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Chapter 3
The Impact of Collaborative Scheduling and Routing for Interconnected Logistics: A European Case Study

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Abstract Interconnected logistics system can play an important role towards having a more sustainable green freight transport. Recently, after introducing the concept of Physical Internet (PI), researchers have started to explore the opportunities and challenges that a collaborative and interconnected network could create in different aspects of the supply chain. In this research, we study the last mile delivery as well as vehicle dispatching problems under the assumptions of collaborative supply chain networks while assuming that modularized boxes are applied inside the network from the provider to the final customer. Our research aims at proposing a more efficient resource planning with the minimal number of empty vehicle movements running on roads that ultimately leads to decrease carbon dioxide emission. The assumptions have been tested and verified using real data coming from a major retail company in Europe.

Keywords Collaborative scheduling · Routing · Interconnected logistics · Physical Internet · Last mile delivery · Vehicle dispatching

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1 Introduction

In 2011, the European Commission published a white paper in which it formulated the long-term ambition to reduce greenhouse gas emissions from transport by at least 60% by 2050 compared to 1990. The emissions increased by 26% compared with 1990 levels. This increase comes despite past improvements in the efficiency of transport and is broadly in line with increases in the level of economic activity as measured by gross domestic product (GDP) as well as increases in demand for transport. Road transport accounts for 72% of total greenhouse gas emissions of the sector. Further increasing the efficiency of the logistic system in road transport will play a key role in limiting the increase of road transport emissions.

Nevertheless, total transport demand is predicted to continue growing during the 2020–2030 period in line with 2010–2020 patterns (1.5% for freight transport (tonne km)) and at lower rates between 2030 and 2050 (0.8% for freight transport).

Integrated measures addressing both production and consumption would therefore be needed in the long run in order to reduce the greenhouse gas emissions from transport by 60% by 2050 (European Environmental Agency 2018).

In order to make a better use out of logistics resources and to exploit synergies between different distribution service providers, the concept of Physical Internet (PI) and interconnected networks were introduced (Montreuil 2010). PI proposes to use a new framework of interconnected logistics especially designed for resource sharing, real-time identification, and routing through open facilities to use transport infrastructure more efficiently and reduce environmental impact.

Within this framework, all products are encapsulated in smart, modularized, ecofriendly and standard boxes loaded and then handled, stored, and transported through shared facilities and across open networks.

There are two significant characteristics of the Physical Internet: encapsulation and collaboration.

Encapsulation: The Physical Internet does not manipulate physical goods directly. Instead, it manipulates exclusively containers that are explicitly designed for the Physical Internet and that encapsulate physical goods within them (Montreuil 2011). These dedicated containers for the Physical Internet have modular dimensions and standardized interfaces for handling and communication.

Collaboration: The Physical Internet provides universal and standardized interfaces and protocols to reduce the frictions in supply chain horizontal collaboration. For any logistics services providers, as long as they accept the operational protocols to handle, move, store, transport, and use the Physical Internet containers, they become the members, beneficiaries, and collaborators in the Physical Internet despite their potential competitive relationships in businesses.

The main contributions of our research are to address two major problems in supply chain management under PI assumption when modularized boxes are used as containers for different products: (1) last mile delivery integrated with bin packing problem and (2) vehicle dispatching problem.

1.1 Sustainable Last Mile Delivery

Even though passenger mobility has received considerable attention in the literature and in practice in the recent years (Gentile and Noekel 2016; Alonso-Mora et al. 2017), other contributions to new research and technology are found for the modeling of last mile delivery within urban areas. Applications can be found in different industries to tackle the issues around last mile delivery in urban areas. To name a few, we can mention DPD (https://www.dpd.com/), Green Link (http://green-link.co.uk) or self-service parcel stations from DHL Packstation, LaPoste Pickup Station, etc.

The most commonly used vehicles for deliveries in the last mile delivery (including the request made via online shopping) are vans or trucks. The increase in e-commerce and related deliveries in cities is contributing to the increase in van traffic resulting in more pollution. For example, in the UK, these vehicles are responsible for 15% of total kilometers traveled on roads in 2015 compared to 10% in 1993 (Bates et al. 2018). In addition, these vehicles have contributed in 13.3 million tonnes of CO_2 equivalent to emissions in 2014 (Zanni and Bristow 2010). In this research, we focus on two aspects of the urban logistics systems in order to reduce the number of necessary vehicles and kilometers traveled by them in the network. In addition, we aim at shed light on how the available space inside the vehicles can be used more efficiently to avoid circulating empty vehicles on roads. Both topics are defined within the framework of Physical Internet.

1.2 Last Mile Delivery and Bin Packing Problem

The last mile delivery problem has been recognized as one of the most expensive, least efficient and one of the main responsible to polluting inside the supply chain networks. In urban areas, traffic infrastructure is used for the purpose of delivering goods that results in traffic jams (Ehmke 2012). Not having a good planning system for the last mile delivery causes heavier traffic that affects service quality and the final cost (Eglese 2006). The body of literature is quite rich when it comes to the last mile delivery. Here, we briefly mention the most relevant papers to our work.

In Gendreau et al. (2006), the authors propose a Tabu search in order to solve the vehicle routing problem with capacity and route length restrictions. The Tabu search consists of examining successive neighbors of a solution and selects the best. The authors use a generalized insertion procedure that repeatedly removes a vertex (which represents a customer) from its current route and reinsert it into another route. This is the neighborhood of a solution. In order to avoid cycling, solutions that were recently examined are forbidden and inserted in a constantly updated Tabu list.

In Bortfeldt (2012), the author presents a hybrid algorithm for the three-dimensional loading capacitated vehicle routing problem. It includes a Tabu search algorithm for the routing part and a tree search algorithm for packing boxes into vehicles. The Tabu search starts with a randomly generated solution. Then, for each route found by the Tabu search, the tree search algorithm tries to generate a packing plan where all boxes are placed correctly. Each node of the tree has three elements: a partial solution of placements, a set of free boxes that must be placed, and a list of potential placements. The algorithm tries to add placements for each free box until all are placed, or a time limit has been reached, or one box has no possible placement.

In Massen et al. (2012), for a similar problem, it uses an ant colony algorithm combined with a column generation algorithm which is used to solve large linear programming programs. Column generation generates only the variables which can potentially improve the objective function.

