the same location but do not need to be. The parameter l_i is the loading or unloading time of node i. If $i \in T$, it can be interpreted as the time required to transfer passengers from the bus to the van, and if $i \in R$, it is the time it takes to drop off passengers or finish a parcel delivery.

The model is defined on a graph network $G = (V, A)$. The nodes in set $V = R \cup T \cup O \cup O^f$ are respectively the requested destinations, the bus visits to each bus stop, and the initial and final vehicle depots. The set of arcs A contains all the feasible arcs connecting the nodes in set V:

$$A = (O \times T) \cup (T \times R) \cup (R \times R) \cup (R \times T) \cup (R \times O^f) \cup (T \times T) \cup (O \times O^f)$$

where $O \times T$ are arcs connecting vehicle depots to transfer nodes; $T \times R$ connect transfer nodes to requests destinations; $R \times R$ are arcs connecting requests destinations to each other; arcs $R \times T$ connect requests destinations to transfer nodes; in $R \times O^f$ we have arcs from requests destinations to vehicles final depot; in $T \times T$ we have arcs connecting transfer nodes and those are used only by the requests, so vehicles are not allowed to travel in these arcs; finally, $O \times O^f$ include arcs from initial to final depots and are used by vehicles which will not be used. During the generation of set A, we do not include self-loops, i.e., arcs from and to the same node (i, j).

Each arc $(i, j) \in A$ has a known travel time t_{ij}. The subset $A^r \subset A$ contains arcs that parcels and passengers are allowed to use, i.e., arcs between transfer nodes and destinations, and it is defined by $A^r = (T \times R) \cup (R \times R)$.

The first set of decision variables used is x_{ij}, which is binary and indicates whether a van uses arc $(i, j) \in A$. Another set of binary decision variables is y^r_{ij}, which indicate whether a request $r \in R$ traverses arc $(i, j) \in A^r$. Lastly, for nodes $i \in R \cup O \cup O^f$, a continuous decision variable h_i indicates the departure time of a van from i. When $i \in T$, h_i is a parameter defined by the bus timetable plus the loading and unloading service time l_i. h_i ensures synchronization between the vans and the buses.

3.4.1 Scenario A

Our model is based on the one proposed by Masson et al. (2017), who presented a vehicle routing problem with time window (VRP-TW) formulation plus capacity constraints for the transfer nodes. Here, we do not consider transfer node capacity, but we need more control over the movement of parcels and passengers, primarily due to the different level of service that passengers require. Therefore, we extended their model by adding the decision variable y^r_{ij}, which are used to check the requests trips and calculate their travel time. Moreover, we distinguish between the two types of cargo through the objective function, as explained in Section 4.3. We prioritize the level of service for passengers, $r \in R^p$, by minimizing their travel time. Another difference is that, since we have two types of cargo, vans must have capacities specific to each type. Following, we present the mathematical model used for Scenario A.

$$\min \quad z_1 = \sum_{r \in R^p} \sum_{(i,j) \in A^r} (t_{ij} + l_i) y_{ij}^r \tag{3.1}$$

$$z_2 = \sum_{(i,j) \in A} t_{ij} x_{ij} \tag{3.2}$$

$$\text{s.t.} \quad \sum_{j \in T \cup O^f} x_{oj} = 1 \qquad \forall o \in O \tag{3.3}$$

$$\sum_{i \in R \cup O} x_{io} = 1 \qquad \forall o \in O^f \tag{3.4}$$

$$\sum_{(i,j) \in A} x_{ij} = \sum_{(j,i) \in A} x_{ji} \qquad \forall i \in R \cup T \tag{3.5}$$

$$\sum_{i \in T \cup R} x_{ij} = 1 \qquad \forall j \in R \tag{3.6}$$

$$\sum_{(i,j) \in (T \times R)} y_{ij}^r = 1 \qquad \forall r \in R^c \tag{3.7}$$

$$\sum_{(i,j) \in (T^p(r) \times R)} y_{ij}^r = 1 \qquad \forall r \in R^p \tag{3.8}$$

$$\sum_{i \in T \cup R} y_{ir}^r = 1 \qquad \forall r \in R \tag{3.9}$$

$$\sum_{(i,j) \in A^r} y_{ij}^r = \sum_{(j,i) \in A^r} y_{ji}^r \qquad \forall r \in R \tag{3.10}$$

$$\sum_{r \in R^c} y_{ij}^r \leq q_c x_{ij} \qquad \forall (i,j) \in A^r \tag{3.11}$$

$$\sum_{r \in R^p} y_{ij}^r \leq q_p x_{ij} \qquad \forall (i,j) \in A^r \tag{3.12}$$

$$h_j \geq h_i + t_{ij} + l_j - M(1 - x_{ij}) \qquad \forall (i,j) \in A \tag{3.13}$$

$$x_{ij} \in \{0,1\} \qquad \forall (i,j) \in A \tag{3.14}$$

$$y_{ij}^r \in \{0,1\} \qquad \forall r \in R, \forall (i,j) \in A^r \tag{3.15}$$

$$h_i \geq \mathbb{R}^+ \qquad \forall i \in V \tag{3.16}$$

The objective function has two components: z_1, given in (3.1), which minimizes the passengers' routes in the sense of making their rides as short as possible; and

z_2, given in (3.2), which minimizes the delivery vehicles' routes, again meaning minimizing total drive time. Therefore, the two components z_1 and z_2 express the passengers' convenience and the transportation provider's objective, respectively. These two objectives are optimized lexicographically, with z_1 being optimized first.

The set of Constraints (3.3)-(3.6) controls the movement of the vans. In constraints (3.3) and (3.4), we assure that all vans will leave and come back to a depot. Remember that, since variables x_{ij} do not specify which vans traversed an arc, it is not possible to guarantee that it will come back to the depot from which it departed. Constraint (3.5) assures vehicle flow conservation for a node. Constraint (3.6) assures that all request destination nodes are visited by a van. These are classic flow starting and conservation constraints in VRP formulations.

The next set, constraints (3.7)-(3.10), controls the movement of the parcels and the passengers. In constraint (3.7), we have that parcels' requests may departure from any transfer node. Meanwhile, passengers have a preferred bus, so constraint (3.8) limits their departures to transfer nodes visited by their preferred bus. Constraint (3.9) indicates that all requests must arrive at the requested destination. Constraint (3.10) assures request flow conservation.

Next are the vehicle capacity constraints, constraints (3.11) and (3.12). They assure that it will not carry more parcels or passengers than it is able to. Constraint (3.13) is a classic scheduling constraint. In VRP-TW problems, it is used to assure that requested nodes are visited within their time windows. Our problem does not consider time windows for destination nodes, but we need this constraint to assure that a van will, at least, meet the bus as it arrives at a bus stop, or, at most, make sure a van is waiting for the bus at the bus stop. For this reason, synchronization constraints seem like a more appropriate label for these constraints. Remember that h_i is a constant when $i \in T$. Moreover, the parameter M is used to linearize this constraint, and its value should be high enough to not cut off a feasible solution, while small enough to provide a tight LP relaxation during the solution process executed by the MIP solver. It can be set to a reasonable size of the desired vehicles' total working time. Finally, constraints (3.14)-(3.16) state the domains of our decision variables.

3.4.2 Scenario B

Next, we divide the problem into two parts —delivering the packages and transporting the passengers— in order to model Scenario B. This task is simple because bus capacity is not taken into account. In essence, we must solve the two problems independently in order to arrive at the solutions for this scenario. First, we reduce Scenario A's formulation to the problem of transporting only the passengers. This is achievable by:

- making $R = R^p$;
- removing constraints (3.7) and constraints (3.11), since these are exclusive to parcels.

Next, to reduce Scenario A's formulation to the problem of delivering only parcels:

- make $R = R^c$;
- remove objective function (3.1), and remove constraints (3.8) and constraints 3.12, since these are exclusive to passengers.

3.4.3 Scenario C

Similar to the prior scenario, Scenario C also demands for splitting the problem into two parts. For passengers, it is the same as in Scenario B. For parcels, the model should be reduced to a Vehicle Routing Problem with Multiple Vehicles. The changes are as follows:

- make $R = R^c$;
- make $A = (O \times R) \cup (R \times R) \cup (R \times O^f) \cup (O \times O^f)$, removing set T, since there are no transfer nodes anymore and parcels are directly loaded and delivered by vans;
- modify constraints (3.3), (3.5), and (3.6), to remove set T;
- remove objective function 3.1;
- remove constraints (3.8) and (3.12);
- remove constraints (3.7), (3.9), and (3.10), since it is not necessary to control the flow of requests anymore;
- remove constraints (3.13), since it is not necessary to synchronize to buses anymore.

3.4.4 Scenario D

Finally, Scenario D is regarded as a "shared" transportation problem because users travel together in the same last-mile vehicle. The model applied to parcels is the same as that in Scenario C. However, for passengers, it turns into a Vehicle Routing Problem with Time Windows, where time constraints only apply to departure. As there are no buses, we assume that the informed preferred bus time is the preferred departure time riding a delivery vehicle. To model the preferred departure time, we use parameter $H^r, \forall r \in R$ to set the time that a vehicle will depart transporting passenger r. The necessary modifications are:

- make $R = R^p$;
- make $A = (O \times R) \cup (R \times R) \cup (R \times O^f) \cup (O \times O^f)$, removing set T, since there are no transfer nodes anymore;

- modify constraints (3.3), (3.5), (3.6), (3.9), and (3.10), to remove set T;
- modify constraints (3.7), originally used to start the flow of parcels, to start the flow of passengers instead;
- remove objective function (3.1);
- remove constraints (3.8), because these constraints require passengers to leave from transfer nodes;
- add the following constraints, which assure that passengers will leave the urban center at their preferred time:

$$h_j \geq H^r - M(1 - y^r_{ij}) \qquad \forall r \in R, \forall (i,j) \in O \times R \tag{3.17}$$

$$h_j \leq H^r y^r_{ij} + M(1 - y^r_{ij}) \qquad \forall r \in R, \forall (i,j) \in O \times R \tag{3.18}$$

3.5 Numerical Experiments

Comparing the proposed integrated approach (Scenario A) against non-integrated approaches (Scenarios B to D), this section assesses their operational performance. We first explain how we created the instances based on an actual location. Then, after solving the proposed models using a commercial solver, we illustrate the outputs. Then, after solving the proposed models using a commercial solver, we show runtime, solution quality, and an example of the output. Lastly, we present a case study derived from the proposed models and the generated instances. It begins with comparing the total drive times between the various scenarios and then demonstrates the trade-offs between passenger convenience and a shorter vehicle route. Finally, we concentrate on package distribution and demonstrate the advantages of integrating it with bus lines.

3.5.1 Instances Generation

The destinations of the sets of requests were generated based on the city of Akaiwa in Okayama Prefecture, an actual place in rural Japan. This area was picked because it has the characteristics assumed in our model. We could not get statistics on the actual demand for personal transportation and parcel delivery in the area; therefore, we produced these numbers based on our best estimates. A public online repository of General Transit Feed Specification (GTFS) files from services operating in Japan was used to acquire information on the bus routes operating in the area ("GTFS-JP", 2019). Transit agencies share temporal and geographic information about their services using the GTFS data standard. For more details about GTFS, we refer the interested reader to "GTFS Static Overview" (2022).

Several bus routes are available in the feed from Akaiwa City. However, for our instances, we selected one that only operates three daily buses departing from the bus stop that we considered the Bus Terminal. These buses leave at 10:20, 13:50, and 15:30. We created a script to generate random points near or along the bus route in low-density areas. These places are considered potential destinations in the villages and communities. We obtained datasets containing geographic and demographic information from "Statistical Maps of Japan" (2020) to find the areas with low population density.

