



Delft University of Technology

Smart Method for Self-Organization in Last-Mile Parcel Delivery

van Duin, Ron; Vlot, T.S.; Tavasszy, Lorant; Duinkerken, M.B.; van Dijk, Bernd

DOI

[10.1177/0361198120976062](https://doi.org/10.1177/0361198120976062)

Publication date

2020

Document Version

Final published version

Published in

Transportation Research Record

Citation (APA)

van Duin, R., Vlot, T. S., Tavasszy, L., Duinkerken, M. B., & van Dijk, B. (2020). Smart Method for Self-Organization in Last-Mile Parcel Delivery. *Transportation Research Record*, 2675(4), 260-270. Article 2674. <https://doi.org/10.1177/0361198120976062>

Important note

To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

Green Open Access added to TU Delft Institutional Repository

'You share, we take care!' - Taverne project

<https://www.openaccess.nl/en/you-share-we-take-care>

Otherwise as indicated in the copyright section: the publisher is the copyright holder of this work and the author uses the Dutch legislation to make this work public.

Smart Method for Self-Organization in Last-Mile Parcel Delivery

J.H.R. van Duin^{1,2}, T.S. Vlot³, L.A. Tavasszy⁴,
M.B. Duinkerken⁵, and B. van Dijk⁶

Transportation Research Record
1–11

© National Academy of Sciences:
Transportation Research Board 2020
Article reuse guidelines:

sagepub.com/journals-permissions

DOI: 10.1177/0361198120976062

journals.sagepub.com/home/trr



Abstract

Parcel delivery operators experience an increasing pressure to meet the strongly growing demand for delivery services, while protecting city livability and the environment. Improving the performance of the last mile of delivery is considered key in meeting this challenge as it forms the most inefficient, expensive, and environmentally unfriendly part of delivery operations. A primary cause is a significant duplication of service areas, resulting in redundant vehicle kilometers traveled. In this paper, a new method is presented that allows for the allocation of parcels to delivery vehicles and construction of vehicle routes in real time through an auctioning system. These tasks are performed in a self-organizing manner by vehicles, parcels, and a supporting platform, to allow for collaborative and intermodal delivery. The performance of this new method is tested and compared against the currently used techniques using an agent-based simulation model. The new method manages to greatly improve the efficiency, robustness, and flexibility of delivery operations.

The e-commerce industry has developed rapidly in recent years, which has also translated into a steep increase in the demand for parcel delivery services (1). Parcel delivery operators are pressured by their customers, shareholders, and society to meet this demand, yet also to safeguard city livability and minimize the negative environmental impact of delivery operations (2). The last mile of delivery especially hinders them from meeting this challenge, being the most inefficient, hence costly and environmentally unfriendly, part of the delivery process (3). A fundamental cause is the duplication of operators' service areas, resulting in redundant distance traveled by delivery drivers (1, 4–6). This is considered an important barrier to overcome to successfully cope with the boost in parcel delivery demand while enhancing the performance of the last mile. A field that attempts to improve operational efficiency of delivery operations is carrier collaboration, defined by Dai and Chen (7) as an alliance between carriers to optimize delivery operations by sharing transportation requests and spare vehicle capacity (8–10). This could translate into freight routing through multiple operators and transportation modes, also referred to as intermodal delivery. Examples of collaborative delivery can be found within the fields of freight transportation (7, 11) and crowdsourced delivery (12). However, because of computing speed requirements, these techniques are only

suited for static or small dynamic problem instances, such as studied by Setzke et al. (13) and Kafle et al. (14). In both works, driver availability and schedules are known in advance, therefore only a single model run is required to create solid schedules. The authors acknowledge their methods' limitations with regard to scalability and applicability. Namely, in reality operators often have to deal with incomplete information, disturbances occurring in real time, and many different drivers. Pan et al. (15) argue that logistics systems should evolve into self-organizing systems, meaning that they can function on local interactions between actors rather than through the guidance of a central entity (16). It is hypothesized that self-organization can enhance the robustness and

¹Faculty of Technology, Policy & Management, Delft University of Technology, Delft, The Netherlands

²Research Centre Sustainable Port Cities, Rotterdam University of Applied Sciences, Rotterdam, The Netherlands

³Movares, Utrecht, The Netherlands

⁴Faculty of Technology, Policy & Management, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands

⁵Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, Delft, The Netherlands

⁶Prime Vision, Delft, The Netherlands

Corresponding Author:

J.H.R. van Duin, j.h.r.vanduin@tudelft.nl

flexibility of logistics systems. Nonetheless, the concept of self-organizing logistics has not yet been applied to the domain of last-mile parcel delivery. Therefore, in this paper a method that facilitates self-organization in last-mile parcel delivery is proposed that aims to bridge this gap and pave the way for a more efficient and environmental friendly last mile. This method moreover allows for multi-hop and intermodal parcel delivery and is able to respond to aspects such as dynamically appearing vehicles, parcels, and disturbances in real time. Lastly, the method gives parcels the autonomy to choose their own means of transportation to ensure the best fit with the wishes of the receiving customer. This paper is organized as follows. The second section contains a review of the literature on current last-mile parcel logistics processes and the various concepts in the field of self-organizing logistics, highlighting the scientific gaps this paper fills. The third section describes the proposed method for self-organized last-mile parcel delivery. Subsequently, in the fourth section the implementation of both methods is discussed, which is used to evaluate the proposed method. Furthermore, the performance indicators used and details of the case study are provided. In the fifth section, the results of the experiments are presented. Lastly, the sixth section concludes with a summary of the findings and recommendations for future research.

Literature Review on Self-Organizing Logistics

Current Parcel Allocation and Vehicle Routing Techniques for Last-Mile Delivery

Ahead of the last-mile parcel delivery process, all parcels need to be allocated to a specific delivery route, and an optimal driving route needs to be calculated for each delivery vehicle. Ideally, these steps are taken together, with the goal of minimizing the combined travel distance of all vehicles. However, in reality these steps are typically performed sequentially to reduce organizational and computational complexity. First, allocation of parcels to delivery routes relies on delivery zones, each containing a cluster of postal codes. Delivery zones are constructed by solving the vehicle routing problem (VRP), taking into account constraints such as vehicle capacities, delivery time windows, delivery stop durations, and work-shift durations (17). Rather than calculating the optimal zone division on a daily basis, delivery zones are often fixed for multiple weeks or months. A resulting disadvantage hereof is that daily fluctuations in parcel volumes and delivery addresses are not compensated for in zone partition and can lead to suboptimal vehicle routes. Moreover, this can result in large differences between driver workloads. Secondly, the delivery

operator constructs the optimal route for each delivery vehicle separately. This is done by solving the traveling salesman problem (TSP), while adhering to time window constraints and preferred stop sequences of drivers (18).