Only very small instances for the bin packing problem have been solved to optimality. Some exact methods were proposed by Martello et al. (2000). For bigger instances, only heuristic methods have been developed. In Hifi et al. (2010), the authors consider the assignment of items to identical bins. The packings have to be feasible, and their aim is to minimize the number of bins needed. n items characterized by a width w_i, a height h_i, and a depth d_i ($i = 1,2,\ldots\ldots,n$) are put in identical bins with width W, height H, and depth D. By using integer linear programming, they are able to find solutions for the bin packing. The constraints that must be satisfied are expressed as inequalities.

In Levine and Ducatelle (2004), an ant colony optimization is presented, in order to solve bin packing and cutting stocks problems. It is inspired by the capability of ants to find the shortest path between their nest and a food location by using pheromone trails.

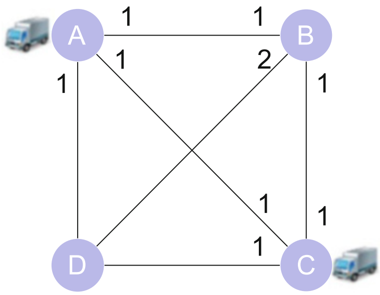
The authors in Fanslau and Bortfeldt (2010) present a tree search algorithm to solve the 3D container loading problem for weakly or strongly heterogeneous items (i.e., same or different dimensions). They fill a container by adding blocks which are arrangements of one or more oriented boxes (items). The blocks are placed in residual spaces. In order to find the best block for a residual space, a tree search is used.

Our research is closest to the works of Gendreau et al. (2006) and Massen et al. (2012); however, our research in this chapter focuses on the impact of horizontal collaboration for the last mile delivery in the context of Physical Internet. This leads to better usage of capacities and reducing the operational cost as well as the number of vehicles required to deliver products.

1.3 The Vehicle Dispatching Problem

Physical Internet hubs are the places where modularized containers are sorted, assembled, and packed into vehicles. According to the concept of the Physical Internet, the short-range transportation is encouraged, which means that if possible, all the transportation activities are ideal to be limited between a Physical Internet hub and one of its neighboring hubs. The rational of such a recommendation is to

Fig. 3.1 An example to illustrate the concept of the vehicle dispatching problem



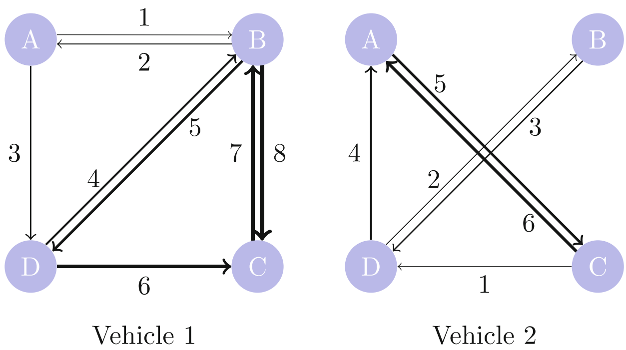


Fig. 3.2 A feasible solution to the example in Fig. 3.1

maximize the overall social benefit of truck drivers so that they are able to come back home after their daily jobs. In this section, we will introduce an optimization problem called the vehicle dispatching problem inside the PI context. Here, in transportation demands between any two linked hubs (in terms of how many trailers of modularized boxes to ship) and the current locations of all the available vehicles designated for the network (assuming all vehicles are homogeneous with the transportation capacity equal to 1 trailer), the decision-makers need to design a vehicle dispatching plan for each vehicle such that all the transportation demands are satisfied and the entire vehicle traveling cost is minimized. For example, in Fig. 3.1, there are four PI hubs, i.e., A, B, C, and D. The traveling distance between any two connected hubs is 1 and the transportation demands are listed in the figure. For instance, there is one trailer to be transported from hubs A to B and two trailers to be transported from hubs B to D. Initially, there are two vehicles positioned at hubs A and C, respectively.

Figures 3.2 and 3.3 depict two different dispatching plans for the vehicle dispatching problem shown in Fig. 3.1. In the solution shown in Fig. 3.2, vehicle 1 initially resided in Physical Internet hub A takes the path $A \Rightarrow B \Rightarrow A \Rightarrow D \rightarrow B \Rightarrow D \rightarrow C \Rightarrow B \Rightarrow C$ with traveling cost 7 while the other vehicle initially positioned at hub C takes the path $C \Rightarrow D \rightarrow B \Rightarrow D \rightarrow A \Rightarrow C \Rightarrow A$ with traveling cost equal to 6. Note that the arcs in the walks symbolized as $\Rightarrow$ indicate that a vehicle is fully

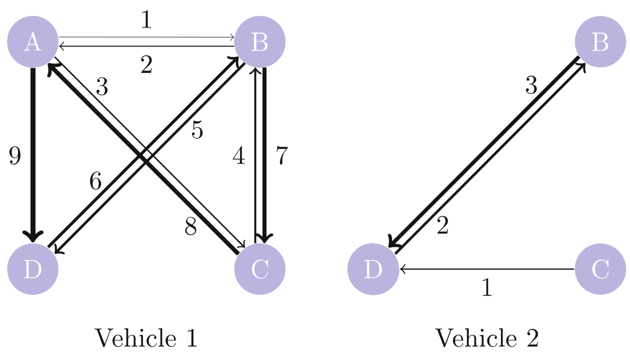


Fig. 3.3 An optimal solution to the example in Fig. 3.1

loaded. Oppositely, the arcs with symbol $\rightarrow$ represent the empty moves of a vehicle. Therefore, it can be observed that in the solution shown in Fig. 3.2, all the transportation demands can be fulfilled and the total traveling cost for such a dispatching plan is equal to 14 with 4 empty vehicle movements. Figure 3.3 shows a better dispatching solution for the same problem. In this solution, vehicle 1 takes the path $A \Rightarrow B \Rightarrow A \Rightarrow C \Rightarrow B \Rightarrow D \rightarrow B \Rightarrow C \Rightarrow A \Rightarrow D$, and vehicle 2 takes the path $C \Rightarrow D \rightarrow B \Rightarrow D$. Apparently, the total traveling cost for this solution is 12, and the number of empty vehicle movements has been reduced to 2 instead of 4 compared to the solution shown in Fig. 3.2. Actually, the solution shown in Fig. 3.3 is an optimal one for the vehicle dispatching problem in Fig. 3.1. The purpose of the proposed vehicle dispatching problem for the Physical Internet is very meaningful since it aims to seek the best resource dispatching plan with the minimal number of empty vehicle movements and thus ultimately the least carbon dioxide emission.