All the generated random locations were separated into 26 sets of instances, labeled from *a* to *z*, initially with a total of 30 locations for each set. Next, 20 locations were randomly set to be parcel request, while the 10 left are set to be passenger request. Within each set, smaller instances, with less parcels or passengers, are obtained by random removal of requests. So, set *a* contains, for example, instances *a_5_5* (with 5 passengers and 5 parcels) and *a_10_20* (with 10 passengers and 20 parcels), as well as the other combinations of number of passengers and parcels, as described in Table 3.2, which also summarizes details about the instances. There is no significant difference between each set, except the locations assigned to them.

Finally, the OpenRouteService routing engine, which is freely available, was used to determine the driving distances and times between the destinations and the bus stops. A maximum of 18 bus stops, including the assigned bus terminal and warehouse bus stops, had to be selected due to restrictions on the size of the distance matrix retrieved from the routing engine. The generated instances are available in the online repository https://github.com/naraqb/instances-hybrid-lm-pt. As mentioned, we assumed that passengers would determine when they wanted to board the bus. This time was also chosen randomly between the three buses.

TABLE 3.2: Summary of instances parameters

Sets of instances	26 (a to z)
Number of passengers	[5, 10]
Number of parcels	[5, 10, 15, 20]
Number of bus lines	1
Number of buses per line	3
Number of bus stops	18
Number of delivery vehicles	5
Loading time l_i	4 min
Vehicle capacity	
Scenario A	$q_p = 3$, $q_c = 7$
Scenario B	$q_p = 3$, $q_c = 7$
Scenario C	$q_p = 3$, $q_c = 20$
Scenario D	$q_p = 3$, $q_c = 20$

3.5.2 Model Implementation and Verification

The Gurobi Optimizer version 9.0 commercial MIP solver and the appropriate Python libraries were used to solve each model after their implementation, in Python 3.8. We used a computer with an Intel Core i7 3.2 GHz and 32 GB of memory, with an optimization time limit of two hours. Table 3.3 shows the minimum, maximum and average run time, grouped by scenario, and number of passenger and parcels in the set of instances. All instances were solved to optimality within the time limit, except some with 20 parcels. For these instances, we show in Tables 3.4a and 3.4b the solution quality, given by the gap between lower and upper bounds obtained by the solver.

Since this is an MIP problem, as we increase the instance size, it is expected that an exact solver will take longer to prove an optimal solution, and, by setting time limits, the solution quality will decrease. This can be demonstrated by a naive estimation of the problem size, considering its combinatorial nature. A feasible solution to our problem is essentially the assignment of requests to transfer nodes, i.e., getting off an assigned bus at an assigned bus stop. The assignment task is then followed by the routing of the delivery vehicles, solving a TSP, which is expected to be performed in a reasonable time. Thus, the growth in difficulty is due to the possible number of assignments of requests to transfer nodes. Considering $|R|$ requests, each request $r \in R$ can be assigned to $|T|$ transfer nodes, generating $|T|^{|R|}$ combinations. In our instances, the size of $|T|$ is equal to the number of bus stops, 18, times the number of buses per line, 3. Thus, we can see how even small instances, with a total of 10 requests, already present a very large amount of possible feasible solutions.

We also created a visualization tool to plot the routes on a map in order to see the results the solver produced and to confirm whether or not the routes and schedule were satisfactory and correct. So, Figure 3.3 illustrates instance *f_5_10*, with 5 passengers and 10 parcels, and the obtained solution. The lines connect the locations to be visited by a van in its route; they do not represent actual road directions.

TABLE 3.3: Average, minimum and maximum runtime in seconds to solve instances with each listed number of parcels and passengers.

Passengers	Parcels	Average	Min	Max
Scenario A				
5	**5**	0.5	0.3	1.0
	10	3.3	0.7	14.5
	15	73.0	3.4	1257.2
	20	629.9	20.9	7211.8
10	**5**	0.7	0.5	1.6
	10	8.7	1.5	100.7
	15	170.4	5.0	1696.4
	20	2420.8	14.9	7233.9
Scenario B, solving for parcels				
	5	0.2	0.1	0.5
	10	3.1	0.7	13.0
	15	136.5	6.7	1965.4
	20	1154.6	19.2	7200.4
Scenarios C and D, solving for parcels				
	5	0.03	0.01	0.05
	10	0.34	0.12	0.7
	15	2.6	0.8	11.1
	20	14.1	5.4	38.1
Scenarios B and C, solving for passengers				
5		0.07	0.06	0.08
10		0.14	0.13	0.15
Scenario D, solving for passengers				
5		0.20	0.04	0.39
10		55.1	12.2	166.8

3.6 Case Study

Our three-part case study helps to address the question, "What benefits may such a service offer at the operational level?". We first assess the drive time of the proposed service. Then, we show the tradeoff between the operational and passenger

TABLE 3.4: Optimality gaps after solver runs for 2 hours

(A) Gaps in Scenario A

Passengers	Parcels	Set	Gap (%)
5	**20**	**n**	3.68%
10	**20**	**c**	2.80%
		g	3.53%
		k	3.43%
		n	2.38%
		q	1.74%
		w	5.86%

(B) Gaps in Scenario B, solving for parcels

Parcels	Set	Gap (%)
20	**e**	0.12%
	n	0.55%
	w	0.4%

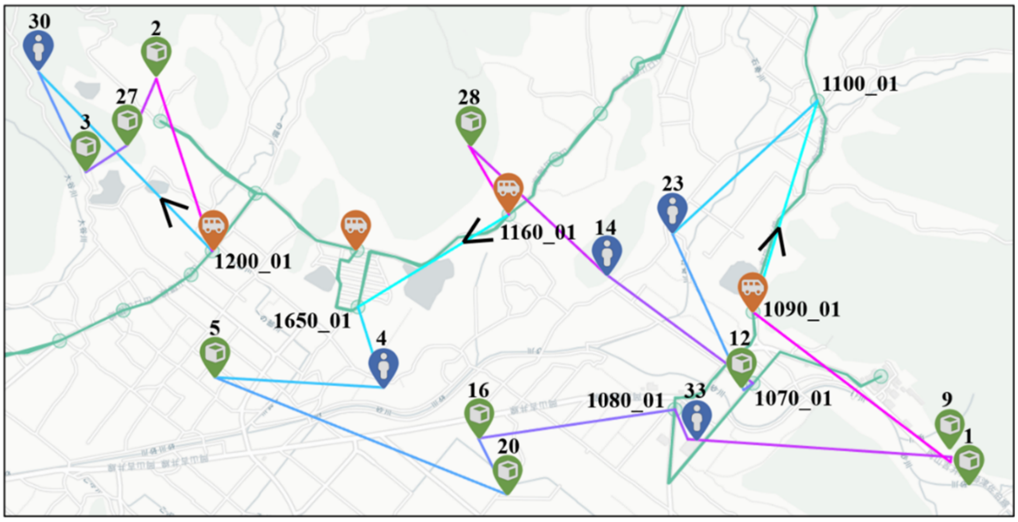


FIGURE 3.3: Visualization of instance *f_5_10* with 5 passengers and 10 parcels. To the right, the solution obtained by the solver. Locations with label finishing in "_01" are bus stops. The arrows indicate vans' movement direction.

perspectives. Finally, we assess the service once more, limited only to package delivery.

3.6.1 Comparison of Total Drive Time between Scenarios

Here we compare the operational perspective indicators, total drive time of last-mile delivery vehicles, between all four scenarios. This analysis allows us to visualize the savings obtained when implementing an integrated system using the non-mixed and non-integrated scenarios as the baseline, as indicated.

The distributions plotted in Figure 3.4 are the results in travel time for all 26 sets of instances for varying numbers of passengers and parcels. The results for Scenarios B to D are obtained by summing the results of the separated problems, as explained in Sections 3.4.2, 3.4.3 and 3.4.4. Table 3.5 lists the mean drive times shown in Figure 3.4, as well as the relative differences between each increasing level of integration, Scenario C, B, and A, in this order, taking Scenario D, no integration, as the baseline.

An intuitive result is the performance of Scenario D: the long distances and lack of integration naturally cause longer drive time since trucks go to the village and then return. Observe that Scenarios C and D use trucks with a bigger capacity (of 20 parcels) than the vans used in Scenarios A and B. If a smaller capacity were used, more trucks, or more trips, would be required, worsening the results.

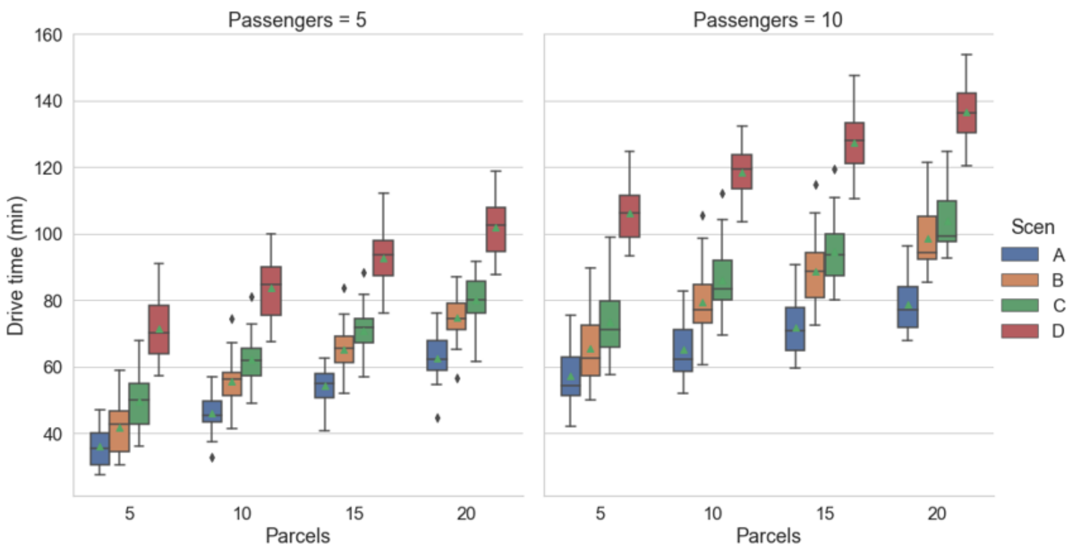


FIGURE 3.4: Distributions of drive time obtained for all sets of instances for the indicated numbers of passengers and parcels. The green triangles indicate the mean value.

The gap between Scenarios D and C indicates the benefit of the first level of integration, assigning passengers to an integrated service. In Table 3.5, we see that this ranges from 21% to 31%. Significant savings are obtained because of the low capacity of vans for passengers assumed in all scenarios (of only 3 passengers, the same as a basic taxi). As we introduce a second level of integration, for parcels, from

Table 3.5: Average Drive Time in each Scenario and the relative difference from higher to lower degrees of mixing and integration.
Pass. means passengers. **Parc.** means parcels.

		Average Drive Time (min) in Scenario:				Relative Differences			
Pass.	**Parc.**	D	C	B	A	**D to C**	**C to B**	**B to A**	**D to A**
5	**5**	36.1	41.8	49.8	71.4	-30%	-11%	-8%	-49%
	10	46.1	55.7	62.2	83.8	-26%	-8%	-12%	-45%
	15	54.2	65.1	70.9	92.6	-23%	-6%	-12%	-41%
	20	62.7	74.8	80.2	101.8	-21%	-5%	-12%	-38%
10	**5**	57.1	65.5	73.5	106.2	-31%	-8%	-8%	-46%
	10	65.1	79.4	85.9	118.6	-28%	-5%	-12%	-45%
	15	72.0	88.9	94.7	127.3	-26%	-5%	-13%	-43%
	20	78.9	98.5	103.9	136.6	-24%	-4%	-14%	-42%

Scenario C to B, the savings in drive time end up not being as significant, ranging from 4% to 11%. This can be explained by two facts: the vans assigned to the bus stops in Scenario B have a much small capacity than the trucks in Scenario C; and the vans are scattered along the bus route. In our instances, with a low volume of parcels, the truck does not need to return to the depot in the main town many times, and this capacity advantage reduces the savings obtained by using the buses. However, the vehicles' capacity and which bus stop should be assigned to be depots of vans are design choices, and their optimization is beyond the scope of this study. Nonetheless, our method demonstrates the benefits under a given choice.

