Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 30 (2018) 90–100

Transportation Research Procedia

www.elsevier.com/locate/procedia

EURO Mini Conference on "Advances in Freight Transportation and Logistics" (emc-ftl-2018)

Stochastic last-mile delivery with crowdshipping

Katarzyna Gdowska[a,d]*, Ana Viana[b,d], João Pedro Pedroso[c,d]

[a]*AGH University of Science and Technology, Faculty of Management, ul. Mickiewicza 30, Cracow, Poland*
[b]*Instituto Superior de Engenharia do Porto, Rua Dr. António Bernardino de Almeida, 431, Porto 4200-072, Portugal*
[c]*University of Porto, Faculty of Sciences, Rua do Campo Alegre 1021/1055, Porto 4169-007, Portugal*
[d]*INESC TEC, Dr. Roberto Frias, Porto 4200, Portugal*

Abstract

For the predicted growth of e-commerce, supply chains need to adapt to new conditions, so that delivery can be fast, cheap and reliable. The key to success is the last-mile product delivery (LMD) – the last stage of the supply chain, where the ordered product is delivered to the final consumer's location. One innovative proposal puts foundations in a new delivery model where a professional delivery fleet (PF) is supplemented partially or fully with crowdshipping. The main idea of crowdshipping is to involve ordinary people – in our case in-store shoppers – in the delivery of packages to other customers. In return, occasional couriers (OC) are offered a small compensation. In hitherto formulated problems it was assumed that OCs always accept delivery tasks assigned to them. In this paper we consider OCs as independent agents, which are free to reject assignments. The main contribution of the paper is an original bi-level methodology for matching and routing problem in LMD with OCs and the PF. The goal is to use crowdshipping to reduce the total delivery cost in a same-day last-mile delivery system with respect to occasional couriers' freedom to accept or reject the assigned delivery. We introduce probability to represent each OC's willingness to perform the delivery to a given final customer. We study the OCs' willingness to accept or reject delivery tasks assigned to them and the influence of their decision on the total delivery cost associated to both the OCs' compensation fees and the delivery cost generated by the PF used for the delivery of remaining parcels.

Selection and peer-review under responsibility of the scientific committee of the EURO Mini Conference on "Advances in Freight Transportation and Logistics" (emc-ftl2018).

Keywords: Last-mile delivery; crowdshipping; vehicle routing; ocassional couriers, crowd logistics

* Corresponding author. Tel.: +48 12 617 43 34.
E-mail address: Katarzyna Gdowska kgdowska@zarz.agh.edu.pl; Ana Viana aviana@inesctec.pt; João Pedro Pedroso jpp@fc.up.pt

Selection and peer-review under responsibility of the scientific committee of the EURO Mini Conference on "Advances in Freight Transportation and Logistics" (emc-ftl2018).
10.1016/j.trpro.2018.09.011

1. Introduction

For the predicted growth of e-commerce to USD 500 billion in the US in 2018 (Lee et al., 2016) from 13.8% in 2015 to 17.1% in 2020 in the UK (Mckinnon, 2016), business models for last-mile delivery (LMD) of parcels – the last stage of the supply chain, where the parcel is delivered to the final consumer's location – need to innovate and consider fast, cheap and reliable ways of delivery. High speed and low costs are indicated as the key to success of LMD (Chen and Pan, 2016). Innovative ideas for efficient and low-cost LMD are needed, since it is estimated that from 13 to 75% of the total supply chain costs are generated in the last leg of delivery (Gevaers et al., 2011). Furthermore, as LMD significantly contributes to traffic congestion and pollution emission, logistics companies should search for solutions that may enable delivery in urban and suburban territory (Suh et al., 2012; Slabinac, 2015; Thompson, 2015).

One innovative concept follows the socio-economical idea associated to sharing economy (Habibi et al., 2017) – it puts foundations for a new delivery model where a professional delivery fleet is supplemented partially or fully with *crowdshipping*. The main idea of crowdshipping is to involve ordinary people in the delivery of packages to final consumers.

In this paper we consider crowdshipping which aims at encouraging individuals to occasionally "carpool" a parcel – to pick-up and deliver goods on the way to their own destinations. The concept was discussed (but not implemented) by Wal-Mart and DHL (Barr and Wohl, 2013; DHL, 2013). It differs from crowdsource-based services such as AmazonFlex (Reilly, 2015) in the following: in AmazonFlex drivers have to pick up packages from stations and deliver them to recipients, while the Wal-Mart's idea uses in-store shoppers, who are willing to drop off packages for online customers on their route back home. The latter policy is much more aligned with the objectives of reducing traffic congestion and emissions. In return, occasional couriers are offered a small compensation to partially reimburse their travel costs. The fee is small enough to prevent turning this system into on-demand crowdsource based delivery business. As the participants are usually free to use any mean of transportation to perform the delivery, we refer to them using the term "occasional couriers".

