Louvain School of Management

Crowdshipping with Anticipated Crowdshipper Availability: An Approximate Dynamic Programming Approach

Author(s): Amine SADIKI
Supervisor(s): Jean-Sébastien Tancrez and Emma Innocente

Academic year: 2024-2025
Dissertation for the master of
Business Engineer [120] with a Specialized Focus
Daytime schedule

Declaration Regarding AI Tool Usage in Master's Thesis

We recognize that AI tools might be valuable aids during the master's thesis work, but they are not infallible. Remember that transparency fosters trust, and acknowledging AI's role enhances the credibility of your work.

Therefore, when deciding to use such a tool, you need to adhere to the following principles of responsible use of AI.

1. **Critical Evaluation:**
    - We critically assessed the AI-generated output, ensuring its alignment with our research objectives.
    - Any modifications or corrections were made based on our expertise and domain knowledge.
2. **Transparency:**
    - We acknowledge the use of Deepl Traduction transparently, emphasizing that it contributed to our work but did not replace human judgment.
    - Our commitment to transparency ensures the integrity of this thesis.
3. **Ethical Considerations:**
    - We actively monitored for biases or unintended consequences introduced by the AI tool.
    - Our ethical responsibility guided our decisions throughout the research process.

Declaration

.

During the preparation of this master's thesis, the author utilized Deepl Traduction for the following purpose:

1.[REASON]: The tool was used to translate complex terms encountered in this master's thesis and to reformulate certain sentences in an academic manner.

2. After using Deepl Traduction the author diligently reviewed and edited the content produced by the tool. We take full responsibility for the final content presented in this thesis.

By signing this declaration, we affirm that the content of this master's thesis reflects our original work, augmented by the responsible use of AI.

Date: 16 May 2025

Signature: Amine Sadiki,

Abstract

Crowdshipping is a collaborative delivery method in which private individuals, known as 'crowdshippers', deliver parcels during their personal journeys in exchange for a remuneration based on the detours made. This delivery method has the potential to be an interesting way of reducing delivery costs and environmental impact. However, it raises significant challenges in terms of the dynamic crowdshippers-to-parcels assignment, in a context where present assignment decisions affect future ones and future arrivals of parcels and crowdshippers are uncertain. This is all the more pronounced in peer-to-peer crowdshipping systems, which are characterised by highly heterogeneous journeys and no restrictions on origin or destination.

This master's thesis is based on the Approximate Dynamic Programming (ADP) approach developed by Innocente and Tancrez (2025) in which the crowdshipping platform uses an ADP algorithm to dynamically assign parcels to crowdshippers. While the existing literature generally considers that crowdshippers declare themselves available at the exact moment of their journey, we explore a model in which crowdshippers announce their availability in advance. This anticipated information is modelled through a parameter ε, which represents the number of periods between the announcement of availability and the actual time of the journey.

Our contributions consist of a comparative analysis of the ADP approach and the myopic one, integrating this anticipation parameter. We determine how the relative efficiency of the ADP approach varies according to several configurations of the problem: the delivery window, the problem size, the crowdshipper-to-parcel arrivals ratio, the cost structure as well as an alternative scenario introducing uncertainty about parcel arrivals.

The results of 210 experiments show that the introduction of anticipation reduces the comparative advantage of the ADP approach over the myopic one. Indeed, as the information horizon extends, the capacity of the ADP approach to postpone assignments in hope of better opportunities becomes less relevant. In addition, we note that this reduction is accentuated when the system initially has large optimisation possibilities: a high crowdshipper-to-parcel arrivals ratio, a larger delivery window and a cost structure making delivery via crowdshipping attractive. Finally, fluctuations in parcel arrivals have a limited impact on the relative efficiency of the ADP approach, because parcels with the same characteristics at a decision period t, are aggregated and considered as a single parcel that can be delivered by a crowdshipper.

Acknowledgments

First of all, I would like to thank Mr. Jean-Sébastien Tancrez for his valuable comments and advice throughout the writing of this master's thesis.

I would also like to express my gratitude to Mrs. Emma Innocente for her availability and the time she took to help me understand the model.

Finally, I would like to thank my family and friends who supported me during the writing of this thesis, as well as during my academic cursus in general.

Table of Contents

1. Introduction *7*

2. Literature review *11*

3. Problem Formulation *16*

3.1. Exogenous information 18

3.2. State variables 18

3.3. Decisions variables 19

3.4. Objective functions 20

3.5. Transition function 22

4. Solution methodology *23*

5. Computational experiments *29*

5.1. Experimental settings 29

5.2. Overall observations 32

5.3. Multifactor analysis of the effect of anticipation ε 34

5.4. Impact of anticipating availability of crowdshippers (ε) on the delivery rate and relative deviation reduction 37

5.5. Impact of anticipating the availability of crowdshippers (ε) under parcel arrivals fluctuations 39

6. Conclusion *40*

7. References *41*

8. Appendices *49*

8.1. Appendix 1: Belgium NUTS3 regions 49

List of Tables

Table 1.: Summary of the literature review 15

Table 2.: Notations for formulation problem 17

Table 3.: Notations for solution methodology 23

Table 4.: Parameter values for numerical experiments 30

Table 5.: Relative efficiency of the ADP approach and assignable crowdshippers per parcel. 32
Table 6.:Impact of anticipating the availability of crowdshippers, under varying fixed and variable costs ... 36
Table 7.: Relative deviation reduction, under varying values of anticipation ε ... 38
Table 8.: Impact of parcel arrival fluctuations on the relative efficiency of the ADP approach and relative deviation reduction, under varying values of anticipation (ε) ... 39

List of Figures

Figure 1.: Timeline of crowdshippers announcements/availabilities with anticipation (ε) ... 18
Figure 2.: ADP algorithm with anticipating the availability of crowdshipper (ε) ... 26
Figure 3.: Impact of the delivery window on the relative efficiency of the ADP approach anticipating the availability of crowdshippers (ε) ... 34
Figure 4.: Impact of the size of the system on the relative efficiency, for varying values of the crowdshipper to parcel arrivals ratio ... 35
Figure 5.: Impact of the crowdshipper to parcel arrivals ratio on the relative efficiency ... 35
Figure 6.: Delivery rates of both ADP and myopic approaches, under varying values of crowdshipper-to-parcel arrivals ratio ... 37

1. Introduction

Over the last few years, e-commerce has significantly expanded, accounting for 19.4% of global retail sales in 2023 (Innocente and Tancrez, 2025; Statista, 2024). This has led, on the one hand, to an increase in consumer expectations in terms of delivery times, flexibility and reliability, and on the other hand, to a need for companies to reduce last-mile delivery (LMD) costs. Indeed, Pourrahmani and Jaller (2021) define last-mile delivery as a major challenge because it represents 40% of total supply chain costs in the United States, as well as 40% of the energy consumed and emissions generated by the e-commerce sector.

As a result, retailers have been working on ways to optimise last mile deliveries through various solutions; optimising vehicle routes (Savelsbergh and Van Woensel, 2016), adopting electric vehicles (Morganti and al., 2014) or using consolidation centers where parcels are grouped together before being delivered (Crainic and al., 2009). In recent years, crowdshipping has attracted growing interest from researchers, who see this model as a promising solution to the challenges of the LMD (see Section 2.).

According to Arslan and al. (2019), "Crowdshipping refers to a logistics concept in which ordinary citizens, referred as crowdshippers, carry out deliveries during their pre-planned personal trips, rather than relying on professional or dedicated couriers". This model is enabled by digital platforms, which collect real-time data on crowdshippers and parcels, and dynamically allocate deliveries accordingly (Arslan and al., 2019; Alnaggar and al., 2021; Le and al., 2019; Mohri and al., 2023). In the industrial world, many companies such as Amazon (via Amazon Flex), Walmart (with Spark Delivery) and start-ups such as Hitch and Roadie are testing this delivery model. This growing interest is because it combines flexibility, sustainability and cost control.

In practice, crowdshipping is based on digital platforms, which play a central role in coordinating parcels and crowdshippers. These platforms continually collect information on the routes proposed by crowdshippers, the characteristics of the parcels and the preferences of users (Alnaggar and al., 2021). They determine the most relevant combinations using assignment algorithms, considering parameters such as distance, time constraints and route coherence (Mohri and al., 2023). Some platforms have user rating systems, compensation for detours and incentive levers to encourage the availability of crowdshippers (Le and al., 2019).

In addition, there are several forms of crowdshipping, depending on the different interactions between the actors involved. In a peer-to-peer configuration, although the acronym (C2C) suggests two parties, there are three distinct actors; a sender (who can be either a private individual or a company), a receiver, and a crowdshipper, who is a private individual who transports a parcel during his personal journey (Le and al., 2019). In parallel, the business-to-consumer crowdshipping model is also based on three parties: a sending company, a receiver, and a crowdshipper. In this type of crowdshipping, the sending company acts as a base and orchestrates deliveries. This model has already been implemented by some retailers. In their work, Mousavi and al. (2024) highlight this model using Walmart as an example. Walmart offers its customers the opportunity to deliver parcels to other shoppers on their return journey after a purchase, thereby optimising the use of existing journeys.

Beyond the diversity of its configurations, we can highlight the potential advantages of crowdshipping, which explain its growing interest. While Mohri and al. (2023) note that this approach also helps to reduce fixed and operational costs while facilitating more agile distribution, Pourrahmani and Jaller (2021) point out that it allows companies to significantly reduce their delivery costs by taking advantage of private individuals' journeys without having to invest in a dedicated fleet. Sawik (2024) emphasises the flexibility and speed of deliveries because this model allows supply to be adjusted in real time to market needs, unlike traditional systems, which are often more rigid and less responsive.

Nevertheless, crowdshipping has some structural limits that explain why it has not been widely adopted. Le and al. (2019) review the operational and behavioural obstacles in crowdshipping, and explain that the variable, non-guaranteed availability of crowdshippers complicates any planning management. Mladenow and al. (2016) highlight consumers' safety concerns, explaining that they are reluctant to entrust the delivery of their parcels to non-professionals, especially if there is no clear contractual structure.

Finally, the commitment of crowdshippers remains a critical factor in this delivery method. This depends on the incentives offered (economic, social or environmental) and can vary depending on the season, the geographical area or the working hours available (Le and al., 2019; Yildiz, 2021).

This master's thesis is based on a peer-to-peer collaborative delivery context, where private individuals agree to deliver parcels during their personal journeys. In this configuration, parcels with certain characteristics (origin, destination, period of arrival in the system and delivery window) and crowdshippers announcing their availability to deliver a parcel arrive stochastically in the system. In this context, decisions about allocation must be taken day by day, and the system aims to find the optimal parcel-crowdshipper combinations, to maximise the total value of crowdshipping deliveries compared with traditional delivery.

We compare two assignment policies; the myopic policy, where decisions are made considering only the current state of the system without regard to future opportunities, and the approximate dynamic programming (ADP) policy, which incorporates an estimate of the future value of parcels to make better decisions in the long term.

By introducing the notion of known-in-advance information, which refers to the fact that a crowdshipper declares itself available to deliver a parcel several periods in advance rather than at the very moment of its actual availability, the central point in this policy comparison is to determine to what extent this known-in-advance information - modelled through the parameter ε which represents the number of periods since a crowdshipper has announced its availability - allows the performance of the ADP policy to be improved in comparison with the myopic policy. More specifically, the main objective of this master's thesis is to answer the following research question: "To what extent can advance information of crowdshipper availability improve the efficiency of an ADP approach compared to a myopic one in a dynamic peer-to-peer delivery system?"

To address this problem, we use the approximate dynamic programming algorithm developed in Python by Innocente and Tancrez (2025). At each period, an optimisation problem is solved using Gurobi optimisation software to assign parcels to crowdshippers based on their characteristics (origin, destination, period of entry into the system). Then, a backward step estimates the future value of each type of parcel to compare the gain from assigning it directly with the gain from postponing the decision into the future. This process enables the system to improve its decisions through learning iterations.

This remainder of the master's thesis will be structured as follows. Section 2. presents the literature review. We explore the theoretical and the methodological studies, focusing on the different optimisation models solving assignment problems. Section 3. first presents the peer-to-peer dynamic parcel-to-crowdshipper assignment problem. Section 4. presents the methodology of the ADP algorithm. Section 5. presents the computational experiments and the analysis of the results. Section 6. conclude our work.

2. Literature review

Over the past decade, crowdshipping has been widely studied in the academic literature. Several recent studies (Alnaggar and al., 2021; Pourrahmani and Jaller, 2021; Le and al., 2019) provide a global and theoretical background for the sector and highlight the opportunities and challenges it presents. Efficient assignment of parcels to the various crowdshippers available has become an important area of investigation within operational research, mobilising various optimisation tools. It is in this context that this literature review focuses on the different approaches developed for the dynamic crowdshipper-to-parcel assignment problem. It focuses on the studies capable of managing both uncertainty and the dynamic aspect of decision-making.