The shortest travel time, as expected, is obtained by mixing the two types of cargo and integrating bus lines into their transport, the last level of integration and the proposed approach, Scenario A. The second-to-last column in Table 3 shows the average savings, ranging from 8% to 14%, when mixing passengers and parcels in the last mile and in the buses (B to A). Finally, the last column compares the two extremes considered, a non-integrated system to a mixed and integrated one (D to A), with savings ranging from 38% to 49%. These high values are expected since this shift eliminates the long trips performed by the trucks and divides them among buses and vans.

We recognize that a transportation service performance goes beyond driving time. However, within the scope of operational optimization, the driving time is the most used indicator, used in many other works. So, here we discuss our results and whether they agree with other authors.

Posada and Häll (2020) compared the total driving distance between integrated and not integrated approaches. In their case study, they used instances with our assumed characteristics of rural instances, with destinations roughly clustered around bus stops, and also found a significant reduction, ranging from 6.32% to 20.69%. Note that this is driving distance and not driving time, which are different indicators, although correlated. Our results and theirs agree that integrated transportation has the potential to reduce driving time in passengers' transportation.

The work in Ghilas et al. (2016b) compared their proposed approach to a standard PDP with time windows, checking two indicators: total cost of the service; and total driving time by the last-mile vehicles. We note that, in their case, using the scheduled lines, or bus lines, was optional. So, there were solutions where the scheduled lines were not used, and therefore no benefits were observed. In our models, the use of bus lines is either mandatory (Scenarios A, B, and C for passengers) or not allowed (Scenarios C for parcels and D) since our goal is to evaluate the performance/benefits of full implementation of the service such as in Scenario A. Therefore, our results are not directly comparable to theirs, for the mentioned reason, and because we used different instances and they did not consider passengers. However, we both found benefits in integrated transportation, obtaining significant savings in total driving time, primarily when destinations are clustered around transfer locations (bus stops).

Concluding this discussion, we highlight that, in our results, since the passengers are prioritized, they are always delivered before parcels when mixed in the last mile.

We demonstrated the advantage of such a system from an operational perspective, even when prioritizing the passenger perspective. Our results agree with other studies and reinforce that it is feasible to mix passengers and parcels since the mixed aspect did not neutralize the benefits of integration.

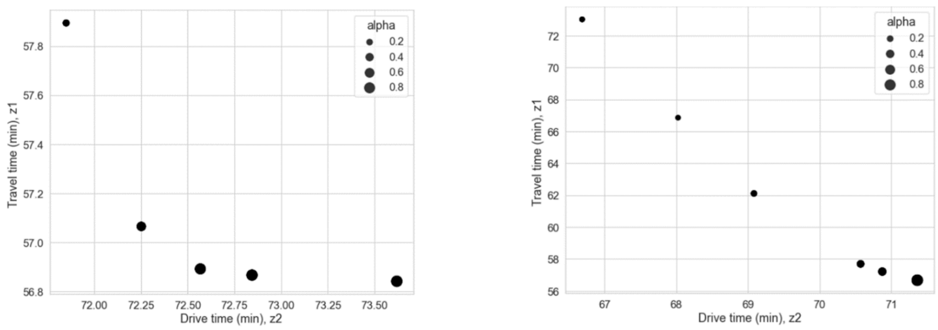
3.6.2 Analysis of Trade-off between Passenger Ride Time and Vehicle Drive Time

Our model prioritizes the passenger perspective by optimizing first the total ride time of the passengers. As explained in Section **??**, the two objective functions z_1 and z_2 are conflicting. In this section, we experiment with applying different weights to these objectives in a weighted objective function to visualize the trade-off between them. The weighted multiobjective function is shown in Equation 3.19.

$$min \quad \alpha z_1 + (1-\alpha) z_2 \tag{3.19}$$

To look at the different degrees of priority of the two objectives, the Pareto efficient points were found for $\alpha \in [0.01, 0.02, \ldots, 0.99]$. Figure 3.5 shows the results of solving two instances (b_10_20 and i_10_20) with 10 passengers and 20 parcels for the indicated weights. The effect of reducing the priority of passengers' convenience is that solutions will contain trips where parcels are delivered before passengers if such trips are shorter. Therefore, visualizing the efficient points allows a decision-maker to choose appropriate weights so that passenger convenience and vehicle usage are balanced.

In Figure 3.5a, travel time ranges from 56.8 min to around 57.8 min, while drive time ranges from around 72 min to 73.5 min, which is a small range, only one minute, and it might even be imperceptible for the passengers. In Figure 3.5b, however, the total travel time ranges from 56 to 72 min, which is more noticeable.



(A) Instance b_10_20 (B) Instance i_10_20

Figure 3.5: Pareto efficient points of selected instances.

The tradeoff is that improving the quality of service for the passengers comes at the cost of increasing total drive time from around 67 to 71 min.

In practice, reducing the priority of passengers' convenience, i.e., reducing α, is that solutions will contain trips where parcels are delivered before passengers if doing so yields shorter trips. The service might be negatively impacted if passengers feel that parcels take precedence over them in the priority line. Visualizing the tradeoff allows a decision maker to choose solutions according to their interest: they might find it competitive to favour the passenger's experience at the expense of higher vehicle usage.

However, visualizing the tradeoff means finding Pareto points for each instance by solving for all α values, and the computational time required to do so highly depends on the instance. It might be impractical in many cases. In the context of mixed and integrated transportation, developing an efficient approach to finding such Pareto points is out of the scope of the present work. However, we would like to emphasize that it might be a promising research direction since, to the best of our knowledge, algorithms developed for this context do not consider a tradeoff between operational goals and quality of service. In a related field, in the context of DARP, Paquette et al. (2013) developed a multicriteria heuristic to deal with the challenge of generating Pareto points between service costs and user inconvenience. Thus, this related and existing body of research is a valuable source of insights to develop solutions to draw a Pareto frontier for our problem as well.

3.6.3 Analysis of Direct Delivery vs Integrated Delivery of Parcels

In this analysis, we disregard passenger transportation and focus only on benefits for delivery services, asking whether using buses jointly with delivery vehicles offers any advantage in comparison to only using delivery trucks, i.e., a traditional, direct, non-integrated approach. We compare Scenario D to Scenario B, both solved only for parcels, and calculate the average savings in drive time of D relative to B, shown in Table 3.6. Figure 3.6 shows the distributions from which those averages were calculated.

TABLE 3.6: Average savings in Drive Time caused by changing from non-integrated (Scenario D) to an integrated (Scenario B) delivery scheme.

	Drive Time (min)		
Parcels	**B**	**D**	**Savings (%)**
5	17.4	25.4	31.7
10	31.4	37.9	17.5
15	40.8	46.6	12.7
20	50.4	55.8	9.8

As we increase the quantity of parcels, we get a smaller saving in time. While those savings depend heavily on the instance, we observe a trend of decreasing savings, with the most savings obtained when there are the fewest parcels. A related conclusion was reached by Masson et al. (2017) in their case study: as the amount of cargo increases until the trucks' capacity, the trucks will travel less because they need to return to the depot fewer times to reload, whereas city freighters need frequent trips back to the bus stops to reload. Therefore, this operational advantage explains why a transportation system integrated to include fixed lines such as bus routes is

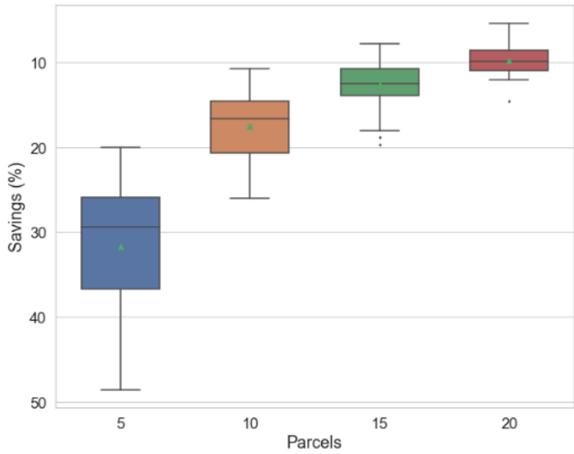


FIGURE 3.6: Distributions of savings in drive time. Observe that the y axis is reversed. The green triangles indicate the mean value.

more suitable for rural areas: it exploits the low volume and long distances typical to that setting.

Chapter 4

An extended formulation: Pickup and Delivery with Priority

4.1 Chapter Contributions

- The model proposed in the previous chapter is extended to include more practical aspects, such as pickup of requests and heterogeneous fleet.
- In the presence of pickup, desirable routes become more complex, and the concept of priorities in hybrid and mixed services is described and modeled.
- A budget constraint is included to allow for deviation from shortest routes, which are necessary to respect priority.
- New sets of instances are generated, that include pickup requests and respective priorities.
- Two models are proposed to respect the priorities. Both models use the same constraints, but have different sets of objective functions. They are compared in terms of route quality, which is measured according to a tailored metric.

4.2 Motivation

The main motivation to extend the model proposed in the previous chapter is to include some features that enrich the service, allowing a wider range of services and to improve it as a decision-making tool. So, in this motivation section, we brings reasons that justify such an extension to include four new features: pickup, heterogeneous fleet, budget limitation, and a better prioritization method. Finally, we reinforce that the motivation adding the research gap regarding priority in mixed transportation service described in the literature review, Section 2.2.

Previously, we described and developed a transportation service that performs only delivery of passengers and parcels. In terms of modeling and optimization problems, a natural extension of delivery routing models is to extend to include pickup as well. In the real market, such an extension can be justified by demand. Such is the case in situations modeled by DARP, where passengers request pickup from a location and dropoff at another location. The previous chapter focused only the flow from a city hub to remote areas. But, the reverse flow is also relevant, in case a passenger is at home and demands transport to the city hub and is willing to transfer to public transit. Including pickup in the service is, therefore, necessary.

Also in the previous chapter, we discussed the conflict between operational perspective and passenger perspective, in Section 3.6.2. The emphasis on each perspective was modelled by assigning a weight to each respective objective function. However, choosing proper weights can be too abstract for a decision-maker. It is necessary, then, to incorporate an element more familiar to them. For this reason, we suggest to constraint the quality of the service offered by using budget constraints. Furthermore, maximizing service quality often means using all necessary resources available, such as all vehicles. The inclusion of budget restriction will also allow the model to decide an appropriate fleet choice to fulfill the transport require. From the previous chapter, we have modelled four scenarios, representing conventional and integrated approaches separatelly. In a model that is able to decide fleet choice, all four scenarios can be capture by this single model. Thus, extending the model to include heterogeneous fleet and budget constraints is relevant to analyze the proper mix of conventional or integrated service.

4.3 Problem Statement

The optimization problem tackled consists of fulfilling a set of transportation requests, considering the customers' inconvenience with the service and under budgetary constraints. The requests might be fulfilled by hybrid vehicles, or traditional ones, to be defined later. The users of this service are passengers, who requested the transportation for themselves, and parcel customers, who are waiting to dispatch a parcel from their location or for it to be delivered to them. These requests have a respective origin and destination, and an assigned priority.