Self-Organizing Logistics Systems

Through self-organization, simple behavior and interactions of local agents can form complex collective structures without the guidance of a central controlling body (16). This phenomenon is present in fields such as biology, chemistry, and sociology, and has among others inspired the idea of self-organizing logistics systems (19). This relatively new and developing field possesses three characteristics: openness, intelligence, and decentralized control (15). First, openness entails that no barriers exist for actors that want to enter or exit the system, making the system more resilient. The second characteristic, intelligence, means that all agents in the system can collect, process, and store information about their state and direct environment, autonomously execute decisions, and interact with other agents. Thirdly, in a self-organizing logistics system, agents are self-controlled, which allows for improved customer orientation, robustness, and flexibility (20).

Appleby and Steward (21) developed a self-organizing system where each telephone call was represented by an electronic ant that leaves a chemical trail of pheromones on its path to signal other ants how to avoid congested areas. This solution greatly increased the robustness of the system. A similar idea was pursued by Claes et al. (22) for the purpose of improving vehicle routing. In their work, ant-like agents collect information about traffic density and pass this information on to infrastructure systems, so that other vehicles can be informed of the state of traffic and make the best routing choice to avoid congestion. Furthermore, Morley (23) described a self-organizing logistics system at the truck painting facility of General Motors. In this facility, vehicles need to be painted by one of several painting booths, where the aim is to minimize the costs incurred when a booth has to switch to another paint color. By means of an auction system, painting booths could place bids on painting jobs, effectively cooperating with others to choose the best booth for the job. Self-organization is also studied in the context of freight transportation. However, in contrast to ant colonies that cooperate to reach a shared objective, freight carriers are self-interested and compete for transportation requests. Nevertheless, carriers recognize the advantages of sharing transportation requests to improve vehicle utilization (24). A possible way to facilitate cooperation is by auctioning transportation requests by the extended contract net protocol (ECNP) (25). In this protocol, shipping companies bid against each other

to win transportation tasks. Van Duin et al. (11) have developed a sealed multiple auction approach based on the ECNP that assigns a shipment to the carrier offering the best service quality and price. On completion of an auction, tasks cannot be reassigned. Lee and Kim (26) diverge from this latter characteristic and propose a brokerage system that tries to find the best match between trucks and delivery tasks in an on-going fashion. In their method, new bids can be entered for past auctions until a specific deadline is reached. The trucks that lose their allocated task re-enter the bidding market. Song and Regan (27) present a similar solution, but allow carriers to reevaluate their accepted tasks and ask other carriers with overlapping routes to submit a bid to take over their load. Lai et al. (24) have built on the idea of exchanging transportation requests among carriers by means of an iterative auction. During every round, carriers can decide which shipments they want to sell and buy. When all exchanges have taken place, the auction stops. The concept of auctioning transportation tasks is not only found in freight transportation. This decentralized method to divide shipment requests has made its way into the field of transportation on demand, which is relevant for dial-a-ride services for elderly and handicapped people and emergency vehicle systems, among others. Traditionally, transportation on demand services are managed by central entities in charge of vehicle dispatch. However, real-life large-scale dynamic problems with many transportation requests are almost impossible to solve quickly. Bertelle et al. (28) have introduced a decentralized approach resembling the ECNP to solve the dynamic transportation on demand problem using three agent types: clients, vehicles, and a central interface. On receiving a transportation request, vehicles use an insertion heuristic to calculate the additional effort of accepting that request. Next the vehicles negotiate with each other to find out which vehicle is best suited to fulfill the request. El Falou et al. (29) build on this idea by introducing an adapted route-planning algorithm reducing computational efforts. They propose two additional vehicle negotiation strategies, reducing the number of messages exchanged between the agents. Xing et al. (30) and Nourinejad and Roorda (31) study a variation of the transportation on demand problem termed the dynamic ridesharing problem, that involves matching drivers and passengers with comparable itineraries to make their trip together and save costs. They have adopted an agent-based modeling approach where a negotiation process between drivers, nodes, and routing agents determines which drivers and passengers are matched. The last concept of self-organization in logistics reviewed is that of the physical Internet (PI) (15, 32–34). The PI is inspired by the digital Internet and is an open, collaborative, and standardized transportation concept through which

containerized freight moves through a network from hub to hub in a self-organizing manner. Similar to data packets in a digital network, optimal routes are calculated in real time. The concept of the PI is hypothesized to significantly increase efficiency, transparency, scalability, and robustness of the transportation network (33, 35). However, the literature on the verification of these effects by means of simulation is still in its infancy. Sarraj et al. (34) propose a routing technique to move containers from origin to destination. A case study of hypothetical PI-enabled supermarket distribution in France shows a significant decrease in costs and CO₂ emissions and increased fill-rates of transportation vehicles. Crainic and Montreuil (35) have translated the PI vision to the context of city logistics. They have presented the notion of the “Hyperconnected City,” combining the fields of city logistics and the PI. These authors have taken intermodal transportation to a new level by also allowing for crowd-sourced delivery of shipments. Similar to the work of Sarraj et al. (34), this concept uses modular containers in which multiple goods shipments are merged. Scholz-Reiter et al. (36) presented another vehicle routing technique based on the Internet routing protocol termed “distributed logistics routing protocol.” Resembling communication structures observed in the transportation on demand literature, the protocol relies on continuous communication between packages (requesting transportation), vehicles (requesting transportation tasks), and vertices (storing real-time information of packages and vehicles that pass by) in a physical transportation network. A strength of this protocol is that both packages and vehicles can appear dynamically. However, parcels do not have autonomy in choosing the vehicle that is best suited to their needs.