The remainder of this chapter is as follows: in Sect. 2, we introduce the integrated last mile delivery and 3D bin packing problem followed by the numerical results of the model presented in Sect. 3. In Sect. 4, the vehicle dispatching problem and its associated computational results are depicted. We conclude the chapter in Sect. 5 by also shortly discussing about potential future research avenues.

2 Last Mile and Bin Packing Problem

The last mile problem in the Physical Internet aims to deal with the final deliveries of the orders (encapsulated in modularized boxes) from hubs to its served customers. As illustrated in Fig. 3.4, there are five customers (A, B, C, D, and E) in the region that is served by a Physical Internet hub. Each customer has a list of modularized boxes (three types in this example, colored by red, green, and yellow, respectively) that should be delivered by a truck originally located at the hub. Taking customer E as example, 1 red box, 1 green box, and 2 yellow boxes are ordered, and these boxes

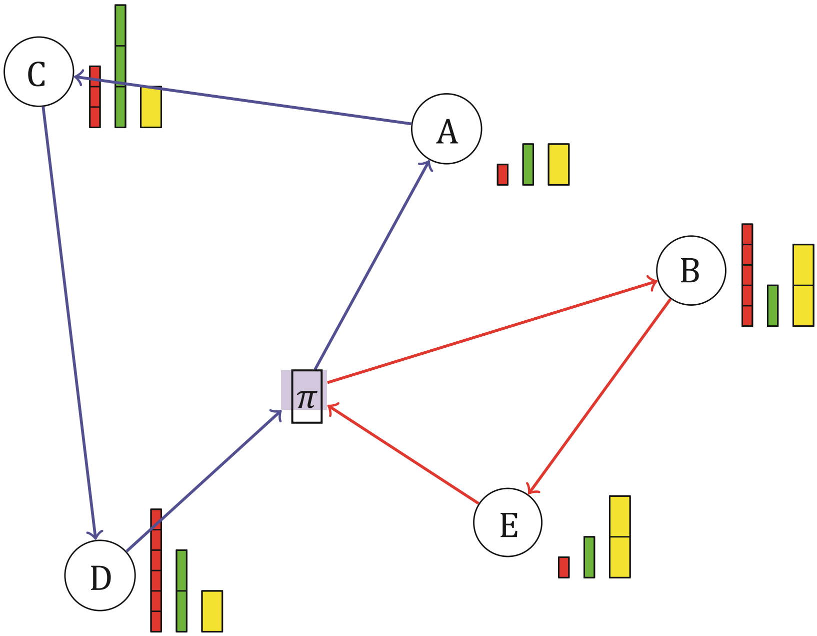


Fig. 3.4 The last mile delivery problem

should be delivered in batch. Thus, the major decisions for the operator of the PI hub are as follows:

1. How many vehicles should be used to fulfill the delivery task?
2. For each vehicle, which customers should be served?
3. For each vehicle, after assigning the served customers, which visiting sequence should be adopted by the driver in order to minimize the total traveling distance?

In this vehicle routing problem (VRP), each vehicle has a weight and volume capacity for its trailer. However, compared to the traditional capacitated VRP, here, the dimensions of the modularized boxes should also be taken into account when checking the feasibility of a routing plan for a vehicle. Figure 3.5 shows the necessity of the consideration in two-dimensional space. For example, let the internal size of a trailer be rectangle *ABCD*, and the hatched area is the occupied space by other modularized boxes. Box *FKGH* is the next container to be packed into the trailer which has the volume exactly equal to the current available space (i.e., the rectangle *FECD*). Although the overall sum of volume does not exceed the trailer's capacity, the box *FKGH* could not be packed into the trailer even when we allow the rotation of the box.

Secondly, the visiting sequence of clients for a vehicle poses the constraints on the packing sequence of the corresponding modularized boxes ordered by the customers. Such a consideration is referred to be as the rule of "Last-In, First-Out." For example, as shown in Fig. 3.4, there is one vehicle whose visiting

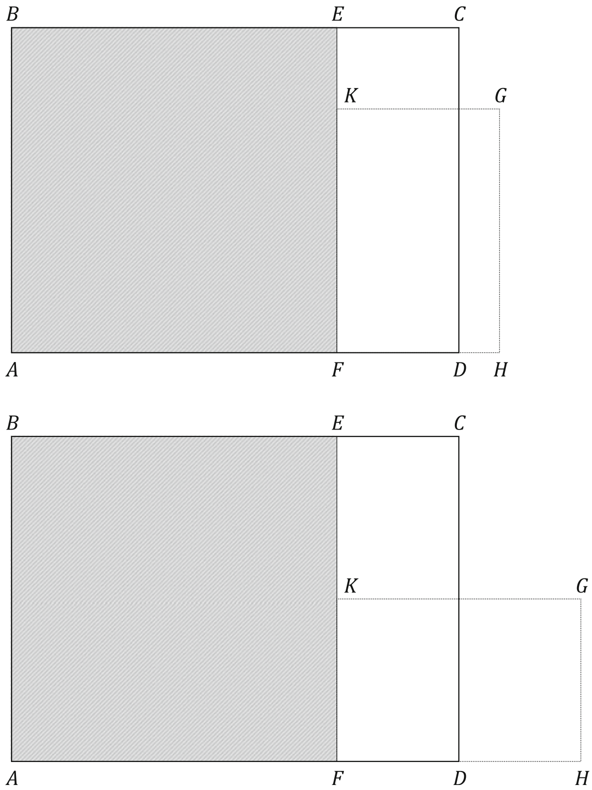


Fig. 3.5 The necessity to consider the dimensions of the modularized boxes in packing

sequence is $\pi \rightarrow B \rightarrow E \rightarrow \pi$. Therefore, the modularized boxes ordered by customer B should be packed in a way that when the vehicle arrives at B, all the boxes cannot be hindered by other boxes to the downstream customers when discharging. We refer the proposed problem for the Physical Internet as the vehicle routing problem coupling with 3D bin packing.

2.1 Problem Description

In this subsection, we provide the detailed problem description of the problem by introducing the input information as well as the general objective and constraints.

Input Parameters

- The geographical information of all the customers for the last mile delivery
- The modularized boxes ordered by all the customers (i.e., numbers, dimensions, and weights)

- The weight/volume capacities of the vehicles (assume that all the vehicles are homogeneous in this study)

3 Objective

The main objective of the proposed problem is to find out the best routing strategy such that the total traveling distance of all the vehicles are minimized (while reducing the total number of vehicles used for the delivery).

