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Assessing the Impact of Inventory Deployment and Sharing Policies on Hyperconnected Last-Mile Furniture Logistics

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Abstract: *Open asset sharing is one of the concepts that form the bases of the Physical Internet. Naturally, interests of different parties are conflicting in such a setting, especially when existing assets that have been independently owned by participants are now shared. Moreover, the benefits of hyperconnected supply chains can vary significantly according to the strategies of participants. Therefore, it is important to consider the operating strategies of participants to successfully implement a hyperconnected logistic system. In this research, we examine using simulation the impact of inventory policy on the performance of last mile delivery of furniture and large appliances in an urban setting under scenarios where retailers are openly sharing their logistic assets, storage and delivery. Results show significant differences in savings achieved through open asset sharing depending on the inventory deployment and sharing policies, highlighting the importance of behavior of participants for successful implementation of Physical Internet enabled hyperconnected logistics.*

Keywords: *Physical Internet, Hyperconnected logistics, Last mile delivery, Product deployment, City logistics, Open asset sharing, Open shared storage, Open shared delivery, Furniture and large appliances, Simulation, Scenario analysis*

1 Introduction

Openly shared logistic infrastructure is one of the fundamental concepts of the *Physical Internet*. (Montreuil, 2011). Openly sharing independently owned logistic assets, such as storage space or delivery vehicles, can be the first step towards hyperconnected supply chains. However, to maximize the benefits of the *Physical Internet*, operating strategies of participating companies must adjust to the new logistic environment. In fact, the impact of the *Physical Internet* on logistic operations can differ significantly depending on operating strategies of participating companies, notably their inventory strategy. For example, when logistic assets are openly shared, logistic operations would be improved the most when inventories are deployed smartly across a network of distribution centers (DCs) so that the most optimal routes can be taken, whereas they are not improved by having inventories idle at a DC. Therefore, it is important to take operating strategies into consideration when demonstrating the potential benefit brought by exploiting the *Physical Internet* concepts and protocols.

Most of the furniture and large appliance retailers, which are the focus of this study, operate no more than one DC to serve a city area, without sharing any logistic asset with other retailers in the area. Goyal at el. (2016) have shown the significant advantages of hyperconnected supply chain on the last mile delivery of furniture and large appliances in a city, yet without explicitly considering inventories.

This study aims to extend the study started by Goyal et al. (2016) with a much further elaborated city logistic model embedding the notions of product and inventory, and to demonstrate the impact of inventory strategy on the performance of urban last-mile logistic operations.

A simulation-based scenario analysis is performed, using as testbed a fictitious square shaped city. Overall nine scenarios are tested, combining alternatives about specific facets. For example, relative to then overall degree of logistics hyperconnectivity, three alternatives are tested: dedicated logistics, hyperconnected storage, and hyperconnected storage and delivery. Dedicated logistics represents the typical current operations and forms a baseline. The other two alternatives represent *Physical Internet* inspired alternatives, with open shared delivery is assumed to be done through a third-party urban delivery service provider (urban deliverer).

Where multiple DCs are available, two alternative inventory deployment strategies are tested: one-time deployment and forecast-based overnight deployment. One-time deployment indicates that, upon receipt from supplier, product units are placed in a DC and not moved afterward before being shipped to customers. Each unit of a given product may be deployed in a distinct DC so as to optimize the inventory of the product in each DC give the expected demand forecast in each demand zone. Forecast-based overnight deployment indicates that the set of orders to be delivered is not known upon deployment, the retailers deploying inventories so that products are distributed in an optimized way among the four DCs given the forecast demand in each zone. The efficiency of one-time deployment and forecast-based overnight deployment is compared with order-based overnight deployment at each simulation run. Order-based deployment indicates that order information is known upon deployment and available products are moved if necessary so that all deliveries can be made from the nearest DC. In real world operation, order-based overnight deployment can be achieved if delivery information is known in advance, either due to longer time window for delivery or by crossdocking at each DC, and shipments are prepared at night.

When delivery operation is done by an urban deliverer, two alternative levels of inventory information disclosure to the urban deliverer are assumed and compared: minimum disclosure and selective disclosure. With minimum disclosure, retailers assign DCs to each customer and give only the assignment information to the urban deliverer. With selective disclosure, retailers share inventory status of products to be delivered so that the third party company can decide from which DC the products are to be shipped.