Most works addressing optimization problems in the above mentioned forms of crowdshipping refer to same-day delivery (e.g. Archetti et al. (2016), Arslan et al. (2016), Dayarian and Savelsbergh (2017), Devari et al. (2017) or Suh et al. (2012)). They combine delivery performed by *occasional couriers* (OC) and the *professional fleet* (PF) in the following way: if some packages remain not assigned to OCs, they are delivered by the PF. In result, society benefits from reducing the number of freight vehicles (in the case of Wal-Mart) and companies reduce their total delivery costs (in both cases). The professional delivery fleet may belong to the retailer or to another company. It is assumed that the PF is homogeneous and its size is big enough to serve all the deliveries which have not been crowdshipped. A retailer's objective is to minimize the total delivery cost, i.e. the delivery costs generated by the PF and the compensation paid to the OCs.

Although this is an area yet to be explored, some problem variants have been addressed as matching and vehicle routing problems, by e.g. Agatz et al. (2011), Archetti et al. (2016), Arslan et al. (2016), Dayarian and Savelsbergh (2017), Kafle et al. (2017), and van Cooten (2014). The majority of presented models are static; however dynamic models like the one by Dayarian and Savelsbergh (2017) are more suitable for LMD with crowdshipping due to the dynamic character of crowdsourcing in general. Typically, the matching problem is formulated as a single-parcel single-OC assignment (i.e. the bipartite matching problem), and the routing problem is solved for the PF and remaining parcels. When OCs are not involved, the problem is just the standard Capacitated Vehicle Routing Problem (VRP), which provides an upper bound on the total cost of the original problem. All these problems are deterministic: delivery tasks and available OCs are known at the start of a given time horizon.

The Wal-mart's concept of LMD with crowdshipping includes a fast decision-making process, since in-store shoppers are available only for short period during which they can be asked to fulfill a delivery task. Dynamic OCs' pricing and matching is connected with the PF routing, as the overall solution represents the reduction of the total delivery costs. Archetti et al. (2016), after conducting research on optimizing a LMD system with OCs, emphasize the importance and difficulty of properly choosing a compensation scheme.

Before we offer a delivery task to an OC at a given compensation fee, we need to get a solution of the VRP. Therefore, the VRP in LMD with crowdshipping need to be solved quickly, and the optimality gap should not be large. This issue has been already examined for different delivery systems not necessarily involving crowdshipping.

For instance, results of solving the Travelling Salesman Problem with Pickup and Delivery (TSP-PD) (i.e. a single-route VRP) in real time with exact methods are presented by O'Neil and Hoffman (2017), and a dynamic approach with a priori calculated possible routes for a multiple-route VRP is discussed by Lagos et al. (2017) for the Vehicle Routing Problem with Probabilistic Customers (VRP-PC), and by Coslovich et al. (2006) for the Dial-a-Ride Problem with Time Windows (DARP-TW).

Compensation schemes influence the number of OCs, and their willingness to accept a delivery task even if it requires taking a detour from their initial route, as well as the selection of localizations to be crowdserviced and those which are to be served by the PF. To the authors' best knowledge, the literature on compensation schemes for crowdshipping is scarce and hitherto analytical studies employ compensation schemes based on fixed PF delivery costs and fixed compensation fees for OCs. Analytical studies presented by Archetti et al. (2016), Arslan et al. (2016) or Kafle et al. (2017) aim at minimizing total delivery costs through Integer Programming (IP).

In all cases, the cost of delivering a parcel to a final consumer is pre-defined, both for the PF (based on the distance) and OCs (based on the detour from their intended travel route). This is probably one of the main weaknesses of currently proposed static models. Moreover, none of the models by Dayarian and Savelsbergh (2017) seem to have conveniently addressed dynamic compensation schemes, which are an important avenue for further research.

Compensation schemes may be categorized with respect to the way of computing the OC's fee and the PF's delivery costs. For example, Archetti et al. (2016) adopted fixed fees both for the PF and OCs – the PF's delivery cost was based directly on the distance, and OCs' compensation fees were calculated proportionally to the cost incurred by the PF on the same distance. To the authors' best knowledge, a stochastic approach to optimizing the LMD with OCs and the PF has not been investigated yet. Moreover, a methodology of dynamic pricing in crowdsource-based business models has not been proposed yet.

In all the discussed optimization models for LMD with crowdshipping it was assumed that the probability of accepting the assigned delivery task was equal to 1. None of the hitherto developed models actively influences on OCs' willingness to accept jobs; that is hardly possible in deterministic models with almost completely fixed compensation schemes. Although available OCs are usually willing to serve, we should never take it for granted that every OC accepts every feasible assignment. Therefore, more realistic models must consider some randomness in the process of acceptance, to represent the OCs' free will. Several facts should be taken into account: (i) there is no guarantee that an OC will accept the task proposed; (ii) it is likely that the probability of accepting a task increases with the amount offered; (iii) the optimum amount that should be offered for a given task depends on the costs incurred by the PF, and hence depends also on its current solution.

As an example, consider a problem in one dimension. If a company located at $x = 0$ has to perform deliveries to customers at $x = -5$ and $x = -10$, it probably should not propose a delivery at $x = -7$ to be crowdserviced. However, a delivery by an OC to a final consumer at $x = +10$ should be incentivized, as it will clearly reduce costs incurred by the professional delivery fleet.

