A data-driven compensation scheme for last-mile delivery with crowdsourcing

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Todas as correções determinadas pelo júri, e só essas, foram efetuadas.

O Presidente do Júri,

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Abstract (EN/PT)

A recent relevant innovation in last-mile delivery is considering the possibility of goods being delivered by couriers appointed through crowdsourcing. In this work, we focus on the setting of in-store customers delivering goods ordered by online customers on their way home. We assume that not all proposed tasks will be accepted, and use logistic regression to model the crowd agents' willingness to undertake a job. We develop a novel compensation scheme that determines reward values, based on the current professional fleet's routes and on the couriers' probabilities of acceptance, by employing a direct search method that seeks to minimize the expected cost.

Uma importante inovação em *last-mile delivery*, consiste na possibilidade de recorrer a estafetas ocasionais para efetuar o transporte de encomendas. Neste trabalho abordamos o cenário em que clientes de loja se tornam potenciais distribuidores de encomendas solicitadas por clientes online, realizando as entregas a caminho de casa. Consideramos que nem todas as propostas de entrega serão aceites, e utilizamos regressão logística para modelar a probabilidade dos estafetas ocasionais aceitarem a tarefa proposta. É desenvolvido um novo esquema de compensação que visa determinar o valor de remuneração a atribuir, baseado nas rotas da frota profissional e na probabilidade de aceitação, através da implementação de um método de procura direta que minimiza o custo esperado.

Keywords: last-mile delivery, crowdsourcing, dynamic compensation scheme, probability of acceptance, logistic regression model, direct search, optimization and machine learning.

Summary

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Abbreviations

- APL: Automated Parcel Locker
- IP: Integer Programming
- OC: Occasional Courier
- PF: Professional Fleet
- VRP: Vehicle Routing Problem
- VRPOD: Vehicle Routing Problem with Occasional Drivers

Chapter 1

Introduction

Last-mile delivery with crowdsourcing

Last-mile delivery has become a topic of great interest due to the increase of e-commerce in recent years[1], paired with the share of costs owned by the last stage of the supply chain — a value comprising up to or even exceeding 50% of the total delivery cost [22] — making it a key differentiator among large e-commerce competitors. The extra mileage induced by this growing demand, with delivery vehicles contributing between 16 and 50 percent of vehicle emissions in urban areas [9], urges for new environmentally sustainable solutions [31]. A transition from traditional logistic systems' strategies to more sophisticated ones is necessary to satisfy the current online market's increasing demand and at the same time meet sustainability requirements, which can only be achieved through innovation. One such innovation falls within the scope of the sharing economy/collaborative consumption[2], a solution that considers crowdsourcing the delivery of goods — crowdshipping — by enabling ordinary citizens to partake in the process

[1] with a total annual revenue of US$547,690M and 270.1M users as of 2019 and estimated to grow by 31% in the U.S. by the year 2023 – Figure 1.1 – (Statista Digital Market Outlook — `www.statista.com`).

[2] as defined by Hamari et al. [20], collaborative consumption is "the peer-to-peer-based activity of obtaining, giving or sharing the access to goods and services, coordinated through community-based online services"

of transportation from the hub/depot to the final destination.

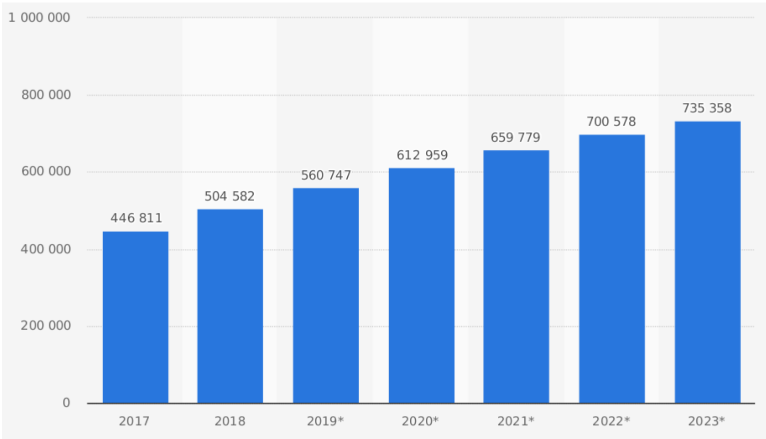

Figure 1.1: Retail e-commerce sales in the United States from 2017 to 2023, in million U.S. dollars (www.statista.com)

In this work we deal with the crowdsourcing scenario of in-store customers taking up delivery tasks on their way home to serve online customers. This endeavour promotes greater efficiency by making better use of existing urban traffic flows and consequently cutting on the work done by the company's professional fleet. As a result of less freight vehicles being used, company's costs are reduced while also benefitting society from the reduced traffic congestion. With regard to online shopping types of delivery, despite the large interest on same-day delivery, still most consumers prefer the cheapest form of home delivery, with an estimated share of 23 percent of consumers preferring same-day delivery and a share of 70 percent selecting the cheapest delivery option (Joerss et al. (2016)). Last-mile delivery with occasional drivers can answer to both market needs by providing reduced costs to the company that can potentially reflect a reduction on the cost to consumers, and by providing same-day delivery through the use of in-store customers as an immediate resource to perform deliveries.

This concept was first discussed by Walmart [5], a strategy that could potentially increase their competitiveness against Amazon by making use of their physical stores as an advantage to gather potential couriers, the in-store customers, to perform same-day delivery to online customers. However the company would later test the implementation of a different crowdsourcing delivery service, similar to the AmazonFlex, called Spark Delivery [26] that, combined with third-party crowdsourced delivery providers, utilizes independent couriers to perform deliveries by providing a platform with the ability to sign up for windows of time that better fit their schedule, order details, navigation assistance and other features, with drivers being offered a fixed value per order conducted. DHL [13] was also one of the first to discuss the idea of taking advantage of existing traffic flows of the public through crowdsourcing deliveries, by providing a service in the city of Stockholm, with a platform that allowed recipients to define the delivery conditions, including the compensation paid. Users of the platform would then decide on what deliveries to perform. The company would later launch in the U.S. a new service that helps online retailers satisfy customer demands for same- or next-day delivery called DHL Parcel Metro [14]. The service uses customised software that enables the creation of a 'virtual delivery network' of locally hired couriers along with crowdsourced couriers.

Most studies involving crowdsourced deliveries with a supporting professional fleet, address the problem as a matching and vehicle routing problem in which occasional couriers (OCs) are matched with delivery tasks and the remaining deliveries are attributed to the professional fleet (PF) after solving a capacitated vehicle routing problem. Available OCs and delivery tasks are usually assumed to be known beforehand.

In this work we base our study on the model proposed by Archetti et al. [1] for vehicle routing with occasional drivers, in which a company uses the services of OCs available to perform a single delivery, with the packages remaining being delivered by a fleet of professional drivers. The goal of that work is to determine the subset of deliveries to be outsourced for minimizing total delivery costs, which comprise costs incurred by the professional fleet and compensation fees paid to occasional couriers.

Compensations paid to OCs are a fundamental variable of the problem as they influence the costs and determine the sets of customers to be outsourced; but defining an appropriate compensation scheme proves to be a big challenge. Compensation schemes are typically defined as fixed cost per delivery, based on the PF's service cost, or based on the detour made by OCs. For a scheme based on fixed costs, determining the optimal amount is key to the success of the model, which is also true for compensation schemes based on the PF's service cost. Regarding schemes based on the detour incurred by OCs, determining the cost of serving a customer is another key issue. As stated by Archetti et al. (2016), the most adequate compensation schemes may be those based on the cost of serving customers; however, determining the service cost of customers in routing problems is considerably difficult, a challenge that increases if we consider the possibility of crowdsourcing some of the customers. Furthermore, the deterministic assumptions made by authors in crowdshipping studies, usually include considering an unlimited supply of available OCs that always accept the proposed delivery task, when in fact this availability and willingness, in a realistic scenario, should be dependent on the compensation offered. In an attempt to capture some randomness in the process of acceptance by OCs, Gdowska et al. [16] investigate a stochastic approach to the last-mile delivery with occasional drivers and professional fleet. The authors consider that not all tasks have equal probability of being accepted, and that it is likely that this probability increases with the compensation offered. They consider a probability p associated to each delivery task and develop a stochastic model by integrating it into an existing framework.

Optimization and machine learning

Although machine learning can be viewed as a subfield of optimization, given that usually the goal of classification and regression is to minimize the test error, in our work we make the distinction between machine learning and optimization methods by considering the first to act indirectly on the improvement of a given cost function whereas optimization methods usually act in a direct manner. As stated by Goodfellow et al. [18] on the distinction between machine learning and optimization, typically in machine learning problems we evaluate our model's performance on a test set by considering some performance measure P, that is optimized indirectly by minimizing another cost function $J(\theta)$ with the purpose of improving measure P. In pure optimization, however, the goal is to directly minimize the cost function J.

Machine learning can be used in combination with optimization to improve existing models. Bengio et al. [6] investigate the recent studies that address combinatorial optimization problems complemented by machine learning. The authors distinguish between two types of utility of machine learning. One that pertains to reduce computational effort by generating faster approximations through supervised decision learning, and one that pertains to learn the best performing behaviour (policy) through reinforcement learning. Heuristic optimization developments can take advantage of machine learning methods in various forms, e.g., problem size reduction through clustering [30] or principal component analysis [3], population initialisation of evolutionary algorithms with opposition-based learning [29], objective function modelling with neural networks [21], or operator adaptation through reinforcement learning [34].

Utilizing machine learning as a complement to optimization can take solutions a step further by improving existing models in their efficiency and real-world efficacy. In this work we introduce a novel compensation scheme produced at the intersection of machine learning and optimization by using the former to model consumer behaviour that will be used as input to an optimization heuristic method.

Our Contributions

The model proposed by Archetti et al. is deterministic, as it assumes that crowdshipping agents always accept a delivery task. Gdowska et al. extend that model by replacing the deterministic compensation fee with a fixed compensation value that is associated to a fixed probability of acceptance. This implies that delivery tasks are not guaranteed to be accepted by OCs. Following up on Gdowska's explorations, in this work we combine machine learning and optimization to build a model for acceptance probabilities and a compensation scheme that aims at determining an approximation of the optimal reward.

Our first contribution is to build upon the model by Gdowska et al. and introduce probabilities modeled by logistic regression, where data comes from the real-world — in our case from a questionnaire made to potential couriers for assessing their willingness to accept a delivery task in the "in-store" setting.

Our second contribution is to develop a dynamic compensation scheme taking into account the OCs willingness to engage in a delivery task. This contrasts with other schemes proposed in the literature of last-mile delivery with OCs, where compensation schemes are usually defined as a fixed cost multiplied by the courier's travel distance/time or calculated with respect to other characteristics of the delivery task (e.g. a fee per package or in proportion to the fleet's incurred cost), with delivery assignments assumed to be accepted. Dynamic pricing systems are still a recent subject under study in the crowdsourcing literature and with only a few implementations in the real world, as is the case for the Uber's pricing algorithm [19]. We propose a new dynamic compensation scheme in which a direct search algorithm is employed for finding the compensation value that minimizes the expected cost function modeled by Gdowska et al., taking acceptance probabilities as input.

Chapter 2

State-of-the-art

2.1 Probability of acceptance

Few studies have been made regarding the willingness of crowdshipping agents to accept proposed tasks. Existing literature usually deals with the courier/customer preferences regarding some service features to provide useful insights into crowdsourcing initiatives. However, literature on the study and modeling of probabilities to investigate the impact of crowdshipping on last-mile product delivery costs is still scarce. Punel et al. [28] study the factors that influence the acceptability and preferences of crowdshipping on different market contexts through a survey using stated choice scenarios, identifying determinants such as preference for unique attributes and personal and experiential factors that explain acceptance variations in crowdshipping. Several innovative features are included in the survey, such as driver expertise, rating and more consumer control over the delivery task planning. Preference results for delivery features show high value for speed, cost and reliability and also good rankings for new features such as driver reputation and tracking. Results show that the sense of community does not play such a significant role for crowdshipping attractiveness compared to the social interaction component and the novelty seeking factor.