Lastly, the paper explores an advanced form of collaboration where inventories can be borrowed between retailers as necessary when the same products are sold by multiple retailers.

The paper is structured as follows. Section 2 briefly reviews relevant studies from the literature. Section 3 describes the simulation experiment design. Section 4 provides an analysis of the scenarios to be tested. Section 5 provides and analyzes the experimental results. Lastly, conclusion section 5 summarizes the findings and provides suggestions for future studies.

2 Literature Review

As this paper aims to bring the study of Goyal at el. (2016) one step further by elaborating simulation testbed and analyze the impact of inventory policy on the performance of hyperconnected logistics system in urban area, it therefore owes the most to Goyal at el. (2016).

The benefit of horizontal cooperation in supply chain has been shown in many studies and practices, yet it is hard to implement practically due to the nature of competition (Simatupang et al., 2002; Cruijssen et al., 2007). Specifically to furniture industry, Audy et al. (2008, 2011) studied the collaboration models among Canadian furniture companies sharing transportation to United States. Significant improvements in transportation was achieved in overall but, at the same time, it was also shown that the collaboration must be designed carefully to be successful as benefits for participating companies are not same.

In an urban setting, there also have been movements to improve logistic operations by urging collaboration between companies. The implementation of urban consolidation center is one of the examples. (BESTUFS, 2007; Van Duin et al, 2010) The urban consolidation center enables collaborative transportation in a city. Crainic et al. (2016) suggested *Physical Internet* based city logistics which enables further collaboration in logistics operation such as open distribution center.

Regarding the inventory deployment problem addressed in the paper, which can be seen as a lateral transshipment problem, many studies exists about lateral transshipment and inventory policy. Paterson et al. (2011) gives a comprehensive reviews on lateral transshipments. However, to the extent of authors' knowledge, there was no study in inventory deployment among the multiple DCs serving the same region and relating the deployment decision to delivery routing performance. The inventory allocation decision upon replenishment, on the other hand, can be seen as a two-echelon inventory allocation problem with imaginary central warehouse as ordering policy is fixed, like the retailer balancing and inventory allocation problem studied by McGavin et al. (1993).

3 Simulation Experiment Design

A fictitious city is created as a simulation testbed using AnyLogic 7.2.0 University as shown in Figure 1. The city comprises 60 hexagon-shaped districts and demand density varies by districts as presented in Figure 1. The edges of the districts represent a main road network of the city. Four DCs of each retailer, yellow (1), green (2), blue (3) and red (4), are located at each corner of the city. Manufacturers are conceptually represented outside of the city with highways and water ways connected to the city. Note that the location of manufacturers does not necessarily represent relative distance to the city.