The literature on optimization problems in LMD with crowdshipping is scarce. Even the most recent publications indicate the need for further exploration and studies to enrich the existing body of research work. In this paper we contribute to this area by exploring a stochastic process of assignment acceptance by OCs and incorporating it in the existing methodology. In our research we focus on modelling LMD with crowdshipping where an OC may reject a delivery task. We assign random probability to each pair (OC, delivery task), so that we can model OC's willingness to serve. As there are no available benchmark instances for the LMD systems under investigation, we represent randomness using basic random number generators. We report and analyze preliminary results, based on small instances.

The remainder of this paper is as follows. In Section 2 we present the state of the art. We review the most representative pricing and waging strategies used in real crowdsource based business models, as well as compensation schemes implemented in optimization problems for LMD with crowdshipping. Special attention is given to the Vehicle Routing Problem with Occasional Drivers (VRPOD) by Archetti et al. (2016), since it can be seen as a main point of reference for our research. In Section 3 a bi-level methodology for matching and routing problem is presented. The first level is deterministic and is based on the IP model for the VRPOD, while the second level consists of a stochastic model aiming at minimizing expected delivery costs with respect to uncertainty of OCs' accepting a given delivery task. Next, in Section 4, results of computational experiments are reported. As dynamic compensation fee schemes seem to be an important and non-trivial aspect of managing LMD system with crowdshipping, in Section 5 we highlight some directions for future research.

2. State-of-the-art

Pricing and waging strategies play a key role in crowdsource based projects, since an inappropriate compensation scheme can lead to low capital efficiency, task starvation or the absence of crowd workers (Goel et al., 2014; Mao et al., 2012). In this section we provide general background of compensation schemes in crowdsourcing projects and review solutions for LMD with crowdshipping in terms of compensation schemes. We also present differences between a stochastic approach to LMD with OCs and the deterministic model by Archetti et al. (2016).

Since the matching and routing problems for the LMD with crowdshipping are NP-hard, the associated Integer Programs cannot be solved efficiently using exact algorithms except if P = NP; in practice, exact algorithms can tackle only small instances. This is why the majority of works have considered heuristic algorithms for solving realistic instances, except for Arslan et al. (2016) and van Cooten (2016), who solved either small instances or simplified problems. Archetti et al. (2016) proposed for LMD with crowdshipping a multi-start heuristic that combines variable neighborhood search and tabu search. Kafle et al. (2017) decompose the problem into a winner determination problem and a simultaneous pickup-and-delivery problem with soft time windows, and propose a tabu search based algorithm to iteratively solve the two subproblems. In a different methodological work, Wang et al. (2016) propose several pruning techniques to reduce the size of the network considerably for solving a min-cost network flow problem.

2.1. Pricing and waging strategies in crowdsource based business models

In a crowdsource based project there are typically two groups of stakeholders (customers and crowd-workers), which have the following objectives: (1) customers aim to maximize the utility derived from tasks within limited budget, while (2) crowd-workers aim to maximize their own utility by choosing tasks to complete and setting their price. Each crowd-worker is willing to do a task if the price is greater than his/her private minimum cost. Having proper pricing, compensation scheme and effective task assignment are the main challenges for any crowdsourcing project. A growing popularity of crowdsource-based business models stimulates the development of new pricing and compensation schemes for making available on the crowdsourcing market. For example, a decade ago the most popular pricing scheme was bidding (Singer and Mittal, 2011), while nowadays compensation fees are computed using numerous multipliers, which take into account, among others, workers' flexibility and covering demand peaks (Hall et al., 2015; Zha et al., 2017).

Cachon et al. (2017) present the topology of five pricing and compensation schemes for crowdsource-based business models: (1) fixed contract – fixed price for customers and fixed compensation for workers; (2) dynamic price contract – dynamic price for customers and fixed compensation for workers; (3) dynamic wage contract – fixed price for customers and dynamic compensation for workers; (4) commission contract – dynamic price for customers, dynamic compensation for workers, fixed commission, and fixed rate between price and compensation fee; (5) optimal contract – dynamic price for customers, dynamic compensation for workers, no commission, and no conditions on relation between price and compensation.

Arslan et al. (2016) provide a very brief review of compensation schemes for OCs used in five crowdsourcing based delivery companies: fees for OCs are based either on hourly rate (Deliv, Kanga, AmazonFlex) or on the number of parcels delivered (Renren Kuaidi, Trunkrs). None of the reviewed companies uses a mixed compensation scheme combining working hours and the number of parcels. The companies require the following information from OCs: OCs should either specify his/her time period (Deliv, Renren Kuaidi, Kanga, AmazonFlex) or time, origin and destination (Kanga). Unfortunately, there is no information how these data are used in computing the OC's compensation fee.

Frehe et al. (2017) provide a study of cash flows for a purchase-and-deliver crowdshipping system, where items bought on-line are crowdshipped with OCs. There is no PF, and the provider of a crowd logistics platform acts as a middleman. On-line shoppers and OCs make transactions on delivery via the platform and the provider charges a fee on every deal. Matchings between on-line shoppers and OCs are based on a bidding mechanism. Unfortunately, the authors discuss neither the pricing method nor the compensation scheme in terms of the crowd logistics platform and the brick-and-mortar store.

Dynamic pricing is studied and some outcomes are already implemented in practice but in other sectors of crowdsourcing market: for example, in participatory sensing a reverse auction based mechanism is used for dynamic bid price claiming (Lee and Hoh, 2010), and in ridesharing Uber utilizes their surge price algorithm known as the UberX service (Hall et al., 2015).