Gatta et al. [15] study the crowdsourcing scenario of taking up delivery tasks on the metro system of Rome by using automated parcel lockers (APLs) as pick-up/drop-off points. They estimate the probability of acting as a crowdshipper as well as of adopting a crowdshipping service depending on different service configurations. Estimation is performed by means of a preference survey that identifies the most important features associated with willingness to participate, both on the demand and on the supply side. The administration of two specific surveys during October 2017 – one to 240 inhabitants of the city of Rome (demand-side survey) and the other one to 240 of its metro users (supply-side survey) – produced the data used in that study. Two multinomial logit models were developed to estimate the willingness to adopt the crowdshipping service and to act as a crowdshipper. The proposed service conditions are most influential to the studied probability. Results show that APLs location is the most important feature, ranking above remuneration. With regard to the demand side, results show that control over the delivery date and time schedule are most valuable to consumers. Preliminary results also suggest that potential crowdshipping supply in Rome surpasses the potential demand.

Marcucci et al. [25] investigate under which conditions individuals would be willing to act as crowdshippers, as well as the most attractive conditions to potential consumers of this service. With regard to crowdshippers, they investigate how much compensation is expected per delivery, how many additional stops, maximum acceptable deviation from destination and what type of transport vehicle is preferred. An inquiry was issued to 200 university students with 87 percent claiming to be willing to participate as crowdshippers, while 93 percent would participate on the demand side. For crowdshippers, the percentage drops if the package size is not small or if remuneration is less than 5€. For the demand side, the percentage drastically decreases if customers cannot contact the crowdshipping company, if there is no direct contact with the crowdshipper or if no package tracking is possible/available. Women are more likely to receive goods via crowdshipping while men are more likely to act as crowdshippers. Also, maximum additional travel distance estimation for crowdshippers averages 2.4 km. The most important aspect is remuneration with students expecting to earn between 5 and 10€ on average per delivery, a value above the average remuneration offered by existing initiatives that typically ranges between 2 and 4€. Authors hypothesize that students overestimation of the economic gain per delivery is probably linked to the short understanding of the real goal of crowdshipping. Moreover, that students do not take into account that trips are not dedicated and as a result overestimate the effort for executing the delivery.

Yildiz and Savelsbergh [33] focus on the example of on-demand meal delivery platforms to study service coverage and capacity planning problems, and analyse the effect of delivery offer acceptance-probabilities on profit. Authors analyse the case for which couriers may not accept a delivery offer, with complementing company-employed drivers servicing rejected delivery tasks, and investigate the effects of delivery offer rejections on the optimal service area. They show that as the acceptance probability decreases and the unit-time cost of drivers increases, the radius of the optimal service area decreases. Authors analyse the effect of acceptance probabilities by conducting a numerical experiment and show how profit changes for different courier offer acceptance probabilities. They also show that benefits from using professional drivers to undertake remaining tasks increases when couriers' acceptance-probability decreases and when unit revenue, i.e., unit amount charged to the restaurant by the delivery platform - increases. They also analyse the case where the delivery acceptance probability is a function of the distance from the restaurant to the drop-off location and show that the effect of delivery offer rejections becomes more pronounced when unit revenue increases and also that, when drop-off locations tend to be distant from the restaurant, distance-dependent delivery task rejection has a higher impact. Regarding the acceptance probabilities of orders that are distance dependent, authors analyse the impact of company-employed drivers on profit for three settings: 100 percent probability of acceptance, delivery acceptance without company drivers to service remaining tasks, and delivery acceptance with company drivers. They show that the benefit of company drivers available to service requests declined by OCs decreases when the delivery acceptance probability depends on the distance from the drop-off location to the restaurant.

Devari et al. [12] investigate crowdsourcing by exploiting the social networks of retail store customers. They model the probability of a product being delivered with logistic regression. Data is obtained from a survey with 101 participants from the United States and tries to analyse the minimum level of friendship required for people to accept or deliver products to their peers. The survey also analyses the monetary compensation and maximum extra time for which people are ready to participate in product delivery. They consider, with regard to the participants, the variables willingness-to-spend-extra-time, income levels, age and gender. Despite analysing expected compensation from crowdsources, authors do not include this variable in the logistic model and assume, since OCs and customers have some level of acquaintance, that: 1) no compensation is paid to OCs for each delivery task; 2) OCs always accept the delivery task at hand. They analyse the impact of crowdsourcing with social networks on last-mile product delivery costs as well as the environmental impact of diesel run delivery trucks. They show that last-mile costs can be greatly reduced by using crowdsourcing, with friends taking about an average of extra 10 minutes per delivery, and that pollutants emission reduction can be of up to 55 percent.

2.2 Compensation schemes

Regarding crowdsourcing services, to our extent of knowledge there are no studies on compensation schemes addressing the agents' probability of acceptance. A vast literature exists, but most compensation schemes remain static and unrealistic by ignoring the agents' willingness to accept proposed tasks.

Archetti et al. [1] implement a multi-start heuristic for the last-mile delivery system in a setting involving a company with a fleet of capacitated vehicles that may also use the services of occasional couriers available to make a single delivery using their own vehicle in return for a small compensation. They consider two compensation schemes. One based on the extra mileage for an OC and another based on a fixed delivery cost associated with serving a customer. The authors show that significant cost savings can be achieved for settings with a considerable number of OCs with high flexibility, while recognising the results large dependency on the compensation value. They suggest that new and innovative compensation schemes are essential to further developments on this subject.

Arslan et al. [2] explore a setting of crowdsourced deliveries that take advantage of excess capacity on urban traffic flows. They use the example of a service platform that automatically creates matchings between delivery tasks and occasional drivers, with tasks and drivers arriving dynamically throughout the day. The platform uses a supplementing fleet of dedicated vehicles to service tasks that were not matched with crowdsources. They propose a rolling horizon framework and develop an exact solution approach to solve the matching problem each time information is updated. Compensations are defined as being proportional to the cost of serving all customers without occasional drivers. The authors present examples of crowdsourcing delivery platforms that offer same-day delivery, and compare their respective compensation schemes that vary between hourly rates and per package remuneration, with hourly rates being the most popular compensation method in the United States. Their study results show that using occasional drivers potentially increases cost-efficiency and reduces vehicle miles by 37 percent, compared to traditional last-mile logistics.

Cachon et al. [8] study several contractual forms, on a service platform with self-scheduling providers, that vary in whether prices and/or wages respond to demand. They consider the following contracts: a fixed contract, defined as a fixed fee for customers and fixed reward for providers; a dynamic wage contract – fixed price for customers and dynamic compensation for providers; a dynamic price contract – dynamic price for customers and fixed reward for providers; and a commission contract that simulates Uber's surge pricing by choosing both price and wage dynamically, but with the added constraint of a fixed ratio between the two. The authors show that, for most cases, the commission contract achieves close to optimal profit, concluding that all collaborators can benefit from surge pricing.

Kafle et al. [23] consider cyclists and pedestrians as crowdsourcing agents willing to deliver parcels with a truck carrier and to carry out jobs for the last-leg and first-leg parcel delivery/pickup by submitting bids. The truck carrier problem is solved by decomposing it into two subproblems. The first one pertains to solving a winner determination problem, defined as finding the subset of combinatorial bids that maximizes revenue, while the second one is converted into a simultaneous pickup and delivery problem with soft time windows. A Tabu Search based algorithm is developed to iteratively solve the two subproblems. Compensations paid to occasional drivers are calculated as the sum of the time for traversing the route and the time for parcel transfer at the relay point, multiplied by the time value of the driver. The time value for any occasional driver is defined through competitive bidding between the drivers. The authors' results on large size instances show that total cost and total truck mileage can be greatly reduced with cyclists as crowdsources, compared to delivery without crowdsourcing. They conclude that the crowdshipping system's attractiveness depends on aspects such as penalty rate for serving customers outside the declared time windows, truck unit cost, OC time value, and OC delivery mode.

Van Cooten [32] examines the concept of using excess capacity within the crowd's traffic flows to perform deliveries, by providing an arc-based integer optimization formulation and a path-based heuristic approach to solve the routing and matching problem. The author compares two cost models where, in the first, private couriers receive a fixed fee per parcel and in the second, private couriers receive a compensation per minute of their detour, possibly in combination with a fixed price per parcel, while assuming that the costs of using a professional driver are 1.1 times higher than that of private drivers. Numerical results show that the crowdsource delivery platform is both cost-efficient and beneficial in environmental terms with the potential to save up to 14 percent points on kilometers. He also notes that the system's efficacy largely depends on the number of available OCs.

Hall et al. study the effects of Uber's surge pricing. The surge pricing algorithm works by balancing supply and demand through the assignment of a simple multiplier that determines the "surged" fare by multiplying the standard fare, which is based on the time and distance traveled. Riders receive the new price in the platform and must accept the value before a request is sent to close-by drivers. Compensations paid are defined by the allocation of a higher hourly income to drivers in order to incentivize them to work in areas and schedules of high demand. Authors use two examples to illustrate the economics of Uber's surge pricing algorithm. The first example displays the effects of successful surge pricing in action, and argues that efficiency gains come from an increase in the supply of driver partners and also from an allocation of supply to customers that value rides the most.

The second example focuses on a natural experiment caused by a surge outage on new year's eve during a period of peak demand, in which case authors verified that in the absence of surge pricing, marketplace efficiency decreased drastically. They conclude that the best evidence for the effectiveness of Uber's surge algorithm is the strong consistency of the expected wait time for a ride, a value that, regardless of demand conditions, is almost always less than 5 minutes.

Ho-Yin Mak [24] investigates the setting of in-store customers taking up delivery tasks to serve online customers, and its potential impact on the retailers operational and marketing strategies. The author considers two reimbursement modes for crowdshipping: reimbursing OCs their incurred delivery costs, or providing an additional reward on top of their incurred costs as a cross-channel subsidy — cross subsidy between the online and in-store channels. In the cost-based scheme, the reimbursement amount equals the average incremental cost incurred per delivery. In the cross subsidy scheme, the retailer may set the reimbursement levels above the OCs' incurred costs. Results show that a cost-based reimbursement scheme improves both the retailer's profits and consumer surplus for cases where consumers' valuation for the product is weakly correlated with their incurred cost while the cross subsidy model is more favorable for the cases where this correlation is strong.

Paloheimo et al. [27] present a case study for applying crowdsourcing to library deliveries in Finland. They find that each crowdsourced delivery reduced an average of 1.6 km driven by car, despite 80 percent of the deliveries being made within less than a 5 km distance. Drivers were attracted by a rich combination of value propositions including monetary compensation and health benefits with most drivers using bicycles and compensations paid to crowdshippers ranging from 2 to 5 €. They also estimate a potential for transport footprint reduction, for Finland. Authors demonstrate that an existing consumer service can quickly adopt crowdsourced deliveries with real sustainability benefits.

Dahle at al. [10] investigate the setting in which a company uses its own fleet of vehicles to perform deliveries and also uses the services of occasional couriers. They compare between a compact and an extended formulation for the problem and test the impact of reduction tests and symmetry breaking constraints. In their work, the authors take into account the OCs behaviour by iteratively proposing routes to OCs and resolving with one or more new constraints if one or more OCs are not content with the compensation offered. For the purpose of analysing the solutions, authors assume that the acceptance behaviour of the OCs is known, even though it is unknown to the company. Three compensation schemes are analysed: In the first scheme, the company gives a fixed and equal compensation for each served request. In the second scheme, compensations are proportional to the cost of travelling directly from a pickup to a delivery location. In the third scheme the compensation scales proportionally with the extra cost incurred from the detour made by the OC. The computational results show that using occasional drivers can produce substantial cost savings even when a suboptimal compensation scheme is used, with savings ranging from 10 to 15 percent for the tested instances. Authors show that the development of dynamic compensation schemes that better reflect the behaviour of the OCs has the potential for greater cost savings.

Dayarian et al. [11] explore the setting of in-store customers supplementing company drivers and undertaking tasks to deliver online orders on their way home. They consider the highly dynamic nature of the environment and develop two rolling horizon dispatching approaches: one that considers the state of the system when making decisions, and one that incorporates probabilistic information about future orders and OC availability. Authors do not address the compensation aspect and simply assume that using in-store customers is cheaper than using PF but recognize that compensation may have to be dependent on the detour made by the OC.

