

Louvain School of Management

Assessing the benefits of more complex commitment strategies in dynamic assignment in the context of crowdsourced deliveries

Mathematical formulation and computational experiments

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Abstract

Crowdsourcing has the potential to reduce the negative side effects – whether environmental or economic or even related to the quality of the service – of freight transport but requires fast decision making as drivers are available for a short time to fulfill a task. Besides, the stochasticity and dynamics in this assignment problem requires assignment decisions to be taken before the availability of future resources and/or tasks gets known. Efficient optimization techniques are thus needed to provide optimal solutions with a short computation time. We therefore develop a dynamic matching algorithm along with a commitment strategy in order to capture real-time changes in the system. In this master thesis, we aim at demonstrating the value of implementing more complex commitment strategies since Agatz et al. (2011) suggest that using sophisticated optimization methods instead of simple greedy matching rules can substantially improve the performance of the system. Yet, existing papers are limited to implementing rather simplistic strategies. Instead of simply deciding to confirm the first match found with the risk of missing a better solution in the future or waiting until the last minute with the risk of losing an already good solution, we tackle these risks by evaluating the detour we can expect in the future using a probability distribution. This provides an objective criterion allowing to know with more certainty what the future holds in terms of detour and upon which to decide if it is reasonable to confirm tentative matches to drivers at time t or if, on the contrary, it is interesting to wait because we can expect a better solution in the remaining delivery time. The results appear to be conclusive as this strategy leads to a reduction between 13,88 and 43,88% of the detour to deliver a package via crowdshipping as well as of the cost of crowdshipping between 8,97 and 28,56%, compared to the four main strategies in the existing literature, which confirms the assumption by Agatz et al. (2011). It also appears in the results that the commitment strategy designed in this master thesis provide better results than any other strategy of the existing literature, whatever the values of the parameters of the model.

Key words: Crowdshipping; Dynamic assignment; Commitment strategy

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Table of contents

Abstract	- 2 -
Acknowledgment	- 3 -
List of Tables.....	- 5 -
List of Figures	- 6 -
List of Appendices	- 7 -
1. Introduction.....	- 8 -
2. Literature review.....	- 12 -
3. Problem Setting.....	- 16 -
4. Solution procedure	- 18 -
5. Computational Experiments.....	- 24 -
5.1 Experimental Setting	- 24 -
5.2 Potential benefits of using more complex commitment strategies	- 25 -
5.3 Impact of variations in the parameters	- 30 -
6. Conclusion	- 34 -
7. References.....	- 36 -
8. Appendices.....	- 38 -

List of Tables

Table 1 – Algorithm solving the dynamic setting.....	20
Table 2 – Detour, cost of crowdshipping, proportion of crowdshipped parcels, number of parcels per optimization run, time needed to commit with the Late-Late, Early-Early, Late-Early, Early-Late strategies, relatively to the commitment strategy presented in this master thesis.....	27
Table 3 – Average detour over all settings of each experiment with the Late-Late, Early-Early, Late-Early, Early-Late strategies, relatively to the commitment strategy presented in this master thesis.....	30

List of Figures

Figure 1 – Distribution of detours from the empirical data used in this master thesis.....	23
Figure 2 – Graphic layout of the packages and drivers' journeys.....	24
Figure 3 – Impact of the relative cost of crowdshipping on the detour for the Late-Late, Early-Early, Late-Early, Early-Late strategies and the strategy implemented in this master thesis.....	27
Figure 4 – Impact of the maximum detour allowed on the detour for the Late-Late, Early-Early, Late-Early, Early-Late strategies and the strategy implemented in this master thesis.....	28
Figure 5 – Impact of the proportion of parcels to drivers on the detour for the Late-Late, Early-Early, Late-Early, Early-Late strategies and the strategy implemented in this master thesis.....	29
Figure 6 – Impact of relative cost of crowdshipping on the proportion of parcels crowdshipped and the unit cost of crowdshipping.....	31
Figure 7 – Impact of the maximum detour allowed on the proportion of parcels crowdshipped, the detour and the traditional delivery distance.....	32
Figure 8 – Impact of relative cost of crowdshipping on the proportion of parcels crowdshipped and the detour.....	33

List of Appendices

Appendix 1 – Summary of the existing models presented in this literature review and contribution of the model of this master thesis.....	38
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1. Introduction

In addition to being 95% oil dependent and consuming half of the oil produced worldwide, the transport sector induces 20% of global anthropogenic climate warming emissions (European Commission, 2020). More specifically, freight transport and service trips – although accounting for roughly one fifth of urban traffic – contribute much more to its negative side-effects than passenger related transport. Rai et al. (2018) classify these adverse effects in 3 categories: social (physical consequences of pollutant emissions on public health), environmental (pollutant emissions and the use of non-renewable natural resources) and economic (congestion, wear-and-tear of road infrastructure and decreasing city accessibility). In particular, the last mile delivery is the most expensive part of the freight transportation chain, alone representing up to 28% of the total delivery cost (Wang et al., 2016) and 40% of the used energy and generated emissions (Pourrahmani and Jaller, 2021). Parcel and express deliveries being among the fastest-growing sectors in urban transport due to the rise of e-commerce urges to find an alternative to current practices.

At the same time, information technologies are transforming passive consumers into active actors in services (Paloheimo et al., 2016). Anticipating and integrating these new technologies in the shipping industry makes the emergence of new delivery modes possible, enabling to improve the performance and decrease the negative impacts of goods delivery. These innovations range from delivery by ground drones or e-scooters to vehicle automation, pick-up boxes or crowd logistics. Nonetheless, for each of these Information and Communication Technologies related innovations, a wide range of operational, business, legal and behavioral problems have yet to be tackled (Punel and Stathopoulos, 2017).

One such innovative solution is crowdshipping, which is part of a broader change taking place in today's society – referred to as the “sharing economy” – in which physical assets become services. This trend allows consumers to enhance the use of resources through the redistribution, sharing and reuse of excess capacity in goods and services. Technology makes the sharing of assets both cheaper and easier, enabling to implement it on a larger scale. This is particularly convenient for expensive assets that are underused by their owners – such as cars – allowing them to make money out of these (Archetti et al., 2016).

In the case of crowdshipping, the use of excess capacity in vehicles to deliver goods is key. Crowdshipping consists in getting ordinary people rather than delivery companies (e.g. UPS or FedEx) to deliver packages along the way of an existing vehicle trip – ideally with as little detour as possible (Paloheimo et al., 2016) – in exchange for monetary rewards (Allahviranloo

and Baghestani, 2019). This practice only requires a platform enabling to connect drivers with customers (Macrina et al., 2020). Variations of crowdshipping can also make use of the spare capacity of buses (Trentini et al., 2015) or taxis (Li et al., 2014) to deliver parcels across the city.

Although a majority of crowdshipping start-ups have appeared in the United States (e.g. Postmates, Deliv, Roadie, Kaargo, UberRush), crowdshipping platforms are spread globally with some in Australia (e.g. PostRope, PPost), Colombia (e.g. Rappi), Nigeria (e.g. Max), China (e.g. Renren Kuaidi) and in Europe (e.g. Nimber in the UK and Norway, Trunkrs in the Netherlands, PiggyBaggy in Finland) or even across countries, e.g. Parcelio or Quincus (Punel and Stathopoulos, 2017). Crowdshipping can be launched as much by established firms, e.g. retailers like Amazon, Walmart, Google, eBay and logistics firms like DHL, Deliv or Instacart as by independent companies (Allahviranloo and Baghestani, 2019). However, despite the strong market interest, only a small part of all crowdshipping companies succeed in establishing a business viable on the long-term by attracting and maintaining users. The above highlights the critical role that behavior and acceptance plays in the viability, efficiency and maturing of crowdshipping delivery concepts (Punel and Stathopoulos, 2017).

The benefits of crowdshipping can take various forms depending on the stakeholders. For senders, advantages range from added value features such as tracking, transparency or flexibility since, while traditional deliveries are fixed and planned in advance, fast delivery is a key factor for crowdshipping (Macrina et al., 2020) to lower operating costs (Punel and Stathopoulos, 2017). Crowdshipping indeed allows to remove the need for any significant infrastructure such as warehouses, vehicle fleets and their maintenance, fuel costs and employed drivers – the compensation offered being often inferior to an employed drivers' salary (Macrina et al., 2020) – which enables low overhead costs and gives the opportunity to scale relatively fast when demand evolves. Taking the perspective of the parcel receivers, the latter expect faster, more personalized and cost efficient delivery services, which crowd logistics could offer (Rai et al., 2018). As potential carriers are concerned, crowdshipping enables them to add an income to their commute (Punel and Stathopoulos, 2017). Nevertheless, these benefits depend largely on the existence of a sufficiently large and dense local crowd network and can be considerable in particular for companies with a weak bargaining power towards traditional parcel delivery companies or that cannot afford to implement an own delivery network (Rai et al., 2018). From a broader societal perspective, crowdshipping has the potential to reduce the vehicle activity required for parcel deliveries – thus cutting their traffic- and energy-footprints (Punel and Stathopoulos, 2017) – such as a reduction in polluting emissions, energy

consumption, noise and traffic congestion (Macrina et al., 2020). However, the impact on sustainability depends on several factors, including the crowd's modal choice, the consolidation of parcels and above all whether deliveries are made along the way of an existing trip, resulting in a minimal detour, thus maximizing the reduction in natural resource use. In practice, this means that although the environmental impact of goods transportation by means of crowdsourced deliveries is validated, further research should still address potential environmental risk factors (Rai et al., 2018).