2.2. Compensation schemes in optimization problems in LMD with crowdshipping

In analytical works addressing LMD with crowdshipping the most popular compensation scheme is the one based on fixed costs calculated with respect to distances and/or some characteristics of delivery tasks. The authors usually assume that OCs never reject their assignments due to the reimbursement amount, although it is sometimes pointed out as a significant unrealistic simplification of the problem.

LMD with OCs and the PF is analyzed as a part of bigger crowd logistics system by van Cooten (2016). The objective is to minimize the total delivery cost generated by the single-parcel assignment for OCs and routing the PF, which delivers the remaining parcels. In this model, delivery costs generated by the PF are the sum of fixed costs associated with every parcel. Total delivery cost is to be reduced by assigning some parcels to OCs instead of the PF. The author considers two simple compensation schemes for OCs: the first is based on one fixed fee per parcel, while the second combines fixed fee per parcel (the fee is lower than the one offered in the first scheme) with variable delivery cost for every minute of the detour made by an OC. No matter what compensation scheme is employed in the model, the time of the OC's detour is limited in advance by the maximum value. Thus an OC cannot be matched with a delivery task requiring a detour longer than the pre-defined limit.

Archetti et al. (2016) discuss two compensation schemes for the single-parcel assignment problem. In the first compensation scheme fees for OCs are computed based on the fixed delivery cost associated with serving a customer. OC's fee is independent from his/her destination. Delivery cost generated by the PF is based on the driven distance; the delivery cost per mile is fixed. The second compensation scheme associates the OC's fee with the detour he/she takes from the initial route. Delivery cost associated with the PF is the same as in the first scheme.

A compensation scheme based on the extra distance is employed also in the crowdshipping model presented by Wang et al. (2016), where OCs deliver parcels from one parcel station to another. OCs are associated with their usual routes and the fixed cost is calculated on the mileage of the detour they make. To simplify the problem, the authors do not verify OC's travel patterns, but calculate the detour made by an OC based on the Euclidean distance between each two points.

Arslan et al. (2016) introduce a dynamic pickup-and-delivery model which combines matching of parcels both to the PF and OCs and define the routes for the PF. This approach is significantly inspired by the Share-a-Ride Problem studied by Agatz et al. (2011). The OC's compensation fee is the combination of a fixed fee per delivery and a per-mile fee for the detour. The PF's delivery costs depend only on the distance driven. The objective is to minimize the total system-wide delivery costs incurred by the PF and OCs. To capture randomness of parcel orders and availability of OCs, both Agatz et al. (2011) and Arslan et al. (2016) consider an event-based rolling horizon. The parcel–OC matching is repeated whenever a new OC checks in or a new delivery task appears in the system. Arslan et al. (2016) also present a Mixed Integer Linear Programming model for a static single-parcel assignment problem. For transforming it into a multi-parcel assignment they suggest solving the Traveling Salesman Problem with Time Windows and Precedence Constraints (TSP-TW-PC) as a subproblem. The PF routing is not mentioned explicitly.

Kafle et al. (2017) analyze a LMD system with time windows with OCs and the PF. OCs participate in the last leg of the LMD system, which means that they are supposed to pick-up assigned parcels from a PF car and deliver them to the final consumers' locations. Remaining parcels are to be delivered by the PF car. The problem is a multiple-parcel assignment where OCs bid for assignments. The objective is to minimize the total cost consisting of the sum of payments for selected bids, the PF operating cost, and time penalty cost for not fitting in the customers' time windows. Pricing and compensation schemes are based on fixed values. The PF delivery costs are based on the total mileage and unit transportation costs. OC's compensation fee is 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 crowdsource. The third component of the objective function is collectively determined by selected bids and truck schedule due to parcel relay.

2.3. The Vehicle Routing Problem with Occasional Drivers

The Vehicle Routing Problem with Occasional Drivers was presented by Archetti et al. (2016) for the same day LMD with crowdshipping. Each OC may be assigned at most one delivery tasks, and all remaining parcels must be delivered by the PF. The objective is to minimize the total delivery costs, which consist of the sum of delivery costs incurred by PF and the sum of compensation fees offered to OCs. It is also assumed that the capacity of every single parcel does not exceed the capacity of OCs' vehicles. The problem can be represented by a complete directed graph, $G=(N,E)$, where N is the set of nodes and E is the set of arcs. Set N consists of a depot/store (node 0), customers' locations (subset C) and OCs' destinations (subset K). The notation used is presented in Table 1 and the associated Integer Program is written as model (1a)–(1m).

Table 1. Notation used in the IP model for the VRPOD and Algorithm 1.