Yildiz and Savelsberg [33], in the context of on-demand meal delivery, investigate the novel challenges associated with managing crowdsourced delivery capacity with self-scheduling and self-selection of delivery orders to perform, by proposing a modelling approach that captures service coverage decisions, self-selecting behaviour of couriers and delivery capacity composed of OCs and PF. Authors examine the courier per delivery compensation associated with an optimal service area and the effect of varying unit-revenue and vehicle speed on courier compensation. They extend that analysis by also considering a per-mile courier compensation. That analysis shows that optimal service coverage area and profit are highly dependent on OCs' earning expectations. Furthermore, their numerical experiments reinforce the increased efficacy and profit that crowdsourced deliveries supplemented by PF may provide.

2.3 Further developments

In this work we introduce a data-driven approach to model the agents' probability of acceptance by applying a machine learning algorithm, namely logistic regression, to real world data gathered through a survey. What differentiates our logit model from the ones presented in the existing literature is the fact that we incorporate compensation offered to OCs into the model, by considering this variable to largely influence the OCs' willingness to accept a proposed task. Our goal is to obtain a model that describes acceptance probability as a function of compensation offered. This is a fundamental characteristic of the model as it defines one building block of the developed dynamic compensation scheme.

Dynamic compensation schemes are still scarce in related literature.

Reviewed studies generally address the compensation methods by considering some static features of the problem, e.g., OCs detour, PF travel distance or fee per parcel. We start by considering a very relevant feature for our problem – probability of acceptance – and assume the naturally occurring high dependency between compensation value and the willingness to accept a delivery task.

We then use our logistic regression model to describe the acceptance probability and introduce a novel compensation scheme that determines an approximation of the optimal reward value, based on the compensation values and their associated modeled probabilities that minimize the cost function. This is done through the implementation of an optimization heuristic method. Compensations are, therefore, obtained with regard to the willingness of crowdshippers.

2.4 Logistic Regression

Logistic regression is a machine learning technique, within the class of generalized linear models, used in classification problems to estimate a binary output value on the conditional probability of $p = P(Y = 1|X = x)$, with X being a predictor variable and Y the target variable. Probabilities p for the output variable are converted to log odds — logits —, where:

$$\mathrm{logit}(p) = \log(\frac{p}{1-p}).$$

Intercept and coefficients' estimation is done by fitting a line to the data using maximum likelihood, through the following linear expression

$$\log(\frac{p}{1-p}) = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n,$$

with parameter β_0 corresponding to the intercept value and parameters $\beta_1, ..., \beta_n$ corresponding to n independent variables' coefficients.

For a given feature vector x_i and its associated class y_i, maximum likelihood estimation determines the parameters $\beta_0, \beta_1, ..., \beta_n$ that maximize the equation

$$L(\beta_0, \beta_1, ..., \beta_n) = \prod_{i=1}^{N} p(x_i)^{y_i}(1 - p(x_i))^{1-y_i},$$

for N observations.

Writting the linear expression in terms of the probability p, results in the following sigmoid function:

$$p = \frac{1}{1 + e^{-(\beta_0+\beta_1 x_1+...+\beta_n x_n)}}.$$

The target class is typically estimated by considering the binary value that is closer to the evaluated probability, a value that is dependent on the distance from the class decision boundary defined at $\beta_0+\beta_1 x_1+...+\beta_n x_n = 0$. Describing a prediction with probabilities has the advantage of providing an additional information on how strong the predictions are. In this work we focus not on the binary class prediction but on the predicted class probabilities [17] obtained from the fitted sigmoid function that we use to describe the crowd agents' behaviour. Our goal is to use these probabilities as input to a dynamic compensation scheme that determines a fee based on the couriers' willingness to accept a proposed delivery task, which is our problem's target variable.

Chapter 3

Methodology

Modeling the agents' willingness to participate in crowdsourcing requires real world data. With the advent of the IoT, social networks and easy-to-access data, mining for information that might hint on users' behaviour is a growing trend, with data mining techniques now becoming an important tool for analysing consumer behaviour and tendencies.

A recent field of study called behavioral analytics pertains to assess new insights into the behaviour of consumers by analysing large volumes of raw data.

When considering the crowdsourcing setting of taking up in-store customers to fulfill a delivery task, applying machine learning may assist in determining the willingness of individuals to engage in the proposed tasks. Assuming the company's free access to customers' buying habits and personal information, several variables can be taken into consideration for knowledge extraction. These variables can be intrinsic and long-term like personal beliefs or personality, i.e., consumer personality could reveal his/ her tendency to engage in crowdsourcing – personality mining [[4], [7]]; other variables can derive from the current events upon delivery proposal, such as time of day or climate, as people are less willing to carry groceries over an additional distance on a rainy day or during rush hour. Additional variables, and arguably the most influential ones, include the characteristics of the delivery task itself that directly influence the courier's decision upon proposal, such as package size, package weight, distance to be covered, etc. Investigations into the consumers' preferences and inclinations can be performed by analysing the in-store buying behaviour of customers with the purpose of estimating the client's willingness to accept an outsourcing task. Accounting for other extrinsic variables (e.g. weather, hour, weekday), may also improve the estimate.

Despite the potential of previous approaches, the most effective information to have regarding a specific setting as the one described, is the acceptance historical record of each and every in-store customer that is to be proposed a delivery task. However, this information can only be gathered *a posteriori*, and also collecting a large enough dataset would require a long time. In the absence of historical data that is relevant to the problem, information must be gathered by consulting the public on this matter through a questionnaire on the relevant features of the described setting. Such setting can encompass a vast number of variables. We focus on three very relevant characteristics of the delivery task: weight of the package, additional distance covered and compensation paid. We therefore simplify the problem by considering some features of the delivery task itself and ignore other aspects that might influence people to accept or decline the task at hand.

In this section a description of the conducted survey is presented, followed by the data processing and curve fitting stages. A description of Archetti's method is presented, followed by a brief introduction to the stochastic version of the expected cost function, which is the basis for the ensuing detailed direct method implementation.

3.1 Questionnaire

A total of 155 observations were gathered through a survey of 20 questions assessing the distance respondents would cover with respect to the weight of the package and the compensation value. The surveyed population is mostly comprised of college students (52%), an IT company's employees (30%), military personnel (13%), and a smaller sample of a diverse group of people. All respondents resided in Portugal with ages ranging from 18 to around 60.

After a brief presentation of the problem setting, the survey is divided into 4 sections each regarding a compensation value of 0, 2, 4 and 5 €. In each section respondents must answer what is the additional maximum distance they are willing to travel for a given maximum package weight. Suggested weights are 1, 2.5, 5 and 10 kg and distances are 250, 500, 1000 and 2000 m. A null option for distance is also introduced.

At the time of surveying, the Portuguese hourly minimum wage rounded to 3.4 € per hour, considering 40 labor hours per week and a 600 € monthly minimum wage (`www.pordata.pt`). Thus, the top compensation value offered consisted of roughly 147 percent the hourly minimum wage.

Figure 3.1 shows the histograms of survey results for the selected attributes of the problem setting. Each histogram represents distances respondents would cover for a given compensation value, considering all package weight values. Frequency refers to the survey's absolute observation count for each weight and distance class. As expected, frequency for (nonzero) additional distances is, in general, inversely related to the package weight and increases with compensations.

Surprisingly, the number of respondents who were ready to make a delivery for free is non negligible. This suggests people have a perceived positive outcome regarding the presented setting, most likely due to the implied sustainability of the crowdsourcing concept. This is in line with Hamari

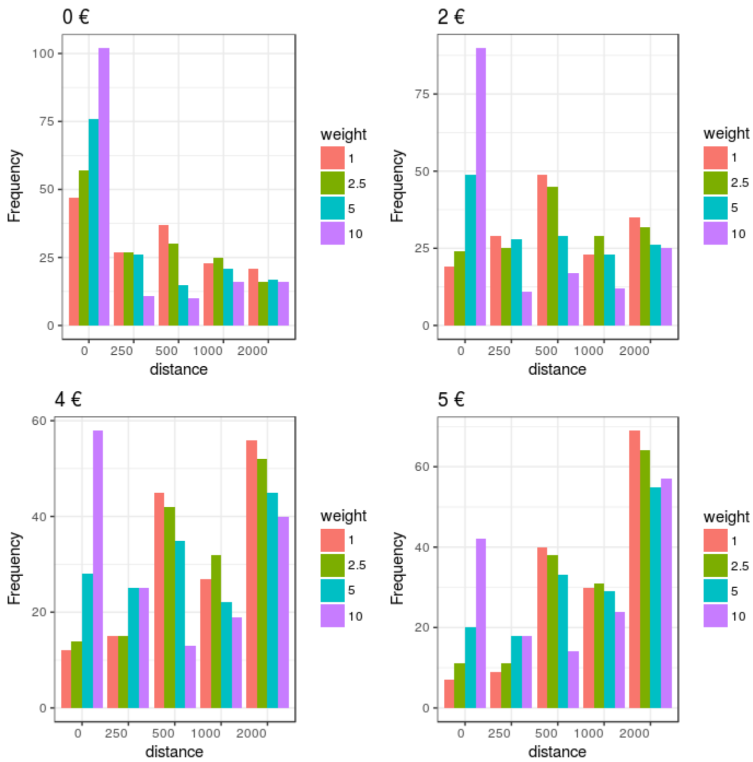

Figure 3.1: Histograms of survey results for the 3 attributes - reward, weight and distance. Zero distance means respondents would not accept the delivery task.

et al. [20] investigations into the motivations behind attitudes and behaviour towards collaborative consumption, in which authors use self-determination theory to analyse how extrinsic and intrinsic motivations influence people's intentions in that matter. They consider as intrinsic motivators sustainability and enjoyment, while extrinsic motivators are reputation and economic gain. They conclude that perceived sustainability is an important factor in the formation of positive attitudes towards crowdsourcing but economic benefits are a stronger motivator for intentions to participate in crowdsourcing. Our results reflect how possibly perceived sustainability engages a significant percentage of people to potentially participate even without any economic gain (possibly even with economic loss given that an effort at the expense of the OC is needed to execute the delivery task). But clearly the expected payout for the task is most influential to users adhesion to crowdsourcing. In reality, people's behaviour and attitudes are influenced by a combination of motivators, but our data can only directly account for the economic influence.

One interesting observation pertains to the non linear frequency increase with compensation for increasing distances. This might have to do with the way respondents interpreted travel distances in the survey. For each travel distance an estimated travel time was illustrated to facilitate the interpretation of the effort people would have to engage when performing the delivery. This was done by suggesting, for the lower distances of 250 and 500 m, a travel time of 3 and 6 minutes if performed on foot; and for the higher distances of 1000 and 2000 m, a travel time of 2 and 4 minutes if performed by car. The means of transport assumed to be used by OCs is obviously not important to our study, since we do not care about delivery speed, but individuals might have interpreted the suggested travel times/modes as options for each survey question. This would explain how two trends seem to arise in each histogram, one for the two lower distances and another for the two higher distances, and how respondents seem to divide into those two groups: the ones that prefer to do deliveries on foot and the ones that instead prefer to deliver by car. Assuming the possible misinterpretation of suggested travel modes by respondents, we observe that in the first histogram (0€ reward) lower distances are preferred, meaning customers might prefer to deliver on foot. But with the increase in compensation, individuals tend to select higher distances which means travelling by car might be preferred, with an increase proportional to compensation for the higher distance in each interpreted group.

Some inconsistent results can be observed in histograms for 4€ and 5€, on the frequency bars associated to a distance of 250 m. Contrary to the expected trend, for both histograms, the two highest weight values are observed more often than the two lowest values, with each pair having about the same frequency value. This might be explained by the fact that, since both histograms represent the highest reward values and the 250 m value is the lowest possible non zero travel distance, most surveyed individuals equally considered the highest weight values as their minimum delivery effort for the relatively short distance and high reward.