First, it should be noted that there has been a clear evolution in the methodology of the various works in the field. These are gradually moving away from deterministic models - in which all information is assumed to be given and fixed - towards more adaptive, anticipatory approaches centred on real-time decision-making. Studies such as those by Dayarian and Savelsbergh (2020) and Li and al. (2024) highlight the importance of better managing uncertainty, decentralisation and decision-making in the design of urban delivery models.

To better understand the reasons that led to this evolution in the methodology used, it is useful to look back at the first contributions based on determinist hypotheses. Archetti and al. (2016) laid the foundations with Vehicle Routing Problem with Occassional Drivers (VRPOD). Subsequently, other researchers have enriched this model by integrating additional features such as time windows (Macrina and al., 2017, 2020a, 2020b; Yu and al., 2022), multiple deliveries (Macrina and al., 2020a), mixed fleets (Pugliese and al., 2021, 2023), as well as intermediate pickup points and multi-modal routes (Pugliese and al., 2021).

With a desire to better represent real decision-making and planning, other studies exploring dynamic approaches have emerged. These are known as online methods, in which decisions are continuously re-evaluated as new information becomes available. Several studies, such as those by Sun and al. (2018), Arslan and al. (2019), and Hou and Wang (2021), propose dynamic models by updating assignments as soon as a new crowdshipper appears. Other researchers opt for a replanning logic at regular intervals (Soto Setzke and al., 2017; Tao and al., 2023). While Archetti and al. (2021) combine these two concepts in their online version of VRPOD. It should be emphasised that these different methods are ‘reactive’; they make it possible to adapt to the evolution of the system. However, these models remain deterministic in the sense that a deterministic model is simply re-optimised based on the complete information available at a given point in time.

Gradually, researchers have integrated the notion of uncertainty into their work as an integral component, in particular on the arrival of parcels or the availability of crowdshippers. Behrend and al. (2019) develop in an integrated object sharing and crowdshipping problem, what they call 'an exact method' that considers the capacity of crowdshippers and the flexibility of the journeys they can make. They extend this approach in Behrend and al. (2021) to a multi-period framework, where parcel arrivals are random and crowdshipper availability is known in advance. They use forecasting scenarios in a multi-period framework, demonstrating that this anticipation improves the performance of the model. Yildiz (2021b) proposes a stochastic demand model in a context where couriers register their trips in advance, based on a Monte Carlo simulation approach.

Some researchers have worked on models based on the fact that the arrival of parcels is known the availability of crowdshippers in other words is uncertain. In this context, Dahle and al. (2017) set up a two-stage stochastic programme, where an initial decision is made under uncertainty before another correction decision is made based on the crowdshippers actually retained. Their model was subsequently enhanced by Skålnes and al. (2020), who proposed a multi-stage version better suited to a context where the offer is continually evolving. Mousavi and al. (2022) incorporate mobile depots and show how their strategic location can mitigate the effects of uncertainty.

Other articles go further and combine parcels and crowdshippers uncertainty. Raviv and Tenzer (2018) model a routing problem with transshipment as a stochastic dynamic program. Yildiz (2021a) proposes an extension based on the capacity usage cost. Goyal and al. (2024), on the other hand, use a multi-stage stochastic model to optimise both profit and service level in a system with hybrid fleets. Dayarian and Savelsbergh (2020) use a sampled scenario planning approach in their same-day delivery problem by mobilising in-store customers as potential deliverers. This approach measures the cost difference of assigning a parcel immediately or waiting for a better match.

In addition to crowdshipping, studies have explored the use of approximate dynamic programming (ADP) with known information in logistics areas where there is uncertainty. Powell (2011) as well as Topaloglu and Powell (2006) have developed ADP policies capable of exploiting information known in advance, such as resource availability, using lookahead policies or parameterised value functions.

Practical applications are based on this fundamental work. Lebedev and al. (2020) use an ADP algorithm in e-commerce to determine policies for the pricing of delivery slots and show that advance information on demand leads to better profitability of these policies. Finally, a thesis conducted at the University of Twente applies an ADP algorithm to the dynamic stacking of containers, exploiting anticipated knowledge of arrivals and departures to minimise the expected number of rearrangements (Boschma and al., 2023).

Following the development of ADP methods in other fields of logistic, researchers have started to integrate these methods into crowdshipping assignment problems. Mousavi and al. (2021) develop ADP algorithms based on value function approximation (VFA). Stoia and al. (2024) illustrate the use of CFA in a crowdshipping context with expiring resources. Subsequently, Mousavi and al. (2024) propose a dynamic pickup-and-delivery problem, with random arrivals of parcels and crowdshippers. Their method is based on a forward-pass ADP algorithm inspired by large-scale fleet management. The results obtained show significant cost savings (up to 25%) and an improvement in the rate of orders filled. However, their system is based on a single collection point (the shop), which greatly simplifies the management of spatial uncertainty.

A few researchers have explored the idea of crowdshippers declaring their availability to deliver a parcel in advance. Initially, Savelsbergh and Ulmer (2024) put forward in their review the fact that the early commitment of crowdshippers is an effective solution for reducing operational uncertainty. In the same vein, Behrend and al. (2021) propose in their multi-period modelling an announcement delay (under the parameter α which represents the number of anticipated announcement periods) which makes it possible to base planning on scenarios which incorporate anticipated knowledge of the crowdshippers' availability. Finally, Boysen and al. (2022) study the context in which the employees of a distribution centre voluntarily commit to making deliveries during predefined time slots; what they call "Committed couriers".

This master's thesis applies a dynamic approximate programming approach to a peer-to-peer crowdshipping system, in which parcels and crowdshippers arrive progressively over time. This configuration implies uncertainty, both spatial and temporal, and to the best of our knowledge, few studies have developed an ADP method in a context as decentralised as that of peer-to-peer.

In this context, we aim to discover what effect anticipated knowledge of crowdshipper availability may have on assignment decisions. This anticipation is modelled using a parameter ε which represents the number of periods between the moment a crowdshipper announces its availability and the moment it becomes active in the system. This information complement enables the system to compare the value of an immediate assignment with that of a possible postponement of assignment thanks to the expected arrival of crowdshippers already announced.

Table 1. provides a structured synthesis of the literature reviewed in this section. The references are classified by model type (deterministic, stochastic, dynamic and ADP).

This master's thesis is based on the model developed by Innocente and Tancrez (2025), which uses a forward-pass algorithm combined with value function approximation to assign parcels to crowdshippers in a dynamic peer-to-peer setting. As the algorithm is provided in the context of this research, its implementation, adaptation and the exploration of a new research question are the key contributions of this thesis.

Specifically, our contribution is that we have investigated the impact of anticipated information about availability of crowdshipper, modelled thought a parameter ε which represents the number of periods between the announcement of availability and the actual time of the journey:

- Through our experiments, we show that anticipating the availability of crowdshippers reduces the comparative advantage of the ADP approach over the myopic approach.
- We develop this general trend and show that this reduction in efficiency is accentuated when the system initially has better optimisation opportunities.
- We explore the impact of fluctuations in parcel arrivals on the relative efficiency of the ADP approach.

Reference	Model Type	Uncertainty	Dynamic	Anticipation	Key Features
Archetti and al. (2016)	Deterministic (VRPOD)	×	×	×	Foundational model on occasional drivers
Macrina and al. (2017, 2020a, 2020b), Yu and al. (2022)	Deterministic	×	×	×	Extensions: time windows, multi-deliveries, transshipment
Pugliese and al. (2021, 2022, 2023)	Deterministic	×	×	×	Collection points, multi-modal, machine learning
Boysen and al. (2022)	Semi-deterministic	×	✓	✓	"Committed couriers" from logistics centers
Sun and al. (2018), Arslan and al. (2019), Hou and Wang (2021)	Reactive dynamic	×	✓	×	Reoptimization triggered by new events
Soto Setzke and al. (2017), Tao and al. (2023)	Reactive dynamic	×	✓	×	Replanning at regular intervals
Archetti and al. (2021)	Hybrid dynamic	×	✓	×	Online VRPOD combining replanning and adaptation
Behrend and al. (2019, 2021), Yildiz (2021a, 2021b)	Stochastic	✓	✓	✓	Multi-period modelling, capacity considered
Yildiz (2021a, 2021b)	Stochastic	✓	✓	×	Monte Carlo simulation, transshipment
Dahle and al. (2017), Skålnes and al. (2020)	Two-/multi-stage stochastic	✓	✓	×	Supply evolution over time
Dayarian and Savelsbergh (2020)	Sample Scenario Planning	✓	✓	✓	Same-day delivery using in-store customers; uses scenario-based cost comparison
Goyal and al. (2024)	Multi-stage	✓	✓	×	Joint optimization of service level and profit
Şardağ and al. (2024),	Dynamic with incentives	✓	✓	×	Dynamic pricing and incentive mechanisms
Savelsbergh and Ulmer (2024)	Theoretical review	✓	✓	✓	Critical review and future research directions
Powell (2011)	Theoretical review	✓	✓	✓	Theoretical foundation of ADP, including anticipative policies and value function approximation
Mousavi and al. (2022, 2024)	ADP	✓	✓	×	ADP algorithm with in-store customers, mobile depots
Topaloglu and Powell (2006)	ADP	✓	✓	✓	Lookahead policies for resource allocation under known information
Lebedev and al. (2020)	ADP	✓	✓	✓	Pricing of delivery slots in e-commerce with known demand in advance
Boschma and al. (2023)	ADP	✓	✓	✓	Container stacking using ADP with information on arrivals/departures known in advance.
Innocente and Tancrez (2025)	ADP (forward and backward pass)	✓	✓	✓	ADP algorithm with value function approximation for dynamic parcel-to-crowdshipper assignment
This master's thesis	ADP (provided model)	✓	✓	✓	Empirical analysis of ADP performance under anticipated crowdshipper availability (ε)

Table 1.: Summary of the literature review

3. Problem Formulation

The main objective for a peer-to-peer (P2P) crowdshipping platform, where spatial uncertainty is at a maximum, is to make the best possible use of the resources available, meaning assigning parcels to crowdshippers while reducing the delivery cost of crowdshipping compared to traditional delivery. These crowdshippers are neither employees nor people hired in advance; they randomly join the system by declaring their availability and make deliveries during their personal journeys.

This master's thesis is based on the paper by Innocente and Tancrez (2025), which deals with a dynamic parcel-to-crowdshipper assignment problem in the presence of uncertainty, regarding the future availability and characteristics of both parcels and crowdshippers. In our research framework, we introduce the parameter ε which represents the number of periods between the moment when a crowdshipper announces itself as available and the moment of its actual journey. This anticipation allows the system to reduce the uncertainty about the availability of crowdshippers.

The system operates over a discrete planning horizon, where time is divided into a finite set of T decision periods. It covers a geographical area that is discretised into a finite set of $\mathcal{D}$ zones (e.g. the NUTS3 regions in Belgium, see Appendix 1.). All these zones can serve as origin or destination for parcels or crowdshippers, with no restrictions on locations such as shops or homes.

Each parcel, denoted $l \in \mathcal{L}$, is characterised by;

- An origin $o_l \in \mathcal{D}$,
- A destination $d_l \in \mathcal{D}$,
- A period of entry into the system $\theta_l \in T$, which corresponds to the first period in which the parcel can be delivered.

Each parcel has a delivery window defined by a number of periods, modelled trough the parameter δ. Therefore, a parcel can be at most $\delta + 1$ periods in the system. Parcels that share the same origin, destination and arrival date are seen by the system as a single parcel that can be delivered by a crowdshipper. All parcels do not have to be assigned to a same crowdshipper. Each crowdshipper, denoted $r \in \mathcal{R}$, is characterised by;

- An origin $o_r \in \mathcal{D}$,
- A destination $d_r \in \mathcal{D}$,
- An announcement period $\theta_r \in T$, on which he announces its future journey to the system.

Considering the parameter ε, a crowdshipper is available for delivery at period $\theta_r + \varepsilon$. The assumption is that a crowdshipper is only available to deliver a single parcel in a single period. This assumption remains reasonable, because they deliver the parcels during their personal journey and therefore have no interest to make several successive stops.
Table 2. summarises all the notations used to formulate the assignment problem.