Variables
x_{ij} – 1, if a PF car traverses arc (i,j); 0, otherwise
y_{ij} – load carried by a PF car on arc (i,j);
z_i – 1, if customer i is served by a PF car; 0, otherwise;
w_{ik} – 1, if customer i is served by OC k;
Parameters
c_{ij} – cost of traversing arc (i,j) by a PF car;
p_{ik} – compensation paid to OC k for serving customer i;
Q – capacity of a PF car;
q_i – size of the parcel to be delivered to customer i;
β_{ik} – 1, if customer i can be served by OC k

$$\text{minimize } z=\sum_{(i,j)\in E} c_{ij}x_{ij}+\sum_{i\in C}\sum_{k\in K} p_{ik}w_{ik} \tag{1a}$$

$$\sum_{j|(i,j)\in E} x_{ij}=\sum_{j|(j,i)\in E} x_{ji}=z_i,\forall i\in C \tag{1b}$$

$$\sum_{j|(0,j)\in E} x_{0j}=\sum_{j|(j,0)\in E} x_{j0}=0 \tag{1c}$$

$$\sum_{j|(j,i)\in E} y_{ji}=\sum_{j|(i,j)\in E} y_{ij}=\begin{cases} q_i z_i,\forall i\in C \\ \sum_{i\in C} i=0 \end{cases} \tag{1d}$$

$$y_{ij}\le Qx_{ij},\forall (i,j)\in E \tag{1e}$$

$$y_{i0}=0,\forall i\in C \tag{1f}$$

$$w_{ik}\le \beta_{ik},\forall i\in C,\forall k\in K \tag{1g}$$

$$\sum_{i\in C} w_{ik}\le 1,\forall k\in K \tag{1h}$$

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

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

$$z_i\in\{0,1\},\forall i\in C \tag{1k}$$

$$w_{ik} \in \{0,1\}, \forall i \in C, \forall k \in K \tag{1l}$$

$$y_{ij} \geq 0, \forall (i,j) \in E \tag{1m}$$

The objective function (1a) aims at minimizing the total costs. Constraints (1b) and (1c) are for PF routing: constraints (1c) guarantee that every route begins and ends in the depot/store, while constraints (1b) ensure that each customer assigned to the PF is visited by the PF only once. Constraints (1d) prevent subtours in the PF's routes, constraints (1e) guarantee that a PF car's capacity is not exceeded, and constraints (1f) ensure that the PF car goes back empty to the store. Constraints (1g) and (1i) refer to OCs: constraints (1g) guarantee that delivery tasks are assigned to those OCs which are able to fulfill them, while constraints (1i) ensure that each OC is paired with at most one customer. Constraints (1j) guarantee that every customer's location is visited exactly once – either by the PF or an OC.

The IP model for the VRPOD is deterministic, with the assumption that once a customer is matched with an occasional courier, the OC must accept the assignment. The remaining customers are served by the PF and the associated routing problem is solved. In this paper we extend the work by Archetti et al. (2016) in the way crowdshipping is dealt with. We replace the static deterministic compensation fee, p_{ik}, implicitly accepted by an OC, with a stochastic version where a certain (fixed) compensation fee for serving a customer is associated to the probability of acceptance (also fixed), reflecting OC's willingness of accepting the task or not. As all the rejected jobs must be performed by the PF, every rejection influences the PF routing problem and the total delivery cost.

3. Methodology

Archetti et al (2016) considered same-day LMD in a setting where each OC may be assigned at most one delivery task, and all remaining parcels are to be delivered by the PF at the end of the day. We consider a slightly modified situation, where each customer's order may be selected for outsourcing to an OC or not, but we do not keep track of the particular OC to whom it is proposed. Each customer is identified by his/her individual location. Since we deal with single-parcel assignment, we can use "delivery task" and "customer" as synonyms. We assume that the homogeneous professional backup fleet is capable to deliver all the remaining parcels, possibly with several routes. Availability of customers at their places is assumed to be unlimited, so we do not have to consider any time window during which delivery must be performed.

Introducing probability makes the problem more realistic: when a delivery is proposed to an OC, the acceptance of that task is not guaranteed – though, if accepted, the company must pay the fee offered. Our approach results in a stochastic model, where the possibilities of both acceptance and rejection must be considered, and the expected outcome is computed. At the first stage, we determine the subset of customers whose deliveries are proposed to OCs; at the second stage, we observe deliveries which were rejected by OCs and we include them in the PF's route. Notice that the fixed amounts considered for the compensation and for the probability of acceptance are still a simplification; in reality, the OC's willingness to undertake a task should be based on the OC's own destination, on the customer's location, and on the amount of the compensation fee.

For a given observation of the acceptance of deliveries by OCs, the problem is similar to a static VRP; we denote its optimum by $VRP(C')$, where C' is the subset of customers to be served (we are abusing notation, assuming an existing underlying graph and a known depot). We consider this problem to be static, but we must deal with all the combinations of acceptance/rejection of delivery tasks by OCs.

The expectation for the total cost when proposing a subset $A \subseteq C$ of customers to be outsourced is (2):

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

where p_i is the probability that delivery to customer i is accepted by an OC for a fee K_i, and the full set of customers is C.

Here, we associate the amount of the compensation fee exclusively with the customer to be served – a fixed value, which may be set randomly, or may be based on customer's location or parcel's size, etc. The compensation fee is not related to the OC's coordinates, so we do not track OCs' final destinations. This allows us to focus on the graph $G=(C,E)$ $G=(C,E)$ representing customers. For each customer there is a fixed probability that delivery to his/her place is accepted by an OC. Probability of acceptance may be set randomly or, more realistically, be based on historical data.