While freight transportation via truck, rail or container ships remains the most cost-effective means of transportation for the line-haul – partly because of the economies of load consolidation – it is much less efficient for the last stage of the supply chain where items are delivered to their final destination (Wang et al., 2016). Leveraging the advantages of crowdshipping in the last-mile delivery and of truck delivery in the line-haul is therefore likely to enhance global delivery efficiency compared to pure-truck delivery (Kafle et al., 2017).

At the same time, many challenges have come up with the rise of crowdshipping. Carriers are typically occasional and therefore non-professional drivers, which can lead to issues of liability, trust and reputation. Besides, fostering acceptability of new delivery modes can appear challenging (Punel and Stathopoulos, 2017). Then, crowdshipping can also be seen as a threat for Logistics Service Providers owing to a potential significant reduction of their business volume as numerous start-ups are creating business models based on a low cost structure and the power of community (Rai et al., 2018).

Crowdshipping requires fast decision making as drivers are available for a short time to fulfill a task. Besides, the stochasticity and dynamics in this assignment problem requires assignment decisions to be taken before the availability of future resources and/or tasks gets known. Efficient optimization techniques are thus needed to provide optimal solutions with a short computation time. We therefore develop a dynamic matching algorithm along with a commitment strategy in order to capture real-time changes in the system. The commitment strategy aims at confirming tentative matches proposed by the assignment model at each iteration by balancing the quality of the current solution with the probability of finding a better solution in the future, making the model non-myopic.

In this master thesis, we aim at demonstrating the value of implementing more complex commitment strategies when assigning parcels to drivers in the context of crowdshipped deliveries since Agatz et al. (2011) suggest that using sophisticated optimization methods instead of simple greedy matching rules can substantially improve the performance of the

system. We therefore establish a commitment strategy that aims at taking into account the uncertain nature of future driver arrivals in an attempt to improve system performance.

The remainder of the paper is structured as follows. In the next section, we review the related literature and position the contribution of this master thesis. The problem setting is presented in Section 3 while Section 4 describes the solution procedure with the proposed dynamic assignment model and commitment strategy. In Section 5, we discuss the experimental results. Finally, we end this master thesis in Section 6 with a conclusion summarizing the main results and proposing ideas for future research.

2. Literature review

Crowdshipping is receiving more and more interest in academia even though its study remains challenging due to the novelty, lack of operational uniformity and data (Punel and Stathopoulos, 2017). This literature review discusses existing literature on dynamic assignment models as well as on models seeking to match tasks to resources in contexts more or less similar to that of this master thesis. This section also reviews the various types of commitment strategies implemented in the existing literature.

The issue of dynamically assigning resources to tasks over time, called dynamic assignment problem, comes up in numerous applications in transportation. In the field of freight transportation in particular, fleets of vehicles are managed with orders arriving continuously over time. The arrival of customer demands is commonly assumed to be random – known only through a probability distribution – over time, but it may also be the case for vehicles. Assignment decisions thus have to be taken before the availability of future resources and/or tasks gets known. In their paper, Spivey and Powell (2004) put forward several features particularly relevant in the context of this master thesis. The authors address the dynamic assignment problem where a resource can serve only one task at a time. They propose an adaptive, nonmyopic algorithm that iteratively solves sequences of assignment problems no larger than what would be required of a myopic¹ model, which appears to outperform standard myopic models, widely used in practice.

The models presented in the following aim at matching tasks to resources in contexts more or less similar to that of this master thesis. The characteristics highlighted in each of these allow to draw a distinction between them as well as to position the contribution of this master thesis and are summarized in *Appendix 1*.

While in Arslan et al. (2018), ad hoc drivers can deliver multiple parcels along a journey – therefore requiring to take heed of the route sequence, making the problem more challenging – Archetti et al. (2016) only enable a single parcel to be assigned to each vehicle. In their paper, Arslan et al. (2018) formulate the problem in a dynamic version heuristically solved using a rolling horizon, which means that the static matching model is solved each time new information becomes available (exact solution approach). The authors assess the possible benefit of crowdshipping under various assumptions about the behavior of the ad hoc drivers

¹ Myopic models ignore any forecasts of the future based on currently available data, using only the information available at the time the decision is made. However, this process appears to be suboptimal since even an experienced dispatcher would hold a driver for a better load later despite an acceptable assignment now.

and the results suggest that the last mile is more cost-efficient with vehicle-mile savings up to 37% compared to a traditional delivery system. In their paper, Archetti et al. (2016) include the use of occasional drivers in the study of the vehicle routing problem, also known as Vehicle Routing Problem with Occasional Drivers (VRPOD) in the setting of a same-day Last-Mile Delivery. In their static problem setting without time windows, the model is based on an integer programming formulation for the VRPOD. They then develop a multi-start heuristic combining tabu search and Variable Neighborhood Search. They conclude that while it is possible to achieve substantial cost savings if there are large numbers of drivers available with a large amount of flexibility, the results depend heavily on the compensation offered. However, setting up the appropriate and cost-effective compensation plan is one of the key implementation challenges related to crowdshipping. Similarly, Agatz et al. (2011) designed a ridesharing model based on the minimization of the total system-wide vehicle miles incurred by occasional drivers as well as their individual travel costs. Seeing that, in this instance, each driver can be assigned with one delivery task to the maximum, the problem can be modelled as a bipartite matching problem. The bipartite graph is solved with a binary integer problem using a rolling horizon model – to deal with real-time updates – where the confirmation of matches is delayed for a given time period, and a greedy model where matches are confirmed immediately as found without waiting for further potential better solutions. The simulation results show that using sophisticated optimization methods instead of simple greedy matching rules can substantially improve the performance of ridesharing systems but also that the success of ridesharing is heavily dependent on a sufficient number of users.

Although the model introduced by Arslan et al. (2018) is less restrictive than the ones presented by Archetti et al. (2016) and Agatz et al. (2011) with respect to the possibility to make multiple deliveries along a same journey, these models ensure that each parcel is delivered by at most one driver (no transfer of parcels between drivers). In their respective papers, Chen et al. (2017) and Allahviranloo and Baghestani (2019) put forward the possibility for parcels to be delivered by more than one occasional driver, making modeling more complex. In this case, transfers between drivers need to be time synchronized : e.g., occasional drivers are required to meet at a specific location and at a specific time. The resulting Multi-Driver Multi-Parcel Matching Problem (MDMPMP) is defined as follows: the problem of assigning parcels to drivers and defining the transfer point in order to minimize the total cost. A static version of the problem is formulated by Chen et al. (2017) as an Integer Linear Programming model which incorporates drivers' maximum detour and capacity limits. The authors suggest two heuristics to solve the problem due to the high computational complexity. Their study concludes that crowdshipping

can be an economic viable and sustainable solution depending on the spatial characteristics of the network and drivers' schedules and that the added benefits increase with an increasing number of participating drivers and parcels.

Both Macrina et al. (2017) and Gdowska et al. (2018) build on the VRPOD model introduced by Archetti et al. (2016). Macrina et al. (2017) innovate by introducing time windows constraints for both occasional drivers and customers as well as multiple deliveries and the split delivery policy² for occasional drivers. After testing and comparing their models with the one proposed by Archetti et al. (2016), they are able to show the benefits of enabling multiple deliveries and using the split delivery policy. In turn, Gdowska et al. (2018) consider that drivers have the freedom to refuse an assignment (agent-oriented approach), using probability to define each occasional driver's willingness to accept the delivery to a specific final customer (stochastic perspective of the problem). Gdowska et al. (2018) also study the occasional drivers' willingness to accept or refuse a delivery assigned to them as well as the impact of the occasional driver's decision on the total delivery cost. This study highlights and substantiates the need for a new methodology to calculate suitable compensation fees for occasional drivers – taking into consideration the dynamics associated with the delivery process (dynamic compensation mechanism) – which could be used for controlling a LMD system by actively encouraging occasional drivers to accept a task. Similarly, some systems such as that presented by Kleiner et al. (2011), are adaptive to each participant's individual preferences, giving freedom to users to deviate from the optimal solution. Comparably, Ghoseiri et al. (2011) propose a Dynamic Rideshare Matching Optimization model but enable drivers to pick up multiple passengers and passengers to be transported by multiple drivers as well as take into account the preferences of each of the actors in the system. The objective is to maximize the total number of assignments in a given planning horizon as well as to identify the feasible routes to be driven by the drivers. Passengers are assigned to drivers with respect to proximity in time (waiting time to pick-up) and space (detour distance for vehicles and relocation distance for passenger) and compatibility of characteristics and preferences (age, gender, smoke, pet restrictions, number of connections and maximum number of people sharing a ride) among the passengers, drivers and passengers onboard.