Notation	
$\mathcal{L}$	Set of parcels, $l \in \mathcal{L}$
$\mathcal{R}$	Set of crowdshippers, $r \in \mathcal{R}$
$\mathcal{D}$	Set of small zones, $o_r, o_l, d_r, d_l \in \mathcal{D}$
θ_l	Start of the delivery window of parcel l, first decision time when parcel l is available for delivery
θ_r	Decision time at which crowdshipper r announces their availability for a future delivery.
ε	Number of decision periods between the moment a crowdshipper r announces their availability and the moment of their actual journey
n	Waiting time of parcel l in the system when it is assigned, $n = \theta_r + \varepsilon - \theta_l$
$\delta + 1$	Length of delivery window for parcels
$c^n_{o_r,d_r,o_l,d_l}$	Contribution of assigning crowdshipper with origin o_r and destination d_r to parcel with origin o_l and destination d_l having already waited n decision times for delivery
L^0_t	Set of parcels first available for delivery at decision time t
R^0_t	Set of crowdshippers declaring their availability at decision time t
L^X_t	Set of parcels assigned at decision time t
L^A_t	Set of parcels available for delivery at decision time t, $L^A_t = L^A_{t-1} - L^0_{t-\delta-1} - L^X_{t-1} + L^0_t$
R^A_t	Set of crowdshippers available for delivery at the time t, i.e. those whose availability was declared no later than t and whose journey has not yet taken place, $R^A_t = R^A_{t-1} - R^0_{t-\varepsilon-1} + R^0_t$

Table 2.: Notations for formulation problem

Not all parcels have to be delivered by a crowdshipper, and not all crowdshippers are necessarily assigned to a parcel. The objective of the system is to determine, at each period t, the assignments between parcels and crowdshippers, with the aim of maximising the overall gain from assigning parcels via crowdshipping compared with traditional delivery. This gain is expressed as the difference between the cost of traditional delivery and the cost of delivery via crowdshipping.

In the following, we formulate this parcel-to-crowdshipper assignment problem based on five key components of a dynamic system developed by Powell (2019); exogenous information, state variables, decision variables, transition function and objective function.

3.1. Exogenous information

At each period t, parcels and crowdshippers arrive in the system stochastically according to a Poisson distribution. The arrival of parcels and crowdshippers are independent processes.
We define:

- L_t^0 : Set of parcels arriving in the system during the decision period $t-1$ and t,
- R_t^0 : set of crowdshippers who declare their availability for delivery that will take place ε periods later, i.e. whose availability is announced during decision period t.

Each crowdshipper announces their availability to deliver a parcel at a certain period t, from that moment, they can be assigned to a parcel, although their actual trip will only take place ε periods later. Announcements take place between two decision periods and are considered by the system in the next decision period.

Figure 1. illustrates the temporal dynamics of the announcements of crowdshippers and effective availabilities for an announcement anticipation $\varepsilon = 2$ periods.

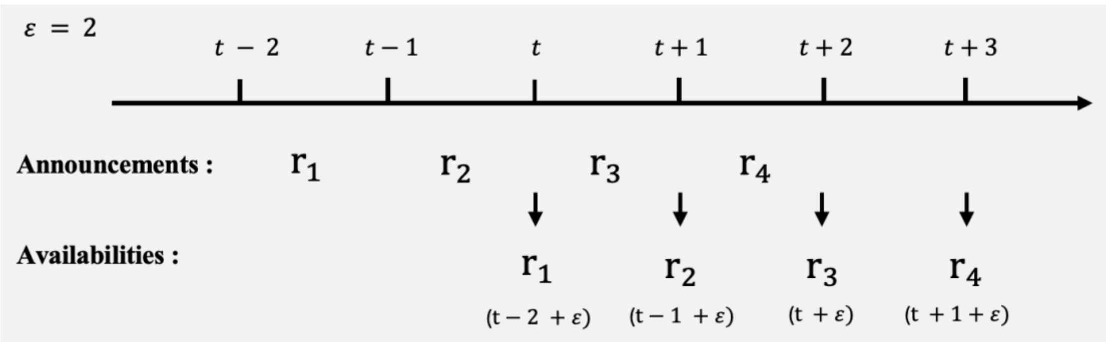


Figure 1.: Timeline of crowdshippers announcements/availabilities with anticipation (ε)

3.2. State variables

At any period t, the state of the system is determined by:

- L_t^A : The set of parcels available for delivery during the period t,
- R_t^A : The set of crowdshippers available to make a delivery during the period t.

A parcel is available for delivery as soon as it arrives in the system at period θ_l, and as long as it has not been assigned, it remains available until its delivery window $\theta_l + \delta$ has expired. In our model, the construction of the set L_t^A follows the following logic: at each period t, the set is initialized with the new parcels arriving during this period. Then, parcels that have not been assigned to a crowdshipper in the previous period are added. Finally, we remove parcels that were assigned at time $t-1$, and parcels whose delivery window has expired. This logic ensures that only parcels that are still eligible for assignment are saved in the system;

$$L_t^A \leftarrow L_t^0 + L_{t-1}^A - L_{t-1}^X - L_{t-\delta-1}^0$$

A crowdshipper announces their availability at period θ_r, and is considered available for delivery from that period up to their actual journey at $\theta_r + \varepsilon$. At each period t, the set of crowdshippers available to deliver R_t^A is initialised by replicating the set R_{t-1}^A. We then remove the crowdshippers whose journey has taken place in decision time $t-1$, meaning those that arrived in the system between decision times $t-\varepsilon-1$ and $t-\varepsilon$. Then we add the crowdshippers declaring their availability between decision times $t-1$ and t.

The logic is therefore as follows;

$$R_t^A \leftarrow R_{t-1}^A - R_{t-\varepsilon-1}^0 + R_t^0$$

3.3. Decisions variables

At each period t, the decision is made to assign the parcels available for delivery L_t^A to the crowdshippers available for delivery R_t^A. This decision is expressed by a binary variable;

$$x_{r,l}^t = \begin{cases} 1 & \text{if crowdshipper } r \text{ is assigned to parcel l at decision time } t \\ 0 & \text{otherwise} \end{cases}$$

However, it should be noted that a parcel can be assigned to a crowdshipper whose journey does not take place in period t, but later in the future at period $\theta_r + \varepsilon$. Given that the assignment problem is re-optimised at each period t, anticipated assignments can be revised according to new information.

The variable $x_{r,l}^{t}$ is subject to constraints that define the feasible region of the system, defined as the set X. The constraints are generalised by presenting them for the sets $\mathcal{R}$ and $\mathcal{L}$.

1. A parcel can only be assigned once:

$$\sum_{r \in R_t^a} x_{r,l}^{t} \leq 1 \quad \forall l \in L_t^A \tag{1}$$

2. A crowdshipper can only deliver one parcel:

$$\sum_{l \in L_t^a} x_{r,l}^{t} \leq 1 \quad \forall r \in R_t^A \tag{2}$$

3. The parcel must have been in the system when the crowdshipper is available:

$$\theta_l \cdot x_{r,l}^{t} \leq (\theta_r + \varepsilon) \quad \forall r \in \mathcal{R}, \forall l \in \mathcal{L} \tag{3}$$

4. Delivery must respect the parcel's time window:

$$(\theta_r + \varepsilon) \cdot x_{r,l}^{t} \leq \theta_l + \delta \quad \forall l \in \mathcal{L}, \forall r \in \mathcal{R} \tag{4}$$

5. Binary nature of the variables:

$$x_{r,l}^{t} \in \{0, 1\} \quad \forall l \in \mathcal{L}, \forall r \in \mathcal{R} \tag{5}$$

3.4. Objective functions

The objective of our problem is to determine the optimal assignment of crowdshippers to parcels over time, while maximising the expected benefit of crowdshipping compared with traditional delivery. This objective is defined in Equation (6), as the sum of all the contributions C_{o_r,d_r,o_l,d_l}^{n} of each assignment decision $x_{r,l}^{t}$, to all the possible parcel-crowdshipper combinations at decision period t;

$$max \left[\sum_{r \in R_t^A} \sum_{l \in L_t^A} C_{o_r,d_r,o_l,d_l}^{n} \cdot x_{r,l}^{t} \right] \tag{6}$$

The objective function (6) is based on a contribution function (7), noted c_{o_r,d_r,o_l,d_l}^{n}. This expresses the benefit of assigning a crowdshipper to a parcel. Each crowdshipper is characterized by their origin o_r, destination d_r and the period θ_r, at which they declared their availability. In the same vein, each parcel is characterized by their origin $o_{l,}$, destination d_l and period arrival θ_l.This contribution is defined as the difference in cost between traditional delivery and crowdshipping, as detailed in Equation (7). In this way, the system will decide to assign parcels to crowdshippers only if the contribution is strictly positive. Thus, if a parcel has not been assigned in our system, this means that no crowdshipper with a lower cost than traditional delivery has been found.

$$C^n_{o_r,d_r,o_l,d_l} = \underbrace{\left(fc^{TD} + vc^{TD} \cdot dist_{o_l,d_l}\right)}_{\text{Cost of traditional delivery}} \cdot \left(1 + \mu \cdot (\delta - n)\right) - \underbrace{\left(fc^{C} + vc^{C} \cdot dev_{o_r,\,o_l,d_r,d_l}\right)}_{\text{Cost of crowdshipping delivery}} \quad (7)$$

We model the cost of delivery by crowdshipping as a two-part remuneration; a fixed compensation that is noted fc^C, as well as a variable compensation that we defined by $vc^C \cdot dev_{o_r,d_r,o_l,d_l}$. This variable compensation is proportional to the detour distance dev_{o_r,d_r,o_l,d_l} that must be made by a crowdshipper to deliver a parcel, to consider the additional costs involved in delivery (gas, time, effort). The logic behind variable compensation is consistent with the work of Boysen and al. (2022) as well as Mousavi and al. (2024), which highlight that individuals who take longer detours expect proportional compensation.

The cost of traditional delivery has the same structure; it is composed of a fixed cost per delivery, noted fc^{TD}, and a variable cost, noted $vc^{TD} \cdot dist_{o_l,d_l}$, proportional to the distance between the origin o_l and the destination d_l of the parcel. Therefore, the total cost of a parcel l delivered by traditional delivery is defined by $fc^{TD} + vc^{TD} \cdot dist_{o_l,d_l}$.

In our model, traditional delivery is considered as a fixed service duration corresponding to $(\delta + 1) + 1$ decision periods. Any parcel that has not been delivered by crowdshipping before the end of the delivery window $\theta_l + \delta$, will be delivered by traditional delivery. Using traditional delivery as the reference for our system, this assumption implies that no penalty needs to be applied to a parcel that has not been assigned to a crowdshipper, its delivery cost is simply the cost of traditional delivery. However, crowdshipping offers the possibility of faster deliveries, and Cheng and al. (2022) consider this to be an advantage, pointing out that the faster a parcel is delivered, the more interest the customer has in this accelerated service. An economic advantage is granted to crowdshipping to take account of this time dimension in the contribution function. This advantage is modelled through a time bonus, noted μ (%), per period saved. The greater the waiting before delivery of a parcel, the less rapid the delivery is, and it is therefore valued less highly in the contribution function.

3.5. Transition function

At each period t, an update of the system is necessary to represent the evolution of the system between two decision periods. This transition between the state at period t and that at period $t + 1$ depends on the one hand, on the assignment decisions taken at period t, and on the other hand, on the arrival of new parcels and crowdshippers between t and $t + 1$.

Once the optimal assignments have been determined, we can visualise the set of parcels that have been assigned to period t. This set, denoted L_t^X, is defined as:

$$L_t^X = \{\ l \ |\ x_{r,l}^t = 1,\ l \in L_t^A,\ r \in\ R_{t-\varepsilon}^0 \} \tag{8}$$

where the variables $x_{r,l}^t$, satisfy contraints (1-5) and are chosen to maximise the objective function, referred as Equation (6).

At the next decision period in $t + 1$, the set L_{t+1}^A of parcels available for assignment is updated to reflect the decisions taken at period t. Among the unassigned parcels, some may have exceeded their validity limit. These are parcels that have arrived at period $\mathrm{t} - \delta - 1$, which are therefore no longer eligible for delivery by crowdshipping. These parcels are no longer taken into account by the system and are considered to have been delivered by traditional delivery. Finally, there are the new parcels which arrived between period t and $t + 1$, noted L_{t+1}^0. The update of the set of available parcels therefore follows the following logic:

$$L_{t+1}^A \leftarrow L_t^A - L_t^X - L_{t-\delta}^0 + L_{t+1}^0 \tag{9}$$

Concerning the crowdshippers, when $\varepsilon > 0$, they announce their availability ε periods before their journey. From the moment of announcement, they are available for assignment until their journey occurs at period $\theta_r + \varepsilon$. The set of crowdshippers available in period $t + 1$ is updated by removing from R_t^A crowdshippers whose actual journey was supposed to take place in period t. And secondly, by adding those who announce their availability in period $t + 1$;

$$R_{t+1}^A \leftarrow R_t^A\ -\ R_{t-\varepsilon}^0 + R_{t+1}^0 \tag{10}$$

4. Solution methodology

To solve this dynamic assignment problem, we use the approximate dynamic programming approach developed by Innocente and Tancrez (2025) and inspired by Spivey and Powell (2004) who have worked extensively on value function approximation in the context of ADP.