3.1. Description of the bi-level stochastic model and solution method

For solving this problem we propose a heuristic approach where we increase the subset of customers to be served by OCs (starting with an empty set) up to the point where there is not further gain in (locally) adding an additional customer to this subset, as described in Algorithm 1 (see Fig. 1). The first level consists of subset selection; all the possible acceptance patterns are explored in the second level. The most computationally intensive part is hidden in the call to the expectation function E, through Equation (2), which implicitly solves a potentially huge number of VRPs. The output of this algorithm is set A – the set of customers which are to be proposed for crowdshipping.

Algorithm 1: Heuristic method to find subset of customers to be proposed to OCs.

Data:
- graph $G = (\{d\} \cup C, E)$ with depot d and vertices C to be visited
- cost c_{ij} of traversing edge $ij \in E$
- cost r_i of outsourcing delivery to vertex $i \in V$
- probability p_i of outsourcing request for $i \in V$ being accepted

Result:
- subset $A \subseteq V$ of vertices to select for outsourcing

```
1  z* ← E(C, ∅, p)
2  A ← ∅
3  while True do
4      B ← A
5      foreach i ∈ C \ A do
6          z ← E(C, A ∪ {i}, p)
7          if z < z* then
8              i* ← i
9              z* ← z
10             A ← A ∪ {i}
11     if A = B then
12         break
13     else
14         foreach j ∈ A \ {i*} do
15             z ← E(C, A \ {j}, p)
16             if z < z* then
17                 z* ← z
18                 A ← A \ {j}
19 return A
```

Fig. 1. Algorithm 1 – a heuristic method to find subset of customers to be proposed to OCs.

In this method we start by computing the total cost of delivery for the case when none of the delivery tasks is crowdshipped. As all the customers are served by the PF; a typical Capacitated Traveling Salesman Problem is solved and the initial total delivery cost (z^*) is computed. Then, the initial total cost is gradually reduced by "proposing" deliveries to OCs and adding them to set A. After an additional customer is added to set A, we check if removing previously assigned customers would be worthwhile (lines 14 to 18). As mentioned in the beginning of this section, all patterns of delivery acceptance must be taken into account when determining the expected cost associated to each set A (lines 6 and 15). In each pattern, after observing the delivery jobs that have been accepted by OCs, the minimum cost for serving remaining customers is determined. Once an assignment is accepted by an OC, a compensation fee must be paid, even if in the second level associated to a particular acceptance pattern it would become cheaper to deliver to the corresponding customer with the PF.

4. Computational experiments

As there are no benchmark instances for the LMD with OCs and PF in the literature, we conducted computational experiments on randomly generated instances. We consider a system consisting of one depot and 15 customers. Coordinates of customers' locations, the compensation fee for serving each customer, and the probability of OCs' acceptance to serve each customer are randomly and uniformly distributed in $[0,1]$. The cost of traversing an arc by the PF vehicle is considered equal to Euclidean distance between these two vertices. The capacity of a PF vehicle is 50 units and the size of each delivery is an integer number randomly sampled from $\{10,...,20\}$. These settings were used to generate 25 difference instances. Obtained results are summarized in Table 2.

Table 2. Results obtained for 25 random seeds.

Seed r	Set A	# items in A	Items in A [%]	Initial cost	Final cost	Exp. cost reduction	% exp. cost reduction
1	1, 4, 6, 10, 11, 14	6	40%	7.182	6.882	0.300	4%
2	2, 3, 7, 12, 13, 14, 15	7	47%	10.150	8.834	1.316	13%
3	10, 13, 5, 15	4	27%	6.103	5.568	0.535	9%
4	1, 10, 12, 13, 14, 15	6	40%	6.763	6.221	0.542	8%
5	8, 3, 4, 13, 6	5	33%	7.328	7.155	0.173	2%
6	2, 10, 3, 4, 14	5	33%	7.057	5.769	1.288	18%
7	8, 1, 12, 4, 5	5	33%	6.201	5.494	0.707	11%
8	3, 7, 10, 11, 13, 14	6	40%	8.161	7.335	0.826	10%
9	9, 2, 3, 15	4	27%	5.481	4.610	0.871	16%
10	13, 7	2	13%	6.553	5.701	0.852	13%
11	3, 6, 8, 10, 11, 14, 15	7	47%	8.470	6.960	1.510	18%
12	3, 10, 11, 12, 13, 15	6	40%	7.836	6.833	1.003	13%
13	1, 2, 3, 7, 8, 10, 12	7	47%	9.492	8.553	0.939	10%
14	1, 2, 3, 4, 7, 12, 14	7	47%	8.214	6.592	1.622	20%
15	1, 5, 7, 9, 10, 13, 15	7	47%	8.530	7.972	0.558	7%
16	1, 6, 8, 13, 14, 15	6	40%	6.110	5.617	0.493	8%
17	8, 1	2	13%	6.585	5.947	0.638	10%
18	1, 15	2	13%	7.135	6.908	0.227	3%
19	1, 5, 6, 7, 8, 10, 11, 13, 14, 15	10	67%	7.097	5.889	1.208	17%
20	2, 5, 6, 8, 9, 12, 13, 15	8	53%	6.300	5.825	0.475	8%
21	9, 4, 15	3	20%	7.230	6.644	0.586	8%
22	11, 2, 3, 12, 14	5	33%	7.133	6.836	0.297	4%
23	8, 3, 4, 12, 6	5	33%	7.935	7.491	0.444	6%
24	9, 6	2	13%	5.870	5.774	0.096	2%
25		0	0%	7.522	7.522	0.000	0%
	AVERAGE	5	34%	7.298	6.597	0.700	9%
	MINIMUM VALUE	0	0%	5.481	4.610	0.000	0%
	MAXIMUM VALUE	10	67%	10.150	8.834	1.622	20%
	MEDIAN VALUE	5	33%	7.135	6.644	0.586	9%
	MOST FREQUENT VALUE	6	40%	n/a	n/a	n/a	n/a