Constraints

1. The weight/volume capacity for all the vehicles cannot be exceeded.
2. All the modularized boxes assigned to one vehicle should be able to be completely packed into the assigned vehicle.
3. The rule of “Last-In, First-Out” should be respected.
4. All the customers can only be visited once. That is, all the ordered modularized boxes should be arrived at the location of the customers in a batch mode.

In the following section, we explain the algorithms used to solve the above problem.

3.1 Resolution Approach

Both the VRP and the 3D bin packing problems are NP-hard (Pinedo, 2012). In our case, their combination is also NP-hard since both of its subproblems are NP-hard. Consequently, heuristic methods are required to solve the problem. In Gendreau et al. (2006) and Massen et al. (2012), the authors used metaheuristic methods such as Tabu search and ant colony optimization to reach near optimal solutions. Such metaheuristics use randomness to explore better solutions. However, one of the accompanying counter effects of such approaches is that different runs of the same algorithm may result in different final solutions. Since, as mentioned before, the main purpose of this last mile problem is to analyze the potential of the horizontal collaboration, to prevent the generation of inconsistent results affected by randomness, the solving algorithms for the proposed last mile problem are deterministic rule-based heuristics.

The master problem of the proposed last mile problem is dedicated to vehicle routing, and three-dimensional bin packing problem plays the role of a side constraint. Our proposed algorithm introduces an insertion heuristic to solve the VRP as master problem. As commented by Campbell and Savelsbergh (2004), insertion heuristics have proven to be popular methods for solving a variety of vehicle routing problems due to their computational efficiency and the ability to be easily extended to handle complicated constraints (e.g., the three-dimensional bin packing in this study).

Algorithm 1 *

Algorithmic framework to solve the last mile problem

```
N = set of unassigned customers;
R = set of routes, always contains the empty route, initially contains only the empty
route; while N , ∅ do c* = ∞; for j ∈ N do
        for r ∈ R do
            for (i − 1, i) ∈ r do
                        if BinPackingFeasible(r, i, j) and Cost(i, j) < c* then
                    r* = r; i* =
                    i;
                    j* = j;
                    c* = Cost(i, j);
                end if
            end for
        end for
    end for
    Insert (i*,j*);
    N = N \ j* ;
    Update(r*);
end while
```

In the framework above, *BinPackingFeasible*(r,i, j) is a function to check whether the insertion of customer j between $(i - 1)$ and i in the route r is feasible for three-dimensional bin packing such as the non-overlapping of modularized boxes and the Last-In, First-Out requirement. We proposed two methods to evaluate the value of the function *BinPackingFeasible*(r,i, j). The first one is based on the technique of constraint programming. Compared to traditional mathematical optimization, usually in constraint programming, the optimal solutions are not very important since the major task is to seek feasible solutions which satisfy all the constraints. However, in the three-dimensional bin packing problem, since we must obey the laws of gravity and cannot allow "floating boxes," we try to minimize the sum of y_is instead.

Algorithm 2 *

Constraint programming to evaluate BinPackingFeasible(r, i, j)

Parameters:

n = number of modularized boxes to be delivered for a given route; w_i = width of modularized box i; h_i = height of modularized box i; d_i = depth of modularized box i;
p_i = visiting order of modularized box i's customer in the visiting sequence;
W = width of a vehicle;
H = height of a vehicle; D = depth of a vehicle;

Decision variables:

x_i : coordinate along the x-axis of the left-bottom-back corner of i;
y_i : coordinate along the y-axis of the left-bottom-back corner of i;
z_i : coordinate along the z-axis of the left-bottom-back corner of i;
l_{ij} : 1 if box i is at the left of box j, 0, otherwise; b_{ij} : 1 if box i is in b_{ij} the back of box j, 0, otherwise; u_{ij} : 1 if box i is under box j, 0, otherwise;
u_{ij}: 1 if box I is under box j, 0, otherwise;

Algorithm:

for 1 ≤ i, j ≤ n do
  Add the following non-overlapping constraints; $x_i - x_j + W \cdot l_{ij} \leq W - w_i$; $y_i - y_j + H \cdot u_{ij} \leq H - h_i$; $z_i - z_j + D \cdot d_{ij} \leq D - d_i$; if $p_i < p_j$ and $i < j$ then
    Add the Last-In-First-Out constraints;
  $l_{ij} + l_{ji} + u_{ij} + u_{ji} + b_{ji} = 1$; end if
end for
for 1 ≤ i ≤ n do
  Add the following bound constraints;
  $W - w_i \geq x_i \geq 0$;
  $H - h_i \geq y_i \geq 0$;
  $D - d_i \geq z_i \geq 0$;
end for

The second approach is a Bottom-Left-First heuristic algorithm to deal with bin packing.

Algorithm 3 *

Bottom-Left-First like Heuristic to evaluate BinPackingFeasible(r, i, j)

```
Arrange the n modularized boxes based on the increasing order of
p_i; I = {0, 0, 0}, L_z = L_x = 0; for i = 1 to n do
    flag = false;
    for (x, y, z) ∈ I do
        if box i can be put at (x, y, z) and x + h_i ≤ L_x, z + d_i ≤ L_z then flag = true,
            break;
        end if
    end for if flag =false
    then
        if L_x = 0 or L_x = H then
            if box i can be put at (0, 0, L_z) then
                x = 0,y = 0,z = L_z,flag =true,L_z = L_z + d_i,L_x = h_i; else
                if L_z < D then
                    L_z = D,L_x = H,i = i − 1;
                end if
            end if
        else
            for (x, y, z) ∈ I : x = L_x, y = 0 do
                if box i can be put at (x, y, z) and z + d_i ≤ L_z then
                    flag =true,L_x = L_x + h_i,break;
                end if
            end for if flag =false
            then
                L_x = H, i = i − 1;
            end if
        end if
    else
        put box i at position (x, y, z), I = I \ {(x, y, z)};
        I = I ∪ {(x + h_i, y, z), (x, y + w_i, z), (x, y, z + d_i)}; end if
end for
```

It is worth noting that in the above Bottom-Left-First heuristic, when the attempt to position box i at point (x,y,z) causes a failure, it is possible that we allow the rotation of the box and try to put the rotated box at (x,y,z) again. Such an extra consideration would increase the chance of $BinPackingFeasible(r,i,j)$ being true but would result in a longer computational time as well.