Table 3. summarises all the notations used for the solution methodology.

Notation	
β_{o_l,d_l}	Number of occurrences of parcel with origin o_l and destination d_l in the forward pass
α	Smoothing factor
γ	Number of decision times backward the algorithm returns to compute $\hat{v}^n_{o_l,d_l,t-\gamma}$, $\gamma = \delta + 1$
$\hat{v}^n_{o_l,d_l,t}$	Estimate of the value of parcel with origin o_l and destination d_l, having already waited n decision times for delivery, obtained at decision time t
$\bar{v}^n_{o_l,d_l}$	Smoothed estimate of the value of parcel with origin o_l and destination d_l, having already waited n decision times for delivery, obtained after aggregating all estimates up to a given decision time
L^V_t	Set of parcels first available for delivery at decision times $t - \delta \leq i \leq t$
L^S_t	Set of parcels available for delivery at decision time $t - 1$ and first available for delivery at decision times $t \leq i \leq t + \gamma$
R^S_t	Set of crowdshippers first available for delivery at decision times $t \leq i \leq t + \gamma$

Table 3.: Notations for solution methodology

The main objective is to estimate the future value of parcels available for delivery. This knowledge will allow to estimate whether it is strategically more advantageous to postpone the assignment decision to maximise the overall performance of the system in the long term. Indeed, in a context of uncertainty about the arrival of parcels and crowdshippers, present decisions can have an impact on future opportunities. It is therefore essential to take account of the immediate gain from an assignment while considering its effect on future decisions.

In this context, the dynamic approximate programming approach is suitable for solving these very large and uncertain state space problems (Powell, 2007), using approximations rather than exact resolution. Spivey and Powell (2004) and Powell (2007) point out that in many dynamic assignment problems, the size of the space grows exponentially with the number of resources and tasks, making exact methods untraceable.

Equation (11) expresses the main rule of the assignment decision of the approximate dynamics programming algorithm used in our model;

$$max\left[\sum_{l\in L_t^A}\sum_{r\in R_t^A}\left(C^n_{o_r,d_r,o_l,d_l}-\bar{v}^{t+\varepsilon-o_l+1}_{o_l,d_l}\right)\cdot x^t_{r,l}\right] \tag{11}$$

The objective is to find the optimal assignments of parcels to crowdshippers, respecting the constraints (1-5) and considering the sets L_t^A and R_t^A. The introduction of the parameter ε gives the information on the crowdshippers available between the period t and $t+\varepsilon$; the future value of a parcel is therefore estimated at period $t+\varepsilon+1$, i.e. the first period when the information on the crowdshippers availability becomes uncertain again. The algorithm compares the immediate contribution of assigning a parcel l in this known time horizon $[t, t+\varepsilon]$, with the estimated value of postponing the assignment decision in the hope of a better match with a crowdshipper r arriving in period $t+\varepsilon+1$ or later, for which availability is still uncertain. This estimated value is therefore expressed as $\bar{v}^{t+\varepsilon-o_l+1}_{o_l,d_l}$, because the parcel will have waited $t+\varepsilon-o_l+1$ periods since it arrived in the system. In addition, as the actual time of delivery depends on the actual time of availability of crowdshipper $(\theta_r+\varepsilon)$, the number of periods that a parcel has waited before being delivered is calculated as $n=\theta_r+\varepsilon-\theta_l$.

In comparison with myopic policy, where decisions are made based on the current state of the system with known information, our ADP approach incorporates the expected value of future opportunities through the variable $\bar{v}^{t+\varepsilon-o_l+1}_{o_l,d_l}$.

We therefore need to be able to estimate the future value of each parcel. The algorithm Innocente and Tancrez (2025) have developed is based on two steps. Firstly, the forward pass step, in which the arrival of parcels and crowdshippers are simulated and assignment decisions are made within the constraints of the system. Secondly, the backward pass step, in which we go back in time to recalculate the values of the parcels that were present in the system, taking into account the decisions that have been made. The aim is to estimate the value of parcel based on its marginal impact on the value of the system. We consider the state system (L_s^S, R_s^S) at a time $s=t-\gamma$ which represents the γ period of decisions situated before the time t. The idea behind this is to evaluate what the impact would have been if a parcel had been removed from (1) or added to (2) the system at a given moment.

By comparing the total contribution obtained with and without this parcel, we can estimate its intrinsic value. In concrete terms, if the parcel was available at that time, it is removed to measure the loss of value. If it was not, we add it to estimate the potential gain. We can therefore estimate the intrinsic value of a parcel l with the origin o_l and destination d_l, having waited n periods before being delivered.

With the aim of smoothing out the random variability of parcel and crowdshipper arrivals and converging towards a more reliable estimate of the value of each type of parcel, the punctual estimates are gradually smoothed over the decision periods using the parameter α. The formula for smoothing estimates is defined as follows;

$$\bar{v}_{o_l,d_l}^{s-\theta_l} \leftarrow \alpha \cdot \hat{v}_{o_l,d_l,s}^{s-\theta_l} + (1-\alpha) \cdot \bar{v}_{o_l,d_l}^{s-\theta_l} \tag{12}$$

where $\alpha = \frac{1}{\beta_{o_l,d_l}}$.

The parameter α is designed to guarantee progressive smoothing. As it is inversely proportional to the number observations β_{o_l,d_l}, the parameter α is high and gives considerable weight to the first estimates. As the number of observations of a parcel type increases, the α parameter decreases, giving less weight to the estimates. The first estimates therefore initiate the approximation, while the following ones stabilise it and make it more reliable.

Below, Figure 2. presents in detail how the approximate dynamic programming method operates. We conclude this section by explaining each step of the algorithm.

Initialisation (lines 1-3) The algorithm starts by initialising the following sets, for each period $t = 0, \dots, \gamma + \delta - 1$:

- L_t^0: Set of parcels first available for delivery at decision time t,
- R_t^0: Set of crowdshippers declaring their availability at decision time t,
- L_t^X: Set of parcels assigned at decision time t,
- L_t^A: Set of parcels available for delivery at decision time t.

The algorithm starts at the decision period $t = \gamma + \delta$ so that enough information is available to perform the first backtracking.

At each decision period t *during the simulation (lines 4-35)* The algorithm proceeds according to a very specific condition which guarantees the statistical robustness of the estimates ; it continues until each observed origin-destination pairs $(o_l\ , d_l)$ of parcels have been observed a sufficient number of times $(\beta_{o_l,d_l} > b)$ and that these parcel pairs represent at least a% of all parcels seen until now.

Algorithm 1 ADP algorithm when anticipating the availability of crowdshippers

1: `// Initialization`
2: Initialize L_t^0, R_t^0, L_t^X, L_t^A $\quad \forall t = 0, 1, \ldots, (\gamma + \delta - 1)$
3: $t = \gamma + \delta$
4: **for** t **while** $a\%\beta_{o_l,d_l} < b$ **do**
5: `// Forward pass`
6: $R_t^0 \leftarrow$ new crowdshippers r with $(o_r, d_r, \theta_r = t)$
7: $L_t^0 \leftarrow$ new parcels l with $(o_l, d_l, \theta_l = t)$
8: $\beta_{o_l,d_l} \leftarrow \beta_{o_l,d_l} + 1 \quad \forall l \in L_t^0$
9: `// Updating system state`
10: $L_t^A \leftarrow L_{t-1}^A - L_{t-\delta-1}^0 - L_{t-1}^X + L_t^0$
11: $R_t^A \leftarrow R_{t-1}^A - R_{t-\varepsilon-1}^0 + R_t^0$
12: For each (r, l), compute $n = \theta_r + \varepsilon - \theta_l$
13: `// Solving the assignment problem`
14: $x_{r,l}^t \leftarrow$ Solve (11) satisfying (1)-(5) with L_t^A, R_t^A
15: $L_t^X \leftarrow \{l \mid x_{r,l}^t = 1, l \in L_t^A, r \in R_{t-\varepsilon}^0\}$
16: `// Backward parcel value estimation`
17: $s = t - \gamma$
18: $L_s^V \leftarrow \biguplus_{s-\delta \le i \le s} L_i^0$
19: $R_s^S \leftarrow \biguplus_{s-\varepsilon \le i \le t} R_i^0$
20: $L_s^S \leftarrow \biguplus_{s-\delta \le i \le t} L_i^0 - \biguplus_{s-\delta \le i < s} L_i^X$
21: $C(L_s^S, R_s^S) \leftarrow \max \sum_{r \in R_s^S} \sum_{l \in L_s^S} c_{o_r,d_r,o_l,d_l}^n \cdot x_{r,l}^s$ satisfying (1)-(5) with L_s^S, R_s^S
22: **for** $l \in L_s^V$ **do**
23: `// Computing estimates`
24: **if** $l \in L_s^S$ **then**
25: $C(L_s^S - \{l\}, R_s^S) \leftarrow \max \sum_{r \in R_s^S} \sum_{l \in L_s^S \setminus \{l\}} c_{o_r,d_r,o_l,d_l}^n \cdot x_{r,l}^s$ satisfying (1)-(5)
26: $\hat{v}_{o_l,d_l,s}^{s-\theta_l} = C(L_s^S, R_s^S) - C(L_s^S - \{l\}, R_s^S)$
27: **else**
28: $C(L_s^S + \{l\}, R_s^S) \leftarrow \max \sum_{r \in R_s^S} \sum_{l \in L_s^S \cup \{l\}} c_{o_r,d_r,o_l,d_l}^n \cdot x_{r,l}^s$ satisfying (1)-(5)
29: $\hat{v}_{o_l,d_l,s}^{s-\theta_l} = C(L_s^S + \{l\}, R_s^S) - C(L_s^S, R_s^S)$
30: **end if**
31: `// Smoothing estimates`
32: $\bar{v}_{o_l,d_l}^{s-\theta_l} \leftarrow \alpha \cdot \hat{v}_{o_l,d_l,s}^{s-\theta_l} + (1 - \alpha) \cdot \bar{v}_{o_l,d_l}^{s-\theta_l}$
33: **end for**
34: $t \leftarrow t + 1$
35: **end for**

Figure 2.: ADP algorithm with anticipating the availability of crowdshipper (ε)

Forward pass, simulation and state updates (lines 5-11) At each decision period t, new crowdshippers *(line 6)* and parcels *(line 7)* arrive in the system according to a Poisson distribution. Parameter β_{o_l, d_l} is then incremented for each peer (o_l , d_l) *(line 8)*, and the system state is updated.

Solving the assignment problem (lines 13-14) The assignment problem is solved by respecting the constraints (1-5). Solving this problem means maximising the sum of the net contributions of each assignment (r, l), considering the estimated current value of the type of parcel if it were delivered later, as defined in Equation (11).

The set L_t^X is then made up of parcels assigned to crowdshippers making their journey in period t (having announced themselves as available in period $t - \varepsilon$), as defined in Equation (8).

Backward pass, updating parcel values (lines 16-31) This phase involves estimating the value of parcels at decision period $s = t - \gamma$, based on information observed between s and t. The aim of this step is to capture the future impact of an assignment by approximating its marginal contribution to the system. To do this, the sets L_s^V, R_s^S and L_s^S are constructed based on the information received during the forward pass between periods s and t. The set L_s^V is made up of the parcels which arrived between the period $s - \delta$ and s, i.e. those which became available for delivery in this period. The set R_s^S is made up of crowdshippers who have announced their availability between periods $s - \varepsilon$ and t, i.e. those whose journey is scheduled between s and t. While the set L_s^S is initialized from the parcels that have arrived in the system between the periods $s - \delta$ and t, i.e. those whose journey is scheduled between s and t and still unassigned at s.

The algorithm solves the assignment problem between L_s^S and R_s^S, denoted $C(L_s^S, R_s^S)$, while satisfying constraints (1-5).