To the best of my knowledge, existing papers are limited to implementing latest-commit strategies that commit tentative matches as late as possible and/or earliest-commit strategies which immediately commit tentative matches as soon as one is found. Two hybrid strategies

² A split shipment is when a single order containing multiple products is sent in separate shipments.

are also sometimes considered, as in Arslan et al. (2018), in which the authors commit early the matches that involve an ad hoc driver but as late as possible matches that involve a dedicated vehicle and conversely. Although latest-commit strategies allow for decisions that are based on most up-to-date information, consumers and crowdshippers are notified on short notice whether their demand can be met or their crowdshipping service is required, which leads to poorer platform service quality. This also means that the problems solved in the optimization runs in the rolling horizon are likely to be larger (highest numbers of tasks per optimization run) than for any other strategy, with the earliest-commit strategy having the lowest number of tasks. The latter allows to minimize the waiting time for the drivers and the lead time for the tasks but may not be the best strategy in terms of the total system performance. Still according to Arslan et al. (2018), it appears that it is worse to immediately commit to a dedicated vehicle match than to a match with an ad hoc driver. However, these strategies fail to take into account other criteria that may also be of importance. Indeed, Agatz et al. (2011) suggest that using sophisticated optimization methods instead of simple greedy matching rules can substantially improve the performance of the system.

This master thesis makes its contribution in this respect by demonstrating the added value of implementing a more complex commitment strategy – considering the expected detour over the remaining delivery time as an objective criterion to make decisions regarding commitment – in the context of crowdsourced deliveries. The proposed commitment strategy thus takes into account the uncertain nature of future driver arrivals. Contrary to many papers on the topic, this master thesis relies on real data obtained from a Belgian crowdshipping company.

3. Problem Setting

This section presents the setting and features of the dynamic assignment problem seeking to match delivery tasks with drivers while minimizing the total delivery cost.

In a crowd-based service platform, workers – in this case drivers – can decide when and how often to work, meaning the platform can only indirectly control the supply of workers. One way to control supply, which is used in this master thesis, is to make use of a professional fleet – which can belong either to the retailer or to another company such as any classical Logistics Service Providers – to take up tasks for which the use of crowdshipping is neither feasible nor efficient.

This assignment problem considers that drivers and parcels dynamically and randomly arrive once a day and that their arrival processes are independent of each other. We also assume that there are finite numbers of possible resources (drivers) and tasks (parcels) available. This dynamic setting is solved using a rolling horizon approach where the static assignment model is solved once a day (discrete time modelling) based on the current information available. Yet, this problem is non-myopic as it takes into account the probability of finding better assignments for parcels in the future and, as a result, makes it possible not to definitively commit an assignment at time t but to postpone it.

Capacity is assumed non-binding for both occasional drivers and the professional fleet. This seems to be a reasonable assumption, as according to Amazon, 86% of its packages are under five pounds and small enough to be shipped even by a drone, which should therefore pose no capacity issue to fit in the trunk of a regular car. To accommodate a setting in which larger objects need to be transported, an additional constraint on the volume could easily be introduced. It is also assumed that the professional fleet is homogeneous and big enough to serve all the deliveries which cannot be crowdshipped.

We also make the assumption that an occasional driver can only deliver a single parcel along its journey while a parcel cannot be transported by more than one occasional driver (no transfers of parcels between drivers).

Regarding pricing, many business models have been implemented by crowdshipping companies, as presented by Pourrahmani and Jaller (2021): hourly or per time block, fixed per task with possible incremental charges or negotiation and bidding. We assume a pricing scheme consisting of a fixed charge per delivery with an incremental cost per kilometer. This is to compensate for the service of drivers who make little or no detour to make the delivery in order

to guarantee a minimum remuneration. We also include the possibility for the cost per kilometer of crowdshipping not to be identical to that of traditional delivery.

We also make the hypothesis of a maximum authorized detour, suggesting that drivers would not accept to make a detour of more than a certain percent of their initial journey to deliver a parcel. The detours superior to this distance will thus not be taken into account.

We also consider a maximum delivery time, at the end of which the package must imperatively be delivered, either by crowdshipping or by a traditional delivery company in case crowdshipping is neither possible nor efficient.

4. Solution procedure

The dynamic nature of this assignment problem with drivers and parcels entering the system every day is solved using a rolling horizon approach, which consists in solving the following static assignment model at each iteration with the information available.

Sets and indexes :

- $z \in P$: set of parcels;
- $a \in OD$: set of occasional drivers;
- TAP_t : parcels part of the input to the model at time t ;
- $TAOD_t$: occasional drivers part of input to the model at time t ;

Parameters :

- α : relative cost (per km) of crowdshipping to traditional delivery;
- FF : fixed charge (in kms) per delivery by crowdshipping;
- β : maximum percentage of a driver's journey allowed as a detour;
- $DIST_z$: delivery distance (in kms) for parcel z ;
- $ODDIST_a$: journey distance (in kms) for driver a ;
- $DDATE_z$: number of days left to deliver parcel z ;
- DET_{az} : detour (in kms) from driver a 's original journey to deliver parcel z ;
- $ODDATE_a$: number of days left until occasional driver a undertakes its journey;

Decision variables :

- x_{az} : = 1 if occasional driver a is assigned to parcel z , 0 otherwise;
- y_z : = 1 if parcel z is assigned to the professional fleet, 0 otherwise;

$$\min \sum_{z \in P} DIST_z * y_z + \alpha * \sum_{a \in OD} \sum_{z \in P} (DET_{az} + FF) * x_{az} \quad (1)$$

Subject to:

$$\sum_{a \in OD} x_{az} + y_z = 1 \quad \forall z \in TAP_t \quad (2)$$

$$DDATE_z \geq ODDATE_a * x_{az} \quad \forall a \in OD, z \in P \quad (3)$$

$$\sum_{z \in P} x_{az} \leq 1 \quad \forall a \in TAOD_t \quad (4)$$

$$DET_{az} * x_{az} \leq \beta * ODDIST_a \quad \forall a \in OD, z \in P \quad (5)$$

$$x_{az} \in \{0,1\} \quad \forall a \in OD, z \in P \quad (6)$$

$$y_z \in \{0,1\} \quad \forall z \in P \quad (7)$$

The objective (1) is to minimize the total delivery cost, meaning the sum of traditional delivery cost and compensation for drivers' traveling cost consisting of a fixed charge per delivery with incremental cost per kilometer. Constraint (2) ensures that every parcel known and not yet committed is assigned to either the professional fleet or at maximum to one driver (preventing transfers between drivers). Constraint (3) makes sure a parcel will be assigned to a driver only if its journey takes place sometime during the delivery period. Constraint (4) allows for each driver to deliver at most one parcel. Constraint (5) prevents a driver from taking a detour of more than $\beta\%$ of his journey to deliver a package. Constraints (6) and (7) define variables x_{az} and y_z as binary.

This static assignment model will be solved once a day with the information available at that moment. This implies that, at each iteration, parcels and drivers that will be part of the input to the model must be updated. The model assigns each known and available parcel to either a known and available driver or to the professional fleet once a day. Parcels and drivers are considered known at time t if they have arrived in the system before time t and available at time t if the maximum delivery date for the parcel or the date the journey is set to take place have not been reached yet at time t and if they haven't been already definitively committed before time t . Parcels and occasional drivers that are definitively committed thus won't be part of the input to the model in $t+1$ while the ones that are not will. The commitment strategy therefore plays an important role in this. The following algorithm thus enables to update this information, allowing to solve this dynamic setting.