To make a comparison between all the concepts, a set of requirements was derived from the literature. First, the method should rely on decentralized control of parcels and vehicles with simple computational capabilities, thus making it easily scalable to larger problem instances. Secondly, the method should be able to handle dynamically appearing tasks and, thirdly, dynamically appearing vehicles that can make some already scheduled routes suboptimal. The method should also allow for heterogeneity in parcel and vehicle types. Next, the method should allow parcels to have the autonomy to make their own (routing) decisions to pursue the objectives set by the customer. The method should also facilitate a negotiation strategy to allocate transportation requests among competing operators. Moreover, the method should allow delivery drivers to indicate a time window of their delivery shift. Furthermore, the method should allow for intermodal transportation, meaning that parcels can move between vehicles of different operators in the search for the optimal route to their destinations. The

Table 1. Overview of Reviewed Methods for Self-Organizing Logistics

Paper	Decentralized control	Dynamic task appearance	Dynamic vehicle appearance	Autonomy	Negotiation	Time windows	Intermodal	Zone delivery
Social insects								
Appleby and Steward (21)	✓	✓	na	✓	na	na	na	na
Claes et al. (22)	✓	✓	na	na	na	na	na	na
Morley (23)	✓	✓	na	na	✓	na	na	na
Decentralized intelligence in freight transport								
Van Duin et al. (11)	✓	✓	na	na	✓	✓	na	na
Lee and Kim (26)	✓	✓	✓	na	✓	✓	na	na
Song and Regan (27)	✓	na	na	na	✓	na	na	na
Lai et al. (24)	✓	na	na	na	✓	✓	na	na
Transportation on demand								
Bertelle et al. (28)	✓	✓	na	na	✓	✓	na	✓
El Falou et al. (29)	✓	✓	na	na	✓	na	na	na
Xing et al. (30)	✓	✓	na	na	✓	✓	na	na
Internet routing protocol								
Sarraaj et al. (34)	✓	✓	na	na	na	na	✓	na
Crainic and Montreuil (35)	✓	✓	na	na	na	na	✓	na
Scholz-Reiter et al. (36)	✓	✓	✓	na	na	na	na	✓
This research	✓	✓	✓	✓	✓	✓	✓	✓

Note: na = not applicable.

method should also allow delivery drivers to choose a delivery zone to stay close to. Table 1 provides an overview of the reviewed methods for self-organization, scored on these requirements. A solution for last-mile goods delivery containing the combination of the desired features is not present in the current works.

A Method for Self-Organized Last-Mile Parcel Delivery

The proposed method is designed to allocate parcels to delivery vehicles and construct vehicle routes. In contrast to the current situation, this is done simultaneously and dynamically. The method works with three types of active actors: vehicles, parcels, and a central supporting platform. First, the vehicles are intelligent and autonomous entities, capable of representing the delivery driver by making decisions and communicating with other actors. Vehicles and drivers can possess heterogeneous characteristics, such as differences in capacity and CO₂ emissions for vehicles, and different work-shift durations and departing locations for drivers. Drivers are assumed to strive for cost minimization, and may have one or more preferred geographical areas in which to deliver parcels. Secondly, parcels represent the receiving customer by actively and autonomously making decisions in real time in relation to the best path to take toward their final destination. Parcels base these decisions on the delivery priority of the customer, for which there are three options: a focus on cost, speed, or carbon emissions. Lastly, the central platform facilitates the

allocation of parcels to vehicles. At the start of the day, vehicles have empty travel itineraries (i.e., no pickups and deliveries are scheduled yet) and parcels are not assigned to a delivery vehicle. If a vehicle wants to be eligible for parcel delivery, it has to connect to the platform and communicate its delivery time window (start time and end time) and the geographical center of its preferred delivery area for that day. Furthermore, a vehicle has to share its real-time location with the platform. To find a means of transport, a parcel must initiate a transportation auction process, as illustrated in Figure 1.

First, the parcel sends its transportation request to the platform, along with its current location, final destination, and earliest possible departure time. The platform handles transport request auctions in a sequential manner, as holding auctions in parallel might make a vehicle's offer outdated in case it wins another auction and its itinerary changes. Furthermore, the auctions are processed on a first-come-first-served basis. As not all vehicles are relevant for the parcel to contact, the platform chooses the most relevant vehicles that may respond to the transportation request. The closer a vehicle passes by the pickup and delivery location of the parcel, the lower the additional distance will be for the vehicle to drive, hence the more relevant the vehicle becomes. The vehicles that have received the transportation request from the platform first check if they can transport the parcel. If they can, the vehicles calculate the best spot in their itinerary to insert the parcel's pickup and delivery using an insertion heuristic. The further away the parcel's pickup, delivery location, or both, the higher the cost and