The average initial total delivery cost is 7.298, when all the customers are served by the PF. In 24 of the 25 instances we observe a reduction of the expected total delivery cost due to proposing crowdshipping of some parcels. In instance $r = 25$ there is no delivery task to be offered to OCs. In each instance, the final cost is an expected value, since each delivery task in set A may be accepted by an OC or not. If accepted, the compensation fee for serving this customer by an OC is paid and the customer's location is excluded from PF routing. Otherwise, the customer is served by the PF. As every delivery task may be accepted or rejected according to the corresponding probability, we must compute the expected value of the total delivery cost, which consists of the compensation fees paid to OC for accepted tasks and delivery cost incurred by the PF for serving remaining customers. On average, the initial expected cost of delivery is reduced by 9% due to crowdshipped parcels.

Computational experiments were executed on a computer with an Intel Core i7 quad-core CPU with 24 GB of RAM, running at 3.4 GHz, using Mac OS X version 10.13.2. The algorithm was implemented in Python version 3.5.3, using the general-purpose mixed-integer optimization solver for solving VRPs, i.e. Gurobi, version 7.0.2.

5. Conclusions

The main contribution of this paper is introducing an agent-oriented approach to optimization problems in the last-mile delivery with occasional couriers and a professional backup fleet, where pairing OCs with delivery tasks can be considered only as a proposition, since OCs may reject their assignments with some probability. Complementing hitherto known deterministic models, we contributed with a stochastic perspective of the problem. Presented methodology is a good starting point for creating an advanced dynamic compensation scheme, which could be used for controlling a LMD system by actively encouraging OCs to accept a task. This could be done by offering them individually calculated compensation fees, based on historical data concerning the correlation between each OC's willingness to accept a task and the given compensation fee. Real-world data is not currently available, so we used a computationally simulated instance to illustrate the feasibility of the approach and to identify potential bottlenecks, as well as highlight difficulties that may arise in terms of data collection. We believe this still represents a significant contribution to the state-of-the-art and to the study of dynamic compensation fee schemes, which have a huge potential.

This paper identified and justified the need for a new methodology to calculate adequate compensation values for OCs, taking into account the dynamics involved in the delivery process. Both OCs' willingness and fees should be based on probability functions obtained from historical data on each OC, so that stochastic aspects associated to the problem could be represented properly in the model, and a dynamic compensation mechanism could be defined appropriately. This is a natural direction for future research in this area.

Acknowledgements

This work was partially supported by project "TEC4Growth/NORTE-01-0145-FEDER-000020", financed by the North Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, and through the European Regional Development Fund (ERDF).

References

Agatz,N.A.H., Erera, A.L., Savelsbergh, M.W.P., Wang, X., 2011. Dynamic ride-sharing: A simulation study in metro Atlanta. Transportation Research Part B: Methodological 45.9, 1450–1464.

Archetti, C., Savelsbergh, M., Speranza, M.G., 2016. The Vehicle Routing Problem with Occasional Drivers. European Journal of Operational Research 254.2), 472–480.

Arslan, A., Agatz, N., Kroon, L.G., Zuidwijk, R.A., 2016. Crowdsourced Delivery – A Pickup and Delivery Problem with Ad-Hoc Drivers. SSRN Journal.

Barr, A., Wohl, J., 2013. Wal-Mart may get customers to deliver packages to online buyers. Reuters: http://www.reuters.com/article/us-retail-walmart-delivery-idUSBRE92R03820130328. Accessed 19 April 2017.

Cachon, G.P., Daniels, K.M., Lobel, R., 2017. The Role of Surge Pricing on a Service Platform with Self-Scheduling Capacity. Manufacturing and Service Operations 19.3, 368–384

Chen, C., Pan, S., 2016. Using the Crowd of Taxis to Last Mile Delivery in E-Commerce: A methodological research. In: "Service Orientation in

Holonic and Multi-Agent Manufacturing", Borangiu, T., Trentesaux, D., Thomas, A., McFarlane, D. (Eds.). Springer International Publishing, Cham, vol. 640, pp. 61–70.

Coslovich, L., Pesenti, R., Ukovich, W., 2006. A two-phase insertion technique of unexpected customers for a dynamic dial-a-ride problem. European Journal of Operational Research 175.3, 1605–1615.

Dayarian, I., Savelsbergh, M., 2017. Crowdshipping and Same-day Delivery: Employing In-store Customers to Deliver Online Orders. Optimization-Online.org: http://www.optimization-online.org/DB_HTML/2017/07/6142.html. Accessed 4 August 2017.