Estimation of the marginal value of the parcels (lines 22-30) A point estimate value $\hat{v}_{o_l,d_l,s}^{s-\theta_l}$ of a parcel l is calculated for each parcel $l \in L_s^V$;

(1) If $l \in L_s^S$, the model is solved a first time with the parcel, then we remove this parcel and solve the problem a second time. The point estimate resides in the total value difference;

$$\hat{v}_{o_l,d_l,s}^{s-\theta_l} = C(L_s^S, R_s^S) - C(L_s^S - \{\, l \,\}, R_s^S) \tag{13}$$

(2) If $l \notin L_s^S$, we add the parcel to the system and solve the problem, then calculate the marginal impact of this parcel by subtracting the total value of the system without this parcel

$$\hat{v}_{o_l,d_l,s}^{s-\theta_l} = C(L_s^S + \{\, l \,\}, R_s^S) - C(L_s^S, R_s^S) \tag{14}$$

Smoothing of estimates (line 31) The estimates are progressively smoothed, as described in Equation (12), to obtain a reliable estimate, using a coefficient $\alpha = \frac{1}{\beta_{o_l,d_l}}$ factor, which give more weight to the first estimates.

Increment and end of loop (line 33-34) Finally, the algorithm increments the decision period t and the process continues until the stop condition is met.

The approximation of the value function used in our model is inspired by the research of Spivey and Powell (2004). However, Innocente and Tancrez (2025) made changes to the methodology to adapt it to our problem of parcel-to-crowdshippers dynamic assignment in a peer-to-peer configuration.

In the classical methods (Powell, 2007; Ulmer and al., 2018; Bertsekas, 2019), the value of a parcel is estimated based on the precise moment in the time horizon, because optimal decisions can vary depending on the moment. It would therefore be necessary to simulate several scenarios over the entire time horizon to determine the best assignment decisions at each period. Innocente and Tancrez (2025) have modified this logic by estimating the value of a parcel through its attributes: origin o_l , destination d_l, the waiting time before delivery of a parcel n and how much time it has left in its delivery window δ . This simplification is justified by the stationary and repetitive nature of a peer-to-peer delivery system, in which similar decisions recur continuously. As a result, parcels that have the same attributes will have similar estimated values and will lead to similar decisions, regardless of the exact period of their arrival in the system.

5. Computational experiments

In this section, we analyse the impact of anticipating the availability of crowdshippers, on the relative performance of the ADP approach compared to the myopic one. Section 5.1. presents the context of our analyses and the experimental settings. Section 5.2. presents a general analysis of how anticipation ε affects the performance of the ADP approach. Section 5.3. presents a multifactor analysis exploring how the anticipation parameter ε interacts with key parameters of the assignment problem such as the delivery window δ, the total number of parcels L, the crowdshipper-to-parcel ratio and the difference in fixed Δfc and variable Δvc costs between traditional delivery and crowdshipping. In Section 5.4., we analyse the efficiency of the ADP approach compared to the myopic approach, in terms of parcel deliveries and deviation distances. Finally, in Section 5.5., we investigate how the ADP approach performs under uncertainty over parcel arrivals across varying levels of arrival fluctuations.

5.1. Experimental settings

In this section, we present the parameters of the experimental setting, defined on the basis of preliminary tests carried out by Innocente and Tancrez (2025) on real data from two Belgian institutions: Bpost, for the daily volumes of parcel deliveries, and the Federal Planning Bureau, for the flow of crowdshipper trips. These preliminary tests made it possible to create plausible fictitious instances, by allowing the tests to best represent operational reality, while guaranteeing computational feasibility.

As we are dealing with a parcel-crowdshipper assignment problem, the geographical space considered remains a central component. The numerical experiments were carried out using Belgium as a reference; a medium-sized area divided into 44 administrative zones which can serve as origin or destination (e.g. the NUTS3 regions in Belgium, see Appendix 1.). The distances between zones are calculated from the centroids using the Euclidean formula.

Concerning the arrivals of parcels and crowdshippers, the experiments were conducted based on 136 pairs (o_l, d_l) for parcels, and 191 pairs (o_r, d_r) for crowdshippers. As mentioned above, the arrival rates for each decision period t are estimated from data supplied by Bpost and the Federal Planning Bureau. These different rates are used as parameters in a stationary Poisson process, which simulates the randomness of parcel and crowdshipper arrivals.

Parameter settings	
δ	(2,4,6) periods
$\mathcal{L}$	(1000, 2000) parcels
ratio	(0.5, 1.0, 2.0)
ε	(0, 1, 2, 3, 4, 5, 6) periods
Δfc	(0, 20, 40) km
Δvc	(2, 3, 4) €

Table 4.: Parameter values for numerical experiments

Table 4. illustrates the different values that the parameters used in our analyses can take. For each parameter configuration, 100 independent instances are simulated over a time horizon of 100 decision periods, using our ADP policy and the myopic policy as a comparison, to compare the performance of the algorithm.

To analyse the difference in performance between the ADP policy and the myopic policy, we vary several key parameters of the assignment problem (see Section 3.) in our computational experiments. The size of the problem varies through the total number of parcel arrivals over the 100-period horizon, denoted $L = \{1000,2000\}$. We test three ratios of crowdshipper arrivals to parcel arrivals, $\{0.5,1.0,2.0\}$. In our sensitivity analysis to economic parameters, defined in Section 3.4. , three levels of fixed cost are considered, expressed as the difference between traditional delivery and crowdshipping, with the fixed cost expressed in terms of the equivalent distance in kilometers of traditional delivery, Δfc = $\{0, 20, 40\}$. In addition, the variable additional cost of crowdshipping is represented by a multiplicative factor applied to the cost per kilometre of traditional delivery, Δv = $\{2, 3, 4\}$. Innocente and Tancrez (2025) retain these values based on existing literature; Dahle and al. (2019) propose a sensitivity analysis of compensation mechanisms in a crowdshipping context, while Mousavi and al. (2024) evaluate costs in collaborative environments using empirical data.

Finally, three levels of delivery window are analyse for parcels, corresponding to 3, 5 and 7 decision periods, which implies that a parcel can be delivered either on its arrival period θ_l or within the following δ = $\{2, 4, 6\}$ periods. The parameter ε = $\{0, 1, 2, 3, 4, 5, 6\}$, representing the anticipation between the announcement of the availability of a crowdshipper and its actual journey, respects the constraint $\varepsilon \leq \delta$ in our experiments. Indeed, if a crowdshipper announces himself too early $(\varepsilon > \delta)$, he cannot be assigned to a parcel whose delivery window has already expired at the time of his actual journey, making this information useless. The aim of this constraint is to ensure that each announced crowdshipper is relevant within the horizon for assigning a parcel, expressed by the delivery window δ.

Regarding the parameters of the algorithm, the bonus rate is set to $\mu = 5\%$ and the learning period to $\gamma = \delta + 1$ in all our computational experiments (see Section 4.). This choice reflects the assumption that the parcel delivery window δ determines the relevant time horizon for the backward value estimation. The smoothing factor α is defined in Equation (12), as the inverse of the number of occurrences of the origin-destination pairs (o_l, d_l), i.e. $\alpha = \frac{1}{\beta_{o_l,d_l}}$. The algorithm stops when 99% of the pairs have been observed at least 10 times. Innocente and Tancrez (2025) show that beyond this threshold, the results tend to stabilise, and the total contribution no longer changes significantly.

All the tested combinations of parameters lead to 210 experiments. We use PyCharm software to compute the algorithm developed in Python, and the optimisation model is solved using Gurobi optimisation software, all running on 8 computers with 1.8 GHz and 8 GB of RAM.

During our experiments, several metrics are calculate to compare the ADP and myopic approaches, considering the anticipated information on the availability of crowdshippers;

- **Relative efficiency :** defined in percentage terms, as the relative difference between their average contributions out of 100 executions.
- **Assignable crowdshippers :** for each configuration the average number of crowdshippers assignable to a parcel for which the contribution is strictly positive over its entire delivery window.
- **Relative deviation reduction :** expressed as the difference between the average deviation distances observed under the ADP approach and that observed under the myopic one, expressed as a percentage of the myopic average diversions.
- **Delivery rate :** the average numbers of parcels delivered in both ADP and myopic approaches, defined as the average number of parcels effectively delivered by crowdshippers over 100 executions.

5.2. Overall observations

δ	L	ratio	$\Delta fc = 20, \Delta vc = 3$							Average	
			$\varepsilon = 0$	$\varepsilon = 1$	$\varepsilon = 2$	$\varepsilon = 3$	$\varepsilon = 4$	$\varepsilon = 5$	$\varepsilon = 6$		
2	1000	0.5	0.8% 0.2	0.3% 0.2	0.0% 0.2	-	-	-	-	0.5% 0.2	
		1.0	2.0% 0.5	0.7% 0.5	0.0% 0.5	-	-	-	-	0.9% 0.5	0.9% 0.6
		2.0	3.2% 1.0	1.1% 1.0	0.0% 1.0	-	-	-	-	1.4% 1.0	
	2000	0.5	1.7% 0.5	0.6% 0.5	0.0% 0.5	-	-	-	-	0.8% 0.5	
		1.0	3.0% 0.9	1.0% 0.9	0.0% 0.9	-	-	-	-	1.3% 0.9	1.4% 1.1
		2.0	4.6% 1.8	1.4% 1.8	0.0% 1.8	-	-	-	-	2.0% 1.8	
Average $\delta = 2$			2.6% 0.8	0.9% 0.8	0.0% 0.8	-	-	-	-	1.2% 0.8	
4	1000	0.5	1.1% 0.4	0.5% 0.4	0.2% 0.4	0.0% 0.4	0.0% 0.4	-	-	0.4% 0.4	
		1.0	2.2% 0.8	1.3% 0.8	0.6% 0.8	0.1% 0.8	0.0% 0.8	-	-	0.8% 0.8	0.9% 0.4
		2.0	4.8% 1.6	2.2% 1.6	1.0% 1.6	0.2% 1.6	0.0% 1.6	-	-	1.6% 1.6	
	2000	0.5	1.6% 0.8	0.9% 0.8	0.4% 0.8	0.1% 0.8	0.0% 0.8	-	-	0.6% 0.8	
		1.0	3.3% 1.6	1.7% 1.6	0.6% 1.6	0.1% 1.6	0.0% 1.6	-	-	1.1% 1.6	1.1% 1.8
		2.0	6.0% 3.1	2.7% 3.1	1.2% 3.1	0.3% 3.1	0.0% 3.1	-	-	2.0% 3.1	
Average $\delta = 4$			3.2% 1.4	1.6% 1.4	0.7% 1.4	0.1% 1.4	0.0% 1.4	-	-	1.1% 1.4	
6	1000	0.5	0.9% 0.6	0.7% 0.6	0.4% 0.6	0.2% 0.6	0.1% 0.6	0.0% 0.6	0.0% 0.6	0.3% 0.6	
		1.0	2.4% 1.2	1.5% 1.2	1.0% 1.2	0.4% 1.2	0.2% 1.2	0.2% 1.2	0.0% 1.2	0.8% 1.2	0.9% 1.4
		2.0	5.7% 2.3	3.2% 2.3	2.0% 2.3	0.8% 2.3	0.3% 2.3	0.1% 2.3	0.0% 2.3	1.7% 2.3	
	2000	0.5	1.5% 1.1	0.8% 1.1	0.5% 1.1	0.2% 1.1	0.1% 1.1	0.0% 1.1	0.0% 1.1	0.4% 1.1	
		1.0	3.3% 2.2	1.9% 2.3	1.1% 2.2	0.7% 2.2	0.2% 2.2	0.1% 2.3	0.0% 2.2	1.0% 2.2	1.0% 2.6
		2.0	5.7% 4.5	3.5% 4.5	1.9% 4.5	0.9% 4.5	0.3% 4.5	0.1% 4.5	0.0% 4.5	1.8% 4.5	
Average $\delta = 6$			3.3% 2.0	1.9% 2.0	1.2% 2.0	0.5% 2.0	0.2% 2.0	0.1% 2.0	0.0% 2.0	1.0% 2.0	

Table 5.: Relative efficiency of the ADP approach and assignable crowdshippers per parcel.

Table 5. shows the relative efficiency of the ADP approach and the average number of assignable crowdshippers per parcel, depending on the values of δ, $\mathcal{L}$, the crowdshipper-to-parcel arrivals ratio and ε.

The relative efficiency decreases as the anticipation ε of crowdshipper availability increases. This general trend is expressed independently of the characteristics of the system; the delivery window δ, the size of the system L or the crowdshipper-to-parcel arrivals ratio, as shown in the average rows for each ε value in the bottom of every δ-section in Table 5.

This decrease in relative efficiency can be explained by the way in which the two approaches structure their assignment decisions. At each decision period t, the myopic approach makes its assignment decisions on the basis of exact information by assigning a parcel to the crowdshippers whose actual journey is taking place at this period t, i.e. those who have announced themselves at period $t - \varepsilon$. In contrast, the ADP policy makes its assignment policy by comparing the immediate gain of assigning a parcel now with known available crowdshippers in the horizon $[t, t + \varepsilon]$, with the estimated value of postposing the assignment, in the hope of a better match. This trade-off is expressed by Equation (11), in which the estimated future value $\bar{v}_{o_{l},d_{l}}^{t+\varepsilon-o_{l}+1}$ corresponds to the first period when information on the availability of crowdshippers becomes uncertain again, i.e. $t + \varepsilon + 1$.