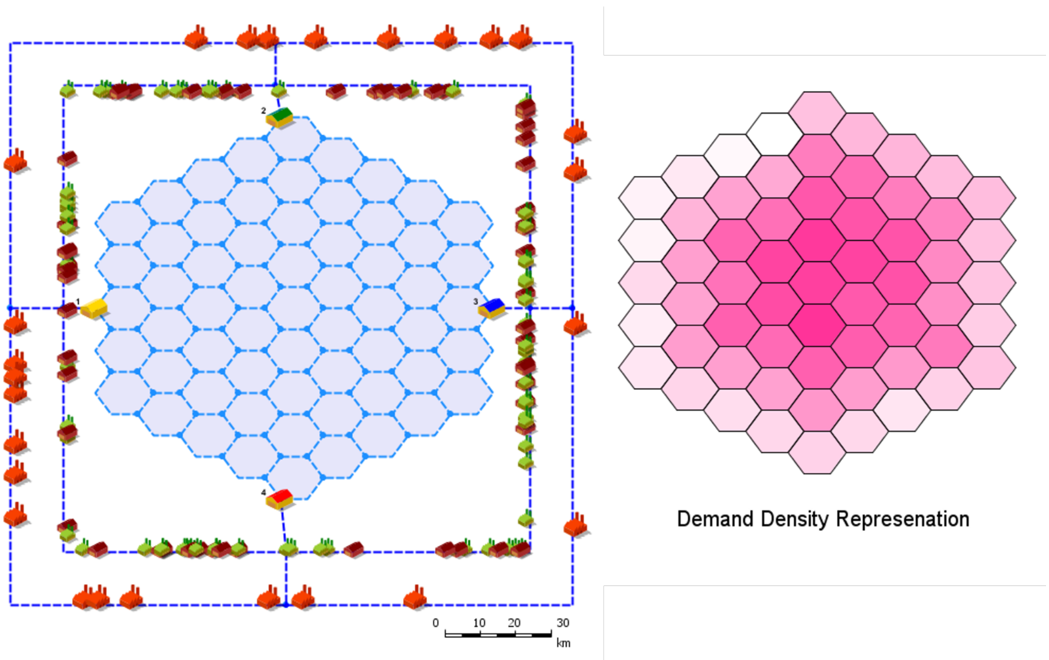

Figure 1: A fictitious City with 4 Retailer DCs and Manufacturers and Demand Distribution

Simulation runs for 2 years (730 days) after a 6 month warm-up period (180 days). Warm-up period is set to 6 months as the longest lead time is no more than 6 months and, moreover, it has been observed that performance parameters such as daily travel distances converges fast.

3.1 Demand generation and product portfolio design

In total, 440 different products are available in this fictitious market. The information of 220 products was scraped from webpages of furniture retailers and doubled as most of the products are provided in different colors. Among the 440 products, 348 products belong to furniture categories such as bed, dresser, and mattress and the rest belong to large appliances categories such as dishwasher, refrigerator, and range. The four retailers sell 176, 177, 186, 190 products respectively and their market shares are almost equally sized in terms of sales volume. Some products are exclusively sold by only one retailer whereas some are sold by multiple retailers; see Figure 2. It is assumed that, when same products are sold by more than one retailer, there is no preference on retailers. That is, customers are equally likely to buy the product from any of the retailers who sell the product if they have inventory available at the moment.

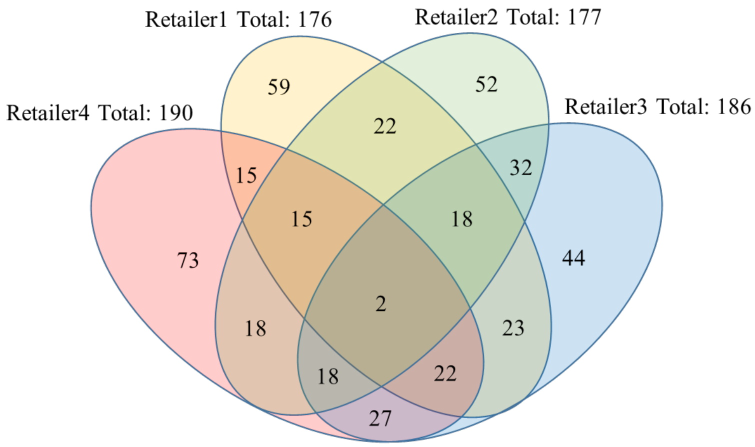

Figure 2: The Number of Products Sold by Retailers by Degree of Overlap

On average, 20 customer orders are satisfied by each retailer per day. Popularity of each product within its category follows the Pareto distribution and demand is generated from the Poisson distribution. When there is no inventory available at the requested retailer, customers may decide to wait, with different probability depending on waiting time, to divert, if the same product is available at other retailers, or to leave. Customer destination is also generated randomly based on the demand density of each district, but with uniform probability within district.

Moreover, due to the nature of furniture and large appliances delivery, both a delivery time and an install time need to be considered for each delivery. The delivery time and the install time is randomly assigned from the triangular distribution with product specific parameters. For example, accent chairs would require relatively short delivery time and no installment whereas refrigerator would require long delivery and install time.

3.2 Manufacturer types

There are 81 manufacturers of different size and type. Three operating types of manufacturers are considered: Onshore/Make-to-Stock(MTS), Onshore/Make-to-Order(MTO), and Offshore/MTO. It is assumed that Offshore/MTS type manufacturers are equivalent to Onshore/MTS for order replenishment operations since most of those manufacturers have onshore DCs. By the operating type of a manufacturer, product lead time differs. Product lead time of Onshore/MTS type manufacturers is between 1 and 7 days, Onshore/MTO between 8 to 29 days, and Offshore/MTO between 30 to 90 days. The manufacturers are also categorized by the contract type. Some manufacturers sell their products through only one retailer exclusively whereas others may supply to multiple retailers.