Notation :

$t \in (1..T)$: time in days;

E_{zi} : detour expectation when there are i days left to deliver parcel z ;

$SOLX_{az}$: = 1 if occasional driver a has been definitively committed to parcel z ,
 0 otherwise;
 $SOLY_z$: = 1 if parcel z has been definitively committed to the professional fleet,
 0 otherwise;
 AP_t : set of definitively committed parcels at time t ;
 KP_t : set of known parcels at time t ;
 AOD_t : set of definitively committed occasional drivers at time t ;
 KOD_t : set of known occasional drivers at time t ;

```

forall  $t$  in  $1..T$  do
  Add  $z$  and  $a$  entering the system to  $KP_t$  and  $KOD_t$ 
   $TAP_t = KP_t - AP_t$ ,  $TAOD_t = KOD_t - AOD_t$ 
  Solve LP (1) – (6)
  forall  $z$  in  $TAP_t$  do
    if  $DDATE_z = 1$  then
      Update  $SOLX_{az}$  and  $SOLY_z$  with the solution of the LP
      Add  $a$  and  $z$  to  $AP_t$  and  $AOD_t$ 
    else
      forall  $a$  in  $TAOD_t$  do
        if  $x_{az} = 1$  then
          Compute  $E_{zi}$ 
          if  $DET_{az} \leq E_{zi}$  then
            Update  $SOLX_{az}$  with the solution of the LP
            Add  $a$  and  $z$  to  $AP_t$  and  $AOD_t$ 
          end if
        end if
      end do
    end if
  end do
  forall  $a$  in  $TAOD_t$  do
    if  $ODDATE_a = 1$  then
      Add  $a$  to  $AOD_t$ 
    end if
  end do
  if  $z$  in  $TAP_t$  and  $DDATE_z \neq 1$  then
     $DDATE_z - 1$ 
  end if
  if  $a$  in  $TAOD_t$  and  $ODDATE_a \neq 1$  then
     $ODDATE_a - 1$ 
  end if
end-do

```

Table 1 – Algorithm solving the dynamic setting.

At each iteration, drivers and parcels entering the system are added to the sets of known parcels and drivers – KP_t and KOD_t . Sets of parcels and drivers to assign at time t – TAP_t and $TAOD_t$ – are then computed as the difference between known parcels and drivers – KP_t and KOD_t –

and already committed ones – AP_t and AOD_t . Based on this information, the static assignment model is solved. However, this solution remains only temporary and still needs to be confirmed or not based on the commitment strategy implemented. Committed parcels and drivers are then added to sets of already committed packages and drivers – AP_t and AOD_t . Data is then updated for the next iteration by decreasing by one day the remaining delivery time – $DDATE_z$ – and time before a journey takes place – $ODDATE_a$ – as well as by adding drivers whose journey has taken place to the set of committed drivers – AOD_t – and then proceed to the next iteration.

The strategy for confirming the tentative matches thus plays a key role in this dynamic assignment problem. Agatz et al. (2011) suggest that using sophisticated optimization methods instead of simple greedy matching rules can substantially improve the performance of the system. Yet, existing papers are limited to implementing rather simplistic strategies : latest-commit strategies (Late-Late), early-commit strategies (Early-Early), strategies that commit early the matches that involve an ad hoc driver but as late as possible matches that involve a dedicated vehicle (Early-Late) and conversely (Late-Early). Therefore, this master thesis makes its contribution by proposing a commitment strategy that aims at taking into account the uncertain nature of future driver arrivals. The strategy implemented in this master thesis differs from those implemented in the existing literature by its complexity since the strategies in the literature only take into account the delivery time by confirming directly or by waiting until the last moment.

Based on the assumption of uniformity of detours, we compute the expectation of the detour over the remaining days to deliver the package and only confirm a tentative match to a driver if the detour at time t is less than what can be expected in the remaining delivery time. Therefore, instead of simply deciding to confirm the first match found with the risk of missing a better solution in the future or waiting until the last minute with the risk of losing an already good solution, we tackle these risks by evaluating the detour we can expect in the future. This provides an objective criterion allowing to know with more certainty what the future holds in terms of detour and upon which to decide if it is reasonable to confirm tentative matches to drivers at time t or if, on the contrary, it is interesting to wait because we can expect a better solution in the remaining delivery time. Concerning tentative matches to the professional fleet, they are committed as late as possible in order to give the best chance to find a match to a driver in the future as the goal remains to use crowdshipping as much as possible when proven efficient.

In more detail, as far as tentative matches to drivers are concerned, when there are several days left to deliver a parcel – i days – we use the expectation of the detour to deliver parcel z when there are $i-1$ days left to complete the delivery (E_{zi-1}) as a decision criterion to commit or not at time t : we commit a tentative match to a driver at time t if the resulting detour is smaller than the expectation E_{zi-1} of the detour in the remaining delivery time ($i-1$ days).

If there are $i > 1$ days left to deliver, we commit if:

$$DET_{az} \leq E_{zi-1}$$

E_{zi} is the expectation of the detour to deliver parcel z when there are i days left to complete the delivery and is computed recursively based on the uniformity distribution as follows:

$$E_{zi} = p_{zi} * \left(\frac{a + E_{zi-1}}{2} \right) + (1 - p_{zi}) * E_{zi-1}$$

a stands for the minimum detour and is assumed equal to 0 since this is what we observe in the 5 data sets.

p_{zi} is the probability to assign parcel z to today's driver when there are i days left to deliver and is computed recursively as follows:

$$p_{zi} = p_{zi-1} - \frac{1}{2} * (p_{zi-1})^2$$

with $p_{z1} = 1$ since if there is only one day left to deliver, we will automatically confirm so the probability to confirm is equal to 1.

The limitation of this approach lies with the uniform distribution assumption which is relatively strong: indeed, as many new drivers are available each day, the detour to be considered would be the shortest one, which would naturally bias the distribution towards higher probabilities for low values, which is confirmed on *Figure 1* showing the distribution of the detours from the empirical data used in this master thesis. With the current tactic, we are therefore probably pessimistic about the length of detours.

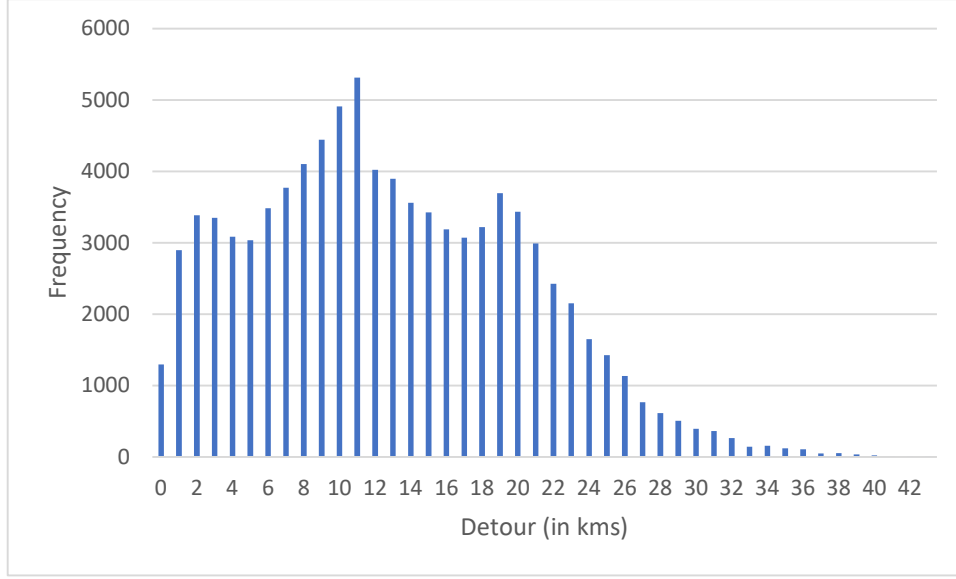


Figure 1 – Distribution of detours from the empirical data used in this master thesis.

When there is one day left to deliver, we commit a tentative match to a driver if it is a better option than traditional delivery, setting upper limit of the detours.

If there is one day left to deliver, we commit if:

$$DET_{az} \leq \min\{\beta * ODDIST_a, (1/\alpha * DIST_z) - FF\}$$

A parcel won't be crowdshipped if it costs more than delivery by the professional fleet. Given that the cost of crowdshipping consists of a part proportional to the detour and of a fixed charge (FF) and that the unit cost (per km) of delivery by crowdshipping is not identical to that of traditional delivery (α), by looking at the objective function, we deduce that drivers whose detour is higher than $1/\alpha * (DIST_z - FF)$ are not economically viable compared to traditional delivery. Also, constraint (5) states that a detour cannot be greater than $\beta\%$ of the driver's initial trip ($ODDIST_a$), meaning that a parcel won't be assigned to a driver whose detour is greater than $\beta * ODDIST_a$. Seeing that when there is one day left to deliver, we commit a tentative match to a driver if it is a better option than traditional delivery, we commit when the detour is inferior to the most binding of those two elements.

5. Computational Experiments

The experiments performed in this section aim at confirming the hypothesis by Agatz et al. (2011) that using more sophisticated optimization methods can improve the performance of the system. The goal is therefore to assess the impact of using the commitment strategy implemented in this master thesis in comparison to the four main strategies implemented in the existing literature, namely latest-commit strategies (Late-Late), early-commit strategies (Early-Early), strategies that commit early the matches that involve a driver but as late as possible matches that involve a dedicated vehicle (Early-Late) and conversely (Late-Early). The goal is also to analyze the impact of the different parameters of this problem on the solution.