We note that the relative efficiency of the ADP approach is at its maximum when $\varepsilon = 0$. This is because the ADP approach fully exploits its comparative advantage over the myopic one. The set of crowdshippers available beyond the current decision period t is entirely unknown, the ADP algorithm can therefore exploit its prediction mechanism over the entire delivery window $[\theta_l, \theta_l + \delta]$ of a parcel to determine whether it is more beneficial to assign this parcel now or postpone its assignment into the future. In contrast, the myopic approach makes decisions based solely on current known information without any prediction mechanism, which can lead to sub-optimal assignments.

However, as the parameter ε increases, the information available at the time of decision period t extends further into the future. The uncertainty that justifies the usefulness of the prediction mechanism used in the ADP approach gradually decreases, which reduces its comparative advantage over the myopic approach. Indeed, when the crowdshippers available in the coming ε periods are already known, the interest in postponing the assignment of a parcel in the hope of a better assignment becomes limited. As a result, the assignment decisions of the ADP approach tend to converge towards those of the myopic approach, which is based solely on the information known at the present time. When $\varepsilon = \delta$, the set of available crowdshippers covers the entire delivery window for a parcel. The ADP approach no longer has any margin for anticipation, which means that the two approaches make the same decisions on the basis of the same set of information.

5.3. Multifactor analysis of the effect of anticipation ε

The objective of this section is to explore the impact of anticipating the availability of crowdshippers on the relative efficiency of the ADP approach, as a function of the different parameters of our problem ; (i) the length of the delivery window, (ii) the size of the problem, (iii) the crowdshipper-to-parcel arrivals ratio and (iv) the cost structure.

i. When ε increases from 0 to 1, the relative efficiency decreases respectively by 66%, 53% and 42% when the length of the delivery window equals 2, 4 and 6. This loss in efficiency is even more pronounced when ε goes from 0 to 2. The negative impact of anticipating the availability crowdshippers is therefore greater when the length of the delivery window δ is short (see Figure 3.).

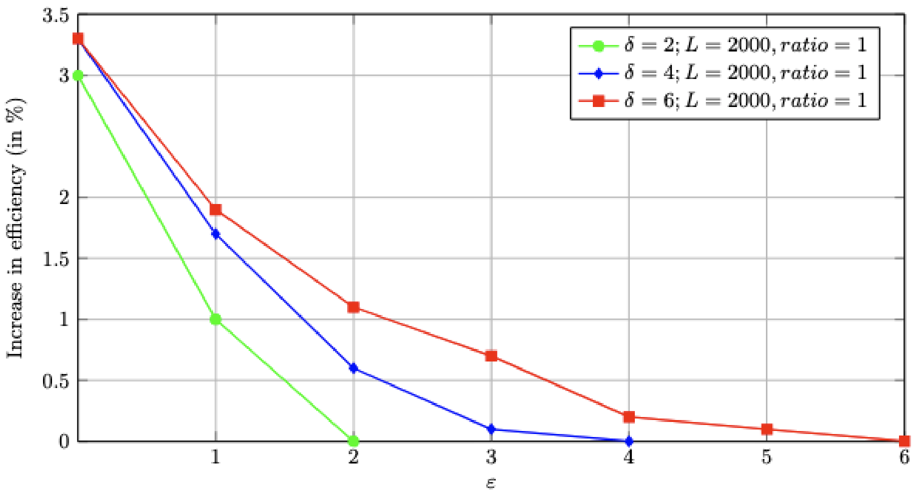


Figure 3.: Impact of the delivery window on the relative efficiency of the ADP approach anticipating the availability of crowdshippers (ε)

In such cases, our ADP approach has less temporal flexibility and postponing an assignment does not guarantee that a better assignment will come along. As a result, the anticipation mechanism of the ADP approach becomes less effective, and its performance tends to converge more quickly with the myopic approach.

ii. The results show that an increase in the size of the problem (L) accentuates the relative decrease in performance of the ADP approach. As shown in Figure 4., the slopes of the curves between the different values of ε are more pronounced when $L = 2000$, indicating a more significant reduction in relative efficiency.

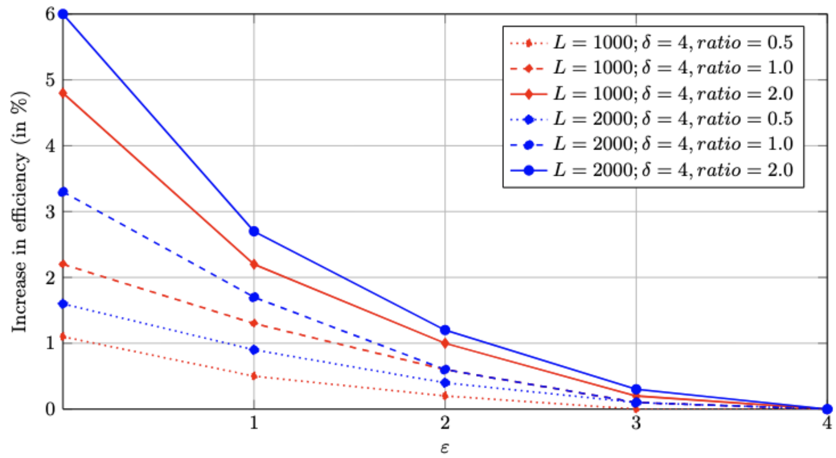


Figure 4.: Impact of the size of the system on the relative efficiency, for varying values of the crowdshipper to parcel arrivals ratio

This can be explained by the fact that in a larger system, our ADP algorithm has more assignment opportunities, which allows it to better exploit its assignment policy when ε is small. However, as ε increases, the ADP approach loses its comparative advantage in trying to predict a future that is progressively less uncertain. In conclusion, this wealth of opportunities makes the algorithm more sensitive to the introduction of the parameter ε.

iii. An increase in the crowdshippers-to-parcel arrivals ratio accentuates the negative impact of anticipating the availability of crowdshippers on the relative efficiency of the ADP approach. Figure 5. shows that the slope of the curves between two successive ε values is sharper as the crowdshipper-to-parcel arrivals ratio increases.

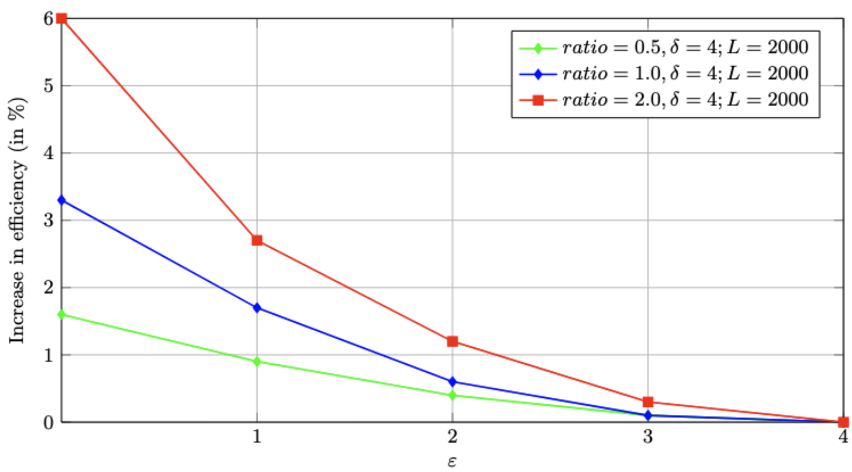


Figure 5.: Impact of the crowdshipper to parcel arrivals ratio on the relative efficiency

This is explained by the way the ADP approach exploits the anticipation of crowdshipper availability as a function of the number of crowdshippers arriving in the system. When a large number of crowdshippers are available (high ratio), the algorithm has a wider choice of assignment possibilities. As a result, when the value of ε is low, it can decide to choose assignments with a high contribution. However, as ε increases, the availability of crowdshippers is becoming more widely known, leaving fewer opportunities to postpone an assignment. The ADP approach therefore loses its comparative advantage in deferring assignments in the hope of a better opportunity.

In conclusion, the richer the initial set of options, the more sensitive the ADP approach becomes to the negative impact of anticipating crowdshipper availability. Conversely, when the crowdshipper-to-parcel ratio is low, the ADP algorithm has fewer opportunities to optimise assignments from the start, which results to a more gradual decline in efficiency.

Table 6. illustrates the impact of the anticipation ε of crowdshipper availability on the relative efficiency of the ADP approach and the average number of assignable crowdshippers r per parcel l, according to several fixed and variable cost structures for crowdshipping delivery.

Δfc	Δvc	$\delta = 4, L = 1000, ratio = 1$					Average	
		$\varepsilon = 0$	$\varepsilon = 1$	$\varepsilon = 2$	$\varepsilon = 3$	$\varepsilon = 4$		
0	2	1.3% 0.7	0.8% 0.7	0.3% 0.7	0.1% 0.7	0.0% 0.7	0.5% 0.7	
	3	1.4% 0.6	0.7% 0.6	0.3% 0.6	0.1% 0.6	0.0% 0.6	0.5% 0.6	0.5% 0.6
	4	1.2% 0.6	0.7% 0.6	0.3% 0.6	0.1% 0.6	0.0% 0.6	0.5% 0.6	
20	2	6.1% 1.5	2.7% 1.5	0.9% 1.5	0.2% 1.5	0.0% 1.5	2.0% 1.5	
	3	2.2% 0.8	1.3% 0.8	0.6% 0.8	0.1% 0.8	0.0% 0.8	0.8% 0.8	1.2% 1.0
	4	1.9% 0.7	0.9% 0.7	0.4% 0.7	0.1% 0.7	0.0% 0.7	0.7% 0.7	
40	2	7.0% 2.3	2.7% 2.3	0.8% 2.3	0.2% 2.3	0.0% 2.3	2.1% 2.3	
	3	6.6% 1.7	2.3% 1.7	1.1% 1.7	0.2% 1.7	0.0% 1.7	2.0% 1.7	1.8% 1.6
	4	3.9% 0.9	2.0% 0.9	0.8% 0.9	0.2% 0.9	0.0% 0.9	1.4% 0.9	
Average		3.5% 1.1	1.6% 1.1	0.6% 1.1	0.1% 1.1	0.0% 1.1	1.2% 1.1	

Table 6.:Impact of anticipating the availability of crowdshippers, under varying fixed and variable costs

iv. The results show that for a given configuration, the negative impact of anticipating the availability of crowdshippers is all the more marked when Δfc is high or Δvc is low. In both cases, these cost structures make crowdshipping more competitive than traditional delivery; this effect can be seen in the last two columns of averages on the right of Table 6. This gives our ADP approach greater flexibility to defer or refuse sub-optimal assignments when $\varepsilon = 0$. However, as ε increases, anticipated information progressively replaces uncertainty, reducing the ability of the ADP approach to predict the future.

Conversely, when Δfc is low or Δvc is high, the ADP approach has less margin and detours are more costly, which makes the assignment possibilities cost-effective. Relative efficiency is therefore lower when $\varepsilon = 0$, but the negative impact of an increase in the parameter ε is more moderate.

In conclusion, the higher the initial optimisation potential of the system, the more this loss of anticipation is reflected in the relative efficiency of the ADP approach.

5.4. Impact of anticipating availability of crowdshippers ($\boldsymbol{\varepsilon}$) on the delivery rate and relative deviation reduction

The objective of this analysis is to compare the impact of anticipating the availability of crowdshippers ($\boldsymbol{\varepsilon}$) on two performance dimensions : the Delivery rate and the Relative deviation reduction.