3.2 Numerical Results

As highlighted in the previous section, the main objective of our integrated last mile 3D bin packing problem is to minimize the operational cost while efficiently using the vehicles' capacity and consequently minimizing the number of empty vehicles circulating in the network. To fulfill such a purpose, in the case study, we created two scenarios for comparison. In the first scenario, two logistics service companies serve their individual last mile networks by their own fleet of trucks, while in the second scenario, these two companies pool the truck resource and collaborate to make the last mile delivery with the consolidated customer demand. In this case study, we considered three kinds of modularized boxes (Landschützer et al. 2015). Table 3.1 summarizes the modularized box dimensions used for the case study.

We have created 6 sets of testing instances with the number of customers for the last mile delivery ranging from 10 to 60 (incremental step is 10). In each set, 10 instances are constructed (therefore, there are 60 instances in total). For example, the data in Table 3.2 represent an instance from the set with customer number equal to 10. There are ten arrays separated by square braces (i.e., []), and in each array, the first two elements are the x-y coordinates of a customer's location, and the last three elements of the array represent the total numbers of different types of modularized boxes that the customer demands. For instance, [11,34,16,2,1] stands for that the customer is located at point ($x = 11$,y $= 34$) and the customer requests 16 boxes of type 1 modularized box, 2 type 2, and 1 type 3.

To create an instance for both scenarios, first of all, we randomly generate the locations of a Physical Internet hub and customers who are served by the hub. Then, for each logistics company, the total numbers of boxes for each box type demanded by each customer are also randomly picked up from given ranges. Once the demands for the two logistics companies are generated, for the second scenario, we simply added the corresponding demands and treated the sum as the demands for the horizontal collaboration case. For example, the box demands for the first and second companies are (European Environmental Agency 2018; Montreuil 2010; Campbell and Savelsbergh 2004) and [6,6,0], respectively. Hence, in the second scenario, the box demand for the same customer is [22,8,1].

Table 3.1 Modularized box choices

Box number	Length (m)	Width (m)	Height (m)
1	0.3	0.2	0.2
2	0.3	0.4	0.3
3	0.6	0.4	0.4

Table 3.2 Instance file example

[11,34,16,2,1], [43,−3,6,6,0],
[−41,47,21,1,1], [34,−41,14,3,1],
[−17,9,16,0,0], [−26,−44,18,6,1],
[19,−21,15,4,0], [−17,46,17,1,1],
[−3,33,14,4,0], [5,31,16,5,1]

Table 3.3 Case study results, for ten customers

Instance A	cost A	nVeh B	cost B	nVeh A+B	cost A+B	nVeh AB	cost AB	nVeh
10_1	458	3	445	2	903	5	563	5
10_2	425	2	339	2	764	4	475	4
10_3	338	2	266	2	604	4	433	4
10_4	352	2	345	2	697	4	427	3
10_5	426	2	441	2	867	4	542	4
10_6	437	2	412	2	849	4	621	5
10_7	299	2	356	3	655	5	521	5
10_8	411	2	555	2	966	4	617	4
10_9	380	2	352	2	732	4	545	4
10_10	526	2	470	2	996	4	554	5

Table 3.4 Case study results, for 20 customers

Instance A	cost A	nVeh B	cost B	nVeh A+B	cost A+B	nVeh AB	cost AB	nVeh
20_1	677	4	770	4	1447	8	983	8
20_2	693	4	690	4	1383	8	1000	8
20_3	860	4	850	4	1710	8	1042	8
20_4	627	5	688	5	1315	10	898	9
20_5	686	4	614	4	1300	8	825	8
20_6	750	4	545	3	1295	7	749	7
20_7	760	4	668	4	1428	8	803	8
20_8	671	3	651	4	1322	7	951	8
20_9	769	4	800	5	1569	9	1105	9
20_10	830	4	801	4	1631	8	974	8

First of all, we examine the performances of both approaches to evaluate *BinPackingFeasible*(r,i, j). After some trials, it turns out that even for relatively small-scale problems, the constraint programming method spent a few dozen of minutes to get the solutions. In contrast, the Bottom-Left-First heuristic is quite fast. Hence, we only use the Bottom-Left-First heuristic to evaluate *BinPackingFeasible* (r,i,j). Tables 3.3, 3.4, 3.5, 3.6, 3.7, and 3.8 summarize the computational results for the 60 instances. In each table, A_cost and B_cost are the total traveling costs for logistics companies A and B, respectively. A_nVeh and B_nVeh are the numbers of the vehicles that companies A and B need to deploy. A+B_cost is the sum of A_cost and B_cost and A+B_nVeh=A_nVeh+B_nVeh, while AB_cost is the total traveling cost, and AB_nVeh is the total number of vehicles used in the case that logistics companies A and B conduct horizontal collaboration. From this numerical experiment, it can be observed that in terms of total traveling cost, horizontal collaboration is much effective than individual scheduling. On average, compared to the case of individual scheduling, the cost saving rate of horizontal collaboration is 32.3%, which is calculated by the following formula.

Table 3.5 Case study results, for 30 customers

Instance A	cost A	nVeh B	cost B	nVeh A+B	cost A+B	nVeh AB	cost AB	nVeh
30_1	1026	6	1280	5	2306	11	1411	13
30_2	1004	5	1079	5	2083	10	1374	11
30_3	1076	6	948	7	2024	13	1416	12
30_4	885	5	964	6	1849	11	1361	12
30_5	1076	5	951	5	2027	10	1450	11
30_6	1021	6	1062	6	2083	12	1378	12
30_7	932	6	897	6	1829	12	1229	13
30_8	994	6	990	6	1984	12	1407	12
30_9	1273	6	996	6	2269	12	1233	12
30_10	896	5	1004	5	1900	10	1282	10

Table 3.6 Case study results, for 40 customers

Instance A	cost A	nVeh B	cost B	nVeh A+B	cost A+B	nVeh AB	cost AB	nVeh
40_1	1075	7	1199	8	2274	15	1654	16
40_2	1407	8	1360	7	2767	15	1881	15
40_3	1107	8	1335	7	2442	15	1756	16
40_4	1458	8	1222	7	2680	15	1699	16
40_5	1236	8	1207	7	2443	15	1694	16
40_6	1415	8	1262	8	2677	16	1713	16
40_7	1148	7	1177	7	2325	14	1691	15
40_8	1296	8	1244	7	2540	15	1758	15
40_9	1286	7	1293	8	2579	15	1650	15
40_10	1131	7	1160	7	2291	14	1747	14