5.1 Experimental Setting

The instances used in the experiments are based on data from the Belgian crowdshipping company *Hytchers*. From the weekly transportation request (parcels) and supply (journeys from drivers), we build 5 different data sets, each with 50 parcels to be delivered and 100 drivers. Delivery and journey distances are computed using Google Maps (actual route distance). The average delivery distance of a parcel is 47,41 kms and the average journey of a driver is 52,03 kms. Unlike many existing studies on crowdshipping that focus mainly on deliveries within congested urban areas, this master thesis considers deliveries between and among cities, as shown in *Figure 2*. The spatial characteristics of the network are of significance since, according to Chen et al. (2017), they affect the economic and sustainable viability of crowdshipping.

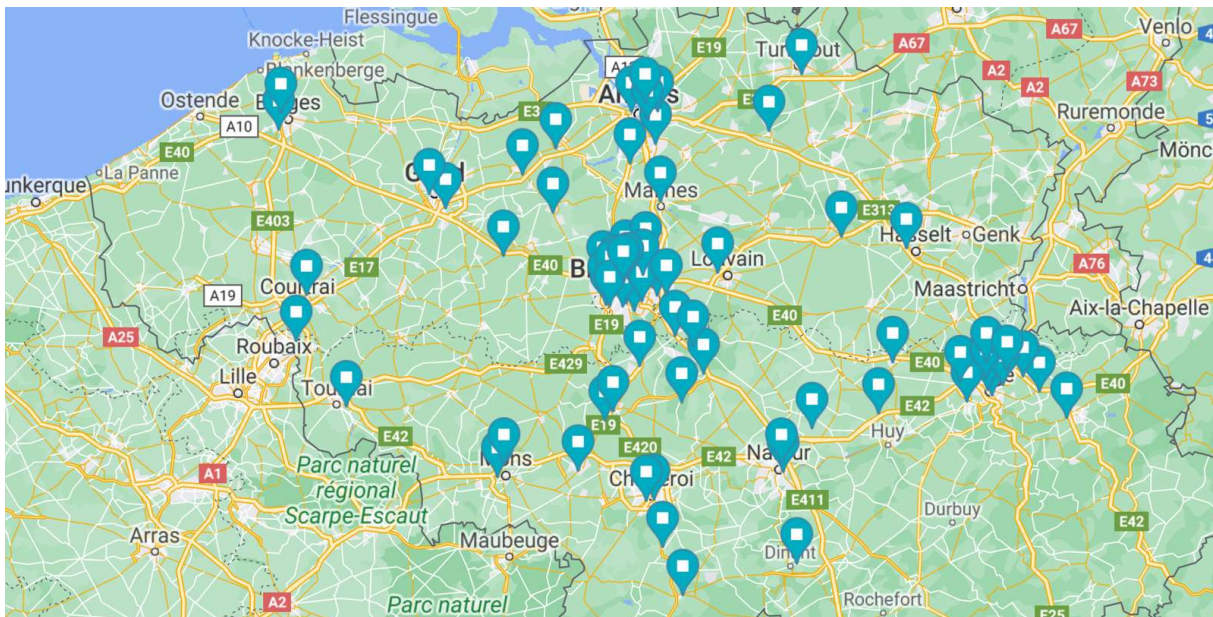


Figure 2 – Graphic layout of packages to deliver.

All 5 models have been implemented in Mosel using the MILP solver of Xpress IVE. All computations are conducted on an Intel Core processor running at 3.2 GHz with 8 GB of RAM.

The computational time per instance is not limited since an optimality gap of 0% is reached in 0,1 sec.

5.2 Potential benefits of using more complex commitment strategies

In this subsection, we discuss the results of the first set of experiments, solving the 5 data sets with the 5 models (one for each commitment strategy) to assess the impact of using a more sophisticated commitment strategy.

The initial setting considers identical cost per kilometer for delivery by crowdshipping and by a professional delivery company ($\alpha = 1$), maximum authorized detour (β) equivalent to 50% of the driver's original trip and fixed delivery charge (FF) equivalent to the cost of 10 kms of extra detour.

The strategy implemented in this master thesis allows 21,6% of parcels to be crowdshipped, with a detour per parcel of 15,74kms (costing 25,64€ on average). On average, there are 14,12 parcels per optimization run and it takes 3,09 days to commit a parcel. *Table 2* gives the average results, relatively to the commitment strategy presented in this master thesis. In the first column are presented the four strategies existing in the literature according to when tentative matches to drivers and to the professional fleet are committed: late referring to a latest-commit strategy, meaning a commitment as late as possible while early to an earliest-commit that immediately commit a tentative matches as soon as one is found. In the second column, we can observe that all four strategies give detours between 13,88 and 43,88% higher than the strategy implemented in this master thesis. This is because matches with drivers will only be confirmed if we do not expect to find a better solution in the remaining days to deliver, unlike other strategies that either wait until the last minute with the risk of missing an already good solution or that confirm immediately with the risk in this case of missing a better solution in the days to come. As for the cost of crowdshipping (column 3), all four strategies give a cost between 8,97 and 28,56% higher than the strategy implemented in this master thesis (yet the benefit is lower than for detours due to the fixed charge per delivery, meaning the cost is not entirely proportional of the detour travelled). This strategy also leads to a greater proportion of crowdshipped parcels than in the Late-Late (-31,48%) and the Late-Early (-42,59%) strategies since both strategies commit tentative matches to drivers as late as possible (thus risking to lose matches to drivers) yet smaller than in the Early-Early (+20,37%) and the Early-Late (+33,33%) strategies that commit as soon that a match to a driver is found (thus securing matches to drivers), as observed in column 4. The drawback of this strategy lies in the larger number of parcels per optimization run (columns 5) as well as a longer time needed to commit a tentative match (column 6) compared to the Early-Early (-49,40% and -67,62%), Late-Early (-37,53% and -48,83%) and

Early-Late (-12,18% and -13,86%) strategies. This can be explained by the fact that we commit as late as possible tentative matches to the professional fleet and commit a tentative match to a driver only if the detour is smaller than what we can expect in the future, meaning parcels remain longer in the system thus requiring more time to commit except for the Late-Late strategy that commit tentative matches to both a driver and the professional fleet as late as possible.

Table 2 also enables to draw a comparison between the four strategies existing in the literature. Regarding detours (column 2), we observe that confirming at the earliest both matches to drivers and to the professional fleet performs the best (+13,88%) right after the strategy of this master thesis while committing at the latest, the worst (+43,88%) and that it is better to confirm matches to the professional fleet late than early (+34,58%) while matches to drivers early than late (+17,54%). These conclusions are in line with the conclusions drawn by Arslan et al. (2018) stating that it is worse to immediately commit to a dedicated vehicle match than to a match with an ad hoc driver. The conclusion is similar when it comes to the cost of crowdshipping as it is partially proportional to the detour, except for the fixed charge per delivery by crowdshipping, as seen in column 3. Regarding the proportion of packages crowdshipped as illustrated in column 4, the strategy giving the best result is to confirm the parcels to drivers early (+33,33%) and then the full early strategy (+20,37%) – both strategies performing better than the one implemented in this master thesis – followed by the full late strategy (-31,48%) and finally the strategy of confirming matches drivers late (-42,59%). Whether we consider the number of parcels per optimization run (column 5) or the time needed to commit (column 6), the conclusion remains the same: the strategy giving the best result is the full early strategy (-49,40% and -67,62%), then the strategy of confirming matches to drivers at the latest (-37,53% and -48,83%) – both giving better results than the strategy implemented in this master thesis – followed by the strategy of confirming them at the earliest (-12,18% and -13,86%) and finally the full late strategy (+10,29% and +10,10%). These conclusions are in line with the conclusions drawn by Arslan et al. (2018) stating that the latest-commit strategy has the highest numbers of tasks per optimization run, with the earliest-commit strategy having the lowest.

Commit occasional driver, professional fleet	Detour	Cost of crowdshipping	Proportion of crowdshipped parcels	Number of parcels per optimization run	Time to commit
Late-Late	+43,88%	+28,56%	-31,48%	+10,29%	+10,10%
Early-Early	+13,88%	+8,97%	+20,37%	-49,40%	-67,62%
Late-Early	+34,58%	+23,81%	-42,59%	-37,53%	-48,83%
Early-Late	+17,54%	+10,87%	+33,33%	-12,18%	-13,86%

Table 2 – Detour, cost of crowdshipping, proportion of crowdshipped parcels, number of parcels per optimization run, time needed to commit with the Late-Late, Early-Early, Late-Early, Early-Late strategies, relatively to the commitment strategy presented in this master thesis.

In the ideal case of perfect information where all the information about parcels to deliver and drivers' journeys is entirely known in advance before launching the model – the information does not arrive dynamically and randomly, requiring no rolling horizon as we launch the model only once with all the information – the proportion of crowdsourced parcels is larger (+37,04%) while the distance (-4,08%) and the cost of traditional delivery (-4,09%) are reduced although this further increases the detour (+14,10%) and the cost of crowdshipping (+9,12%).