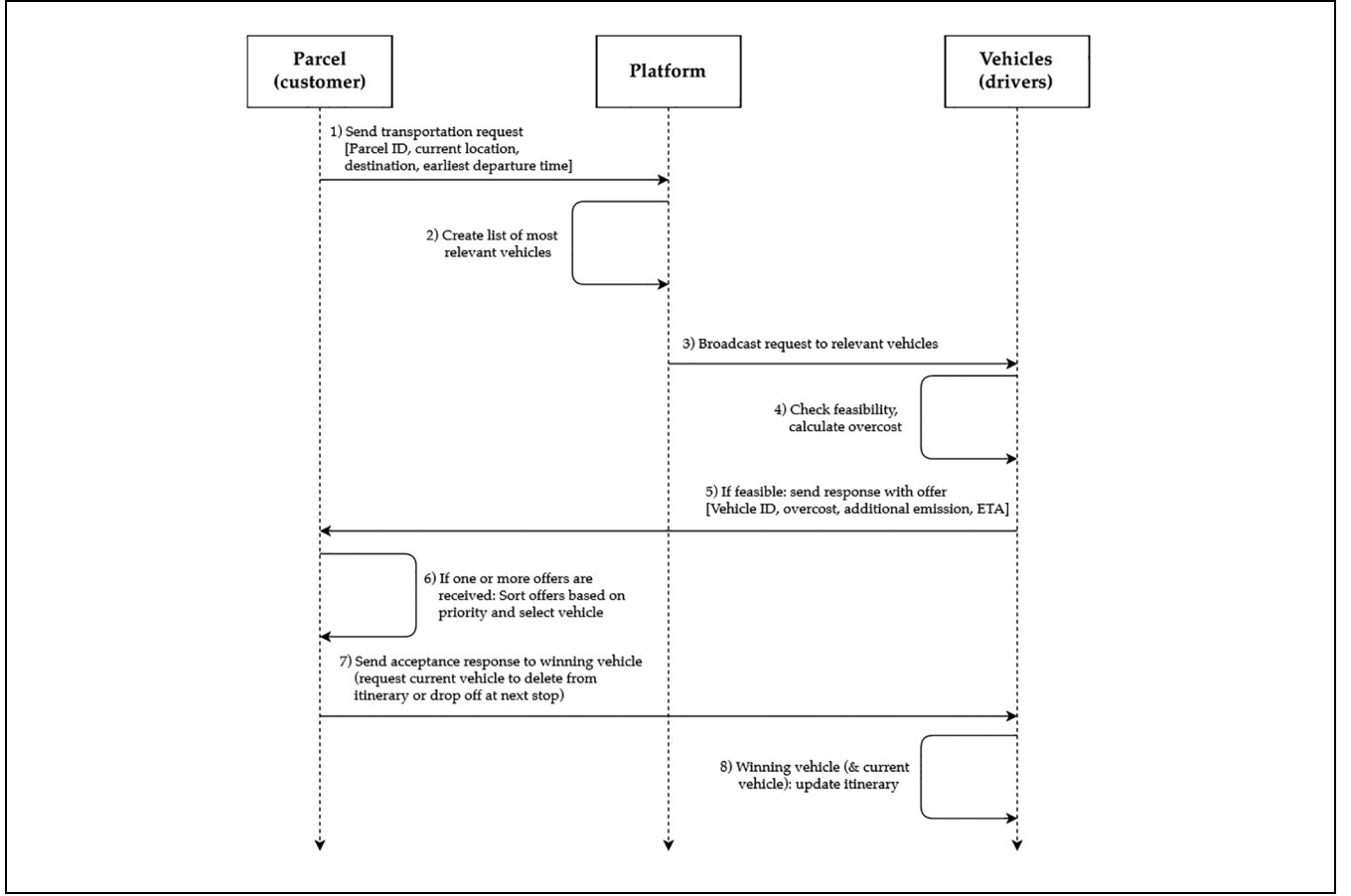


Figure 1. UML sequence diagram of a transportation auction process.

Note: UML = unified modeling language.

additional carbon emissions. The parcel will receive either zero, one, or multiple offers from vehicles to transport it from its current location to its point of delivery. When zero offers are made, the transportation auction stops. When only one offer is made, the parcel directly accepts this offer. When a parcel receives multiple offers, it has to select the offer that best represents the delivery priority of the customer it represents. To this end, it calculates the generalized cost of each vehicle offer by converting the amount of carbon emissions and time of arrival into monetary measures using the customer's value of emissions (VOE) and value of time (VOT), respectively:

$$C_o^{\text{gen}} = C_o + \gamma_p^{\text{time}} * T_0^{\text{arr}} + \gamma_p^{\text{emm}} * E_o \quad (1)$$

where C_o^{gen} represents the generalized cost of offer o including the transshipment penalty if applicable, γ_p^{time} the VOT of parcel p (€/ min), T_0^{arr} the delivery lead time (# time steps), γ_p^{emm} the VOE of parcel p (€/ g), and E_o the additional CO₂ emissions of transportation (g). For each new parcel pickup, each vehicle has to solve a dynamic single VRP with time windows to calculate the

additional effort by using the Dijkstra's insertion heuristic. A transshipment penalty cost is also added to the new offer to account for the handling effort. The difference in cost between not picking the parcel and picking the parcel is called the overcost (C_0). The customers' needs are represented in the parcel's choice behavior. For instance, if a customer has a high preference for zero carbon emissions, the related cost γ_p^{emm} , the value of CO₂ emissions of parcel p (€/ g), is set extremely high. Each parcel thus has its own set of preferences with respect the required arrival time and CO₂ emissions produced. The offer that has the lowest generalized costs is chosen by the parcel, and the winning vehicle inserts the pickup and delivery into its travel itinerary.

The current pricing system should ensure that all actors are fairly charged or compensated for their requested or executed services. Furthermore, the compensation system should provide every actor with the right incentives. For example, two delivery drivers that have delivered the same number of parcels, yet have covered different distances, should not be compensated similarly. Not only is this inequitable, but this also skews

delivery zone choices of drivers as they would be inclined only to deliver in densely populated areas to be able to earn as much as possible. Another aspect to consider related to this is whether customers receiving the parcels should be charged differently based on the distance that needs to be covered to deliver these parcels. Namely, parcel delivery in areas with lower drop densities is more expensive and time-consuming than in areas with higher drop densities. In the proposed model one standard delivery price is charged. A possible solution to this problem could be to let the central platform bear the financial risk induced by cost differences between parcel deliveries. Lastly, the difference in pricing of various delivery priorities should be studied. Parcels prioritizing low carbon emissions and fast delivery drive up the delivery costs of the entire system, and should be charged accordingly. In the proposed method, parcels follow their delivery priority based on a generalized cost function. However, the method could be extended to deal with several different customer requirements.

Throughout the day, the parcel can improve on its choice of vehicle in two ways. First, when the parcel has not yet been loaded into the vehicle, it can send another transportation request to the platform to find out whether it can be reassigned to another vehicle to obtain a better deal. This is only allowed by the central platform for a limited number of times to reduce computational effort. In case a parcel has found a better means of transportation, it will request its current vehicle to delete the parcel from its itinerary. Secondly, a parcel can send a transportation request when it is already en-route and passes by a possible transshipment point, such as a parcel shop or wall of parcel lockers. Hereby, the parcel aims to find a vehicle that can make a pickup at this transshipment point and continue the delivery. If a parcel opts for transshipment, it will request the vehicle it has currently boarded to reschedule the delivery to the location where the transshipment will take place. The parcel will incur a fixed handling penalty for transshipment.