Other consistently irregular results can be observed on all four histograms, at the frequency bars associated to a distance of 1000 m. In all cases, maximum frequency values correspond to a package weight of 2.5 kg. One possible explanation, and connected to the previously made assumption regarding the travel modes, is that considering distances 1000 m and 2000 m are associated to deliveries performed by car, respondents considered a package weight of 1 kg to have no real effect on their implied effort. As a result, most individuals considered the maximum package weight of 2.5 kg to be their real minimum weight to carry by car, which would explain the expected downtrend behaviour right after this value. However, when considering a maximum travel distance of 2 km, possibly because of the effort implied by the long distance, respondents again assume a 1 kg as their minimum carrying weight and as a result, the expected downtrend behaviour can be seen across all weights.

Figure 3.2 shows in one plot how the values for absolute frequency of survey observations, increase with reward and decrease with weight. Each point in each vertical line represents one of the four distances. We can see how, for low rewards or for high weights, the points are mostly aggregated on lower count levels, whereas for higher compensation values and lower weights, points extend to higher count levels.

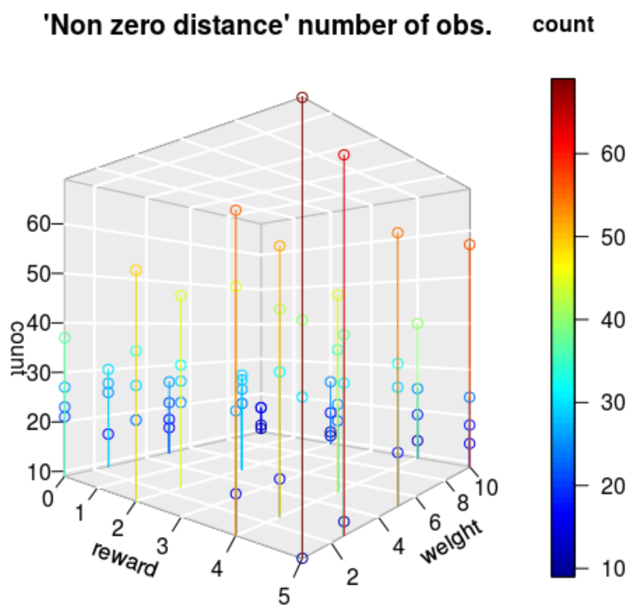

Figure 3.2: Three dimensional plot of absolute frequency for each reward and weight value, considering how many individuals would perform a delivery for any non zero distance.

Figure 3.3 shows the total number of individuals that would not perform a delivery considering each compensation value (plot A), and each weight value (plot B). In plot A an exponential decrease is observed whereas in plot B, the symmetric is observed with more people unwilling to perform a delivery when package weight increases.

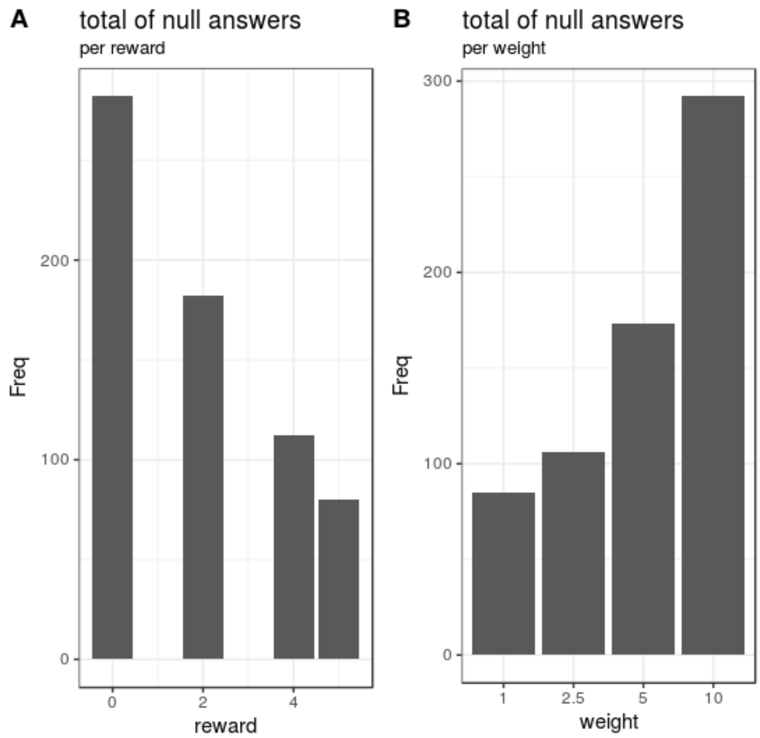

Figure 3.3: Total number of null answers for each proposed delivery considering compensation (A) and weight of the package (B).

Figure 3.4 shows the boxplots of the selected survey distances for each reward value (plot A) and for each weight value (plot B). In plot A, large distance selections increase for higher compensation values, while in plot B selected distances decrease in magnitude with the increase in package weight.

3.2 Data processing and curve fitting

Data was pre processed in order to fit the desired structure for applying the regression, i.e., attribute creation. Weight, reward and distance were defined as attributes, with distances as dummy variables D_n, where n is the column's distance value.

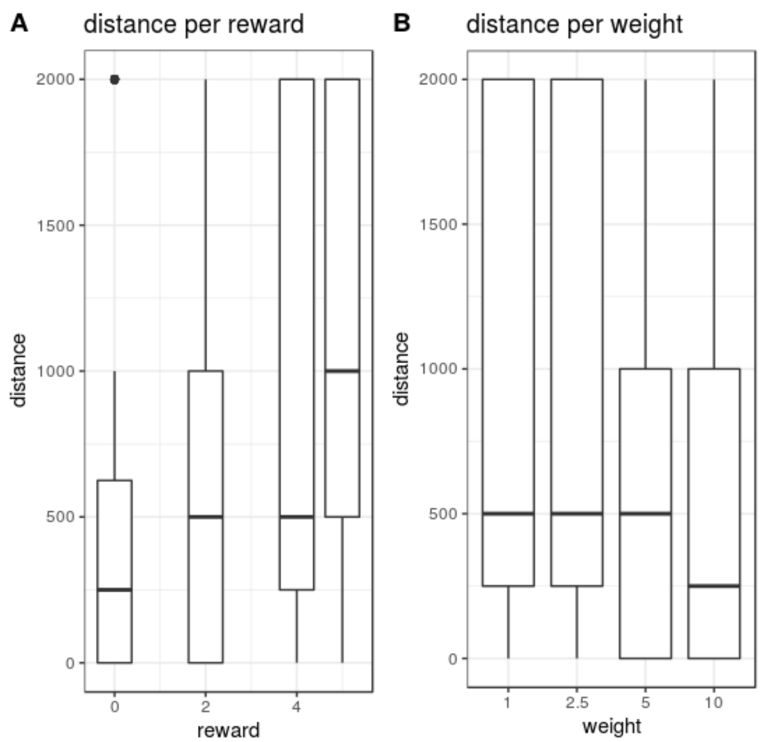

Figure 3.4: Boxplot of selected distances for each reward value (A) and for each weight value (B)

The algorithm for determining the logistic regression takes as inputs the weight and distance values and outputs the sigmoid curve that describes the probability of acceptance per reward value. Before performing the regression, data must be processed to consider all the appropriate observations for the selected problem inputs. Given the input weight, observations are filtered for that particular value and only dummy features that correspond to a distance equal to and/or higher than the input distance are considered. By summing the resultant distance features, we are left with a feature of binary values for each reward observation upon which the logit regression model is built. The sum of the dummy variables is possible because if an individual claims to be willing to carry a package for a given maximum distance then he/she will definitely be willing to carry that same package for a shorter distance. So when considering a given input distance d, by doing the procedure described above we are answering the question "how many of the observations correspond to individuals willing to cover distance d ?", that translates into considering all columns that correspond to $D_n \geq d$.

Table 3.1 shows the 3 attributes created and the distance attribute converted into dummy variables, for a random sample of five survey observations with each row representing the distance a respondent would cover for the considered reward and weight value.

	$reward$	$weight$	$distance$	0	250	500	1000	2000
1	0	1	0	1	0	0	0	0
2	0	1	0	1	0	0	0	0
3	0	1	250	0	1	0	0	0
4	0	1	500	0	0	1	0	0
5	0	1	250	0	1	0	0	0

Table 3.1: a sample of 5 observations obtained from the processed survey data, considering the 3 attributes: $reward$, $weight$ and $distance$.

As an example of how the processing method would handle the data for curve fitting, using the sample above, when considering a weight of 1 kg and a distance d equal to 250 m, in the first step (Table 3.2), the observations would be filtered for that particular weight value and only dummy attributes corresponding to distances equal to or higher than the input distance would be considered. For this example, selected distances would be D_{250}, D_{500}, D_{1000} and D_{2000}. In the second step (Table 3.3), the filtered dummy variables would be summed, resulting in $Y = D_{250} + D_{500} + D_{1000} + D_{2000}$.

	$reward$	250	500	1000	2000
1	0	0	0	0	0
2	0	0	0	0	0
3	0	1	0	0	0
4	0	0	1	0	0
5	0	1	0	0	0

Table 3.2: Dummy variable filtering step.

	$reward$	Y
1	0	0
2	0	0
3	0	1
4	0	1
5	0	1

Table 3.3: Processed dataset, with target variable Y obtained by summing the filtered dummy variables.

This two step procedure determines Y, our target variable, that given an observation of the predictor variable $reward$ outputs the binary value that corresponds to the willingness of accepting the proposed task for the given weight and distance inputs. These vectors of binary values are submitted to the logistic regression algorithm that fits a model to the data, and outputs the intercept and coefficient values that are used to draw the sigmoid representing the probability of acceptance for the input parameters.

Considering an input weight of 5 kg and a distance of 500 m, the fitted curve is described by the sigmoid expression 3.1, denoted by s_1:

$$s_1 = \frac{1}{1 + e^{-(-0.70+0.38x)}} \tag{3.1}$$

with x representing the predictor variable $reward$. As an example, for a reward of 8€ we have $s_1 = P(Y = 1|X = 8)$. After replacing x in Equation 3.1, we obtain a probability of 0.91 of an OC accepting to carry a package of weight up to 5 kg for a maximum detour distance of 500 m, given a compensation of 8€. Figure 3.5 shows the plotted sigmoid. For the selected parameters the fitted curve yields a three-fold cross validation average Mean Squared Error (MSE) of 0.2139.

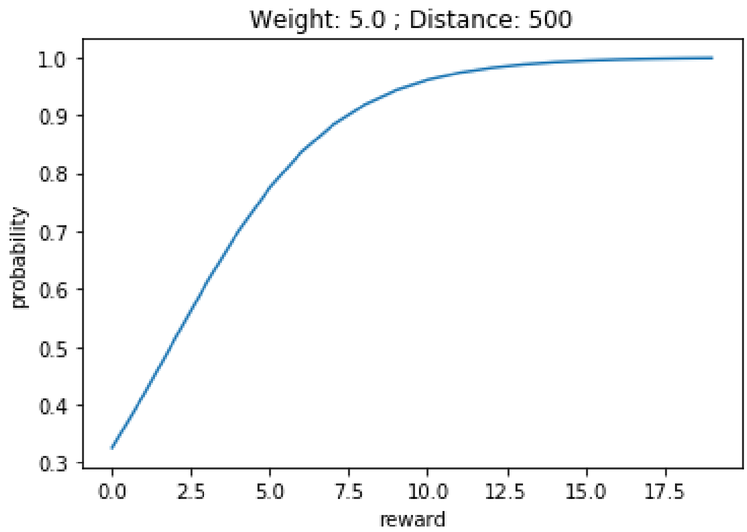

Figure 3.5: Logistic regression curve for a maximum package weight of 5 kg and a maximum detour distance of 500 m.

Three-fold cross validation is performed to evaluate the models' performance by dividing the dataset into three same-length sets of which two are used for training and one is used for validation. Iteratively, each new set goes though validation/testing and MSE is determined at each validation step. Results for the 3 validation sets are averaged for the final MSE value of the logit curve. We do not use accuracy as our error metric because we are not considering the output binary class. Since we are dealing with class probability values and not binary outputs, we consider MSE to be the most adequate metric as it helps us estimate the average distance between the acceptance outcome, reported by surveyed individuals, and the probability output from the logit curve.