In each case, the strategy implemented in this master thesis appears to be robust: whatever the variation of the parameter, the detour (and resulting cost of crowdshipping) remains lower than in all the other strategies, as illustrated in *Figures 3, 4 and 5*.

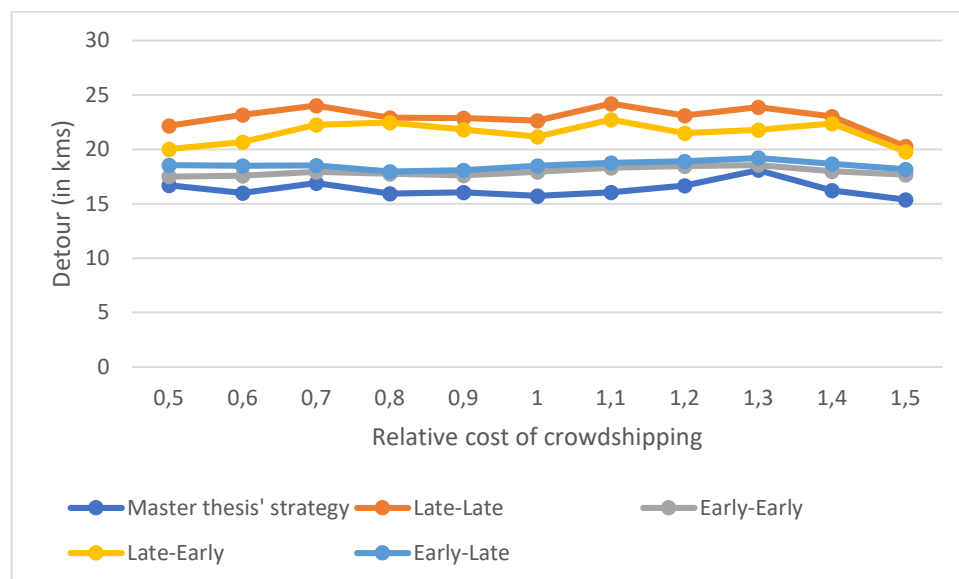


Figure 3 – Impact of the relative cost of crowdshipping on the detour for the Late-Late, Early-Early, Late-Early, Early-Late strategies and the strategy implemented in this master thesis.

When considering the variation of the detour as a function of the relative cost of crowdshipping (α) as illustrated in *Figure 3*, we observe that the strategies consisting of confirming tentative matches to drivers at the latest – the Late-Late and Late-Early strategies – vary in the same way and give very similar results. The same holds for the Early-Early and Early-Late strategies, committing tentative matches to drivers early. The Late-Late and Late-Early strategies perform worse, for any variation of the relative cost of crowdshipping (α), than the Early-Early and Early-Late strategies, suggesting that committing tentative matches to drivers early performs better than at the latest, the strategy implemented in this master thesis giving nevertheless always better results, whatever the variation of this parameter.

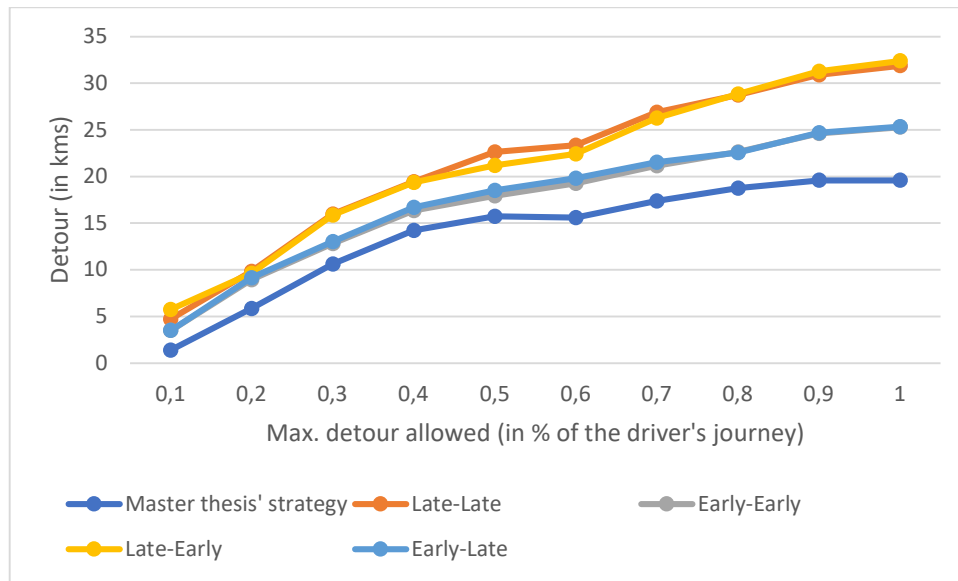


Figure 4 – Impact of the maximum detour allowed on the detour for the Late-Late, Early-Early, Late-Early, Early-Late strategies and the strategy implemented in this master thesis.

The more the constraint of the maximum authorized detour (β) is relaxed, the more the five different strategies differentiate from each other and the greater the contribution of the method developed in this master thesis, as shown in *Figure 4*. Similarly to the previous case (see *Figure 3*), strategies committing tentative matches to drivers at the latest (e.g. the Late-Late and Late-Early strategies) vary in the same way and give similar results, and the same is true for strategies confirming matches to drivers early (the Early-Early and Early-Late strategies). Likewise, the Late-Late and Late-Early strategies perform worse, for any variation of the maximum detour allowed (β), than the Early-Early and Early-Late strategies, suggesting that committing tentative matches to drivers early performs better than at the latest, the strategy implemented in this master thesis giving nevertheless always better results, whatever the variation of the maximum detour allowed (β). *Figure 4* suggest graphically that varying the maximum detour allowed (β) has more impact on the detour than varying the two other parameters – α , the

relative cost of crowdshipping (see *Figure 3*) and the proportion of parcels to drivers (see *Figure 5*) – where the detour remains more stable.

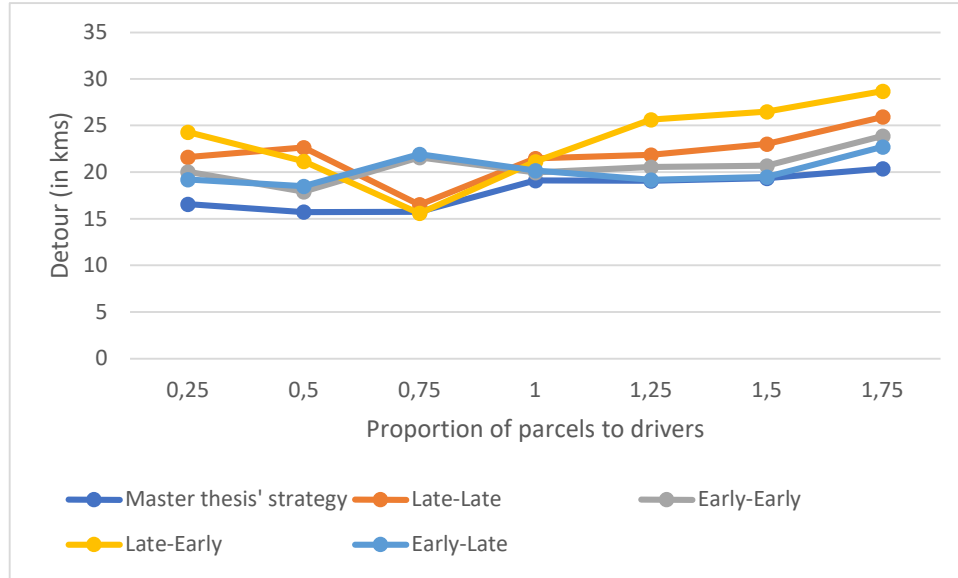


Figure 5 – Impact of the proportion of parcels to drivers on the detour for the Late-Late, Early-Early, Late-Early, Early-Late strategies and the strategy implemented in this master thesis.

Regarding to proportion of parcels in relation to drivers, *Figure 5* shows that when reaching a ratio of 3 parcels for 4 drivers, the benefit of the strategy of this master thesis is diminished. At this point, we also observe a change in trends: while the Late-Late and Late-Early strategies give worse results than the Early-Early and Early-Late strategies (similarly to the two previous cases, see *Figures 3* and *4*), they perform better at this point and even give similar results as the strategy implemented in this master thesis. As in the two previous cases (see *Figures 3* and *4*), the Late-Late and Late-Early strategies vary in the same way and give similar results and the conclusion is identical for Early-Early and Early-Late strategies.

From these results, we can conclude that the goal of this master thesis is reached. We have indeed succeeded in proving that more sophisticated assignment rules – a more complex commitment strategy in this case – allows to improve the performance of the system and obtain better results, and this whatever the value of the parameters of the model. The previous results, by showing that the commitment strategy of this master thesis allows the cut both the detour and the resulting cost of crowdshipping, therefore confirm previous assumptions by Agatz et al. (2011).