Handling transportation request auctions on a sequential, first-come-first-served basis can result in vehicle route inefficiencies that are undesirable for both vehicles and parcels. These inefficiencies can be partly reduced because parcels can opt for vehicle reassignment at the start of a day. However, as vehicle itineraries fill up, parcels have more difficulty finding suitable options for vehicle reassignment, and vehicles may end up with deliveries far from the rest of their delivery route. Therefore, before each round of parcel reassignments, each vehicle has the opportunity to remove (i.e., push out) the parcels in its itinerary that are the least suitable to deliver. A parcel is regarded as less suitable when its delivery location is further away from a vehicle's delivery zone center. By

removing these parcels, vehicles can open up space in their itinerary potentially to transport parcels with delivery locations closer to the vehicles' delivery zone centers.

Three categories of performance indicators were used to analyze the experimentation results: for individual vehicle agents, individual parcel agents, and the system as a whole. Firstly, each vehicle agent keeps track of its distance traveled, operational costs made, and amount of CO₂ emitted during transportation. Furthermore, each vehicle stores how many parcels it has transported. Lastly, two types of utilization are measured: capacity utilization, defined as the maximum number of parcels onboard during a simulation run divided by the vehicle's capacity, and delivery shift utilization, calculated by dividing the total time a vehicle is active by the length of its delivery shift. Secondly, the performance indicators that are collected by the individual parcel agents are its time of arrival, the contributed operational cost, and the contributed carbon emissions. The calculation of the operational costs and carbon emissions starts at the vehicle agents, who calculate the proportional cost and emissions contributed by each parcel. This is calculated based on the origin–destination distance, rather than the actual distance traveled. Namely, the latter could result in unfair charges if, for example, the distance between a parcel's origin and destination is only small, yet it is delivered at the end of a vehicle's route. Lastly, the performance indicators that are calculated on a system-wide level are the total number of vehicle kilometers traveled, operational costs, CO₂ emissions, average vehicle capacity utilization, average delivery shift utilization, and delivery priority compliance. The delivery priority compliance is measured by calculating three values, one for each priority type. First, for all parcels that value fast delivery most, the average time of arrival of these parcels is calculated. Secondly, for all parcels that value inexpensive delivery most, the average operational cost is calculated. And lastly, for the parcels that value low carbon emissions most, the average carbon emission is determined. All three values are compared against the averages of the entire population of parcels.

The new method is implemented using the agent-based modeling simulation paradigm, using parcels, vehicles, and the central platform as agents. To implement the current method, a TSP model is used to determine the optimal routes of individual vehicles. The TSP is solved in steps. First, a random insertion heuristic is performed to create the initial solution. Then, a two-opt improvement heuristic is used to randomly swap-route segments (1,000 iterations per vehicle), guided by a simulated annealing metaheuristic. Lastly, a random insertion heuristic is used to remove final quirks in the vehicle routes. Both implementations were verified using the "R101" vehicle routing problem with time windows (VRPTW)

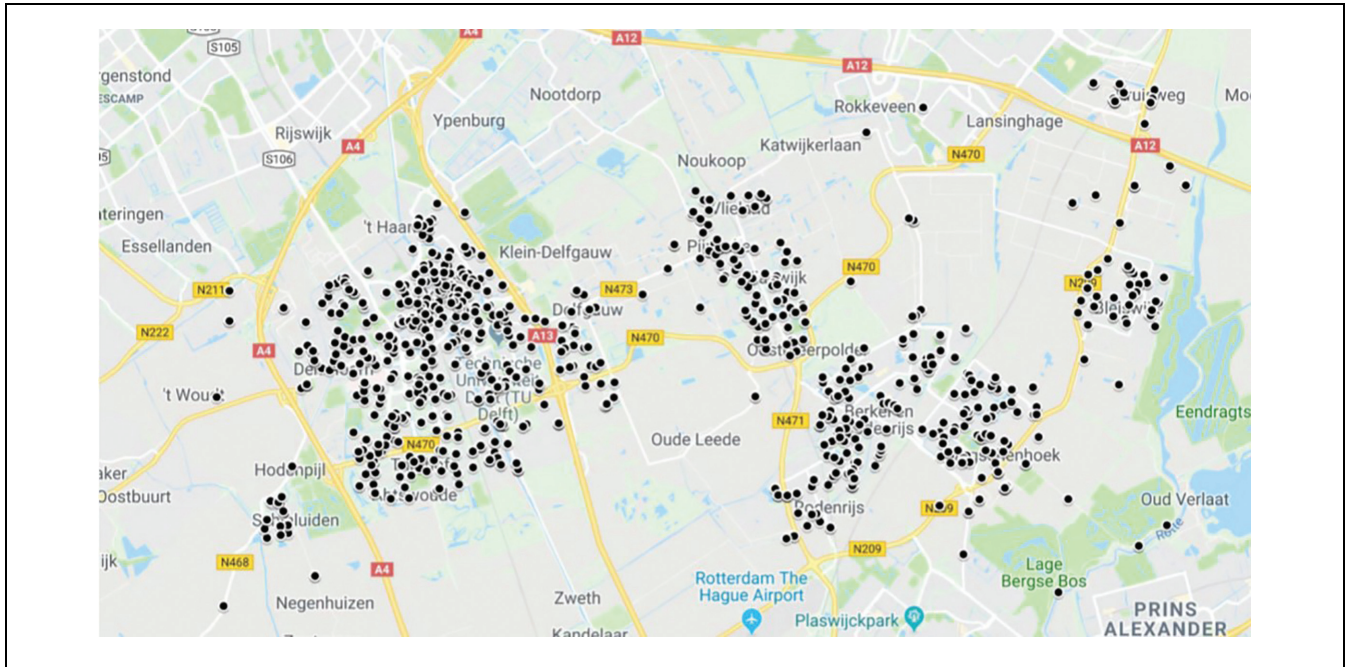


Figure 2. Overview of the delivery addresses (1 cm = 1 km).

instance generated by Salomon (37). Furthermore, validation of both implementations was done using the “Berlin52” TSP instance generated by Reinelt (38). The validation tests showed optimality gaps of below 5%, which was considered acceptable.