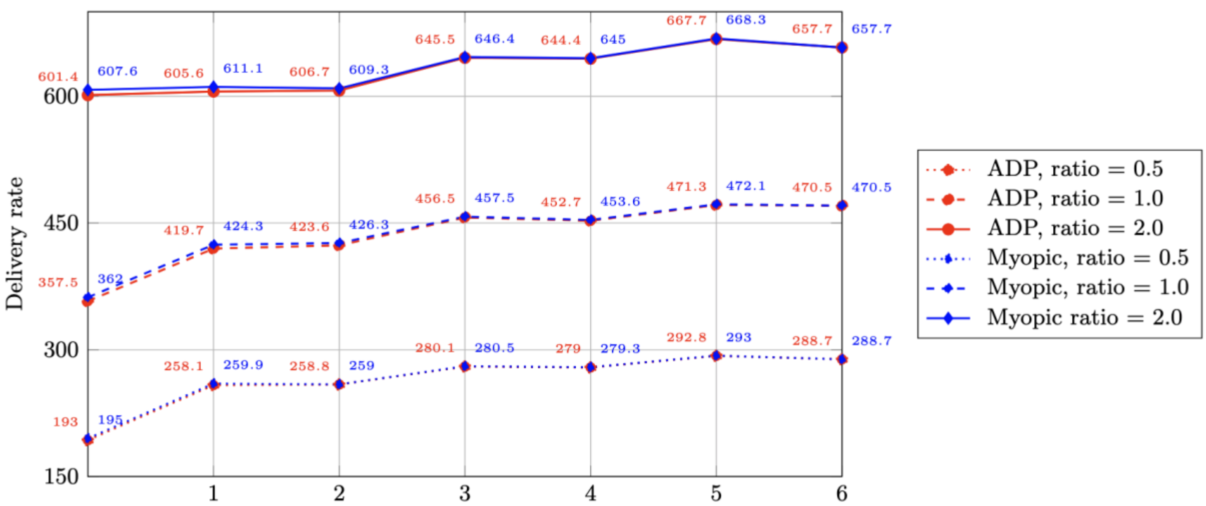


Figure 6.: Delivery rates of both ADP and myopic approaches, under varying values of crowdshipper-to-parcel arrivals ratio

Although the ADP approach is more efficient, we see in Figure 6. that the myopic approach slightly manages to deliver more parcels on average. However, as shown in Table 7. this higher average number of parcels delivered is associated with higher deviation distances.

ε	Relative deviation reduction (in %)
0	30.7
1	16.9
2	7.8
3	4.2
4	1.0
5	0.0
6	0.0

Table 7.: Relative deviation reduction, under varying values of anticipation ε

The delivery rate increases as the value of ε increases. This can be explained by the fact that the algorithm is informed of a greater number of crowdshippers whose actual journey takes place during the delivery window of a parcel, which improves the probability that a parcel will be assigned. We also see a peak in the average number of parcels delivered when $\varepsilon = 5$. In this configuration, there is a balance between the anticipated knowledge of the crowdshippers assignable to deliver a parcel and the fact that the algorithm still has a decision capacity between assigning now or deferring an assignment in the parcel delivery window.

However, this increase in the delivery rate should not be seen as a sign of more efficient optimisation. On the contrary, the ADP approach is gradually losing its comparative advantage, as it is becoming less and less capable of exploiting the uncertainty associated with the future. As ε increases, the ADP algorithm adopts the same behaviour as the myopic approach, assigning parcels on the basis of exact information about available crowdshippers, without anticipating better assignments.

This explains why the delivery rates converge and why the relative deviation reductions become marginal between the two approaches.

5.5. Impact of anticipating the availability of crowdshippers (ε) under parcel arrivals fluctuations

The aim of this analysis is to evaluate how the relative efficiency of the ADP approach, compared with the myopic approach, is affected by the introduction of increased uncertainty over parcel arrival. To do this, the arrival process, which is initially stationary, is replaced by a non-stationary process, in which the number of parcels generated by type (o_l, o_d) at each period t is drawn from a Poisson distribution, with the mean multiplied by a random factor $f = \mathcal{U} \sim (a, b)$. The aim is to simulate realistic fluctuations in parcel arrivals while maintaining the same number of parcel arrivals globally.

f	$\delta = 4, L = 1000, \Delta fc = 20, \Delta vc = 3$					Average	Delivery rate ADP	Delivery rate Myopic
	$\varepsilon = 0$	$\varepsilon = 1$	$\varepsilon = 2$	$\varepsilon = 3$	$\varepsilon = 4$			
Stationary	2.7% 23.2	1.3% 15.1	0.6% 7.0	0.1% 2.5	0.0% 0.0	0.9% 9.6	264.1	265.6
(0.9, 1.1)	2.7% 25.5	1.4% 17.1	0.5% 8.0	0.1% 2.4	0.0% 0.0	0.9% 10.6	264.5	266.4
(0.8, 1.2)	2.7% 23.6	1.4% 17.2	0.5% 8.1	0.1% 3.6	0.0% 0.0	0.9% 10.5	264.4	266.1
(0.7, 1.3)	2.6% 26.2	1.4% 16.0	0.6% 9.1	0.1% 3.6	0.0% 0.0	0.9% 11.0	263.7	265.8
(0.6, 1.4)	2.6% 25.3	1.3% 17.8	0.6% 8.1	0.1% 3.6	0.0% 0.0	0.9% 11.0	264.5	266.6
(0.5, 1.5)	2.5% 25.4	1.3% 20.2	0.6% 9.1	0.2% 2.4	0.0% 0.0	0.9% 11.4	263.8	265.9
Average	2.6% 24.9	1.4% 18.9	0.6% 8.2	0.1% 2.4	0.0% 0.9	0.9% 11.1	264.2	266.1

Table 8.: Impact of parcel arrival fluctuations on the relative efficiency of the ADP approach and relative deviation reduction, under varying values of anticipation (ε)

Table 8. illustrates through the average column on the right, that the uncertainty has no significant impact on the relative efficiency of the ADP approach compared to the stationary configuration. Furthermore, we note that the relative deviation reduction is greater as uncertainty increases, with 11.4% less deviation distance when $f = \mathcal{U} \sim (0.5,1.5)$ and 9.6% in the stationary scenario. Finally, in the last two columns, we see that the delivery rate remains constant across all scenarios, with the myopic approach slightly outperforming ADP in terms of average number of parcels delivered.

These results can be explained by the modelling assumption in the structure of the ADP approach; parcels sharing the same characteristics (o_l, d_l, θ_l) are considered by the algorithm to be a single parcel deliverable by a crowdshipper. As a result, fluctuations (modulated by the factor f) in parcel arrivals have little influence, as they do not affect the number of assignment decisions the algorithm has to make.

6. Conclusion

The objective of this master's thesis is to explore the impact of anticipating crowdshipper availability (ε) on the efficiency of the approximate dynamic programming (ADP) approach. This algorithm is applied to a peer-to-peer crowdshipping system, characterised by heterogeneity of crowdshipper journeys and uncertainty linked to the fact that there are no restrictions on origins and destinations. Our work is based on the model developed by Innocente and Tancrez (2025), on which we analyse the impact of anticipating the availability of crowdshippers, modelled through the parameter ε, which represents the number of periods between the announcement of the availability of crowdshippers and their actual journeys, on the performance of the ADP approach. Two approaches are compared: the myopic approach, which makes assignment decisions based solely on known and accurate information, and the ADP approach, which makes assignment decisions by comparing the contribution of assigning a parcel now with the contribution of postponing the assignment into the future, based on the estimated future value of the parcel.

Our experimental results in Section 5. show that anticipating the availability of crowdshippers tends to reduce the relative efficiency of the ADP approach compared to the myopic approach. Indeed, as explain in Section 5.2., the ADP approach loses its comparative advantage as the parameter ε increases, until the behaviour of both approaches is similar when $\varepsilon = \delta$. We note that this loss of relative efficiency is accentuated when the system initially has large optimisation possibilities; a large delivery window (see Figure 3.), a high number of parcel arrivals (see Figure 4.), a high crowdshippers-to-parcel arrivals ratio (see Figure 5.) as well as a cost structure that makes crowdshipping delivery attractive (see Table 6.). From an operational point of view, our results show that the myopic approach manages to deliver more parcels than the ADP approach (see Figure 6.), but this is coupled with more deviation distances (see Table 7.).

Finally, our results are limited to a sample of configurations. Although this is sufficient to show the general trends associated with each model parameter, this thesis could be extended by considering a broader set of configurations. There are a number of interesting directions for future research, in particular concerning the last analysis in Section 5.5. which, by challenging some constraining assumptions of the model, such as aggregation by parcel type, would make it possible to analyse in detail the potential impact of fluctuations on the relative efficiency of the ADP approach in the presence of anticipation (ε).

7. References

Ackva, C., and Ulmer, M.-W. (2023). Consistent routing for local same-day delivery via micro-hubs. *OR Spectr.* 46, 375-409.
https://doi.org/10.1007/s00291-023-00735-x

Alnaggar, A., Gzara, F., and Bookbinder, J. H. (2021). Crowdsourced delivery: A review of platforms and academic literature. *Omega*, 98:102139.
https://doi.org/10.1016/j.omega.2019.102139

Archetti, C., Savelsbergh, M., and Speranza, M. G. (2016). The Vehicle Routing Problem with Occasional Drivers. *European Journal of Operational Research*, 254(2):472–480.
https://doi.org/10.1016/j.ejor.2016.03.049

Archetti, C., Guerriero, F., and Macrina, G. (2021). The online vehicle routing problem with occasional drivers. *Computers and Operations Research*, 127:105144
https://doi.org/10.1016/j.cor.2020.105144

Arslan, A. M., Agatz, N., Kroon, L., and Zuidwijk, R. (2019). Crowdsourced Delivery - A Dynamic Pickup and Delivery Problem with Ad Hoc Drivers. *Transportation Science*, 53(1):222–235.
https://doi.org/10.1287/trsc.2017.0803

Behrend, M., Meisel, F., Fagerholt, K., and Andersson, H. (2019). An exact solution method for the capacitated item-sharing and crowdshipping problem. *European Journal of Operational Research,* 279, p. 589 - 604.
https://doi.org/10.1016/j.ejor.2019.05.026

Behrend, M., Meisel, F., Fagerholt, K., and Andersson, H. (2021). A multi-period analysis of the integrated item-sharing and crowdshipping problem. *European Journal of Operational Research* 292, p. 483 - 499.
https://doi.org/10.1016/j.ejor.2020.10.034

Boschma, R., Mes, M. R.-K., and de Vries, L.-R. (2023). Approximate dynamic programming for container stacking. *European Journal of Operational Research,* 310, p. 328-342.

https://doi.org/10.1016/j.ejor.2023.02.034

Boysen, N., Fedtke, S., and Schwerdfeger, S. (2021). Last-mile delivery concepts: a survey from an operational research perspective. *OR Spectr*. 43, 1-58. https://doi.org/10.1007/s00291-020-00607-8

Boysen, N., Emde, S., and Schwerdfeger, S. (2022). Crowdshipping by employees of distribution centers: Optimization approaches for matching supply and demand. *European Journal of Operational Research*, 296(2), 539-556. https://doi.org/10.1016/j.ejor.2021.04.002

Cheng, S., Chen, C., Pan, S., Huang, H., Zhang, W., and Feng, Y. (2022). Citywide package deliveries via crowdshipping: minimizing the efforts from crowdsourcers. *Frontiers of Computer Science*, 16(5):165327. https://doi.org/10.1007/s11704-021-0568-5

Crainic, T.-G., Ricciardi, N., and Storchi, G. (2009) Models for Evaluating and Planning City Logistics Systems. *Transportation Science* 43(4):432-454. https://doi.org/10.1287/trsc.1090.0279

Dahle, L., Andersson, H., and Christiansen, M. (2017). The Vehicle Routing Problem with Dynamic Occasional Drivers. *Computational Logistics*, pages 49–63. https://doi.org/10.1007/978-3-319-68496-3_4

Dahle, L., Andersson, H., Christiansen, M., and Speranza, M. G. (2019). The pickup and delivery problem with time windows and occasional drivers. Computers & Operations Research, 109:122–133. https://doi.org/10.1016/j.cor.2019.04.023

Dayarian, I., and Savelsbergh, M. (2020). Crowdshipping and Same-day Delivery: Employing in-store customers to deliver online orders. *Production and Operations Management*, 29(9), p. 2153-2174. https://doi.org/10.1111/poms.13219

Dayarian, I., and Pazour, J. (2022). Crowdsourced order-fulfilment policies using in-store customers. *Production and Operations Management*, 31(11):4075–4094. https://doi.org/10.1111/poms.13805

Goyal, A., Zhang, Y., and Benjaafar, S. (2024). Crowdsourcing Last-Mile Delivery with Hybrid Fleets Under Uncertainties of Demand and Driver Supply: Optimizing Profitability and Service Level. Publisher: SSRN. https://ssrn.com/abstract=4322670

Hou, S., and Wang, C. (2021). Matching Models for Crowd-Shipping Considering Shipper's Acceptance Uncertainty. *In 2021 IEEE International Conference on Autonomous Systems (ICAS)*, Montreal, QC, Canada, 2021, pages 1–6. 10.1109/ICAS49788.2021.9551114

Innocente, E., and Tancrez, J.-S. (2025). Efficient Assignment in Peer-to-Peer Crowdshipping: An Approximate Dynamic Programming Approach. Unpublished yet.