Table 3.7 Case study results, for 50 customers

Instance A	cost A	nVeh B	cost B	nVeh A+B	cost A+B	nVeh AB	cost AB	nVeh
50_1	1280	10	1436	8	2716	18	2175	18
50_2	1676	9	1830	9	3506	18	2279	18
50_3	1595	8	1650	9	3245	17	1964	19
50_4	1355	9	1797	9	3152	18	2262	19
50_5	1615	9	1481	9	3096	18	2199	18
50_6	1521	9	1468	9	2989	18	2301	19
50_7	1577	8	1602	9	3179	17	2084	18
50_8	1593	9	1757	9	3350	18	2047	18
50_9	1283	8	1444	10	2727	18	2058	19
50_10	1356	8	1456	9	2812	17	1837	17

Table 3.8 Case study results, for 60 customers

Instance A	cost A	nVeh B	cost B	nVeh A+B	cost A+B	nVeh AB	cost AB	nVeh
60_1	1916	11	1951	10	3867	21	2557	23
60_2	1663	10	1882	10	3545	20	2465	22
60_3	1811	11	1896	11	3707	22	2537	24
60_4	1779	11	1813	11	3592	22	2626	22
60_5	1672	11	1965	9	3637	20	2456	22
60_6	1812	11	1870	10	3682	21	2402	23
60_7	1954	11	1925	11	3879	22	2738	22
60_8	1837	10	1768	11	3605	21	2611	22
60_9	2008	12	2418	11	4426	23	2978	24
60_10	2056	11	1889	10	3945	21	2937	23

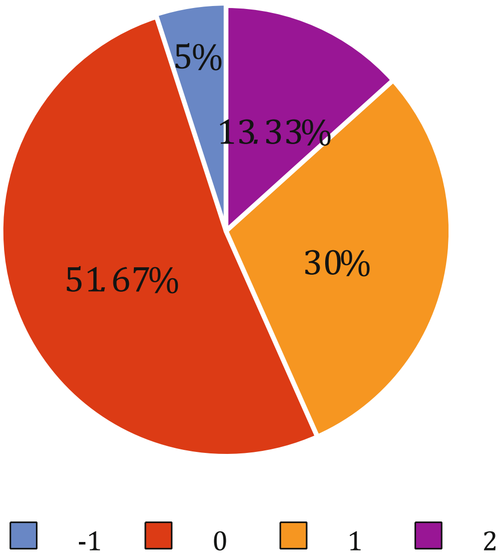


Fig. 3.6 The statistics on the difference of vehicle need on both scenarios

$$\text{cost saving rate} = \frac{\text{A} + \text{B\_cost} - \text{AB\_cost}}{\text{A} + \text{B\_cost}} \times 100\%$$

However, in terms of total number of vehicles used, individual scheduling slightly outperforms collaboration. As depicted in Fig. 3.6, among the 60 testing instances, the percentage that horizontal collaboration uses less vehicles is only 5%. In most of the cases, individual scheduling needs less or equal number of vehicles than horizontal collaboration. However, in around half of the instances, both scenarios ask for the same number of vehicle, and the maximal difference on the number of vehicle used is 2 with percentage 13.33%.

4 Mathematical Model of Vehicle Dispatching Problem

In the following, we will introduce the mathematical optimization model developed for the vehicle dispatching problem in a Physical Internet.
Parameters

- T: an upper bound of the number of arcs for a path for each vehicle.
- K: the set of vehicles.
- $G(N, A)$: the graph representation of a Physical Internet; N is the set of Physical Internet hubs, and A is the set of the arcs connecting hubs.
- $\delta(a) \in N$: the head node of an arc $a \in A$.
- $\sigma(a) \in N$: the tail node of an arc $a \in A$.
- c_a: the traveling cost of arc $a \in A$.
- $l_k \in N$: the initial location of vehicle $k \in K$.
- d_a: the transportation demand for arc a.

Decision Variables

- ${x_{ka}}^t$: a binary decision variable, 1, if vehicle k takes arc a at tth link, 0, otherwise
- $d_{ka} \in Z^+$: the transportation demand portion that vehicle k takes from transportation demand d_a, $a \in A$

Model

$$\mathbf{min}: \sum_{k\in K}\sum_{1\le t\le T}\sum_{a\in A} c_a x_{ka}^t \tag{3.1}$$

s.t.

$$\sum\nolimits_{a\in A} x_{ka}^t = 1, \qquad \forall k \in K, 1 \le t \le T \tag{3.2}$$

$$x_{k\acute{a}}^{t+1} \le x_{ka}^t, \qquad \forall k \in K, 1 \le t \le T, a, \acute{a} \in A, \sigma(a) \ne \delta(\acute{a}) \tag{3.3}$$

$$\sum_{a\in A:\sigma(a)=l_k} x_{ka}^1 = 1, \qquad \forall k \in K \tag{3.4}$$

$$\sum\nolimits_{t=1}^{T} x_{ka}^t \ge d_{ka}, \qquad \forall k \in K, a \in A \tag{3.5}$$

$$\sum_{k\in K} d_{ka} = d_a \qquad \forall a \in A \tag{3.6}$$

$$x_{ka}^t \in \{0, 1\}, d_{ka} \in Z^+, \qquad \forall 1 \le t \le T, k \in K, a \in A \tag{3.7}$$

In the above mathematical model, the objective function (3.1) aims to minimize the total traveling distance for all vehicles. Constraints (3.2) make sure that each link of a

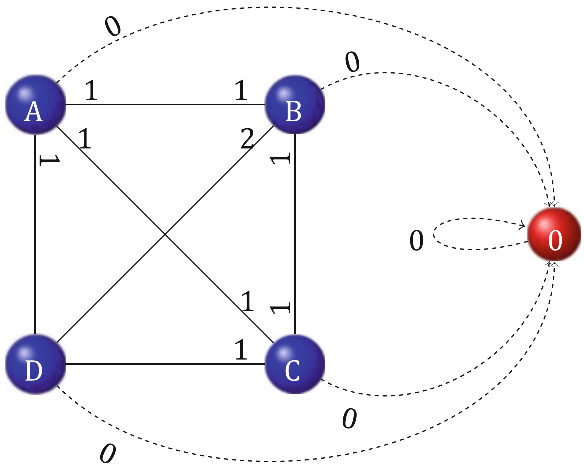


Fig. 3.7 Add dummy node and links for transformation

path for vehicle k should be chosen from the arc set A and only one arc can be chosen. Constraints (3.3) guarantee that a path for vehicle k should be connected.