In this system, the transportation resources are a set of pickup and delivery vehicles, from hereon named vans, and bus lines. Requests might transfer from vans to buses, or vice-versa, along their journeys. The buses move regardless of demand, between bus stops, at a specific timetable. The vans may visit any location in the model, i.e., requests' origin and destination, and bus stops; they have a limited capacity for people and cargo; they are initially parked in a depot and must also finish their route in a specified location, which may be or not the initial location. We assume that buses do not have limitation regarding capacity. Another assumption is that vans and buses are adapted to safely transport parcels and passengers simultaneously.

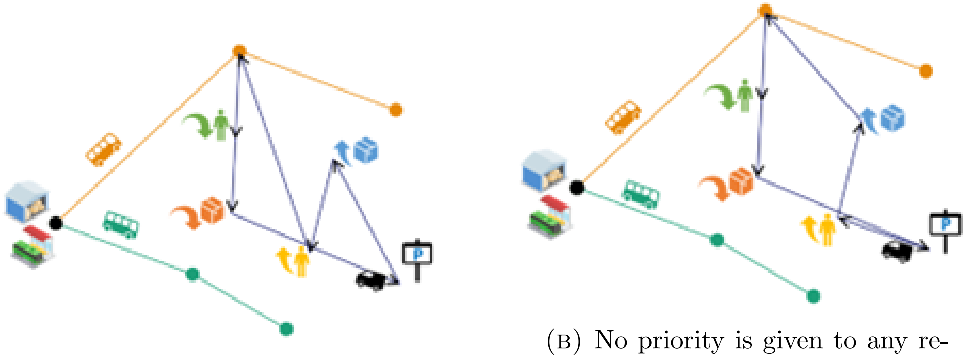
As explained, a key aspect of a hybrid service is respecting the attributes of each request. In our proposed approach, we model this difference using the priority parameter. To some extent, it is safe to assume that passengers perceive time in a more urgent way than parcels: passengers do not desire to have their trip being extended because of stops to handle parcels. A desirable route would turn the parcel service as invisible as possible to the passengers. However, there are some cases where parcels might have a higher priority than passengers, for example, if it is refrigerated. So, while in most cases people must be prioritized, a suitable model should not be so rigid, it must accept some flexibility and output solutions accordingly. To this end, we use the priority parameter, which stablish a hierarchy between the requests, regarding their attributes. The attributes include the type of cargo and the desired service.

The types of cargo are, as mentioned, parcel or passenger and this distinction is relevant to the vehicle's capacity. The desired service are: only delivery; only pick-up; and both pick-up and delivery. To clarify, when a request demands only delivery, it means that it needs a vehicle to reach its destination, but does not require one to leave its origin, as it could reach a bus stop by themselves. The contrary applies to a only pick-up request: it needs a vehicle to depart from its origin, but not necessarily to reach its destination, since it is assumed to be close to a bus stop. Neither applies to requests demanding pick-up and delivery.

An example of prioritization in function of cargo type follows. Consider requests Alice, Bob, Box1, and Box2. Alice needs a vehicle to reach its destination in the city center, while Bob is coming from the city center. Both are willing to transfer to a bus. Box1 must also be sent to the city center, while Box2 is a parcel adressed to an area close to Alice and Bob. Our model would assign type Passenger-Pickup to Alice; Passenger-Delivery to Bob; Parcel-Pickup to Box1; and Parcel-Delivery to Box2. A route that ideally makes the parcel service as invisible as possible to the passengers would be: BusStop $\rightarrow$ Bob $\rightarrow$ Box1 $\rightarrow$ Box2 $\rightarrow$ Alice $\rightarrow$ BusStop. This way, Bob is delivered as soon as possible, and Alice is picked up as late as possible, so her next stop is either her destination or the bus stop. In this case, a suitable prioritization to these requests is: Bob has priority 1 (the highest); Box1 is 2; Box2 is 3; and Alice is 4. This pattern will be applied to our instances, where Passenger-Delivery > Parcel-Delivery > Parcel-Pickup > Passenger-Pickup.

A solution for this problem is a valid route and scheduling plan for the vehicles, such that all requests may travel from their origin to their destination, and, if their journey include riding the bus, the vans movements must be synchronized to the bus timetable. The solution also indicates how many vehicles should be used to complete the request. The cost to move the vehicles is proportional to their driving time. It is also desirable to take into consideration overall customer inconvenience, measured in their total travelled time. Customer inconvenience is a concept that also includes the amount of requests from lower priority levels a request has to visit in its route. However, the budget limits how many cars should be used, and how much time they spent driving. The driving time might be different because of the presence of bus lines. The problem must be solved for a whole planning horizon (e.g., one day) with known and fixed information about requests, bus timetable, travel times on the streets, etc. Thus, a static and deterministic problem.

Figure 4.1 illustrates an instance of the described problem and two possible solutions to show that the shortest route in not always desirable when considering requests' arrival time. There are two bus lines, orange and green, each with two bus stops (colored circles), one van parked in the sign with the P letter, four total requests, two parcels and two passengers, each requesting pickup or delivery service. The different requests colors are to illustrate that they are independent requests, they do not mean the origin-destination pair of the parcel (box) request, for example. For the pickup requests (with an up arrow) their *destination* is the "city center" (black circle). While for the delivery requests (with a down arrow) their *origin* is the "city center". The "city center" is, without loss of generality, one of the bus stops. The difference between the two figures is that Figure 4.1b is a solution minimizing the van's travelled distance. Such an objective is common in pickup and delivery models that focus on vehicle usage. However, when customer satisfaction is on focus, a solution as in Figure 4.1a might be more desirable, where the blue parcel is collected before the yellow passenger, and then the green passenger is delivered before the red parcel. Observe that in Figure 4.1b the yellow passenger would have their trip extended due to parcel collection.



(A) With priority to passengers

(B) No priority is given to any request.

FIGURE 4.1: Example of solutions in settings with and without priority.

4.4 Model Development

4.4.1 Notation and the Underlying Network

In this section, we explain the notation used in our model and for easier reference, Table 4.1 summarizes it, including the decision variables. We consider a set R of customers' requests, including passengers and parcels, which are separated in the sets R^P and R^C. Those two sets are useful to model the van's capacity for each type. The requests might demand pickup, delivery, or both services, and these are separated into sets R^1, R^2, and R^3, respectively. Note that $R^1 \cup R^2 \cup R^3 = R^P \cup R^C$. To each request, two locations are associated: an origin and a destination, denoted by o_r and d_r, $r \in R$, contained in L.

As explained, pickup requests desire to reach a "city center", so, for modeling purposes, we place their destination close to the bus stop that represents the "city center" and set the cost of the movement from the "city center" to the destination

TABLE 4.1: Summary of the notation used in this chapter

Sets and Indices	
R	Set of all requests
R^1	Set of requests that demand pickup
R^2	Set of requests that demand delivery
R^3	Set of requests that demand both pickup and delivery
R^P	Set of passenger requests
R^C	Set of parcel requests
N	Set of all nodes
L	Set of nodes of requests origin and destination location
L^O	Set of nodes corresponding to requests origins
L^D	Set of nodes corresponding to requests destinations
$L^{(1,O)}$	Set of nodes corresponding to pickup requests' origins
$L^{(2,D)}$	Set of nodes corresponding to delivery requests' destinations
V	Set of vans
B	Set of buses
S	Set of physical bus stops
S_b	Set of bus stops that bus b visits
T	Set of transfer nodes
A	Set of all arcs
A^R	Set of arcs that requests may use
A^V	Set of arcs that vans may use
A^T	Set of arcs connecting transfer nodes
A^T_b	Set of arcs connecting transfer nodes that bus b visits
A^T_s	Set of arcs connecting transfer nodes in the bus stop s
i, j	Indices used for nodes
r	Index used for requests
Parameters	
l_i	Loading/unloading time in a node
q^v_P	Vehicle's capacity to carry passengers
q^v_C	Vehicle's capacity to carry parcels
c_{ij}	Traveling time between nodes i and j
o_r	Origin node of request r
d_r	Destination node of request r
o_v	Origin node (starting depot) of vehicle v
d_v	Destination node (returning depot) of vehicle v
ρ_r	Priority of request r
H_b	Time that a bus departs from bus stop b
D	Budget
Decision Variables	
x^v_{ij}	Binary variable: if vehicle v travels from i to j or not
y^r_{ij}	Binary variable: if request r travels from i to j or not
z^r_b	Binary variable, indicator: if request r uses bus line b or not
h_i	Continuous positive variable: time a vehicle arrives at $i \in L$

node to zero and do not constrain this movement to require a van, effectively allowing the request to "walk" to its destination on its own. A similar setup is done to the delivery requests, but to their origin node. The third type of request, pickup and delivery, do not receive this setup because, for the model, both origin and destination must be reached by riding a van. The sets L^O, L^D, $L^{(1,O)}$ and $L^{(2,D)}$, all subsets of L, are useful to model the requests movement, and they mean, respectively, origin nodes of all requests, destination nodes of all requests, origin nodes of pickup requests, and destination nodes of delivery requests. To each request, a priority is assigned, denoted by the parameter ρ_r, which must be integer and greater than or equal to one. Lower ρ values mean higher priority.

The fleet of last-mile vehicles, or vans, is contained in set V and may be heterogeneous, each $v \in V$ has their own capacity q_v^p of passengers, and q_v^c of parcels. We consider requests to be unitary, meaning one single person, and a parcel of standard volume. Vans also have different depots nodes where they depart from and must return to, which might be different real parking locations, or not. The starting depot is denoted by o_v, and the finishing depot is d_v. The set O contains all nodes related to the depots.

Since the fleet is heterogeneous, we can also have vehicles with zero capacity for one type of cargo. In this manner, we can model traditional, non-hybrid and non-integrated services. In our experiments, we include trucks to carry exclusively parcels by setting their capacity to carry passengers (q_v^p) to zero, and not allowing them to enter nodes in the bus network (explained ahead). We also include taxis to carry exclusively passengers. By adding such vehicles, the solution of a particular instance will also be selecting the appropriate mix of services among hybrid/integrated and traditional, according to the limited budget.

Without bus lines, our problem is essentially a pickup and delivery problem for the vans, trucks and taxis, which can be defined on a directed graph to model their movements across the requests. When considering bus lines, we “attach” a bus network to the vans network, allowing requests to travel through both, but not allowing the vehicles to travel *through* the bus network.

To model the bus network, we use S as the set of physical bus stops, while B receives the set of buses, which run along bus stops listed in $S_b = \{s_1, s_2, \ldots, s_u\}, S_b \subset S, \forall b \in B$; in this manner, we can model buses that do not necessarily stop in all bus stops. The nodes where requests may transfer from a van to a bus, or vice-versa, are contained in set $T = \{(b, s), \forall b \in B, \forall s \in S_b\}$. For each transfer point, h_t indicates the time that a bus departs from it, according to the bus timetable. Please note that h_t is a constant when $t \in T$, and it will be used as a variable in any other node, as explained in the next section. To connect transfer nodes, we define the set of arcs A^T, which is the union of two types: those connecting the same bus stop to the next bus visit A^T_s, and those connecting one bus stop to the next in a bus route, A^T_b. Formally:

$$A^T_b = \{(t_{(b,s_1)}, t_{(b,s_2)}), (t_{(b,s_2)}, t_{(b,s_3)}), \ldots, (t_{(b,s_{(u-1)})}, t_{(b,s_u)})\}, \forall b \in B$$

That is, a set that contains the pairs of consecutive bus stops visited by each bus b in its route. Since this represents a route in the real world, we assume that $h_{(b,s_{(u-1)})} < h_{(b,s_u)}$. Another useful set is one that contains arcs connecting the same bus stops in time, as if staying in the same bus stops, but seeing the buses visit it:

$$A^T_s = \{(t_{(b_1,s)}, t_{(b_2,s)}), (t_{(b_2,s)}, t_{(b_3,s)}), \ldots, (t_{(b_{(w-1)},s)}, t_{(b_w,s)})\}, \forall s \in S$$

Here, pairwise sequencing describes the arcs, since we assume $h_{(b_{(w-1)},s)} < h_{(b_w,s)}$ that is, buses visit bus stops in sequence. The resulting network can be seen as a time-space network, as in Figure 4.2, where arcs with solid lines are in $A^T_b, \forall b \in B$, and dashed lines are in $A^T_s, \forall s \in S$.