Table 3 shows the detour – expressed relatively to the strategy implemented in this paper – on average over all values for each parameter. Compared to the results presented in the second column of *Table 2* – which correspond to the results of the initial setting – *Table 3* confirms the

conclusions drawn graphically: the strategy implemented in this master thesis enables to cut the detour travelled by drivers to crowdship parcels compared to all other strategies, whatever the values of the parameters. When considering the detour on average over all values of the maximum detour (β) allowed (column 4), the latter is increased for each of the four strategies of the existing literature compared to the initial setting (column 2), increasing the benefit of the commitment strategy implemented in this master thesis. Regarding the detour on average over all values of the relative cost of crowdshipping (α) and the proportion of parcels to drivers, results show a decrease – for each of the four strategies of the existing literature – compared to the initial situation, suggesting that the strategy of this master thesis still performs better but its benefit is diminished compared to the initial setting. *Table 3* also enables to confirm that the detour is less sensitive to variations in the relative cost of crowdshipping (α) or the proportion of parcels to drivers than to variations in the maximum detour allowed (β).

Commit occasional driver, professional fleet	Initial setting (see <i>Table 2</i>)	Variation of the relative cost of crowdshipping (α)	Variation of the maximum authorized detour (β)	Variation of the proportion of parcels to drivers
Late-Late	+43,88%	+40%	+72%	+22%
Early-Early	+13,88%	+10%	+38%	+13%
Late-Early	+34,58%	+32%	+77%	+29%
Early-Late	+17,54%	+13%	+39%	+13%

Table 3 – Average detour over all settings of each experiment with the Late-Late, Early-Early, Late-Early, Early-Late strategies, relatively to the commitment strategy presented in this master thesis.

5.3 Impact of variations in the parameters

In the second set of experiments, we study the impact of varying the relative cost of crowdshipping (α), the maximum authorized detour (β), the proportion of parcels to drivers as well as the delivery time ($DDATE_z$) on the initial solution by solving the 5 data sets with the 5 models.

Variation of the relative cost of crowdshipping (α)

Focusing on the cost of crowdshipping makes sense since the pricing of crowdshipping platforms is very varied: hourly or per time block, fixed per task with possible incremental charges or negotiation and bidding. In this master thesis, we assume a pricing scheme consisting of a fixed charge per delivery (FF) with an incremental cost per kilometer (α). Moreover the

cost per kilometer as well as the amount of the fixed charge varies enormously as presented by Pourrahmani and Jaller (2021). Setting up the appropriate and cost-effective compensation plan is one of the key implementation challenges related to crowdshipping (Archetti et al., 2016).

The impact of the relative cost of crowdshipping (α) is illustrated in *Figure 6*. An increase in the relative cost of crowdshipping (α) naturally decreases the proportion of parcels crowdshipped while increasing the cost of crowdshipping. For the reader's convenience, we normalize the results of the initial setting – where $\alpha = 1$, meaning an identical unit cost for crowdshipping and traditional delivery – to 100.

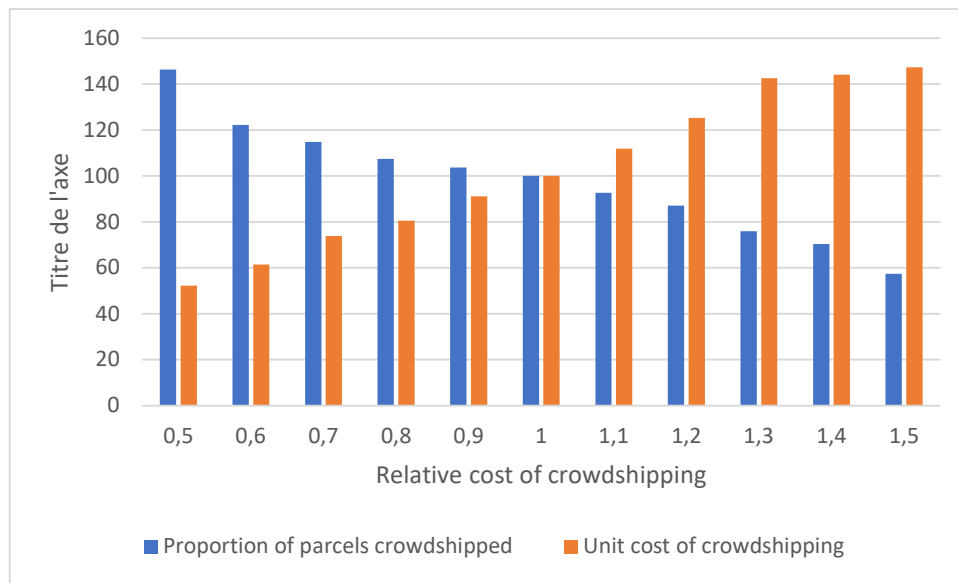


Figure 6 – Impact of relative cost of crowdshipping on the proportion of parcels crowdshipped and the unit cost of crowdshipping.

Variation of the maximum authorized detour (β)

In this master thesis, the maximum allowed detour (β) was set the same for all drivers because no data on their preferences was available and we did not include the possibility for drivers to refuse a delivery if the detour is deemed too long. However, in reality, drivers vary according to their detour flexibility (Arslan et al., 2018) and it is therefore still interesting to analyze the impact of variations in this maximum allowed detour (β).

Figure 7 illustrates the impact of the maximum detour authorized (β) on the proportion of parcels crowdshipped, the detour as well as the traditional delivery distance. As we can observe, an increase in the maximum allowed detour (β) results in increasing the proportion of parcels delivered by crowdshipping since, by allowing longer detours, we increase the number of possibilities for parcels to be delivered by crowdshipping. It also naturally increases the detour since we allow longer detours (and resulting cost of crowdshipped delivery) while decreasing

the traditional delivery distance (and cost). In contrast to the variation in the relative cost of crowdshipping (α), with respect to the proportion of packages crowdshipped and the detour, the impact of the maximum allowed detour is not linear but is steep before the growth slows down after $\beta = 0.5$ to end up stabilizing between 0.8 and 1, which tends to suggest a more logarithmic growth. Moreover, we observe that these two indicators follow a trend and give very similar results. As for the impact of the variation of the maximum authorized detour (β) on the traditional delivery distance, the decrease is more stable. For the reader's convenience, we normalize the results of the default setting – where $\beta = 0.5$, meaning the maximum detour allowed amounts to 50% of drivers' initial journeys – to 100.

Allowing drivers to travel longer detours to deliver parcels decreases the time needed to commit a tentative match as well as the number of parcels at each optimization run by up to 5% when allowing detours up to the size of drivers' journeys. This decrease is possible since, by allowing longer detours, we increase the number of possibilities for parcels to be delivered by crowdshipping, allowing to commit faster. These two indicators give very similar results.

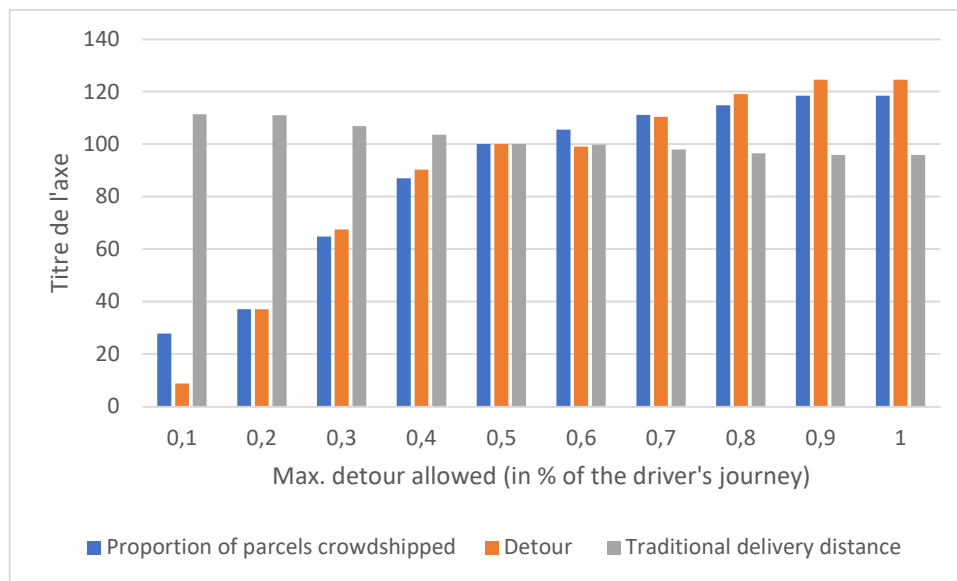


Figure 7 – Impact of the maximum detour allowed on the proportion of parcels crowdshipped, the detour and the traditional delivery distance.