Devari, A., Nikolaev, A.G., He, Q., 2017. Crowdsourcing the last mile delivery of online orders by exploiting the social networks of retail store customers. Transportation Research Part E: Logistics and Transportation Review 105, 105–122.

DHL, 2013. DHL crowd sources deliveries in Stockholm with MyWays. DHL: http://www.dhl.com/en/press/releases/releases_2013/logistics/dhl_crowd_sources_deliveries_in_stockholm_with_myways.html#.WPePVIjhA2w. Accessed 19 April 2017.

Frehe, V., Mehmann, J., Teuteberg, F., 2017. Understanding and assessing crowd logistics business models – using everyday people for last mile delivery. Jnl of Bus & Indus Marketing 32.1, 75–97.

Gevaers, R., van de Voorde, E., Vanelslander, T., 2011. Characteristics and typology of lastmile logistics from an innovation perspective in an urban context. In: "City Distribution and Urban Freight Transport", Macharis, C., Melo, S. (Eds.). Edward Elgar Publishing, pp. 56–71.

Goel, G., Nikzad, A., Singla, A., 2014. Allocating tasks to workers with matching constraints. In: Proceedings of the 23rd International Conference on World Wide Web, Seoul, Korea. ACM Press, New York, New York, USA, pp. 279–280.

Habibi, M.R., Davidson, A., Laroche, M., 2017. What managers should know about the sharing economy. Business Horizons 60.1, 113–121.

Hall, J., Kendrick, C., Nosko, C., 2015. The Effects of Uber's Surge Pricing: A Case Study. Uber Inc. http://economicsforlife.ca/wp-content/uploads/2015/10/effects_of_ubers_surge_pricing.pdf. Accessed 19 April 2017.

Kafle, N., Zou, B., Lin, J., 2017. Design and modeling of a crowdsource-enabled system for urban parcel relay and delivery. Transportation Research Part B: Methodological 99, 62–82.

Lagos, F., Klapp, M.A., Toriello, A., 2017. Branch-and-Price for Probabilistic Vehicle Routing. Optimization-Online.org: http://www.optimization-online.org/DB_HTML/2017/12/6364.html. Accessed 9 January 2018.

Lee, H.L., Chen, Y., Gillai, B., Rammohan, S., 2016. Technological Disruption and Innovation in Last-Mile Delivery: White Paper June 2016. Stanford Value Chain Innovation Initiative in Collaboration with United States Postal Service Office of Inspector General.

Lee, J.-S., Hoh, B., 2010. Dynamic pricing incentive for participatory sensing. Pervasive and Mobile Computing 6 (6), 693–708.

Mao, K., Yang, Y., Li, M., Harman, M., 2013. Pricing crowdsourcing-based software development tasks. In: 35th International Conference on Software Engineering (ICSE), San Francisco, CA, USA. IEEE, Piscataway, pp. 1205–1208.

McKinnon, A., 2016. Crowdshipping: a Communal Approach to Reducing Urban Traffic Levels? https://www.researchgate.net/profile/Alan_Mckinnon2/publication/310833718_Crowdshipping_a_Communal_Approach_to_Reducing_Urban_Traffic_Levels/links/58397ac108ae3a74b49e7021.pdf. Accessed 6 April 2017.

O'Neil, R.J., Hoffman, K., 2017. Exact Methods for Solving Traveling Salesman Problems with Pickup and Delivery in Real Time. Optimization-Online.org: http://www.optimization-online.org/DB_HTML/2017/12/6370.html. Accessed 9 January 2018.

Reilly, D., 2015. Amazon ponders crowdsourcing deliveries with 'On My Way' program. Fortune: http://fortune.com/2015/06/16/amazon-crowd-source. Accessed 6 April 2017.

Singer, Y., Mittal, M., 2011. Pricing Tasks in Online Labor Markets. In: Proceedings of the 11th AAAI Conference on Human Computation. AAAI Press, pp. 55–60.

Slabinac, M., 2015. Innovative Solutions for a "Last-Mile" Delivery – A European Experience. In: 15th international scientific conference "Business Logistics in Modern Management", Osijek, Croatia, pp. 111–129.

Suh, K., Smith, T., Linhoff, M., 2012. Leveraging socially networked mobile ICT platforms for the last-mile delivery problem. Environmental science & technology 46.17, 9481–9490.

Thompson, R.G., 2015. Vehicle Orientated Initiatives for Improving the Environmental Performance of Urban Freight Systems. In: "Green logistics and transportation. A sustainable supply chain perspective", Fahimnia, B. (Ed.). Springer International Publishing, Cham, pp. 119–129.

van Cooten, C., 2014. Crowdsourced Delivery – The Traditional Delivery Method Reinvented. Masters' Thesis, Eindhoven University of Technology: http://alexandria.tue.nl/extra2/afstversl/tm/Cooten_2016.pdf. Accessed 6 April 2017.

Wang, X., Dessouky, M., Ordonez, F., 2016. A pickup and delivery problem for ridesharing considering congestion. Transportation Letters 8.5, 259–269.

Zha, L., Yin, Y., Du, Y., 2017. Surge Pricing and Labor Supply in the Ride-Sourcing Market. Transportation Research Procedia 23, 2–21.