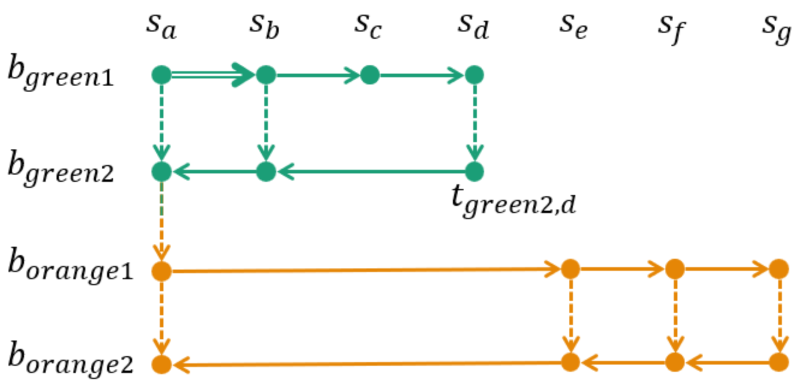


FIGURE 4.2: The bus network, similar to a space-time network.

The set of arcs A^V, in which the vans may travel, is composed of arcs between the vans' respective origin and destination depots, $\{(o_v, d_v), \forall v \in V\}$; arcs between origin depots and requests' origin, $\{(o_v, o_r), \forall v \in V, \forall r \in R\}$; arcs between origin depots and transfer nodes, $\{(o_v, t), \forall v \in V, \forall t \in T\}$; arcs between transfer nodes and destination depots, $\{(t, d_v), \forall t \in T, \forall v \in V\}$; arcs between requests' destination and destination depots, $\{(d_r, d_v), \forall r \in R, \forall v \in V\}$; arcs between requests nodes, excluding arcs connecting a request's destination to its respective origin, $\{(o_r, d_r) \cup (o_r, d_{r'}) \cup (d_r, o_{r'}), \forall r, r' \in R, r \neq r'\}$; arcs connecting transfer nodes to pickup and pickup-delivery requests' origin, and also to delivery and pickup-delivery requests' destination, $\{(t, o_r), \forall t \in T, \forall r \in R^1 \cup R^3\} \cup \{(t, d_r), \forall t \in T, \forall r \in R^2 \cup R^3\}$; and, finally, the reverse of the previous set of arcs, from requests nodes to transfer nodes, $\{(o_r, t), \forall r \in R^1 \cup R^3, \forall t \in T\} \cup \{(d_r, t), \forall r \in R^2 \cup R^3, \forall t \in T\}$.

The set A^R contains the arcs available for requests to use, containing arcs between requests origin and destinations and the bus network. Basically, it is the union of the bus network and the vans network, excluding arcs to the vans' depots. During implementation, each request had their own network, which excludes arcs between their destination and origin, reducing the problem size. Defining a network for each request also allows for customization: if a request has preferred buses, it is easy to constrain the request movement to only those buses. The preferred buses informed by the requests also indicate the time that a request is available for pickup. This is therefore, a type of time-windows. For pickup requests, this is imposed in the origin node, and for delivery requests, this is imposed in the destination node. This time B_r^*, for each request r, is defined as the starting time of the bus service in the preferred buses list.

Finally, we define our model on a directed graph $G = (N, A)$. A is the set of all arcs, $A = A^T \cup A^V$, and to every arc $(i, j) \in A$ there is a cost c_{ij}, corresponding to its traveling time. N is the set including all nodes previously introduced, that is, $N = L \cup T \cup O$. There is a loading and unloading time whenever a van visits a node that represents the time that passengers or parcels need to ride or get off the van, or to transfer from bus to van, or vice-versa. The parameter l_i denotes this time and is defined for all nodes $i \in T \cup L$.

4.4.2 The MIP model

In section, we introduce the Mixed Integer Programming model developed. In a later section, we will use different objective functions to analyze the trade-offs between total service costs and customer inconvenience. For this reason, we start by explaining the main constraints and decision variables.

$$\min \quad f_n \tag{4.1}$$

$$\text{s.t.} \quad \sum_{(o_v,j)\in A^V} x^v_{o_v,j} = 1 \qquad \forall v \in V \tag{4.2}$$

$$\sum_{(i,d_v)\in A^V} x^v_{i,d_v} = 1 \qquad \forall v \in V \tag{4.3}$$

$$\sum_{(i,j)\in A^V} x^v_{ij} = \sum_{(j,i)\in A^V} x^v_{ji} \qquad \forall v \in V, \forall i \in N \setminus \{o_v, d_v\} \tag{4.4}$$

$$\sum_{v\in V} \sum_{(i,o_r)\in A^V} x^v_{i,o_r} = 1 \qquad \forall r \in R^1 \cup R^3 \tag{4.5}$$

$$\sum_{v\in V} \sum_{(i,d_r)\in A^V} x^v_{i,d_r} = 1 \qquad \forall r \in R^2 \cup R^3 \tag{4.6}$$

$$\sum_{(o_r,j)\in A^R} y^r_{o_r,j} = 1 \qquad \forall r \in R \tag{4.7}$$

$$\sum_{(i,d_r)\in A^R} y^r_{i,d_r} = 1 \qquad \forall r \in R \tag{4.8}$$

$$\sum_{(i,j)\in A^R} y^r_{i,j} = \sum_{(j,i)\in A^R} y^r_{j,i} \qquad \forall r \in R, \forall i \in N \setminus \{o_r, d_r\} \tag{4.9}$$

$$h_j \geq h_i + t_{ij} + l_i - M_1(1 - \sum_{v\in V} x^v_{ij}) \qquad \forall (i,j) \in A^V \tag{4.10}$$

$$h_{d_r} \geq B^*_r \qquad \forall r \in R^2 \tag{4.11}$$

$$h_{o_r} \leq B^*_r \qquad \forall r \in R^1 \tag{4.12}$$

$$h_{d_r} \geq h_{o_r} \qquad \forall r \in R^3 \tag{4.13}$$

$$\sum_{r\in R^C} y^r_{ij} \leq \sum_{v\in V} q^v_c x^v_{ij} \qquad \forall (i,j) \in A^V \tag{4.14}$$

$$\sum_{r\in R^P} y^r_{ij} \leq \sum_{v\in V} q^v_p x^v_{ij} \qquad \forall (i,j) \in A^V \tag{4.15}$$

$$\sum_{(i,j)\in A^T_b} y^r_{ij} \leq M_2 z^r_b \qquad \forall r \in R, b \in B \tag{4.16}$$

$$\sum_{(i,j)\in A^T_b} y^r_{ij} \geq z^r_b \qquad \forall r \in R, b \in B \tag{4.17}$$

$$\sum_{b\in B} z^r_b \leq 1 \qquad \forall r \in R \tag{4.18}$$

$$\sum_{v\in V} \sum_{(i,j)\in A^V} c_{ij} \leq D \tag{4.19}$$

$$x^v_{ij} \in \{0,1\} \qquad \forall v \in V, \forall (i,j) \in A \tag{4.20}$$

$$y^r_{ij} \in \{0,1\} \qquad \forall r \in R, \forall (i,j) \in A^R \tag{4.21}$$

$$z^r_b \in \{0,1\} \qquad \forall r \in R, b \in B \tag{4.22}$$

$$h_i \geq \mathbb{R}^+ \qquad \forall i \in N \tag{4.23}$$

The set of constraints (4.2) to (4.6) are classic constraints in VRP formulations, setting the start and conservation of the vehicles' flow through nodes. Constraint (4.2) forces vans to leave their respective depot, while constraint (4.3) forces them to return. Constraint (4.4) assures flow conservation in all nodes connected by valid arcs, except in the depots. Constraints (4.5) and (4.6) reinforce that some requests nodes must be visited, and visited by only one van. Those nodes are the destination nodes of delivery requests ($d_r, r \in R^1$), the origin nodes of pickup requests ($o_r, r \in R^2$), and both origin and destination nodes of pickup-delivery requests (o_r and $d_r, r \in R^3$). The next three sets of constraints, (4.7) - (4.9), control the movement of requests, forcing them to leave their origin, constraint (4.7), to arrive at their destination, constraint (4.8), while constraint (4.9) preserves flow balance in the nodes connected by valid arcs.

Constraint (4.10) schedules the vans visits to nodes by setting the arrival time variable h_i. This variable is actually a constant when $i \in T$, according to the bus timetable. In this manner, it also synchronizes the departure of vans to the departure of buses and guarantees that the van will arrive a bit before the bus and will be waiting for it. The parameter M_1 is used to linearize this constraint (similar to constraint (3.13)) and in our experiments, we set it to the length of the working time desired for the vehicles of 7000 units of time. This number is roughly 1.5 times the size of the bus timetable.

Constraints (4.11) and (4.12) limit arrival time in origin or destination, respectively, respecting the preferred buses time . And constraint (4.13) assures that the origin of pickup and delivery requests will be visited before its destination. The capacity of each van is limited in constraints (4.14) and (4.15), which also consequently states that requests cannot travel through vans' arcs unless a van is using it.

The last set of constraints regard the variable z_b^r, used to limit the visit of requests to transfer nodes belonging to different bus routes, since there is no storage space for parcels, and it is not desirable to leave passengers waiting for the next bus in the bus stop. Constraints (4.16) and (4.17) are indicator constraints, setting the value of the variable z_b^r in case request r uses any arc of buses. Here, the value of

M_2 can be set to the size of the biggest bus line, i.e., $\max_{b \in B} |S_b|$. And constraints (4.18) state the requirement of no more than one bus for requests. Observe that the model can also find solutions where a request does not take the bus, and for this reason this constraint is less than or equal one.

In constraint (4.19) we limit the budget used to service all requests, which is the sum of the costs of using the vehicles. Finally, we have constraints (4.20) - (4.23) stating the domain of the variable decisions.