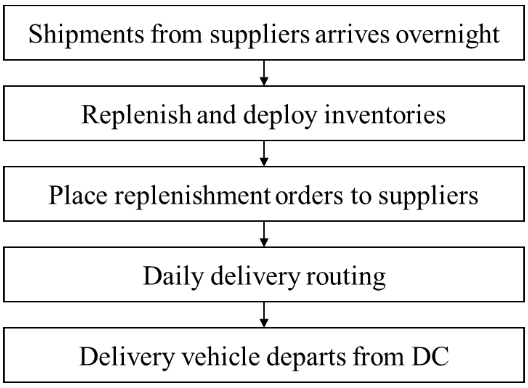

Figure 3: Daily Operation Routine of Retailers

3.3 Inventory management

Daily operation routine of the retailers is as shown in Figure 3. All retailers use the s-S policy and the target inventory levels are set to satisfy most of customer orders without considering inventory holding or ordering costs. As the Poisson distribution is discrete, level of s, reorder point, and S, order-up-to level, is approximated. Another assumption on inventory replenishment is that, for Offshore/MTO and Onshore/MTO manufacturers, retailers order at least six and three month of inventory in addition to safety stock regarding lead time as many MTO type manufacturers does not accept small scale orders. The lead time is assumed to be deterministic.

The s and S level is calculated from the formula shown in table 1. When the equations generate non positive value, we replace it with 1. With this method, expected average service level of 0.99 with minimum 0.98 is achieved.

Table 1: Order-up-to level and Reorder Point Formula

Manufacturer Type	Order-up-to Level	Reorder Point
Onshore/MTS	$\lceil 4L\lambda \rceil$	$\lceil 4L\lambda - 1 \rceil$
Onshore/MTO	$\lceil (4L + 90)\lambda \rceil$	$\lceil 4L\lambda \rceil$
Offshore/MTO	$\lceil (4L + 180)\lambda \rceil$	$\lceil 4L\lambda \rceil$

**L: lead time (days)* **λ: Average demand per day*

3.4 Delivery operation

It is assumed that 17ft truck is used for the last mile home delivery. Along the main road network of the city, delivery vehicles can drive, on average, at 50 km/hr whereas vehicles drive at 40 km/hr within a district. The delivery vehicles move straight to the next stop if it is in a same district and move along the main road network otherwise. Due to the product packaging and shape, maximum utilization of volume and weight capacity of the delivery vehicles is assumed to be 70%. Once routing is determined, all the delivery vehicles depart DCs at 8 am and their workload is no more than 8 hours at any day.

Routing heuristics are used instead of an exact solution method as routing is NP-hard. Initial routes are created by CW heuristic and improved by intra route 2-opt and Or-opt and inter route Or-opt and Swap. Cordeau et al. (2002), Potvin et al. (1995), and Savelsbergh (1992) has shown the performance of diverse routing heuristics. From these study results, the particular combination of construction and improvement heuristics are chosen for this study to achieve a good speed and accuracy. To apply CW heuristic given a set of customer orders and DCs, each customer destination is first assigned to a DC in order of distance to the nearest available DC greedily. The nearest available DC indicates a DC with minimum distance to the customer location among those where there is on-hand inventory. Customers are then grouped by the assigned DC and routes are created by the group with CW heuristic. Note that inter route improvement can only be made when inventory status can support the new routes.

4 Scenario Analysis

Nine scenarios are tested. Scenario 1 represents typical operations in current furniture and large appliances industry: a dedicated logistics. In Scenario 2, storage space of the DCs is openly shared. In Scenario 3-5, delivery is shared as well through an urban deliverer. In Scenario 3, retailers do not disclose the inventory status information to the urban deliverer, whereas in Scenario they share the information. Lastly, in Scenario 5, inventories may be borrowed among retailers for the products sold by multiple retailers to improve delivery routes. Note that the retailers do not share their inventories to fill the lost sales of others as they are competing for sales.

All Scenarios but Scenario 1 are further divided into 2 cases by inventory deployment strategy: one-time deployment (a) and forecast-based overnight deployment (b). In one-time deployment, deployment decision is made only for newly arriving products and the products are not moved once placed in one of the DCs. On the other hand, inventories are moved every night to balance on-hand inventory level at all DCs in case b. The objective of inventory placement is to balance DCs without any preference between DCs as no prediction on future demand before routing for the day is assumed. Order-based overnight deployment scenario is calculated and compared at every simulation run.