Specifically speaking, if $x_{ka}{}^{t} = 1$, that is, vehicle k chooses arc a as the tth link in a path, then the next link in the path should have the starting node same as the ending node of arc a. In other word, if $x_{ka}{}^{t} = 0$, then $x_{ka}{}^{t+1}{}_{0}$ should be 0 for all arcs a^0 with $\sigma(a)$, $\delta(a^0)$. Constraints (3.4) force that a path of a vehicle k to start from the initial node of the vehicle, i.e., l_k. Constraints (3.5) count the transportation demand fulfilled by a vehicle k. Constraints (3.6) ensure that the total transportation demand for an arc a is split by all vehicles. Finally, constraints (3.7) define the domains for all the decision variables.

However, it should be highlighted that the mathematical model listed above cannot be directly used due to some technical limitations of the selected integer programming modeling framework (i.e., for a vehicle k, $x_{ka}{}^{t}$ for all $t \le T$ should be well defined, but T is just an upper bound; therefore, if T is not appropriately chosen, $x_{ka}{}^{t}$ for all $t \le T$ cannot be well defined). To bypass such a modeling difficulty, a simple way is to introduce one dummy node 0 and $(|A| + 1)$ dummy arcs with 0 traveling cost and transportation demand to transform the original graph $G(N, A)$ to another associated graph. Figure 3.7 shows the transformed graph of the network given in Fig. 3.1. As illustrated in Fig. 3.7, the dummy arcs (0,0), (A,0), (B,0), (C,0), and (D,0) are included in the new graph. The role of them is to enforce that once a vehicle k select a dummy arcs in {(A,0),(B,0),(C,0),(D,0)}, it cannot choose other real arcs along the path and once the vehicle is "trapped" in the dummy arc set, the only arc it can select is (0,0).

4.1 Numerical Results

To test the developed integer programming model for the vehicle dispatching problem, we used the P&G Switzerland historical sales order data to construct a case study.

As depicted in Fig. 3.8, in this case study, 11 hubs located in Switzerland are used. They are at Frenkendorf, Bremgarten, Ecublens, Frauenfeld, Langenthal, Petit-Lancy, Schmitten, Studen, Sursee, Wangen, and Winznau (nodes A to K, respectively). Figure 3.9 summarizes the information on the transportation demands, the traveling costs for all arcs, and the initial locations of all vehicles. Note that the distances are in the unit of kilometers and there are six vehicles: two at hub B and one at hubs C, E, I, and J.

After network transformation, the developed mathematical model is solved by IBM ILOG CPLEX 12.5 in a Dell M4700 (CPU 2.60 GHz and 8.00 GB RAM), and the minimal cost is 5821 km.

Similar to the last mile problem, for the vehicle dispatching problem, we also want to quantify the benefit of horizontal collaboration. Therefore, we test our cases for two scenarios where there are two distribution companies in our Physical Internet framework. As shown in Fig. 3.10, it can be seen that operator O_1 consists of hubs A, C, G, I, and J and the rest of hubs belongs to operator O_2. Both operators O_1 and O_2 have the same number of vehicles whose initial locations are also indicated in

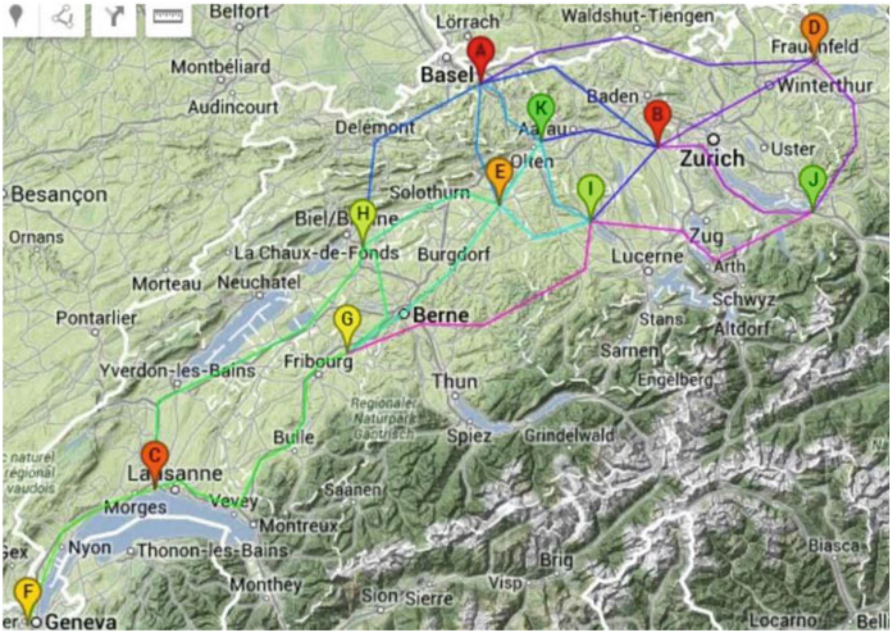
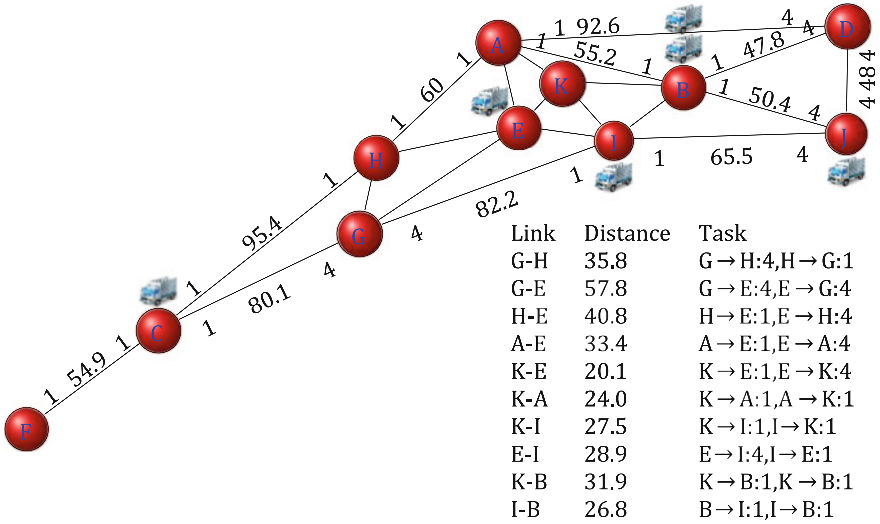