4.4.3 Objective functions and models for analysis

This section introduces three models that, upon solution, bring insights regarding the trade-off between the costs to transport the requests and their respective inconvenience. All models optimize for two or more objective functions. The function f_{Costs} in (4.24) represents the sum of total transportation costs, proportional to the vehicles driving time. The next function, $f_{\text{ReqTravel}}$ in (4.25), represents the total travel time of the customers, including time in the bus. The next function, $f_{\text{ReqArrival}}$ in (4.26), represents the total dissatisfaction of the customers, defined as the sum or their arrival time in request location nodes. This function is used in Cumulative Capacitated Vehicle Routing Problems to minimize the time that a customer is served (Ngueveu et al., 2010). In our case, being served means having the transportation service completed i.e., origin or destination nodes visited, accordingly to the request type. The third objective function is related to the arrival time of the vans in their respective depots, $f_{\text{VehArrival}}$ in (4.27). This function, when optimized, will compact the vehicles schedule, making them arrive at nodes as early as possible.

$$f_{\text{Costs}} = \sum_{v \in V} \sum_{(i,j) \in A^V} c_{ij} x_{ij}^v \tag{4.24}$$

$$f_{\text{ReqTravel}} = \sum_{r \in R} \sum_{(i,j) \in A^R} (c_{ij} + l_i) y_{ij}^r \tag{4.25}$$

$$f_{\text{ReqArrival}} = \sum_{r \in L} h_r \tag{4.26}$$

$$f_{\text{VehArrival}} = \sum_{v \in V} h_{d_v} \tag{4.27}$$

Model VC: Minimizing vehicle costs

The first model seeks to obtain routes that minimize total transportation costs. The two objectives are minimized lexicographically i.e., following a defined hierarchy, so the solution will a be minimal route, and a compact schedule. The hierarchy is as presented below, f_{Costs} and then $f_{\text{VehArrival}}$. The schedule obtained in this case does not consider priorities, therefore being a baseline to compare to our proposed approach, showing how satisfaction improves when priorities are taken into account. The budget constraint is removed from this model, since the solution will be a baseline for the budget.

$$\begin{aligned} lex \quad min \quad & f_{\text{Costs}} \\ & f_{\text{VehArrival}} \\ s.t. \quad & \text{Constraints (4.2) to (4.23), except constraint (4.19)} \end{aligned}$$

Model TT: Minimizing requests travel time

This model minimizes requests traveling time, accordingly to their respective priorities. The total number of objective optimized depends on the different levels of priority, indicated by each requests' ρ parameter. When solving this model, the traveling time of requests with higher ρ will be solved first, and then the next priority level will be solved, in decreasing order, where n is the lowest level. One interesting aspect of the obtained solutions is that they will be, in most cases, favorable for the prioritized requests, but there is no guarantee that they will always arrive first (in the case of delivery-type requests) or depart last (in the case of pickup-type requests). In fact, priority will be more or less respected depending on the budget constraint, which is included in this model.

$$\begin{aligned} \operatorname{lex\,min} \quad & f_{\text{ReqTravel}}(\rho = 1) \\ & f_{\text{ReqTravel}}(\rho = 2) \\ & \vdots \\ & f_{\text{ReqTravel}}(\rho = n) \\ & f_{\text{VehArrival}} \\ \text{s.t.} \quad & \text{Constraints (4.2) to (4.23)} \end{aligned}$$

Model AT: Minimizing requests arrival time

This model follows the same logic regarding the hierarchy of objective functions as the previous model, but using $f_{\text{ReqArrival}}$.

$$\begin{aligned} \operatorname{lex\,min} \quad & f_{\text{ReqArrival}}(\rho = 1) \\ & f_{\text{ReqArrival}}(\rho = 2) \\ & \vdots \\ & f_{\text{ReqArrival}}(\rho = n) \\ & f_{\text{VehArrival}} \\ \text{s.t.} \quad & \text{Constraints (4.2) to (4.23)} \end{aligned}$$

4.5 Numerical Experiments

This section reports the results from a small evaluation experiment with the proposed models. Artificial instances were generated in a similar fashion than those used in the previous Chapter and then solved using a commercial MIP solver. The goal is to verify the model's capabilities (if solutions are as expected, if priority is respected, etc), solution performance, and how solutions change when more budget is allocated, as if simulating a decision-maker's decision process.

4.5.1 Instances Preparation

The instances used to validate this model were generated in the same method as in Section 3.5.1, using the geographical area of Akaiwa City, in Japan. This time, two sets were generated: one set having only delivery-type requests, but a mix of passengers and parcels; the second set has pickup- and delivery-type requests, also with a mix of passengers and parcels. The request type and cargo were randomly assigned to the locations, but total quantity of each was according to Table 4.2. Instances are labeled with the prefix DE when having only delivery, and PD for pickup and delivery.

The set of available vehicles included 3 vans, 2 taxis, and 1 truck. The parking spot of these vehicles was the city center for the taxi and the truck, and the last bus stop in one of the bus lines, for the vans. The vans' capacity was of 4 passengers and 5 parcels. Taxis could carry up to 4 passengers, simultaneously. And trucks could carry 10 parcels.

In this Chapter, we used two physical bus lines: the Green line, also used in the Chapter 3, and the Orange line, which is another bus line existent in the region. The reason to add another line was to show the models capabilities to handle them and to observe in which cases which line would be used, considering that the Orange

Table 4.2: Information about requests in each instance

	Requests Type				
	Passengers		Parcels		
Instance	Pickup	Delivery	Pickup	Delivery	Total
DE_6		3		3	6
DE_7		3		4	7
DE_8		3		5	8
DE_9		4		5	9
DE_10		4		6	10
DE_11		4		7	11
DE_12		5		7	12
DE_13		5		8	13
DE_14		5		9	14
DE_15		6		9	15
DE_16		6		10	16
PD_6	1	2	1	2	6
PD_7	1	2	2	2	7
PD_8	1	2	2	3	8
PD_9	2	2	2	3	9
PD_10	2	2	3	3	10
PD_11	2	2	3	4	11
PD_12	2	3	3	4	12
PD_13	2	3	3	5	13
PD_14	2	3	4	5	14
PD_15	3	3	4	5	15
PD_16	3	3	5	5	16

line is faster. We reduced the number of bus stops used to only 5, since this problem is more complex than the one in the previous Chapter and reducing the number of bus stops is a way to reduce model size. And finally, there were four buses running in each physical bus line: two departing from the city center, and two heading to the city center, however the timetable would allow the to be the same physical bus. An illustrate example of one instance, showing the bus lines topology, stops, and vehicles depots will be provided in a subsequent section.

An important detail is how to assign ρ values for each request. Following the scheme described in Section 4.3, delivery-type requests should generally be delivered before pickup-type requests are served, so they must have higher visit priority. For the instances prepared, in DE instances, delivery-type pasesengers have $\rho = 1$ and delivery-type parcels have $\rho = 2$. In PD instances, it was the following: delivery-type pasesengers have $\rho = 1$; delivery-type parcels have $\rho = 2$; pickup-type parcels have $\rho = 3$; pickup-type pasesengers have $\rho = 4$.

4.5.2 Solution Approach

We report results obtained from solving the previously described artificial instances for the proposed model. The commercial MIP solver used was Gurobi Optimizer version 9.5 and its corresponding libraries for Python 3.8. All experiments were performed on a desktop computer with Intel Core i7 3.2 GHz and 32 GB of memory. Regarding time limit imposed, it was two hours when solving model VC, and 30 min to optimize each objective function in models TT and AT.

The solution strategy was to first solve Model VC (minimizing vehicle costs) and then use its solution to solve the other models. This is a valid incumbent solution for models TT and AT as long as the budget chosen is greater or equal than the solution value for model VC's f_{Costs}. Solving them in sequence has two advantages. First, there is no time wasted finding a feasible solution, since one is already provided; this is usually called hot start in commercial solvers. And second, the minimal cost is used as a baseline to calculate budgets for comparison. In our experiments, we set the budget constraint to be 10%, 30%, and 50% greater than the minimal cost. To clarify, in DE_6, a budget of 10% constrains the budget with vehicle costs to be below $1121 + 10\% = 1233.1$

Here we report solution quality measured in the gap output by the solver. The gap is calculated as the difference between the value of an incumbent solution found minus the upper bound of the linear relaxation, divided by the value of the best incumbent solution found. The gap is given in percentage, the smaller the better, and a gap of 0% means that a solution is proven to be optimal.

TABLE 4.3: Gap (%) obtained when solving model VC

Instance	VC	Instance	VC
DE_6	0	PD_6	0
DE_7	0	PD_7	0
DE_8	0	PD_8	0
DE_9	0	PD_9	0
DE_10	0	PD_10	0
DE_11	0	PD_11	0
DE_12	0	PD_12	0
DE_13	0	PD_13	0
DE_14	0	PD_14	7.6
DE_15	12.8	PD_15	0
DE_16	7.9	PD_16	–

Table 4.3 shows the gap for the model VC for all instances. In Tables 4.4 and 4.5 we see the gaps for model TT. Our models have a combinatorial nature, so naturally the problems' size grow very rapidilly as the instance size increases. This makes it very difficulty for exact solution approaches, such as the one we use, a commercial solver, to prove optimality. For this reason, even for instance size relatively small, such as 14 requests, after two hours running the solver could not prove optimality, and for 16 requests no feasible solution was found.

TABLE 4.4: Gap (%) obtained when solving model TT, DE instances

	10%		30%		50%	
Instance	ρ=1	ρ=2	ρ=1	ρ=2	ρ=1	ρ=2
DE_6	0	0	0	0	0	0
DE_7	0	0	0	0	0	0
DE_8	0	0	0	0	0	0
DE_9	0	0	0	22.6	0	21.8
DE_10	0	28.7	0	30.9	0	27.3
DE_11	0	31.7	0	36.2	0	40.0
DE_12	0.2	46.1	5.0	43.3	0.2	40.3
DE_13	17.1	57.0	14.9	53.7	0.3	57.1
DE_14	45.0	62.2	8.9	33.2	4.4	35.7
DE_15	15.7	42.5	12.5	30.8	7.5	43.3
DE_16	43.7	60.6	29.3	58.8	16.1	49.6

TABLE 4.5: Gap (%) obtained when solving model TT, PD instances

	10%				30%				50%			
Instance	ρ=1	ρ=2	ρ=3	ρ=4	ρ=1	ρ=2	ρ=3	ρ=4	ρ=1	ρ=2	ρ=3	ρ=4
PD_6	0	0	0	0	0	0	0	0	0	0	0	0
PD_7	0	0	0	0	0	0	0	0	0	0	0	0
PD_8	0	0	0	0	0	0	0	0	0	0	0	34.6
PD_9	0	0	0	0	0	0	0	0	0	0	7.0	36.0
PD_10	0	0	0	0	0	0	0	0	0	2.4	8.4	0
PD_11	6.0	0	32.4	0	0.1	3.8	21.9	61.4	0	4.1	49.6	0.6
PD_12	46.7	58.9	42.6	61.3	0	0	32.2	61.3	0	17.3	14.1	61.6
PD_13	22.8	44.1	47.2	19.1	6.2	18.5	28.0	6.0	0.1	14.2	54.5	61.6
PD_14	47.4	54.2	45.5	5.1	6.3	34.0	51.1	70.3	0.1	20.3	49.2	61.6
PD_15	48.2	55.6	48.5	11.4	6.4	34.8	64.1	71.0	0.2	24.6	28.3	63.4

In Tables 4.6 and 4.7 we see the gaps for model AT, and they are very high for almost all instances. The reason is that the objective functions used, minizing arrival time, have a very slow development of the lower bound found by Gurobi. Despite this drawback about the solution quality, it is still possible to analyze the routes obtained to investigate if our models are, in fact, outputting routes that respect priorities, and this analysis is performed in the following section.

TABLE 4.6: Gap (%) obtained when solving model AT, DE instances

	10%		30%		50%	
Instance	ρ=1	ρ=2	ρ=1	ρ=2	ρ=1	ρ=2
DE_6	0	0	0	0	0	0
DE_7	48.9	79.9	53.0	79.6	60.9	80.0
DE_8	66.1	71.3	26.6	69.2	27.6	78.9
DE_9	63.9	0	60.3	84.9	60.7	80.9
DE_10	74.3	91.7	68.3	77.5	62.9	78.7
DE_11	74.0	89.1	68.5	85.4	65.4	82.5
DE_12	86.5	83.7	74.4	87.1	69.8	77.7
DE_13	76.9	85.4	73.0	87.6	71.4	76.7
DE_14	88.6	91.3	89.5	82.0	85.2	88.9
DE_15	91.3	90.8	87.6	87.6	77.9	89.5
DE_16	89.2	92.2	86.9	93.9	84.0	90.3

TABLE 4.7: Gap (%) obtained when solving model AT, PD instances

	10%				30%				50%			
Instance	ρ=1	ρ=2	ρ=3	ρ=4	ρ=1	ρ=2	ρ=3	ρ=4	ρ=1	ρ=2	ρ=3	ρ=4
PD_6	0	0	0	0	0	0	0	0	0	0	0	0
PD_7	0	0	0	0	0	0	0	0	0	0	0	89.1
PD_8	0	0	0	0	54.5	71.7	84.5	86.1	48.5	67.2	87.0	78.5
PD_9	48.4	0	0	0	58.2	84.9	92.8	89.6	62.1	70.3	85.5	85.1
PD_10	71.6	76.4	88.8	82.0	64.2	77.9	86.6	82.8	63.5	81.5	87.8	87.1
PD_11	73.3	71.3	88.4	88.4	65.6	77.6	92.3	89.9	66.9	70.1	91.3	85.5
PD_12	82.8	80.6	90.8	93.5	73.4	84.9	90.0	94.1	72.9	65.3	89.4	84.8
PD_13	81.4	77.6	79.2	90.0	73.6	74.3	87.6	89.5	77.8	71.0	89.9	88.6
PD_14	89.0	92.1	98.4	94.5	74.0	82.4	90.3	89.9	88.0	86.7	90.1	21.3
PD_15	87.1	84.6	88.9	99.6	84.7	82.4	81.5	95.7	87.8	79.3	87.9	95.7

4.5.3 The effect of budget on routes quality

A relevant question when deciding appropriate budget allocation for a specific instance is if more expensive routes are in fact better i.e., if they are respecting priorities. However, measuring if a route is better for the customers is a difficult task. So, in this section we use a tailored metric to verify if model TT and model AT generate routes that seem to satisfy the customers in our artificial instances.