For determining the probability curve of values different from the discrete weight values used (within range 0 to 10 kg), a linear interpolation is performed between the closest known weight values. As an example, when determining the probability curve associated with a weight of 1.7 kg and a distance of 250 m, a linear interpolation between the weight values of 1 kg and 2.5 kg for the same distance, is performed for determining an approximation of the probabilities (figure 3.6).

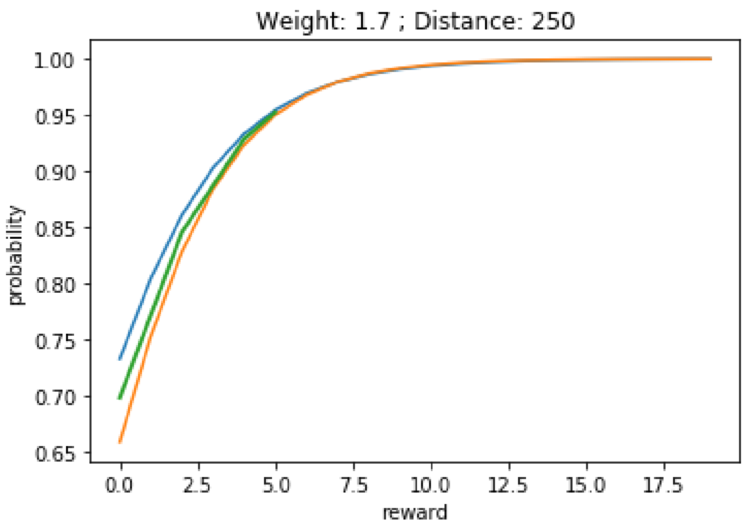

Figure 3.6: Probability curves for weights 1, 1.7 and 2.5 kg in blue, green and yellow respectively, for a detour distance of 250 m. The green curve corresponds to the interpolated values.

On the effect of different delivery conditions over the acceptance probabilities, we compare two curves obtained for extreme values of weight and distance:

The curves plotted in Figure 3.7 and Figure 3.8 are given by the sigmoid functions s_2 (equation 3.2) and s_3 (equation 3.3), respectively:

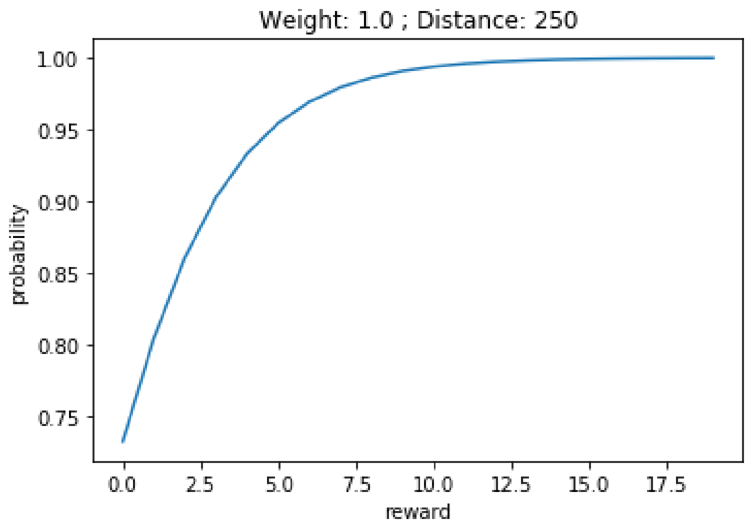

Figure 3.7: Curve describing acceptance probabilities for an input weight of 1 kg and an input distance of 250 m.

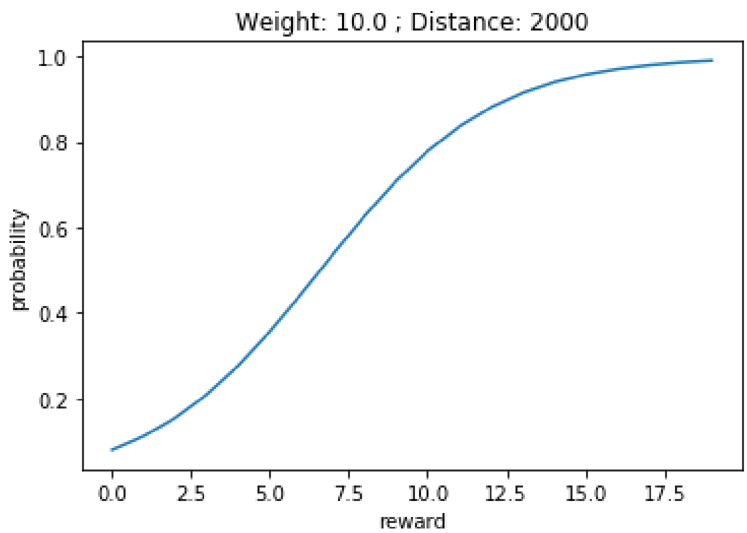

Figure 3.8: Curve describing acceptance probabilities for an input weight of 10 kg and an input distance of 2000 m.

$$s_2 = \frac{1}{1 + e^{-(1.01+0.41x)}} \tag{3.2}$$

$$s_3 = \frac{1}{1 + e^{-(-2.43+0.37x)}} \tag{3.3}$$

The first plot, in Figure 3.7, represents the acceptance probability for a weight of 1 kg and a distance of 250 m, while the second plot, in Figure 3.8, shows the probability curve for a weight of 10 kg and a distance of 2000 m. Comparing both curves we can observe a drastic decrease in probability from the first to the second sigmoid, for the same reward values. Taking for instance a reward of 2.5€, the first curve outputs a probability of acceptance of 0.88 while the second curve outputs a probability of 0.18.

3.3 Minimizing expected cost

Our method for determining the optimal compensation value is built on the model developed by Gdowska et al., that introduces a stochastic approach to the last-mile delivery with crowdshipping. Their work is an extension to Archetti et al. work that determines, for the same setting, the minimum total cost, which comprises compensations offered to OCs and costs incurred by the PF. The authors assume that all OCs accept proposed tasks and that only one task per OC is executed with remaining packages being delivered by the PF. They also assume that an unlimited number of PF drivers is available. Archetti presents an integer programming (IP) formulation used as a benchmark for the developed matheuristic solution of the vehicle routing problem with occasional drivers (VRPOD), which combines variable neighborhood search and tabu search. The problem can be denoted by a directed graph G = (N, A) with node set N and arc set A. Set N includes the location of the depot (node 0), the customers' locations (set

C), and the destinations of OCs (set K). Their IP formulation is as follows:

$$min \sum_{(i,j)\in A} c_{ij}x_{ij} + \sum_{i\in C}\sum_{k\in K} p_{ik}w_{ik} \tag{3.4}$$

$$\sum_{j|(i,j)\in A} x_{ij} = \sum_{j|(j,i)\in A} x_{ji} = z_i \qquad \forall i \in C \tag{3.5}$$

$$\sum_{j|(0,j)\in A} x_{0j} - \sum_{j|(j,0)\in A} x_{j0} = 0 \tag{3.6}$$

$$\sum_{j|(j,i)\in A} y_{ji} - \sum_{j|(i,j)\in A} y_{ij} = \begin{cases} q_i z_i & \forall i \in C \\ \sum_{i\in C} -q_i z_i & i = 0 \end{cases} \tag{3.7}$$

$$y_{ij} \leq Qx_{ij} \qquad \forall (i,j) \in A \tag{3.8}$$

$$y_{i0} = 0 \qquad \forall i \in C \tag{3.9}$$

$$w_{ik} \leq \beta_{ik} \qquad \forall i \in C \forall k \in K \tag{3.10}$$

$$\sum_{i\in C} w_{ik} \leq 1 \qquad \forall k \in K \tag{3.11}$$

$$\sum_{k\in K} w_{ik} + z_i = 1 \qquad \forall i \in C \tag{3.12}$$

$$x_{ij} \in 0,1 \qquad \forall (i,j) \in A \tag{3.13}$$

$$z_i \in 0,1 \qquad i \in C \tag{3.14}$$

$$w_{ik} \in 0,1 \qquad i \in C k \in K \tag{3.15}$$

$$y_{ij} \geq 0 \qquad \forall (i,j) \in A \tag{3.16}$$

with: c_{ij} the cost of traversing arc (i,j); x_{ij} a binary variable specifying if a PF vehicle is traversing arc (i,j) or not; y_{ij} the load that a PF vehicle carries on arc (i,j); z_i a binary value specifying if customers are visited by a PF vehicle; w_{ik} a binary variable specifying if customer i is visited by OC k or not; β_{ik} a parameter specifying if OC k can serve customer i; p_{ik} the compensation value paid to OC k for serving i; q_i demand from customer i; Q the PF vehicle's capacity.

(3.4) is the objective function for minimizing total cost. Constraints ensure that: (3.5) customers are visited by one PF vehicle at most; (3.6) routes start and end at the depot; (3.7) demand is met, subtours are prevented; (3.8) PF's capacity is not surpassed; (3.9) PF vehicle returns empty to the depot; (3.10) customers are served by available OCs; (3.11) OCs serve at most one customer; (3.12) each customer is served exactly once.

Gdowska's extension to Archetti's work considers a stochastic behaviour from the occasional drivers by assuming that not all tasks proposed to OCs will be accepted and that this behaviour is dependent on a probability value that is incorporated into the model. They consider a modified version of the problem where OCs are not identified for matching with delivery tasks; delivery tasks can be either accepted or declined. Our work follows Gdowska's work in the manner that, by introducing the modeled probabilities in their model, we are able to calculate the expected cost with regard to the willingness of the occasional couriers when proposing a subset of customers to be outsourced, with:

$$E(C, A, p) = \sum_{U \in 2^A} \prod_{i \in U} p_i \prod_{i \in A \setminus U} (1 - p_i) \Big(VRP(C \setminus U) + \sum_{i \in U} K_i \Big) \quad (3.17)$$

Equation 3.17 takes as input the set of customers' locations C to be served either by a professional fleet or by outsourcing deliveries, the subset A of customers to be outsourced, and probability p_i that describes courier's i willingness to accept the proposed task. $VRP(C \setminus U)$ solves the vehicle routing problem for the subset of customers to be served by the fleet, i.e., customers for whom deliveries were declined by OCs; while K_i represents the compensation paid to occasional courier i. U corresponds to a subset of accepted vertices for outsourcing and 2^A is the power set that encompasses all configurations of accepted nodes.

Gdowska's model works in two stages: In the first stage, the company decides on a subset of customers whose delivery is proposed to OCs; in the second stage, it observes deliveries that were rejected by OCs and includes them in its PF's route. For a given observation of the declined tasks by OCs, the problem is similar to a static capacitated vehicle routing problem (VRP), solved according to the IP formulation mentioned above. The authors consider all possible combinations of acceptance/rejection of delivery tasks by OCs. The first level of Gdowska's algorithm makes a choice concerning subsets of A, starting from the empty set and increasing it greedily until no further improvement on the cost is observed. For that, it uses Equation (3.17) in a second level, which is responsible for determining the expected cost of a selected subset of A of proposed outsource customers by considering all possible acceptance patterns.

With regard to the previous models, we consider a simplified version of the problem by assuming only one professional vehicle is available to perform deliveries, which means that only one delivery route will be determined. We also assume the vehicle's capacity is unlimited which allows us to ignore the customers' demand and vehicle capacity constraints, and focus on the problem of determining the optimal compensation approximation for the outsourcing agents.

In our model, we make use of Gdowska's algorithm for determining A and the corresponding expected cost; this is attempted for different values of the compensation K (which we consider the same to all customers i), which is our main variable. Then, the corresponding probability of acceptance is determined by means of the logistic regression model (denoted by P), and these two values are sent (as constants) to Gdowska's algorithm (denoted by G). The flow of formation is, therefore: for a given value of K, determine $\bar{p} = P(K)$; then, determine the corresponding expected cost $G(K, \bar{p})$ using Gdowska's method that, for the input K and $\bar{p}$ determines in the first level a subset A of customers to be outsourced; in the second level analyses all acceptance patterns for A taking into account the reward K and the probability value $\bar{p}$, and calculates the subset's expected cost following equation E (3.17). For each acceptance pattern analysis in level two, the VRP is solved for non accepted nodes $C \setminus U$ considering the implementation of the IP formulation presented above. Greedy selection of A in the first level determines the subset with the lowest expected cost, calculated in level two. This value is the result of calling function G in each iteration of the direct method, that tests for different values of K, and their associated probabilities $\bar{p}$, the resulting cost. This is done with the purpose of determining the K value that minimizes expected cost, denoted by K^*, as per the ensuing description.