Fig. 3.8 The network of the case study based on P&G Switzerland data



Link	Distance	Task
G-H	35.8	G→H:4,H→G:1
G-E	57.8	G→E:4,E→G:4
H-E	40.8	H→E:1,E→H:4
A-E	33.4	A→E:1,E→A:4
K-E	20.1	K→E:1,E→K:4
K-A	24.0	K→A:1,A→K:1
K-I	27.5	K→I:1,I→K:1
E-I	28.9	E→I:4,I→E:1
K-B	31.9	K→B:1,K→B:1
I-B	26.8	B→I:1,I→B:1

Fig. 3.9 The case study based on P&G Switzerland

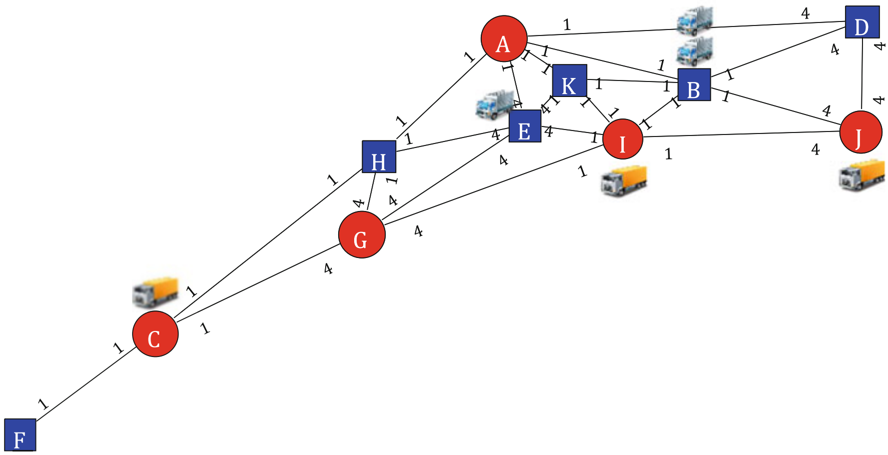


Fig. 3.10 The case study when the network is operated by two operators

Fig. 3.10. Thus, the individual scheduling problems for both O_1 and O_2 are delineated in Figs. 3.11 and 3.12, respectively. After the calculation, we obtain that the optimal costs for both operators are 3822 km and 3387.7 km, that is, 7209.7 km if we took the sum of costs for the two operators. Compared to the scenario of horizontal collaboration, the cost saving amount is 1388.7 km which is equivalent to 19.3% of the total cost for individual scheduling case.

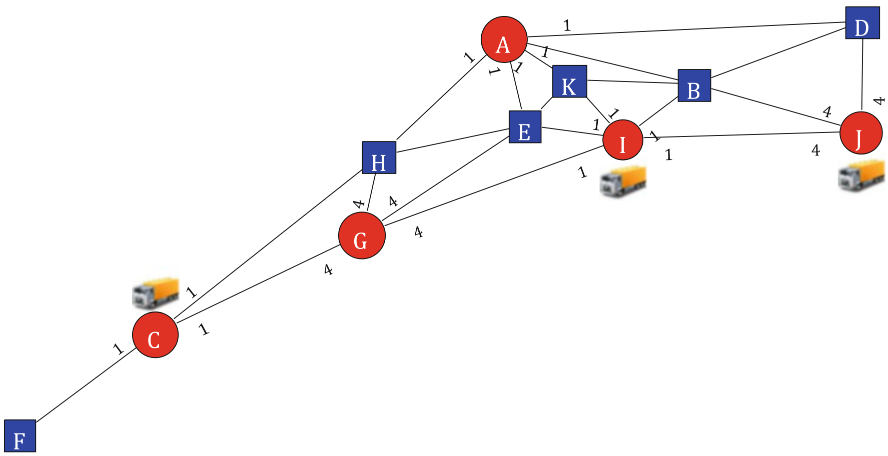


Fig. 3.11 The vehicle dispatching problem for operator O_1

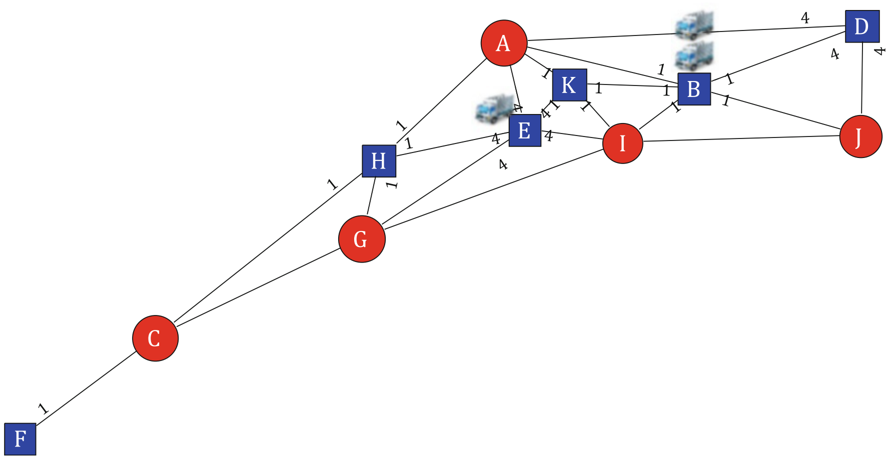


Fig. 3.12 The vehicle dispatching problem for operator O_2

5 Discussions and Conclusion

In this research, we propose two individual optimization problems (i.e., the last mile problem-3D bin packing and the vehicle dispatching problem) in the context of Physical Internet. The last mile problem is a downstream problem which takes the dimensions of the modularized boxes into account for their final distribution to clients. By contrast, the vehicle dispatching problem is a middle stream network problem. Its main objective is to identify the optimal transportation demand split and the best vehicle dispatching plan (i.e., walks for vehicles in the given graph) thus that the cost associated to empty vehicle movements is minimized. Based on these two problems, one of the main purposes of this work has been to quantify the benefit of the horizontal collaboration compared to its counterpart, the individual scheduling, in the world of Physical Internet. We have collaborated with several industrial partners in this project within an EU project. We have been provided with real case studies data which we used to evaluate our algorithms. According to our numerical experiments, the importance and great potential of the horizontal collaboration is highlighted. In the last mile problem, the cost saving rate of the horizontal collaboration can amount to 32%, and in the vehicle dispatching problem, the total vehicle traveling cost can be reduced by 19% if deep collaborations among logistics operators prevail. By reducing the number of empty vehicles circulating in the network, a more sustainable logistic system can be obtained that minimizes environmental impact. We also show the positive effect of horizontal collaborations between different service providers and distributors that make it possible to use resources more efficiently.

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