Case Details: Delft

To test the proposed method, a delivery network is used consisting of 11 vehicle tours in which a total of 729 stops are made to deliver 1,280 parcels in and around the city of Delft, the Netherlands, and its surroundings (see Figure 2). Drop densities of delivery routes range from 2.45 deliveries per km² in rural areas to 43.37 deliveries per km² in urban areas. An origin–destination matrix was calculated in advance based on Euclidean distances multiplied by a detour factor of 1.50. A total of 50 locations are randomly set as possible transshipment points. The length of a simulation run is 780 time steps of 1 min (13 h), to represent a delivery day starting at 07.00 in the morning and ending at 20.00 in the evening. The central platform allows for eight parcel reassignment iterations. For each transportation request auction, three relevant vehicles are selected. The transshipment penalty is set at €0.10.

The assumption is made that one single white-label sorting depot is used by all three delivery operators. The preferred delivery zones of these vehicles are set at the centroid of the coordinates of all delivered parcels by that vehicle in the current tour division. All dedicated delivery

vehicles (see Table 2) participate in their announcement at 07.00, and can start loading and delivery at 08.00. The vehicles must return to the depot no later than 20.00. The origins and destinations or occasional delivery vehicles are set at random, with a preferred delivery zone right in the middle. The start of the delivery time window is set at random, and the end of the delivery time window is calculated as the travel time from the origin to the destination, plus an additional amount of time, chosen randomly between 15 and 90 min. Each vehicle participates its announcement between 120 and 60 min before the start of its delivery time window. For every vehicle type, the durations of a pickup and delivery stop are set at 1 and 3 min, respectively. Parcel agents with the priority of cost are assumed to have VOT and VOE of zero. Parcel agents prioritizing speed are given a VOT of €0.005 per time step. Lastly, parcels with the priority of emissions are given a VOE of €0.1 per gram of CO₂.

Case Results: Delft

This section contains the results of the case study, as well as the three experiments used to test the new method’s ability to improve the efficiency, robustness, and flexibility of delivery operations.

Table 3 shows the resulting system performance indicators of both solutions. First and foremost, the new method is able to greatly reduce the total amount of vehicle distance traveled, by 18.10%. Additionally, since all vehicles possess the same characteristics, the

Table 2. Vehicle Characteristics

Vehicle type	Capacity (# parcels)	Operational cost (€/km)	Average speed (km/h)	Average CO ₂ emission (kg/km)
Light duty vehicle	200	0.44	26	0.230
Passenger car	40	0.26	26	0.094
Scooter	3	0.25	26	0.040
Bicycle	2	0.10	18	0

Table 3. Case results: Delft

Performance indicator	Current method	New method	Difference (%)
Vehicle distance traveled (km)	487.82	399.55	-18.1
Operational cost (€)	214.64	175.80	-18.1
CO ₂ emissions (kg)	112.60	91.90	-18.1
Average cost (€/parcel)	0.29	0.24	-18.1
Capacity utilization (%)	58.40	58.65	0.4
Delivery shift utilization (%)	100	95.05	-5.0

Table 4. Collaborative Case Results: Delft

Performance indicator	Separate delivery	Collaborative delivery	Difference (%)
Vehicle distance traveled (km)	1275.94	959.93	-24.8
Operational cost (€)	561.39	422.36	-24.8
CO ₂ emissions (kg)	293.47	220.78	-18.1
Average cost (€/parcel)	0.26	0.19	-18.1
Capacity utilization (%)	58.65	58.64	-0.0
Delivery shift utilization (%)	97.16	93.25	-4.0

operational costs incurred and amount of CO₂ emitted have reduced by the same percentage. The reduction in vehicle kilometers traveled signifies that vehicles' routes produced by the new method are more efficient. This is also visible in the average distance between stops: 659 and 540 m in the current and the new method, respectively. This includes both the journey from the depot to the first stop and from the last stop to the depot. All parcels have the priority to find the vehicles with the lowest generalized costs. Under the current method, the average costs paid by parcels amounts to €0.29, whereas under the new method this has decreased by 18.16% to €0.24. Next, the capacity utilization differs only slightly in the current and new methods. This is a logical result, as the same number of parcels are transported by the same number of vehicles. The difference can be attributed to parcels being divided differently over the vehicles. Lastly, the overall delivery shift utilization has reduced by 4.95%, to 95.05%, translating into an average of 20 min of unused time by all delivery vehicles under the new method. In other words, a lower number of delivery vehicles could be used to deliver the same number of parcels, which improves the capacity utilization of the vehicles.

Shifting from an industry with multiple stand-alone delivery operators responsible for their own set of delivery tours to an open market place without organizational boundaries is a giant step. Parcel services like PostNL, DHL, GLS, and Fedex are not willing to join their distribution activities. Thus, as a first step, it might be more realistic from an organizational perspective to start with several platforms, each facilitating the delivery operations of a single operator. However, although this reaps some rewards as compared with the current situation, the major issue of delivery area duplication remains. Therefore, the goal of this experiment is to investigate how this solution compares with operating under one single platform. As data for only one delivery operator are available, the existing data set was multiplied by three, effectively creating delivery data for three operators of equal size. To overcome the unrealism of precisely matching delivery addresses, the coordinates of each delivery address were slightly displaced in a random manner. Here, the tours' drop densities were taken into account such that coordinates of deliveries in rural areas were displaced more than those of deliveries in urban areas. The simulation model was run twice: once with

separate delivery operations and once with collaborative delivery operations (see Table 4).

When operators collaborate in their delivery operations, they can reduce the total vehicle distance traveled, total costs, and carbon emissions by 24.8%. Furthermore, operators are able to reduce the cost per parcel delivered from €0.26 to €0.19. The capacity utilization remains almost unchanged, because the same number of parcels are delivered with the same number of vehicles. However, the delivery shift utilization decreases by 4.0% when operators collaborate, indicating less time is spent to deliver all parcels. This large reduction in vehicle distance traveled is primarily because of the consolidation of parcel streams, as opposed to the three separated streams in the current situation. Furthermore, seven experiments were run to test the new method's performance with regard to efficiency, robustness, and flexibility (39).