Le, T. V., Stathopoulos, A., Van Woensel, T., and Ukkusuri, S. V. (2019). Supply, demand, operations, and management of crowd-shipping services: A review and empirical evidence. *Transportation Research Part C: Emerging Technologies*, 103:83–103. https://doi.org/10.1016/j.trc.2019.03.023

Lebedev, D., Margellos, K., and Goulart, P. (2020). Approximate dynamic programming for delivery time slot pricing: A sensitivity analysis. Publisher: arXiv.

https://doi.org/10.48550/arXiv.2008.00780

Li, Y., Archetti, C., and Ljubic, I. (2024). Emerging Optimization Problems for Distribution in Same-day Delivery. Publisher: arXiv.

Macrina, G., Pugliese, L., Guerriero, F., and Lagana, D. (2017). The Vehicle Routing Problem with Occasional Drivers and Time Windows. *Optimization and Decision Science: Methodologies and Applications*, pages 577–587 https://api.semanticscholar.org/CorpusID:67696531

Macrina, G., Pugliese, L., and Guerriero, F. (2020a). A Variable Neighbourhood Search for the Vehicle Routing Problem with Occasional Drivers and Time Windows. *In the 9th International Conference on Operations Research and Enterprise Systems*, pages 270–277, Valletta, Malta. SCITEPRESS - Science and Technology Publications.
10.5220/0009193302700277

Macrina, G., Pugliese, L., Guerriero, F., and Laporte, G. (2020b). Crowd-shipping with time windows and transshipment nodes. *Computers & Operations Research*, 113:104806.
https://doi.org/10.1016/j.cor.2019.104806

Mehmann, J., Frehe, V., and Teuteberg, F. (2015). Crowd logistics: A literature review and maturity model. *Innovations and strategies for logistics and supply chains: Technologies, business models and risk management,* p. 117 - 45.
https://hdl.handle.net/10419/209253

Mladenow, A., Bauer, C., and Strauss, C. (2016). Crowdsourcing in Logistics: Concepts and Applications Using the Social Crowd. *In the 17th International Conference on Information Integration and Web-based Applications & Services (iiWAS2015)*. Publisher: ACM
10.1145/2837185.2837242

Mohri, S.-S., Ghaderi, H., Nassir, N., and Thompson, R.-G. (2023). Crowdshipping for sustainable urban logistics: A systematic review of the literature. *Transportation Research Part E: Logistics and Transportation Review*, 178: 103289.
https://doi.org/10.1016/j.tre.2023.103289

Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., and Lenz, B. (2014). The Impact of E-commerce on Final Deliveries: Alternative Parcel Delivery Services in France and Germany. *Transportation Research Procedia*, 4, 178–190.
https://doi.org/10.1016/j.trpro.2014.11.014

Mousavi, K., Bodur, M., Cevik, M., and Roorda, M.-J. (2021). Approximate Dynamic Programming for Crowd-shipping with In-store. Publisher: arXiv.

Mousavi, K., Bodur, M., and Roorda, M. J. (2022). Stochastic Last-Mile Delivery with Crowd-Shipping and Mobile Depots. *Transportation Science*, 56(3):612–630 https://doi.org/10.1287/trsc.2021.1088

Mousavi, K., Bodur, M., Cevik, M., and Roorda, M.-J. (2024). Approximate dynamic programming for pickup and delivery problem with crowd-shipping. *Transportation Research B: Methodological*, 187:103027. https://doi.org/10.1016/j.trb.2024.103027

Pourrahmani, E., and Jaller, M. (2021). Crowdshipping in last mile deliveries: Operational challenges and research opportunities. *Socio-Economic Planning Sciences*, 78:101063. https://doi.org/10.1016/j.seps.2021.101063

W.-B. Powell (2007). Approximate Dynamic Programming: Solving the curses of dimensionality. *Wiley Series in Probability and Statistics*, vol. 703. https://doi.org/10.1002/9781118029176

Powell, W.-B. (2011). Approximate Dynamic Programming: Solving the Curses of Dimensionality (2nd ed.). *Wiley Series in Probability and Statistics*. 10.1002/9781118029176

Powell, W.-B. (2019). A unified framework for stochastic optimization. *European Journal of Operational Research*, 275(3), 795–821. https://doi.org/10.1016/j.ejor.2018.07.014

Powell, W.-B., Simão H.-P., and Bouzaiene-Ayari, B. (2012). Approximate dynamic programming in transportation and logistics; a unified framework. *Euro Journal on Transportation and Logistics*, 1(3), 237-284. https://doi.org/10.1007/s13676-012-0015-8

Pugliese, L., Guerriero, F., Macrina, G., and Scalzo, E. (2021). Crowd-Shipping and Occasional Depots in the Last Mile Delivery, *Optimization and Decision Science*: ODS, Virtual Conference, November 19, 2020, pages 213–225.
https://doi.org/10.1007/978-3-030-86841-3_18

Pugliese, L., Ferone, D., Festa, P., Guerriero, F., and Macrina, G. (2022). Solution approaches for the vehicle routing problem with occasional drivers and time windows. *Optimization Methods and Software*.
10.1080/10556788.2021.2022142

Pugliese, L., Ferone, D., Festa, P., Guerriero, F., and Macrina, G. (2023). Combining variable neighbourhood search and machine learning to solve the vehicle routing problem with crowd-shipping. *Optimization Letters*, 17(9):1981–2003.
https://api.semanticscholar.org/CorpusID:264557279

Raviv, T., and Tenzer, E. Z. (2018). Crowd-shipping of small parcels in a physical internet.
10.13140/RG.2.2.32169.08809

Şardağ, A., Kizil, K.-U., and Yildiz, B. (2024). Crowdshipping problem with dynamic compensations and transshipments. *Transportation Research Part C,* 166: 104796.
https://doi.org/10.1016/j.trc.2024.104796

Savelsbergh, M., and Ulmer, M.W. (2024) Challenges and opportunities in crowdsourced delivery planning and operations—an update. *Ann Oper Res* 343, 639–661.
https://doi.org/10.1007/s10479-024-06249-1

Savelsbergh, M., and Van Woensel, T. (2016). 50th Anniversary Invited Article—City Logistics: Challenges and Opportunities. *Transportation Science*, 50(2), 579–590.
https://doi.org/10.1287/trsc.2016.0675

Sawik, B. (2024). Optimizing Last-Mile Delivery: A Multi-Criteria Approach with Automated Smart Lockers, Capillary Distribution and Crowdshipping. *Logistics*, 8, 52.
https://doi.org/10.3390/logistics8020052

Skålnes, J., Dahle, L., Andersson, H., Christiansen, M., and Hvattum, L. M. (2020). The Multistage Stochastic Vehicle Routing Problem with Dynamic Occasional Drivers. *Computational Logistics*, pages 261–276.
https://doi.org/10.1007/978-3-030-59747-4_17

Simão, H. P., Day, J., George, A. P., Gifford, T., Nienow, J., and Powell, W. B. (2009). An Approximate Dynamic Programming Algorithm for Large-Scale Fleet Management: A Case Application. *Transportation Science*, 43(2), 178–197.
http://www.jstor.org/stable/25769444

Soto Setzke, D., Pflugler, C., Schreieck, M., Fröhlich, S., Wiesche, M., and Krcmar, H. (2017). Matching Drivers and Transportation Requests in Crowdsourced Delivery Systems. *In Twenty-third Americas Conference on Information Systems*, Boston, 2017.

Spivey, M.-Z., and Powell, W.-B. (2004). The Dynamic Assignment Problem. *Transportation Science*, 38(4):399–419.
https://doi.org/10.1287/trsc.1030.0073

Statista (2024a). Global e-commerce share of retail sales 2027.

Stoia, S., Lagana, D., and Ohlmann, J.-W. (2024). Dynamic Pickup-and-Delivery for Collaborative Platforms with Time-Dependent Travel and Crowdshipping. Publisher: arXiv.

Sun, L., Sun, Y., and Zheng, W. (2018). The Stochastic and Dynamic Vehicle Routing Problem with Crowdshipping. *CICTP 2017: Transportation Reform and Change-Equity, Inclusiveness, Sharing, and Innovation.* Publisher: ASCE Library.
10.1061/9780784480915.159

Tao, Y., Zhuo, H., and Lai, X. (2023). The pickup and delivery problem with multiple depots and dynamic occasional drivers in crowdshipping delivery. *Computers & Industrial Engineering*, 182:109440.
https://doi.org/10.1016/j.cie.2023.109440

Topaloglu, H., and Powell, W.-B. (2006). Dynamic-Programming Approximations for Stochastic Time-Staged Integer Multicommodity-Flow Problems. *INFORMS Journal on Computing*, 18(1):31-42.
https://doi.org/10.1287/ijoc.1040.0079

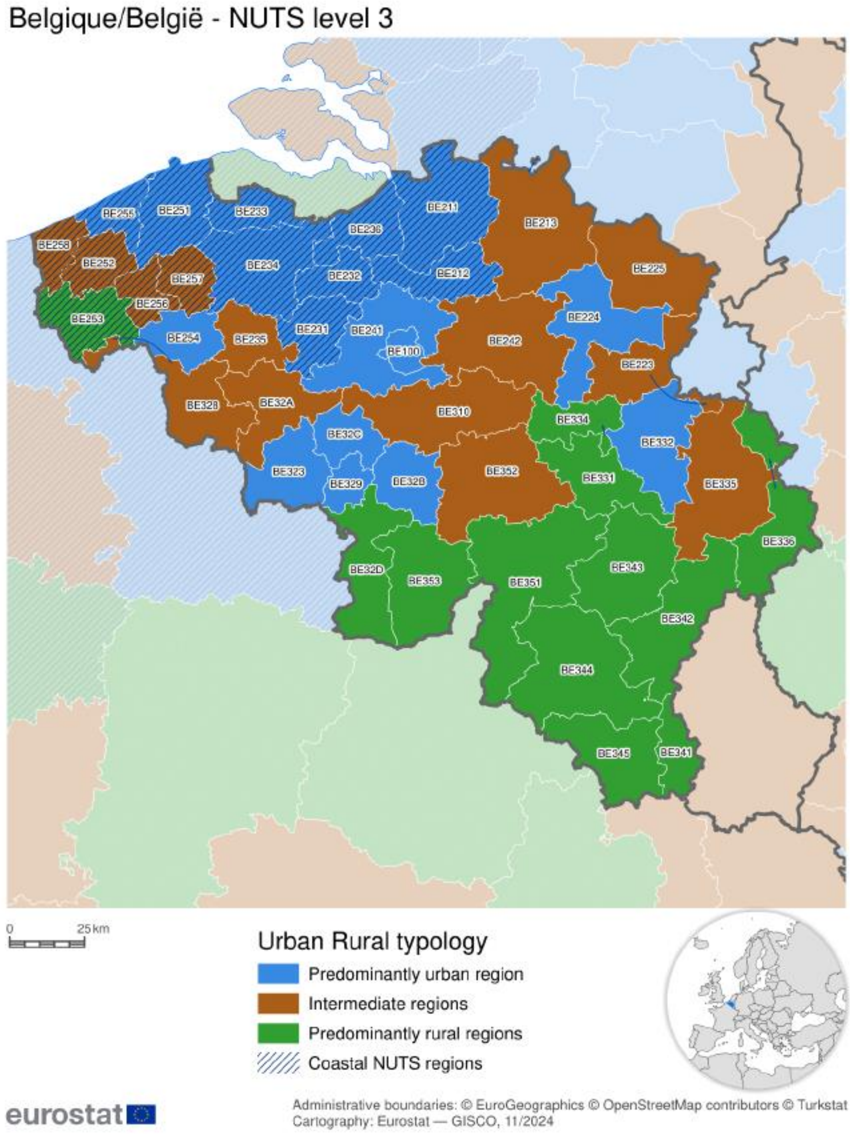
Yildiz, B. (2021a). Express package routing problem with occasional couriers. *Transportation Research Part C: Emerging Technologies*, 123:102994.
https://doi.org/10.1016/j.trc.2021.102994

Yildiz, B. (2021b). Package routing problem with registered couriers and stochastic demand. *Transportation Research Part E: Logistics and Transportation Review*, 147:102248.
https://doi.org/10.1016/j.tre.2021.102248

Yu, V. F., Jodiawan, P., and Redi, A. A. N. P. (2022). Crowd-shipping problem with time windows, transshipment nodes, and delivery options. *Transportation Research Part E: Logistics and Transportation Review*, 157:102545.
https://doi.org/10.1016/j.tre.2021.102545

8. Appendices

8.1. Appendix 1: Belgium NUTS3 regions



UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Chaussée de Binche 151, 7000 Mons, Belgique | **www.uclouvain.be/lsm**