Algorithm 1: Direct search of compensation value

Input:
- minor/major reward $K_{\mathrm{min,maj}}$
- model for probability of acceptance, P
- model for expected cost, G
- instance data C, A and travel cost

Output:
- optimal reward K^*
- minimum expected cost
- subset $A \subseteq C$ of outsourced customers

$K_1 = K_{\mathrm{maj}} - \dfrac{K_{\mathrm{maj}} - K_{\mathrm{min}}}{\varphi}$

$K_2 = K_{\mathrm{min}} + \dfrac{K_{\mathrm{maj}} - K_{\mathrm{min}}}{\varphi}$

while $\mathrm{abs}(K_1 - K_2)$ > *tolerance* **do**

  if $G(K_1, P(K_1)) \leq G(K_2, P(K_2))$ **then**

    $K_{\mathrm{maj}} = K_2$

  else

    $K_{\mathrm{min}} = K_1$

  $K_1 = K_{\mathrm{maj}} - \dfrac{K_{\mathrm{maj}} - K_{\mathrm{min}}}{\varphi}$

  $K_2 = K_{\mathrm{min}} + \dfrac{K_{\mathrm{maj}} - K_{\mathrm{min}}}{\varphi}$

return $K^* = (K_1 + K_2)/2$

Expected cost is minimized through the use of a direct search method — Algorithm 1 — that takes as inputs the reward values $K_{\mathrm{min,maj}}$, the probability model P obtained by logistic regression, and the model for the expected cost G. The algorithm iteratively converges to a locally optimal compensation value K^*.

The direct method works by considering a unimodal function and two ranging points. The goal of the algorithm is to find the minimum of the input function, in our case G, by successively computing two points, K_1 and K_2, within ranging values, $K_{\mathrm{min,maj}}$, while eliminating the range point with the highest function value and replacing it with the new highest scoring point. In the current implementation, the golden ratio φ is used to determine each point's position relative to the ranging values, a method also referred to as golden-section search. This is a heuristic method and therefore optimality is not guaranteed. Nevertheless, it was sufficient for achieving our goal. Ranging points are represented as minor/major rewards. Minor reward K_{min} is set to zero and major reward K_{maj} is calculated as twice the cost of covering the distance from the depot to the farthest vertex. Function G takes as inputs the rewards K_i probed in each iteration and their associated probabilities $P(K_i)$ obtained from the logit regression sigmoid. It outputs the minimum expected cost and the subset A of customers to be outsourced. Figure 3.9 shows costs obtained in an execution of the direct method for a problem setting with 15 vertices and a cost per distance of 0,01 €/m, with each plotted point representing a different reward value probed in each iteration of the algorithm, and the corresponding numbers representing the number of delivery tasks proposed for outsourcing. Reward denotes the compensation value (in €) to be attributed individually to every OC. Point aggregation near the minimum cost value describes the successive decrease in the search range and the convergence to the optimal reward value, in this case 4.78€. Large steps in the cost reduction are a direct result of new best solutions being determined by the search algorithm in terms of outsourcing proposals that minimize the expected cost, as visible by the size of each iteration's resulting subset A. The largest gap in cost is determined for an increase in outsourcing proposals from 4 to 7 outsources, which constitutes a fall from 241,97€ to 224,44€ in total cost as in table 3.4. As previously mentioned, total costs comprise costs incurred by the PF and compensations paid to OCs.

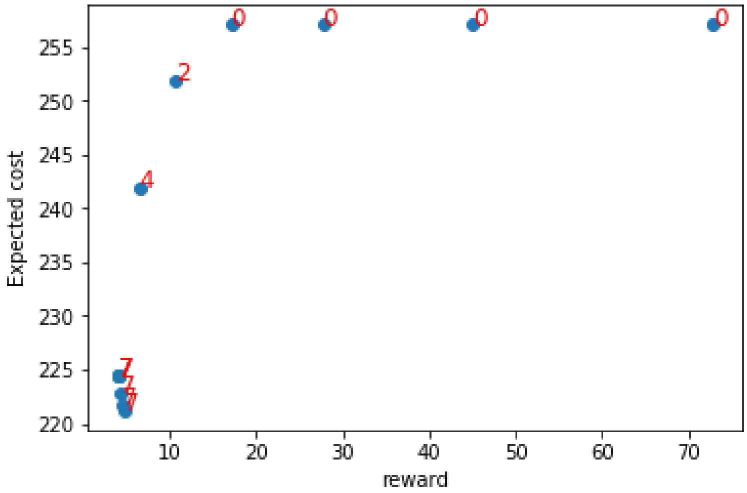

Figure 3.9: Direct search plot of expected cost versus reward for a travel cost of 0.01 €/m.

Table 3.4 shows each iteration, from first to last, of an execution of the direct method for a fixed distance cost of 0,01€/m. Analysed attributes include total expected cost (in €), percentage of improvement relative to the first solution's cost, i.e., without any outsourcing, unit compensation value, number of outsourcing proposals (OC) and subset A of customers' locations to be outsourced. First iterations do not deliver any improvement since probed reward values are too high. The greatest improvement, of 6,821%, is achieved at iteration 7 for which a new set of customers' locations is determined and an increase in outsourced destinations, from 4 to 7, occurs. Once a new set of outsources is proposed, further improvements are small, less than 1.5%, and the compensation value is optimally adjusted at 4,78€. Compared to the initial best solution at the starting iteration, the algorithm converges to an optimal solution responsible for an improvement of almost 14 percent in cost savings, for the considered distance cost value.

Repeated values in table 3.4 do not correspond to a loop but are a re-

Exp. cost (€)	Cost imp. %	reward €	#OC	A
257,07	0	72,74	0	
257,07	0	44,96	0	
257,07	0	27,78	0	
257,07	0	17,17	0	
251,87	2,02	10,61	2	'11', '15'
241,97	5,87	6,56	4	'11', '15', '14', '8'
224,44	12,69	4,05	7	'7', '14', '12', '15', '11', '13', '8'
224,44	12,69	4,05	7	'7', '14', '12', '15', '11', '13', '8'
224,44	12,69	4,05	7	'7', '14', '12', '15', '11', '13', '8'
224,44	12,69	4,05	7	'7', '14', '12', '15', '11', '13', '8'
222,79	13,33	4,42	7	'7', '14', '12', '15', '11', '13', '8'
221,80	13,72	4,65	7	'7', '14', '12', '15', '11', '13', '8'
221,21	13,95	4,78	7	'7', '14', '12', '15', '11', '13', '8'

Table 3.4: Solutions for every iteration of an execution of the direct search algorithm, considering a distance cost of 0,01€/m and a probability model obtained for a weight of 5 kg and a distance of 500 m.

sult of the sectioning property of the algorithm. Each probed reward point is calculated relative to the same distance from each of the ranging points, in this case a distance determined by golden-sectioning the distance between range values. In each iteration the reward point with the highest function value is updated as the new range value and considered for determining the next two reward values, together with the other unchanged range value. This process causes one of the two reward values determined in each iteration to appear again in the next iteration. When the ranging points are being updated alternatively, the reward value with the lowest function value may appear consecutively, which is in fact what happens halfway through the algorithm's iterations.

Chapter 4

Computational analysis

Computational analysis was conducted on four different settings consisting of 15 nodes each, corresponding to 14 customers' locations and one depot, with coordinates randomly generated on a grid of size 12 km x 12 km.

When applying the search algorithm, a cost per unit distance must be defined while taking into account the reward values. A cost that is too low results in no outsourcing when traversing the destinations is cheaper than outsourcing them. In contrast, too high cost results in all vertices being outsourced, when the cost of compensating outsources is in fact cheaper than serving any of the destinations with the professional fleet. We analyse the solutions obtained for values between the extreme conditions of too high and too low distance costs, in order to understand the importance of this parameter on the expected gain.

Two types of analyses were performed. The first analysis investigates the effects of cost per distance variation on the solutions obtained for the same setting, and applied to different probability curves. The second analysis pertains to studying the observed effects of different probability curves on different settings for a fixed cost per distance.

Distance cost dependency analysis

Setting A is subject to the first investigation: analysing for different probability curves the effects of cost per meter variation on the solutions.

Heuristic solutions given by the search method were analysed with regard to the following attributes:

- Cost per distance (€/m): the value (€) of one distance unit (m)
- Compensation (€): reward value attributed individually to every OC
- Total compensation (€): sum of compensations paid to OCs
- Percentage compensation (%): percentage of total cost corresponding to compensations offered
- Expected €: expected total cost in €
- Expected m: expected total cost in meters
- # OC: number of customers' locations proposed for outsourcing
- A: set of customers' locations proposed for outsourcing
- Improvement (%): percentage of improvement of the final solution relative to the initial solution

Expected cost (in €) consists in the sum of the expected travel distance (m) incurred by the professional fleet multiplied by the distance cost (€/m), and the compensations paid to OCs. The PF's distances are calculated with respect to the Euclidean distances between locations to be served. Fees offered to occasional couriers are determined by the compensation scheme and evaluated for different cost values of currency per distance (€/m).

Cost (€/m)	Compensation (€)	Total comp. (€)	% Comp.	Expected cost (€)	% Improvement	Expected cost (m)	A	#OC
0,0001	na	na	na	2,571	0	25707	no out	0
0,0002	0,212	0,424	8,306	5,105	0,718	25522,415	'11', '15'	2
0,0003	0,197	0,591	7,824	7,554	2,053	25179,11	'11', '15', '8'	3
0,0005	0,203	1,624	13,119	12,379	3,690	24758,517	'9', '4', '5', '6', '14', '15', '11', '8'	8
0,0007	0,175	1,925	11,316	17,012	5,465	24302,08	'3', '9', '10', '4', '7', '5', '6', '14', '15', '11', '8'	11
0,001	0,251	2,51	10,339	24,278	5,559	24277,937	'3', '9', '4', '7', '5', '6', '14', '15', '11', '8'	10
0,002	0,191	2,674	5,687	47,019	8,548	23509,533	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,007	0,256	3,584	2,209	162,270	9,824	23181,452	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,01	4,785	33,495	15,142	221,212	13,949	22121,162	'7', '14', '12', '15', '11', '13', '8'	7
0,02	10,194	71,358	19,192	371,814	27,682	18590,689	'7', '14', '12', '15', '11', '13', '8'	7
0,1	17,539	245,546	87,395	280,963	89,071	2809,625	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,2	19,391	271,474	88,692	306,087	94,047	1530,436	'13', '6', '14', '11', '10', '8', '15', '4', '2', '7', '12', '3', '9', '5'	14
1	23,369	327,166	89,947	363,732	98,585	363,732	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14

Table 4.1: Optimal compensation, total compensation, percentage of costs from compensations, total expected cost, percentage of improvement, expected cost in meters, outsourcing set solution and set size for different assumptions of the travel cost per meter with the professional fleet, with a probability curve obtained for a weight of 5 kg and a distance of 500 m.

Table 4.1 summarises the results obtained for setting A with probability curve s_1 (obtained with an input weight of 5 kg and a distance of 500 m – equation 3.1). It shows that for costs equal to or higher than 0,1€/m all vertices (clients) are to be outsourced. A decrease in travel cost affects the output vertices eventually leading the number of outsources to zero at 0,0001 €/m. The subset of outsourced vertices represents all the customers' locations proposed for outsourcing, therefore the order of the elements is not important. Given that we are implementing an heuristic method, unexpected results might arise. One such case can be seen in the table entries regarding a cost per distance of 0,02 and 0,07 €/m. For these values, all destinations are considered for outsourcing; however, for a higher cost per distance value of 0,01 €/m the set size decreases, indicating that this particular solution is possibly better than the two previous entries but given the heuristic nature of the optimization implementation, inferior results are determined for those entries.