First, we start by showing how the two types of objectives used, travel time and arrival time, behave as we increase the available budget. Figures 4.4 and 4.3 show how the travel time decreases dramatically when the budget increases. In the graph, each series represents one instance, and the higher point in each series is related to the minimal cost, as the second, third, and fourth points represent 10%, 30%, and 50% increased budget. It seems clear that the requests can get smaller travel time even with a little increase in the budget.

Figures 4.5 and 4.6 summarizes the results of arrival time for model AT. The relationship between arrival time and costs is not clear, although there is a reduction and a downwards curve in smaller instances (DE_6 and 7, and PD_6 and 7). But as the instances grow bigger, no relation can be confirmed, as DE_16 and PD_9, 11, 12, and 14. Besides the reason that the solution obtained might be of low quality

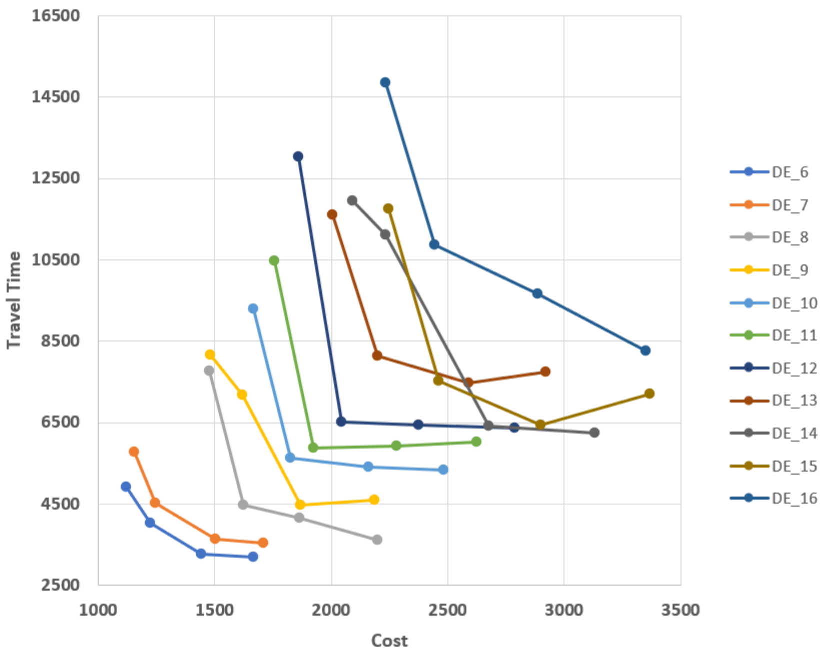


FIGURE 4.3: As the budget increases (represented in the horizontal axis, cost) the total travel time decreases for most DE instances

(because of the high gap), another stronger reason is that arrival times follow the bus timetable, and as the number of requests increase, the vans have to return more often to bus stops and service requests using later buses, naturally increasing arrival time.

Next, we investigate which model generated better, or more suitable routes. We define a route as a sequence of requests locations that starts and ends in a bus stop or depot. As stated, a desirable route is one that "hides" parcel services from the passengers, or higher priority from lower priority. It is difficult to measure route quality, but it is easy to see that grouping requests with the same level of priority leads to routes that make one type of request invisible to the other. By extrapolating the assumption that passengers perceive making visits to parcel locations as a nuisance, the hierarchy between priorities can be used to measure route quality. So, good routes are ones that will visit higher priorities first.

From the request perspective, the relevant locations are those visited when it is riding the vehicle. So, delivery-type requests will visit locations *before* its own

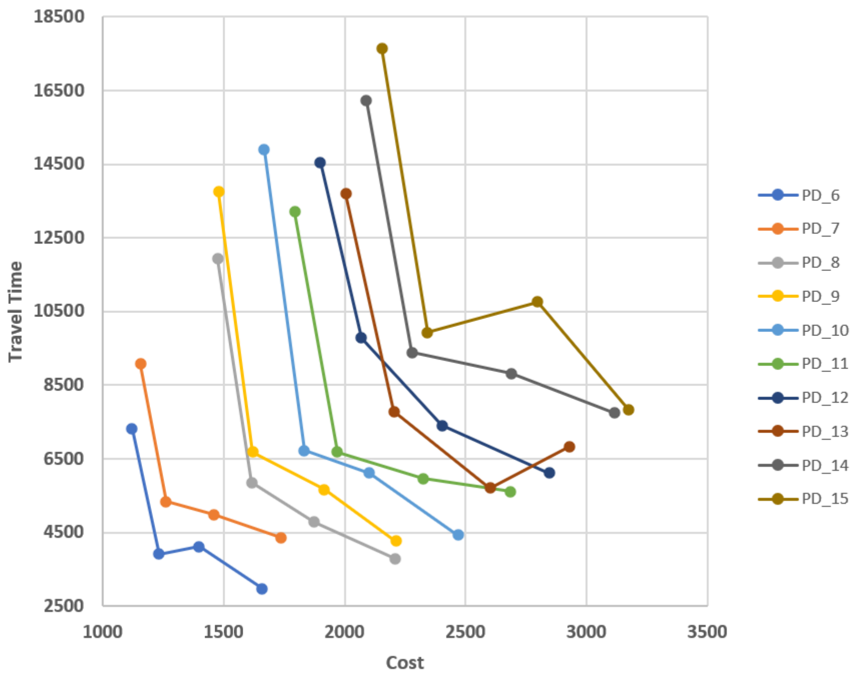


FIGURE 4.4: A higher budget yields smaller total travel times in PD instances as well, except in three instances

destination, while pickup-type requests will visit locations *after* its own origin. This difference is important to calculate the perceived inconvenience. We define perceived inconvenience as following, for each request in a route. For delivery-type requests, it is the sum of all visited locations from requests with *lower* priority than its own. Please note that this sum doesn't include locations with priority equal to its own. The reason for that is that we are trying to measure if a route combines requests with the same priority level. For pickup-type requests, it is the sum of all visited locations from requests with *higher* priority than its own.

To illustrate, we use the results of the same instance, DE_7, but with different budget allocated, 10% and 30%. In Figure 4.7a, the connected circles in green and orange represent the two physical bus lines. The consolidation center and the bus terminal are the two purple circles, and serve as the depot for the taxi and the truck, unused in this solution. The purple circle in the upper part of each figure is the depot for vans. Passenger destinations are represented in red triangles pointing down, while parcel destinations are blue. Triangles pointing up represent pickup requests, and

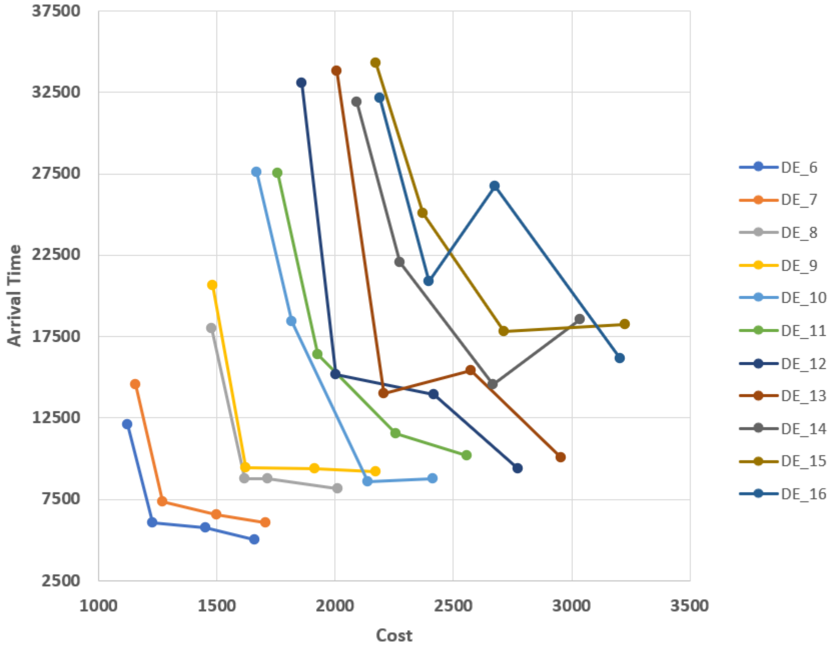


FIGURE 4.5: Total arrival time against budget for DE instances

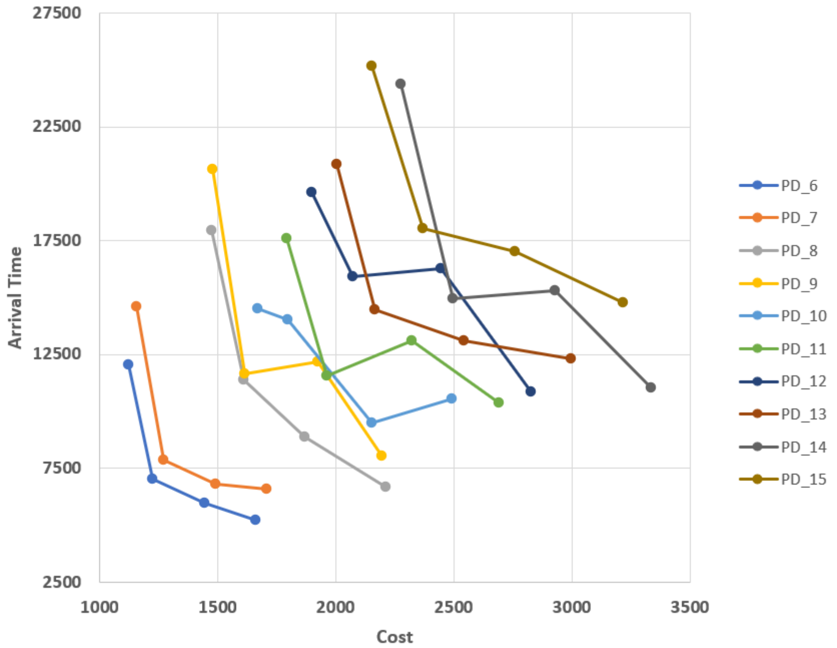
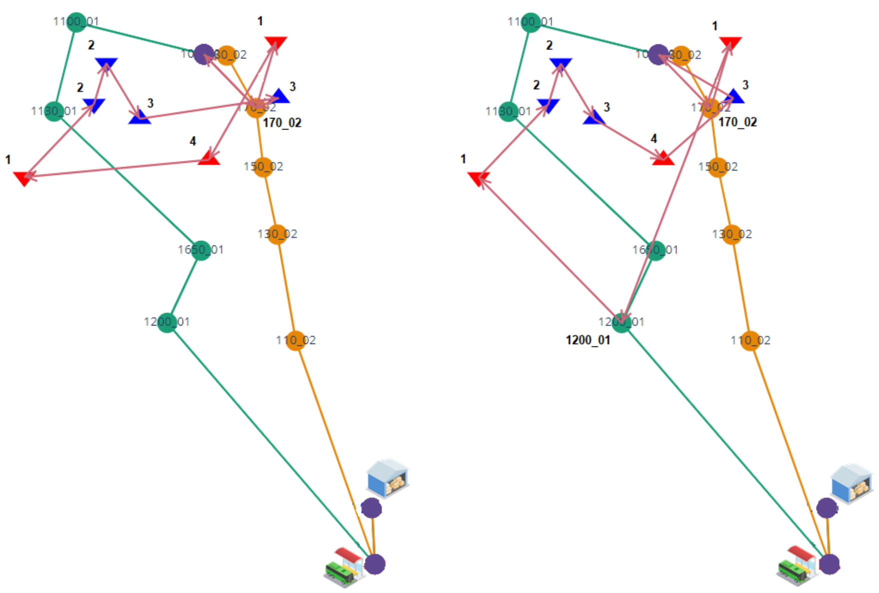