Variation of the proportion of parcels to drivers

The study of the impact of the number of drivers in the platform compared to the number of parcels to deliver seems relevant since attracting and maintaining users is what makes it difficult for companies to establish a lasting business (Punel and Stathopoulos, 2017) as benefits depend largely on the existence of a sufficiently large and dense local crowd network (Rai et al., 2018).

As illustrated in *Figure 8*, when there are more parcels to deliver than drivers, the solution deteriorates: the detour to deliver a parcel by crowdshipping increases by 20%. Similarly, when

the proportion of parcels to drivers is superior to three quarters, half less parcels are delivered by crowdshipping. The impact on the number of packages crowdshipped is greater than that of the detour, yet both are non-monotonic. For the reader's convenience, we normalize the results of the initial setting – when there are 50 parcels for 100 occasional drivers, meaning a ratio of 1 to 2 – to 100.

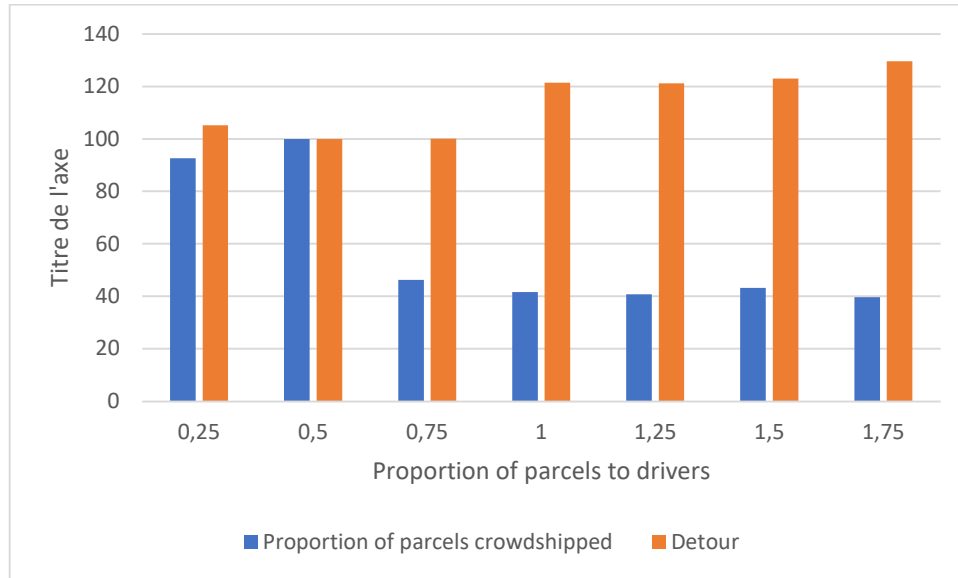


Figure 8 – Impact of relative cost of crowdshipping on the proportion of parcels crowdshipped and the detour.

Variation of the delivery time ($DDATE_z$)

We conclude these experiments by analyzing the last aspect of the problem addressed: after studying the financial aspect (pricing) via the relative cost of crowdshipping, the spatial aspect via the maximum allowed detour and the number of commuters in the system, we tackle the temporal aspect via the delivery time.

Increasing the delivery time ($DDATE_z$) does not necessarily increase the proportion of parcels crowdshipped as expected but it does allow to further reduce the detour by 2,31% if we are granted one more day to deliver a parcel and up to 10,61% if we are granted two more days as well as the cost related to crowdshipping. Nevertheless, increasing the delivery time also increases the time needed to commit a tentative match (+29,53% and +59,33% respectively) as well as the number of packages at each optimization run (+18,6% and +34,25% respectively).

6. Conclusion

Freight transportation (and in particular the Last Mile Delivery) is increasing due to the emergence and explosion of e-commerce and is proving to be highly polluting and inefficient, accounting for up to 28% of the total cost of delivery and nearly 40% of the energy used and emissions generated. There is therefore a great need to find alternatives to the current delivery methods. At the same time, Information and Communication Technologies, by transforming passive consumers into active service actors, are creating enormous opportunities for the development of new delivery modes, including crowdshipping.

Among the many operational challenges posed by crowdshipping, this master thesis makes its contribution by attempting to demonstrate the added value of implementing more complex package-to-driver commitment strategies than those implemented in the existing literature. We propose a commitment strategy that takes into account the uncertain nature of future driver arrivals, the expectation of the detour over the remaining delivery time being used as an objective criterion to decide whether to commit. The results appear to be conclusive as the strategy implemented in this master thesis leads to a reduction between 13,88 and 43,88% of the detour to deliver a package via crowdshipping as well as of the cost of crowdshipping between 8,97 and 28,56%, compared to the four main strategies in the existing literature, which confirms the assumption by Agatz et al. (2011). It also appears in the results that the commitment strategy designed in this master thesis provides better results regarding detours than any other strategy of the existing literature, whatever the values of the parameters of the model.

Varying the parameters of the model – the relative cost of crowdshipping (α), the maximum authorized detour (β), the proportion of parcels to drivers and the delivery time ($DDATE_z$) – allows to draw conclusions about how the model behaves. An increase in the relative cost of crowdshipping (α) naturally decreases the proportion of parcels crowdshipped while increasing the average cost of crowdshipping. An increase in the maximum allowed detour (β) results in increasing the proportion of parcels delivered by crowdshipping and the detour (and resulting cost of crowdshipped delivery) while decreasing the traditional delivery distance (and cost). Allowing drivers to travel longer detours to deliver parcels allows to decrease the average time needed to commit a tentative match as well as the number of parcels at each optimization run. When there are more parcels to deliver than drivers, the solution deteriorates: the detour to deliver a parcel by crowdshipping increases. Similarly, when the proportion of parcels to drivers is superior to three quarters, half less parcels are delivered by crowdshipping. Increasing the

delivery time ($DDATE_z$) allows to further reduce the detour by 2,31% if we are granted one more day to deliver a parcel and up to 10,61% if we are granted two more days as well as the cost related to crowdshipping. Nevertheless, increasing the delivery time also increases the time needed to commit a tentative match (+29,53% and +59,33% respectively) as well as the number of packages at each optimization run (+18,6% and +34,25% respectively).

This research could be extended in several directions. Implementing the service in conjunction with passenger transport, consolidating more deliveries per trip, and transshipment between couriers are among the potential strategies to effectively improve system performance and expand the service beyond just short deliveries in congested urban areas.

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8. Appendices

Appendix 1 – Summary of the existing models presented in this literature review and contribution of the model of this master thesis

	One delivery per trip	Vehicle routing decision	Dynamic/Static	Transfers between drivers	Freedom to refuse an assignment	Objective	Category	Real data	Commitment strategy
Arslan et al. (2018)	Multiple deliveries along a trip	Yes	Dynamic heuristically solved (rolling horizon)	No	No but the stop willingness of each driver is taken into account	Minimize the total cost (compensation + conventional vehicle cost)	Variant of the dynamic pickup and delivery problem	No	Latest-commit, earliest-commit, latest-commit for matches that involve a driver while earliest-commit for matches that involve a dedicated vehicle and vice versa
Archetti et al. (2016)	Yes	Yes	Static	No	Yes	Minimize the total cost (compensation + conventional vehicle cost)	Vehicle Routing Problem with Occasional Drivers (VRPOD)	No	/ (static)
Macrina et al. (2017)	Multiple deliveries along a trip	Yes	Static	Split Delivery Policy : the demand of a customer can be split between several drivers	No	Minimize the total cost (compensation + conventional vehicle cost)	VRPOD with time windows	Solo mon Instances	/ (static)
Chen et al. (2017)	Multiple deliveries along a trip	Yes	Offline problem ignoring possible future request	Yes	No	Minimize the total cost (compensation + conventional vehicle cost)	Multi-Driver Multi-Parcel Matching Problem	Solo mon's benchmark	/ (static)
Allahviranloo and Baghestani (2019)	No	No	Dynamic (non-myopic)	Yes	Yes (auction)	Maximize utility for each carrier regardless of the system status	Pickup and Delivery Problem with Time Windows	Yes	Latest-commit
Cudowski et al. (2018)	Yes	Yes	Static	No	Yes	Minimize the total cost (compensation + conventional vehicle cost)	Matching and routing problem	No	/ (static)
Agatz et al. (2011)	Yes	No	Dynamic (non-myopic)	No	No	Minimize the total system-wide vehicle miles incurred by system users, and their individual travel costs	Dynamic Ride-share Problem	Yes	Latest-commit, earliest-commit
Ghoseiri et al. (2011)	No	Yes	Dynamic (myopic)	Yes	Preferences taken into account	Maximize total number of assignments	Dynamic Rideshare Matching Optimization model	No	Identification of suitable matches
Moi	No	No	Dynamic (non-myopic)	No	No	Minimize the total delivery cost (compensation + conventional vehicle cost)	Dynamic assignment model	Yes	Based on the expectation of the detour over the remaining delivery time