Conclusions and Discussion

In this paper, a method based on self-organization of delivery vehicles and parcels is proposed that facilitates real-time intermodal last-mile parcel delivery. The method incorporates decentralized and autonomous decision-making of parcel agents and allows for relay (multi-hop) delivery. By means of a case study (and six experiments), the performance of the proposed method was evaluated. The case study of Delft showed that the new method manages to improve greatly the last-mile performance with respect to total vehicle distance traveled, operational costs made, and carbon emitted. Moreover, the new method was able to lower the delivery shift utilization of vehicles, meaning that fewer vehicles could have been dispatched to deliver the same number of parcels. The experiments showed that operational efficiency can be increased even further when multiple operators collaborate under a single platform. Further research will focus on the software development of the current developed algorithm embedded in a communication platform with related ordering, planning and invoicing.

In this study the role of public actors is not yet considered. The main goal of this study was to show the potential of a self-organizing concept for parcels. The public actors could support in standardizing data sharing and loading units, providing measures for zero emissions or supporting the creation of the order demand platform. Platform facilitation of operations can be done by a private, independent company. The outcomes will depend on how these market and public-private arrangements are put in place. In this paper the experiments with different parcel preferences are still limited. To extend this research more heterogeneity in preferences could be

added together with the increase of the number of parcels. Although the number of parcels is realistic for the specific case area, many cities have much higher volumes of parcels. To scale up the model with these complexities, the combined approach of discrete choice modeling and agent-based modeling by Marcucci et al. (40) seems to be an interesting direction for further research.

Acknowledgments

This research was conducted as a Master's thesis in Transport, Infrastructure and Logistics at the Delft University of Technology (39). The authors would like to thank the Dutch Topsector Logistics (TKI Dinalog and NWO) for their support of Project SOLiD (NWO project number 439.17.551).

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: J.H.R. van Duin, T.S. Vlot, L.A. Tavasszy, M.B. Duinkerken, and B. van Dijk; data collection: T.S. Vlot; analysis and interpretation: J.H.R. van Duin, T.S. Vlot, L.A. Tavasszy, M.B. Duinkerken, and B. van Dijk; draft manuscript preparation: J.H.R. van Duin and T.S. Vlot. All authors, J.H.R. van Duin, T.S. Vlot, L.A. Tavasszy, M.B. Duinkerken, and B. van Dijk, reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The authors would like to thank the Dutch Topsector Logistics (TKI Dinalog and NWO) for their financial support of Project SOLiD (NWO project number 439.17.551).

References

1. Allen, J., M. Piecyk, M. Piotrowska, F. Mcleod, T. Cherrett, K. Ghali, T. Nguyen, T. Bektas, O. Bates, A. Friday, S. Wise, and M. Austwick. Understanding the Impact of E-Commerce on Last-Mile Light Goods Vehicle Activity in Urban Areas: The Case of London. *Transportation Research Part D: Transport and Environment*, Vol. 61, 2018, pp. 325–338.
2. Schliwa, G., R. Armitage, S. Aziz, J. Evans, and J. Rhoades. Sustainable City Logistics Making Cargo Cycles Viable for Urban Freight Transport. *Research in Transportation Business & Management*, Vol. 15, 2015, pp. 50–57.
3. Gevaers, R., E. Van de Voorde, and T. Vanelander. Characteristics and Typology of Last-Mile Logistics from an Innovation Perspective in an Urban Context. In *City Distribution and Urban Freight Transport* (Macharis, C.,