Significant changes are most observable when comparing the solutions obtained for extreme values of weight and distance: Functions s_2 and s_3 (equations 3.2 and 3.3 respectively). Results for the two probability curves, over twelve different values of cost per distance can be seen in tables 1, and 2 (Appendix).

The best solutions obtained by our method using equation s_2 as the acceptance probability model, were compared relative to an increasing cost per distance, with regard to the total expected cost, percentage of costs attributed to the PF routing and overall improvement of the final solution. Figure 4.1 is the semi-log plot of the described variables (obtained from table 1).

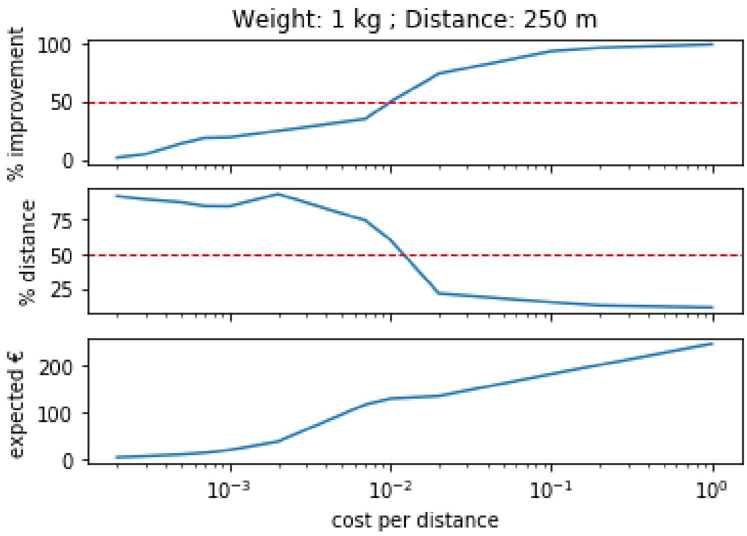

Figure 4.1: Total expected cost, percentage of costs attributed to the PF routing and percentage of improvement for various assumptions of cost per meter, under probability model s_2.

We can observe that, with an increase in the distance cost there is a decrease in PF routing costs (second subplot of figure 4.1) as a direct result of more customers' locations being proposed for outsourcing. The percentage of costs from PF routing is therefore inversely proportional to the percentage of costs from compensations offered to OCs.

Improvement is the percentage of cost reduction for the final solution when compared to the cost of the initial solution (that corresponds to solving the VRP for all customers locations, i.e., without any outsourcing). Increasing the distance cost will eventually lead to close to 100 percent improvement when the percentage of costs attributed to vehicle routing decreases towards zero and the sum of compensations paid to OCs, which does not depend on the distance cost, becomes a small fraction of the initial vehicle routing solution cost, which does depend on the distance cost.

The improvement percentage as a standalone indicator is useful if we consider that an increase in the cost per distance will not affect the OCs expected payout, which is probably not a realistic scenario - some correlation must exist between PF's costs over distance and an OC's expected compensation. In our study however, we consider the OCs' reward expectation to be influenced by the package weight and detour distance only, which means we consider no relation between expected compensation and the PF's cost per meter. We cannot therefore state that 100 percent improvement is achievable. Nevertheless, this indicator is useful for analysing, by comparison, the impact of OCs' probabilities of acceptance on the model.

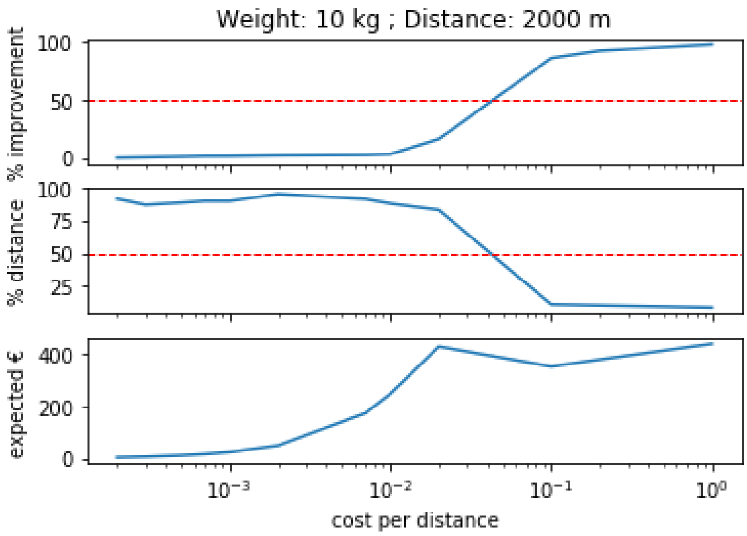

Figure 4.2: Total expected cost, percentage of costs attributed to the PF routing and percentage of improvement for various assumptions of distance cost, under the probability model s_3.

By performing the previous analysis on the same setting (A) but for different values of weight and distance, now using probability model s_3 (obtained from table 2), we are able to observe the effect of using different probability curves on the plot's variables. Looking at figure 4.2, a similar behaviour is apparent but with values on the x-axis being slightly shifted forward. Comparing both plots at the 50 percent value for percentage of improvement and for percentage cost of PF, we can see that for both subplots, the first plot hits the mark at around 10^{-2}, whereas the second plot hits the mark closer to the 10^{-1} value for cost per distance. This shift is a result of lower acceptance probability values, induced by the high weight and distance values, being used by the direct method which makes it less likely that proposed outsourcing destinations will be accepted by OCs, forcing compensation values to rise when cost/distance becomes very high; this, in turn, increases total expected cost to higher values, when compared to the first plot. A low probability of acceptance means that OCs are expensive – require high compensations to achieve a high probability of acceptance – which in turn means that outsourcing deliveries will only become cost effective when the PF routing is more expensive. Thus, improvement increase is observed at higher cost/distance values; as a consequence the distance covered by the PF simultaneously decreases. Improvement percentage for the higher probabilities' curve climbs to higher values earlier than the improvement for the lower probabilities' curve. This means that with higher acceptance probability values, for any fixed distance cost, we can expect greater improvements. As previously noted, with increasing distance costs, expected PF distance tends to zero and the distance cost starts having little effect on the expected cost; cost will mostly depend on the total compensations offered. But since the initial solution is fixed and depends on the distance cost, improvement will keep increasing to 100 percent. Total expected cost will, however, increase linearly with the increase in the logarithm of the cost per distance due to the asymptotic property of the sigmoid curve. This is an observation from our method of analysis and is not an inherent quality of the model. A peak in the expected cost subplot can be seen in figure 4.2. This inconsistency is a result of a suboptimal solution determined by the underlying function G. As described in section 3.3, function G is based on Gdowska's heuristic method for finding the subset of customers to be proposed to OCs. For a given subset A, all acceptance patterns are analysed; however, not all possible subsets A of C (set of customers' locations) are explored. Therefore, far from optimal values might be determined.

Acceptance probability analysis

The second investigation focuses on the comparison between different settings under the same input parameters and analysing results for two different probability models, s_1 and s_3. Settings A,B,C and D are plotted below, for a fixed distance cost value of 0,01€/m and a probability curve described by s_1 (equation 3.1). Descriptive values regarding each instance can be seen in table 4.2. Customers locations are numbered from 2 to 15 and represented in red whereas the depot is node 1 and is represented in blue colour.

Outsourced nodes, set A, are isolated while the remaining nodes are subject to routing – $VRP(C \setminus A)$, with set C representing all customers locations. Different settings offer different solutions, dependent not only on the input parameters but on the configuration of the network, as an underlying routing problem must always be solved. By observing Figure 4.3, representing the network graphs for settings A, B, C and D, we can confirm that outsourced nodes are mostly distant from the depot with routing performed to the closest nodes, except for setting D whose configuration of customers' locations places all nodes at a considerable distance from the depot when compared with the previous settings, which results in all vertices being selected for outsourcing and therefore no VRP solution is presented.

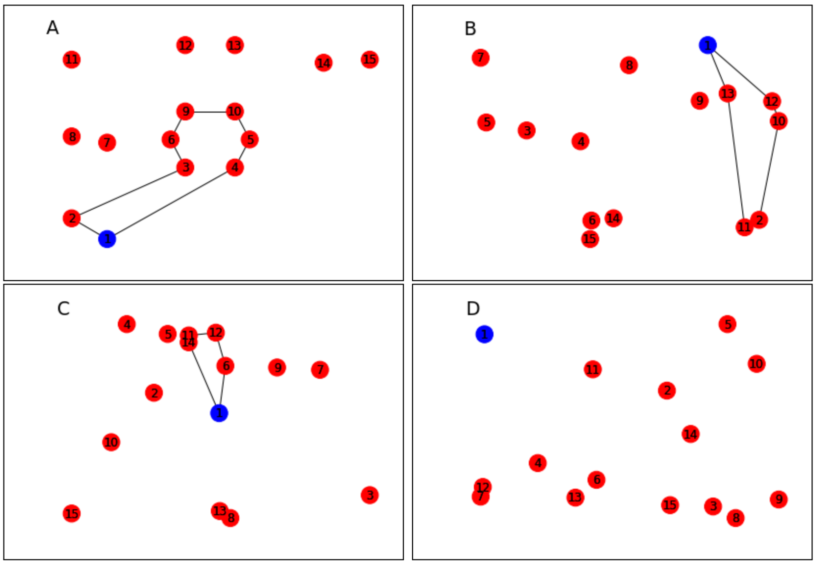

Figure 4.3: Routing and outsourcing solutions for 4 different settings (A,B,C and D), for a fixed cost per distance of 0,01€/m and probability curve s_1.

The following network plots, in Figure 4.4, represent the same four instances, for the same cost per distance value but under different delivery parameters - function s_3. A comparison between these plots and the graphs previously obtained using s_1, reveals an increase in PF routing which means less nodes were proposed for outsourcing due to the lower acceptance probabilities imposed by the higher weight and detour distance values causing a raise in compensation values to the point where more outsourcing proposals would be economically unviable. This can be further supported by the values in table 4.2. Percentage of compensations is the share of total costs corresponding to the sum of compensations paid. From one probability scenario to another, this value decays for all settings, which represents the lower outsource proposals and higher PF routing – less money spent on compensations, more money spent on serving customers by PF. The unit compensation value increases from the first to the second scenario, a result of the lower probabilities forcing compensations up to increase acceptance probabilities and decrease expected cost. An

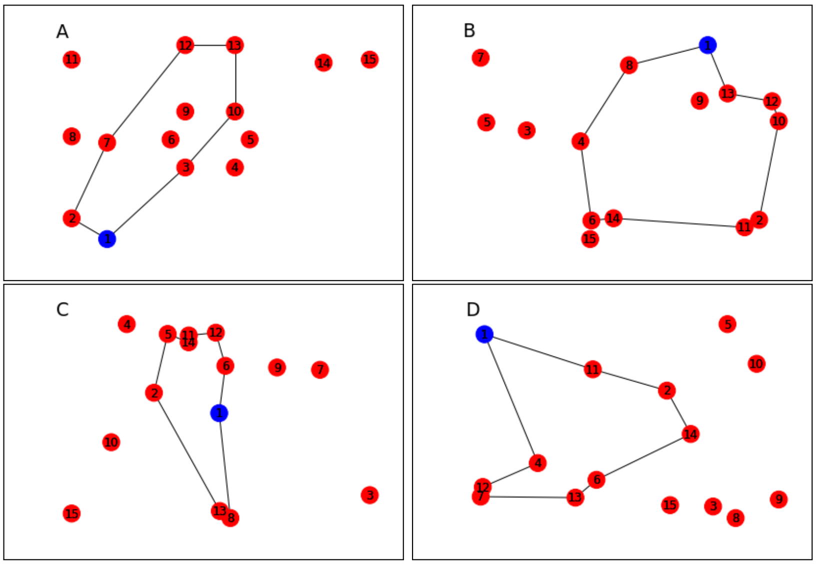

Figure 4.4: Routing and outsourcing solutions for 4 different settings (A,B,C and D), for a fixed cost per distance of 0,01€/m and probability curve s_3.

exception is made to setting A which has a slight decrease in compensation and a modest increase in the number of outsources but ends up spending more on PF routing as evidenced by the increase in the total expected cost. All settings show higher expected costs when under lower acceptance probabilities, a predictable outcome considering that compensations to OCs become more expensive inducing more PF delivery routing and more money spent on fees to OCs willing to deliver. Expected cost for all instances decreases on average 16.65 percent, from probability model s_3 to s_1 as a result of OCs, in the latter model, being more willing to accept a proposed delivery task given that the package weight is lighter and the detour distance is shorter.

	s_1: $w = 5$; $d = 500$			s_3: $w = 10$; $d = 2000$		
	reward	% reward	exp. €	reward	% reward	exp. €
A	4,785	15,14	221,211	3,688	11,87	248,582
B	6,932	19,49	320,053	10,904	15,21	358,478
C	7,276	35,15	206,992	11,507	24,26	284,539
D	5,877	26,00	316,488	12,409	19,38	384,213

Table 4.2: Comparison of results for reward (€), percentage of costs from compensations and total expected cost (€) for two probability models, s_1 and s_3 (with their associated weight w and distance d values), on four different instances (A,B,C and D).