FIGURE 4.6

the same color scheme apply. The number besides each request destination is not its respective id, instead it is their priority level, 1, 2, 3, or 4. There is only a single route that carries requests, performed by a van, which first heads to bus stop 170_02. The sequence of priorities in this route is $1 \rightarrow 4 \rightarrow 1 \rightarrow 2 \rightarrow 2 \rightarrow 3 \rightarrow 3$, then returning to a bus stop to leave pickup requests, and finally returning to the vans' depot. The perceived inconvenience score in this route is, according to our calculation method, equals to 8. The first request in the route, with priority 1, perceives no inconvenience. The second request, priority 4, will have to visit 5 locations with priority higher than its own, having an unecessary longer trip. The third request visits 1 location with priority lower. Fourth and fifth requests each visit the second request, which has lower priority than theirs, adding 2 points to the score. The total is then 8.

The same logic is applied to calculate the score of the two routes in Figure 4.7b, which totals only 1 point from the only request with priority 4, which has to visit a parcel pickup point. This scoring method for the perceived inconvenience might not be a perfect way to measure this subjective indicator, but it captures some of the characteristics that indicates if a route is more desirable or not. The lower the score, the better, so a route of increasing priority indexes, $1 \rightarrow 2 \rightarrow 3 \rightarrow 4$, is a desirable one, while the reverse would not be.



(A) Budget choice of 10%. (B) Budget choice of 30%

FIGURE 4.7: Illustration of solutions obtained for instance PD_7, solved by model TT with 10% and 30% budget choices

Now, we compare the quality of routes obtained from models TT against AT, using the metric developed for the perceived inconvenience. This comparison is made to identify which model outputs better routes. From Table 4.8, model TT generates better routes than AT, consistently obtaining lower scores, except in instances PD_7 in 30%, and PD_12 and PD_14 in 10%. The scores of model VC, which outputs minimal routes, are listed in the table just for illustration since it is not expected that this model takes into consideration any request priority. It is possible to conclude that model TT, which minimizes requests travel time, is more suitable for generating routes that respect requests priorities.

TABLE 4.8: Route quality, as measured by our custom metric, in solutions obtained by the three models

		10%		30%		50%	
Instance	VC	TT	AT	TT	AT	TT	AT
DE_6	0	0	0	0	0	0	0
DE_7	0	0	0	0	0	0	1
DE_8	1	0	6	0	0	0	0
DE_9	1	0	2	0	0	0	0
DE_10	1	0	6	0	0	0	1
DE_11	2	0	6	0	0	0	0
DE_12	10	0	8	0	1	0	0
DE_13	8	0	6	0	0	0	2
DE_14	15	6	14	0	10	0	6
DE_15	0	0	17	0	18	0	5
DE_16	8	2	2	0	1	0	0
PD_6	9	1	9	0	0	0	4
PD_7	15	8	13	1	0	1	8
PD_8	20	1	17	0	9	1	9
PD_9	29	2	26	0	14	2	9
PD_10	37	8	34	0	3	0	2
PD_11	28	0	2	0	8	0	8
PD_12	32	14	6	0	2	0	4
PD_13	25	0	17	0	4	0	4
PD_14	35	14	12	4	4	0	8
PD_15	39	14	14	6	26	0	5

By individual inspection of the solutions, it is possible to see that model TT also makes more use of buses, visiting bus stops more frequently. Model AT probably visits bus stops less because assigning requests to later buses increases their arrival time dramatically, so the model will naturally avoid that. Another remarkable difference between the models is that AT will prefer to use trucks and taxis when there is more budget available; this is expected since exclusive vehicles are faster than buses.

We highlight that, in our instances, all requests had all buses in their list of preferred buses, meaning they would be satisfied taking any bus. Setting requests to prefer any bus was done precisely to show the integration aspect of our model. If requests were more restrictive regarding their preferred bus, i.e., only the morning bus, the solutions found by the model would be more inconvenient, or the van would travel to the city to serve the requests if the budget allowed. Ultimately, a very restrictive choice of preferred buses or a restrictive bus timetable (limited times or few buses) would render many instances infeasible if the budget were also restrictive.

Chapter 5

Concluding Remarks

5.1 Conclusion

The main goal of this research was to propose a transportation service that integrates public transit and the last and first mile of passenger and parcel flows. The objectives also include the development of optimization models to route and schedule the vehicles in the system, which were used to analyze such non-traditional transportation services and assess their performance against traditional ones. The analysis was performed to support the proposed idea, showing the potential benefits many authors from the field claimed were possible.

Three research questions guided this work, and each is discussed and answered in the main chapters of this thesis. The first question regards the existing works integrating cargo and modals, reviewed in Chapter 2. It serves as a starting point to inform ourselves on how these problems are tackled and optimized and the essential factors and relevant analysis. The second and third questions enquire about the formulation and optimization of such a service, considering the specific perspectives of the customers involved.

In the first phase, corresponding to Chapter 3, we described a MIP formulation to optimize the routes of the last-mile delivery vehicles such that they are synchronized to the buses while considering passenger convenience. We generated instances based on a real bus line in the Japanese countryside to validate the model. Also, we evaluated the performance of the proposed service, using the generated instances, against other possible service formats, such as non-mixed and non-integrated ones.

Regarding the drive times of the last-mile vehicles, our analysis concluded that the proposed approach yields the shortest total drive time across the set of instances. This result was expected, but our model allows the visualization of such a benefit. We also showed that, by applying weights to the two objective functions, a decision maker can visualize the trade-off between them and decide to increase the savings in drive time while still observing the passenger perspective.

Focusing on the integrated delivery of parcels, we showed that the savings in drive time decrease as the number of parcels increases. These results indicate the advantage of our proposal when considering operational aspects. The results obtained are valid for the generated instances under a list of reasonable assumptions but not representative of every situation and region, which exhibits a wide array of characteristics. When considering another area, naturally, the analysis should be repeated based on instances that reflect the characteristics of that region. Therefore, we restrict our conclusion to similar situations: remote delivery locations and low volume.

It is likely that the key characteristics that could impact the effectiveness of the proposed service in a particular area include the clustering of requests' origin and destination locations around the bus stops, and the positioning of the vehicle depots. If the vehicle depots are located close to the requests' origin, there would be no need to transfer from the bus to the vehicle, as the vehicle could simply pick them up at the origin. On the other hand, if the requests' destinations are far from the bus stops, it may optimal for the vehicles to visit the requests' origin in the city hub rather than using bus lines.

Ghilas conducted experiments with three different types of geographical distribution of requests nodes: clustered, uniform-random, and clustered-random. In the clustered type, requests nodes are positioned relatively close to bus stops, while in the uniform-random type, nodes are uniformly distributed. The clustered-random type is a blend of the other two, with nodes positioned relatively farther from bus stops. More details about the parameters used to generate these instances can be found in Ghilas's work.

In our analysis, we consider our instances to be of the clustered-random type. During the generation process, the locations should be within a 1km radius of the bus stops, which is a reasonable distance given the size of the area we are considering. However, our objective functions only consider traveled distance and time. If economic variables such as bus fare and last-mile vehicle fare are included in the model to optimize for financial costs, the solutions and metrics that indicate the effectiveness of the service may change. Regarding urban areas, those possibly have different topologies and volumes, so we leave these for future research.

In the second phase of this research, which corresponds to Chapter 4, we further expand the MIP model to include realistic elements such as the pickup of passengers and parcels and a heterogeneous fleet. The question that guided specifically this phase was how to generate routes favourable to each type of request. In the presence of pickup, it now consists of four basic types: passenger demanding delivery; passenger demanding pickup; parcel demanding delivery; and parcel demanding pickup. The solution was to include the concept of priority between groups of requests. A natural question is how to measure a good route. To this end, we developed a custom metric that counts the number of visits to locations with different priority levels.

Moreover, we investigate two possible objective functions to optimize the routes, yielding two models, one minimizing travel times and the second minimizing arrival times. Solving the two models and comparing the obtained routes with our metric led us to conclude that the first one leads to better routes in an integrated setting. Also, switching the balance of operational and passengers perspective from weight choice to budget limitation brings a more natural interpretation to a decision-maker. In our experiments, three budget choices were used, increasing the route quality in a controlled fashion and possibly satisfying the passenger perspective more.

We believe that the primary goal of our research was accomplished. Most importantly, we hope to have contributed to the body of research in innovative mobility solutions, especially with the topic of priority in mixed transportation services.

5.2 Future Research Directions

Mobility and last-mile logistic are a trendy and challenging topic, but recently, exciting possibilities have become available. In the present work, we explored one non-conventional idea. Proposing such a service requires acknowledging the many barriers to it. There are license and safety issues and vehicles must be adapted to different purposes. In conjunction with our approach, we can mention the use of autonomous vehicles in relation to the critical issue of the supply of drivers as an example of other innovative solutions. Such vehicles are often electric, so charging must be incorporated into the problem. Moreover, using the Japanese countryside as an example, in mountainous areas, electric vehicles are significantly affected by variations in road inclination, so incorporating considerations about road choices (choosing a flat road instead of one going uphill) into the model might give rise to an interesting operational problem. Tackling the same geographical aspect, drones to avoid driving uphill when delivering packages might be integrated with delivery vehicles and buses.

Besides technological innovations, future work might focus on further incorporating realistic aspects into the model, so we can consider adding more frequent buses and more bus lines, depending on the geography. In talks with transportation company representatives, we were told about additional services that could be performed by the proposed integrated system, such as newspaper delivery and the transportation of nurses and doctors to visit households. Regarding the former, the service can be modeled as a delivery problem with time windows (which are not considered in our current formulation).

Instances that capture a high level of details from the real world might include multiple bus lines, multiple bus schedules, and all the bus stops included in them. To quantify, in the region that inspired our instances, Akaiwa city, there are three physical bus lines that connect the remote areas to the city center, with a total of almost 60 bus stops, and at least 6 buses running daily on each line. Even with the low level of demand that we considered, 30 requests, the number of feasible solutions is already incredibly high. In our work we limited to only one physical bus line with three buses in Chapter 3, where our solution approach, using a commercial solver, was able to solve most of our biggest instances. And in Chapter 4, we have two physical bus lines with four buses, and, as indicated in the results, the solution quality reduced considerably. To improve on this issue, we suggest as a third line of future work the development of algorithms and strategies to reduce the search space of feasible solutions. As explored in our literature review, the vehicle routing research community has extensively used (meta)heuristic approaches. Developing approaches to obtain reasonable solutions to bigger sets of instances might allow the implementation of a more complex and integrated last-mile service.

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