- and S. Melo eds.), Edward Elgar Publishing Limited, Cheltenham, UK, 2011, pp. 56–73.
4. Boyer, K., A. Prud'homme, and W. Chung. The Last Mile Challenge: Evaluating the Effects of Customer Density and Delivery Window Patterns. *Journal of Business Logistics*, Vol. 30, 2009, pp. 185–201.
 5. Browne, M., C. Rizet, and J. Allen. A Comparative Assessment of the Light Goods Vehicle Fleet and the Scope to Reduce its CO₂ Emissions in the UK and France. *Procedia - Social and Behavioral Sciences*, Vol. 125, 2014, pp. 334–344.
 6. Visser, J., and K. Hassall. The Future of City Logistics: Estimating the Demand for Home Delivery in Urban Areas. *Proc., 4th City Logistics Conference on City Logistics*, Langkawi, Malaysia, 2005, pp. 147–161.
 7. Dai, B., and H. Chen. A Multi-Agent and Auction-Based Framework and Approach for Carrier Collaboration. *Logistics Research*, Vol. 3, 2011, pp. 101–120.
 8. Ergun, O., G. Kuyzu, and M. Savelsbergh. Reducing Truckload Transportation Costs Through Collaboration. *Transportation Science*, Vol. 41, 2007, pp. 206–221.
 9. Gonzalez-Feliu, J., and J. M. Salanova. Defining and Evaluating Collaborative Urban Freight Transportation Systems. *Procedia - Social and Behavioral Sciences*, Vol. 39, 2012, pp. 172–183.
 10. Handoko, S., and H. Lau. Enabling Carrier Collaboration via Order Sharing Double Auction: A Singapore Urban Logistics Perspective. *Transportation Research Procedia*, Vol. 12, 2016, pp. 777–786.
 11. Van Duin, J. H. R., L. A. Tavasszy, and E. Tanigucchi. Real Time Simulation of Auctioning and Re-Scheduling Processes in Hybrid Freight Markets. *Transportation Research Part B: Methodological*, Vol. 41, No. 9, 2007, pp. 1050–1066.
 12. Archetti, C., M. Savelsbergh, and G. Speranza. The Vehicle Routing Problem with Occasional Drivers. *European Journal of Operational Research*, Vol. 254, No. 2, 2016, pp. 472–480.
 13. Soto Setzke, D., C. Pflügler, M. Schreieck, S. Fröhlich, M. Wiesche, and H. Krcmar. Matching Drivers and Transportation Requests in Crowdsourced Delivery Systems. *Proc., 23rd Americas Conference on Information Systems*, Boston, MA, 2017.
 14. Kafle, N., B. Zou, and J. Lin. Design and Modeling of a Crowdsourced-Enabled System for Urban Parcel Relay and Delivery. *Transportation Research Part B: Methodological*, Vol. 99, 2017, pp. 62–82.
 15. Pan, S., D. Trentesaux, and Y. Sallez. Specifying Self-Organising Logistics System: Openness, Intelligence, and Decentralised Control. In *SOHOMA16 Workshop on Service Orientation in Holonic and Multi-Agent Manufacturing* (Borangiu, T., D. Trentesaux, A. Thomas, P. Leitão, and J. B. Oliveira, eds.), Springer, Champaign, IL, 2017, pp. 93–102.
 16. Bartholdi, J., D. Eisenstein, and Y. Lim. Self-Organizing Logistics Systems. *Annual Reviews in Control*, Vol. 34, No. 1, 2010, pp. 111–117.
 17. Dantzig, G., and J. Ramser. The Truck Dispatching Problem. *Management Science*, Vol. 6, No. 1, 1959, pp. 80–91.
 18. Lawler, E. L., J. K. Lenstra, A. H. G. Rinnoy Kan, and D. B. Shmoys. *The Traveling Salesman Problem: A Guided Tour of Combinatorial Optimization*. Wiley, Hoboken, NJ, 1985.
 19. Serugendo, G., M. Gleizes, and A. Karageorgos. Self-Organising Systems. In *Self-Organising Software: From Natural to Artificial Adaptation* (Serugendo, G., M. Gleizes, and A. Karageorgos, eds.), Springer-Verlag, Berlin, Heidelberg, 2011, pp. 7–32.
 20. McFarlane, D., V. Giannikas, and W. Lu. Intelligent Logistics: Involving the Customer. *Computers in Industry*, Vol. 81, 2016, pp. 105–115.
 21. Appleby, S., and S. Steward. Mobile Software Agents for Control in Telecommunications Networks. *BT Technology Journal*, Vol. 12, 1994, pp. 104–113.
 22. Claes, R., T. Holvoet, and D. Weyns. A Decentralized Approach for Anticipatory Vehicle Routing using Delegate Multiagent Systems. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 12, 2011, pp. 364–373.
 23. Morley, D. Painting Trucks at General Motors: The Effectiveness of a Complexity-Based Approach. In *Embracing Complexity: Exploring the Application of Complex Adaptive Systems to Business* (Lewin, R., ed.), Ernst & Young Center for Business Innovation, Boston, 1996, pp. 53–58.
 24. Lai, M., X. Cai, and Q. Hu. An Iterative Auction for Carrier Collaboration in Truckload Pickup and Delivery. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 107, 2017, pp. 60–80.
 25. Fischer, K., J. R. Muller, and M. Pischel. Cooperative Transportation Scheduling: An Application Domain for DAI. *Applied Artificial Intelligence*, Vol. 10, No. 1, 1996, pp. 306–313.
 26. Lee, J. H., and K. H. Kim. An Auction-Based Dispatching Method for an Electronic Brokerage of Truckload Vehicles. *Industrial Engineering and Management Systems*, Vol. 14, 2015, pp. 32–43.
 27. Song, J., and A. C. Regan. An Auction Based Collaborative Carrier Network. Presented at 83rd Annual Meeting of the Transportation Research Board, Washington, D.C., 2004.
 28. Bertelle, C., M. Nabaa, D. Olivier, and P. Tranouez. A Decentralised Approach for the Transportation on Demand Problem. In *From System Complexity to Emergent Properties* (Aziz-Alaoui, M., and C. Bertelle, eds.), Springer, Berlin, Heidelberg, 2009, pp. 281–289.
 29. El Falou, M., A. Malass, M. Itmi, S. Falou, and A. Cardon. An Application of Adapted A* Decentralized Approach for On Demand Transportation Problem. *Proc., IEEE 26th International Conference on Tools with Artificial Intelligence*, Limassol, Cyprus, IEEE, New York, 2014, pp. 930–936.
 30. Xing, X., T. Warden, T. Nicolai, and O. Herzog. Smize: A Spontaneous Ride-Sharing System for Individual Urban Transit. *Proc., 7th German Conference on Multiagent System Technologies*, Springer-Verlag, Berlin, Heidelberg, 2009, pp. 165–176.
 31. Nourinejad, M., and M. Roorda. Agent Based Model for Dynamic Ridesharing. *Transportation Research Part C: Emerging Technologies*, Vol. 64, 2015, pp. 117–132.

32. Ballot, E., B. Montreuil, and R. Meller. *The Physical Internet: The Network of Logistics Networks*. La Documentation Française, Paris, France, 2014.
33. Montreuil, B., R. D. Meller, and E. Ballot. Towards a Physical Internet: The Impact on Logistics Facilities and Material Handling Systems Design and Innovation. In *Progress in Material Handling Research* (K. Gue, ed.), Material Handling Industry of America, Charlotte, NC, 2010, 305–327.
34. Sarraj, R., E. Ballot, S. Pan, D. Hakimi, and B. Montreuil. Interconnected Logistic Networks and Protocols: Simulation-Based Efficiency Assessment. *International Journal of Production Research*, Vol. 52, 2013, pp. 1–24.
35. Crainic, T. G., and B. Montreuil. Physical Internet Enabled Hyperconnected City Logistics. *Transportation Research Procedia*, Vol. 12, 2016, pp. 383–398.
36. Scholz-Reiter, B., H. Rekersbrink, and M. Freitag. Internet Routing Protocols as an Autonomous Control Approach for Transport Networks. *Proc., 5th CIRP International Seminar on Intelligent Computation in Manufacturing Engineering*, Ischia, Italy, 2006, pp. 341–345.
37. Salomon, M. M. VRPTW Benchmark Problems. 1983. <http://web.cba.neu.edu/msolomon/problems.htm>.
38. Reinelt, G. TSPLIB - A Traveling Salesman Problem Library. *ORSA Journal on Computing*, Vol. 3, 1991, pp. 376–384.
39. Vlot, T. S. *Power to the Parcel: A Method for Self-Organization in Last-Mile Parcel Delivery*. Master thesis. Delft University of Technology, 2019.
40. Marcucci, E., M. Le Pira, V. Gatta, G. Inturri, M. Ignaccolo, and A. Pluchino. Simulating Participatory Urban Freight Transport Policy-Making: Accounting for Heterogeneous Stakeholders' Preferences and Interaction Effects. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 103, 2017, pp. 69–86.