Chapter 5

Conclusion and future work

In this work, we introduce a novel data-driven compensation scheme that combines machine learning with optimization. Data collection is performed to infer on people's disposition to engage in a crowdsourcing activity by considering three problem variables - weight of the package, distance of the detour and compensation value. Our results show that people are generally very receptive to the concept, with a significant share of respondents claiming to be willing to participate even without expecting to be rewarded; especially for low package weights - around 70 percent of respondents accepted a delivery proposal for a package of 1 kg. The gathered data was used to build a data processing and logistic regression modeling algorithm that takes weight of the package and detour distance as inputs, and outputs the probability model that describes the couriers' willingness to accept the proposed task. A comparison between resulting probability models reveals a significant influence of package weight and detour distance on the expected payout by OCs. Higher distance and weight values decrease probabilities of acceptance, with consumers expecting higher compensations for their effort.

Our investigations into the performance of a crowdshipping model with the possibility of task rejection by OCs, modeled with logistic regression, include the analysis of different acceptance probability curves for several instances, and the effects of varying the distance cost on the best solutions obtained by the developed direct method.

We show that the distance cost largely influences the expected improvement, with results suggesting that instances with high distance costs can be substantially improved by crowdsourcing deliveries, under our compensation scheme. We also show that the OCs' willingness to accept proposed tasks affects the PF's delivery route and the associated OCs' solution set, with higher acceptance probabilities increasing outsourcing and lowering compensation values, and thus lowering expected cost.

By studying and modeling the willingness of occasional couriers to undertake delivery tasks, we have built a new compensation scheme based on acceptance probabilities that determines an approximation of the optimal reward to be proposed to all occasional couriers in order to minimize the expected cost of serving a set of customers. This was done by considering one probability curve to describe all of the crowd agents' acceptance willingness, a simplification that fixed the delivery conditions in terms of the regarded variables.

In future extensions of our work, a topic for further research is the focus on the calculation of a reward value by considering multiple logit curves — one for each location to be served. Dependency on characteristics of each particular delivery task, such as package weight and distance from couriers' destination to customers' location, should also be considered.

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Appendix

Crowdshipping

Considere o seguinte cenário:

Encontra-se no supermercado a realizar as suas compras. Ao chegar à caixa para efectuar o pagamento, o operador de caixa propõe-lhe levar uma(s) saca(s) de compras extra para entregar a um cliente que vive próximo do seu destino. Pelo seu esforço, será oferecida uma compensação monetária. O seguinte questionário pretende registar qual a distância adicional que estaria disposto(a) a percorrer mediante uma determinada compensação e o peso das compras a transportar.

*Obrigatório

Entrega gratuita

Comece por considerar uma compensação de 0 euros (entregar gratuitamente).

(As estimativas de tempo de deslocação a pé ou de carro são meramente ilustrativas, sendo que o meio de transporte não é importante)

1. **Por 0 euros quantos metros extra faria com uma encomenda de peso até 1 kg ? (uma saca muito leve)** *
   Marcar apenas uma oval.
   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

2. **Por 0 euros quantos metros extra faria com uma encomenda de peso até 2.5 kg ? (uma saca leve)** *
   Marcar apenas uma oval.
   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

3. **Por 0 euros quantos metros extra faria com uma encomenda de peso até 5 kg ? (uma saca pesada)** *
   Marcar apenas uma oval.
   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

4. **Por 0 euros quantos metros extra faria com uma encomenda de peso entre 5 kg e 10 kg ? (no máximo duas sacas pesadas)** *
   Marcar apenas uma oval.
   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

Entrega por 2 euros

Considere agora uma compensação de 2 euros.

5. **Por 2 euros quantos metros extra faria com uma encomenda de peso até 1 kg ? (uma saca muito leve) ***

   Marcar apenas uma oval.

   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

6. **Por 2 euros quantos metros extra faria com uma encomenda de peso até 2.5 kg ? (uma saca leve) ***

   Marcar apenas uma oval.

   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

7. **Por 2 euros quantos metros extra faria com uma encomenda de peso até 5 kg ? (uma saca pesada) ***

   Marcar apenas uma oval.

   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

8. **Por 2 euros quantos metros extra faria com uma encomenda de peso entre 5 kg e 10 kg ? (no máximo duas sacas pesadas) ***

   Marcar apenas uma oval.

   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

Entrega por 4 euros

Considere agora uma compensação de 4 euros.

9. **Por 4 euros quantos metros extra faria com uma encomenda de peso até 1 kg ? (uma saca muito leve) ***

   Marcar apenas uma oval.

   - máx. 250 metros (3 min. a pé)
   - máx. 500 metros (6 min. a pé)
   - máx. 1 km (2 min. de carro)
   - máx. 2 km (4 min. de carro)
   - não o faria

10. **Por 4 euros quantos metros extra faria com uma encomenda de peso até 2.5 kg ? (uma saca leve)** *
Marcar apenas uma oval.

- máx. 250 metros (3 min. a pé)
- máx. 500 metros (6 min. a pé)
- máx. 1 km (2 min. de carro)
- máx. 2 km (4 min. de carro)
- não o faria

11. **Por 4 euros quantos metros extra faria com uma encomenda de peso até 5 kg ? (uma saca pesada)** *
Marcar apenas uma oval.

- máx. 250 metros (3 min. a pé)
- máx. 500 metros (6 min. a pé)
- máx. 1 km (2 min. de carro)
- máx. 2 km (4 min. de carro)
- não o faria

12. **Por 4 euros quantos metros extra faria com uma encomenda de peso entre 5 kg e 10 kg ? (no máximo duas sacas pesadas)** *
Marcar apenas uma oval.

- máx. 250 metros (3 min. a pé)
- máx. 500 metros (6 min. a pé)
- máx. 1 km (2 min. de carro)
- máx. 2 km (4 min. de carro)
- não o faria

Entrega por 5 euros

Considere agora uma compensação de 5 euros.

13. **Por 5 euros quantos metros extra faria com uma encomenda de peso até 1 kg ? (uma saca muito leve)** *
Marcar apenas uma oval.

- máx. 250 metros (3 min. a pé)
- máx. 500 metros (6 min. a pé)
- máx. 1 km (2 min. de carro)
- máx. 2 km (4 min. de carro)
- não o faria

14. **Por 5 euros quantos metros extra faria com uma encomenda de peso até 2.5 kg ? (uma saca leve)** *
Marcar apenas uma oval.

- máx. 250 metros (3 min. a pé)
- máx. 500 metros (6 min. a pé)
- máx. 1 km (2 min. de carro)
- máx. 2 km (4 min. de carro)
- não o faria

15. **Por 5 euros quantos metros extra faria com uma encomenda de peso até 5 kg ? (uma saca pesada)** *
Marcar apenas uma oval.

- máx. 250 metros (3 min. a pé)
- máx. 500 metros (6 min. a pé)
- máx. 1 km (2 min. de carro)
- máx. 2 km (4 min. de carro)
- não o faria

16. **Por 5 euros quantos metros extra faria com uma encomenda de peso entre 5 kg e 10 kg ? (no máximo duas sacas pesadas)** *
Marcar apenas uma oval.

- máx. 250 metros (3 min. a pé)
- máx. 500 metros (6 min. a pé)
- máx. 1 km (2 min. de carro)
- máx. 2 km (4 min. de carro)
- não o faria

Cost (€/m)	Compensation (€)	Total comp. (€)	% Comp.	Expected cost (€)	% Improvement	Expected cost (m)	A	#OC
0,0001	na	na	na	2,5707	0	25707	no out	0
0,0002	0,212	0,424	8,374	5,063	1,518	25316,755	'11', '15'	2
0,0003	0,197	0,788	10,712	7,356	4,613	24521,098	'11', '14', '15', '8'	4
0,0005	0,203	1,421	12,817	11,087	13,746	22173,19	'7', '14', '12', '15', '11', '13', '8'	7
0,0007	0,175	2,275	15,506	14,672	18,466	20959,994	'3', '9', '10', '4', '7', '5', '6', '14', '12', '15', '11', '13', '8'	13
0,001	0,251	3,263	15,667	20,827	18,983	20827,141	'3', '9', '10', '4', '7', '5', '6', '14', '12', '15', '11', '13', '8'	13
0,002	0,191	2,674	6,900	38,756	24,620	19378,01	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,007	2,168	30,352	25,917	117,111	34,920	16730,083	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,01	3,688	51,632	39,807	129,707	49,544	12970,651	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,02	7,549	105,686	78,189	135,167	73,710	6758,371	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,1	10,966	153,524	84,580	181,514	92,939	1815,141	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,2	12,488	174,832	86,977	201,008	96,090	1005,042	'13', '3', '5', '2', '6', '11', '15', '14', '9', '10', '12', '8', '7', '4'	14
1	15,518	217,252	88,395	245,774	99,044	245,774	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14

Table 1: Optimal compensation, total compensation, percentage of costs from compensations, total expected cost, percentage of improvement, expected cost in meters, outsourcing set solution and set size for different assumptions of the travel cost per meter with the professional fleet, with a probability curve obtained for a weight of 1 kg and a distance of 250 m.

Cost (€/m)	Compensation (€)	Total comp. (€)	% Comp.	Expected cost (€)	% Improvement	Expected cost (m)	A	#OC
0,0001	na	na	na	2,5707	0	25707	no	0
0,0002	0,212	0,424	8,263	5,132	0,192	25657,643	'11', '15'	2
0,0003	0,197	0,985	12,849	7,666	0,599	25553,137	'5', '6', '15', '11', '8'	5
0,0005	0,203	1,421	11,185	12,705	1,159	25409,041	'9', '4', '5', '6', '15', '11', '8'	7
0,0007	0,175	1,75	9,885	17,704	1,616	25291,505	'3', '9', '10', '4', '7', '5', '6', '15', '11', '8'	10
0,001	0,251	2,51	9,928	25,281	1,656	25281,399	'3', '9', '10', '4', '7', '5', '6', '15', '11', '8'	10
0,002	0,191	2,292	4,561	50,257	2,251	25128,341	'3', '9', '10', '4', '7', '5', '6', '14', '2', '15', '11', '8'	12
0,007	1,34	14,74	8,416	175,152	2,666	25021,726	'3', '9', '10', '4', '7', '5', '6', '14', '15', '11', '8'	11
0,01	3,688	29,504	11,869	248,582	3,302	24858,159	'9', '4', '5', '6', '14', '15', '11', '8'	8
0,02	10,301	72,107	16,767	430,060	16,353	21503,021	'7', '14', '12', '15', '11', '13', '8'	7
0,1	22,591	316,274	89,413	353,724	86,240	3537,24	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
0,2	24,472	342,608	90,129	380,131	92,606	1900,656	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14
1	28,885	404,39	91,773	440,643	98,286	440,643	'3', '9', '10', '4', '7', '5', '6', '14', '12', '2', '15', '11', '13', '8'	14

Table 2: Optimal compensation, total compensation, percentage of costs from compensations, total expected cost, percentage of improvement, expected cost in meters, outsourcing set solution and set size for different assumptions of the travel cost per meter with the professional fleet, with a probability curve obtained for a weight of 10 kg and a distance of 2000 m.