Table 2: Scenario Configuration

Scenario ID	Open Asset Sharing		Inventory Deployment Strategy		Inventory Information Disclosure		Inventory Borrowing
	Storage	Delivery	One-time deployment	Overnight Deployment*	Minimum Disclosure	Selective Disclosure	
1	-	-	-	-	-	-	-
2a	O	-	O	-	-	-	-
2b	O	-	-	O	-	-	-
3a	O	O	O	-	O	-	-
3b	O	O	-	O	O	-	-
4a	O	O	O	-	-	O	-
4b	O	O	-	O	-	O	-
5a	O	O	O	-	-	O	O
5b	O	O	-	O	-	O	O

** Overnight Deployment stands for forecast-based overnight deployment*

Performance of last mile delivery is measured by average travel distances of delivery vehicle and the average number of delivery vehicles used per day. Average fraction of customer destinations delivered by a DC which is not the nearest to them is also calculated.

4.1 Scenario 1: Independent operation

In scenario 1, each retailer operates with their own DC and delivery fleet independently. This is typical operation of existing retailers in this industry. Scenario 1 forms a baseline to which all the other *Physical Internet* inspired scenarios are compared. Sample screenshot of simulation and daily delivery routes of the 4 retailers are shown in Figure 4. Daily delivery routes are plotted by connecting each stops straight but it is different from actual path of delivery vehicle as vehicles move along the main road network when moving to another district. Note that delivery routes are marked in the same color of their retailer. Also, there are last mile delivery vehicles, with white back, and delivery vehicles from manufacturers, with yellow back.

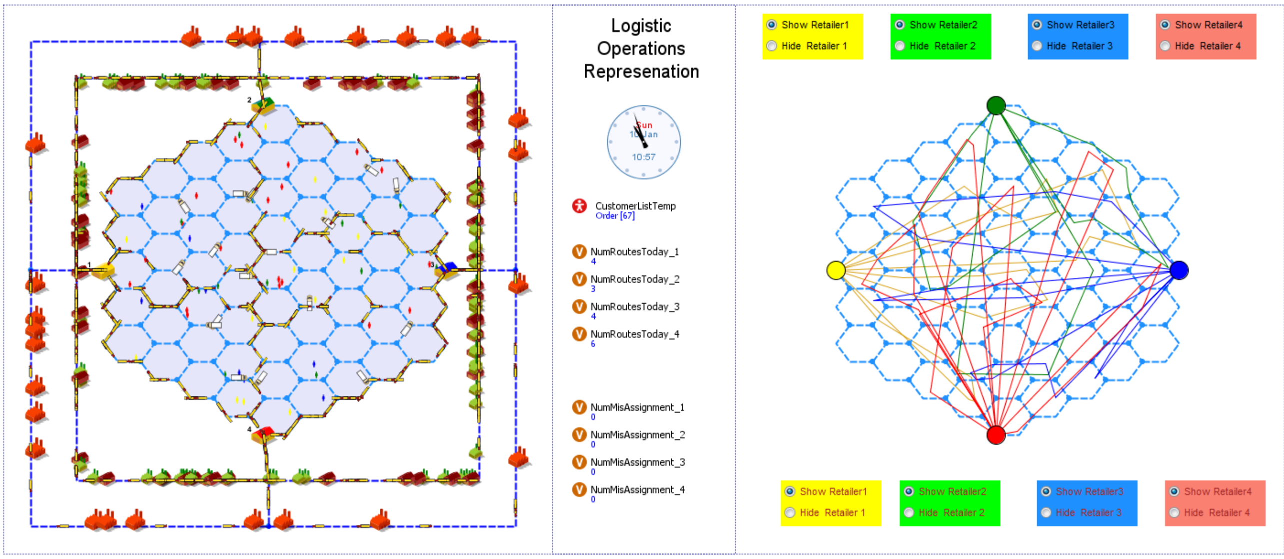

Figure 4: Sample Daily Delivery Routes of Scenario 1

4.2 Scenario 2: Open shared storage

In scenario 2, DC space is openly shared. That is, retailers can place their inventories in any of the 4 DCs and decide from which DC the requested product to be taken to satisfy customer order when the product is available at multiple DCs. Sample daily delivery routes are shown in Figure 5. The routes constructed according to one of the two deployment assumptions, one-time deployment or forecast-based overnight deployment, are represented in solid line and the dotted lines shows alternative routes when inventories are placed perfectly in advance through order-based overnight deployment. In other words, dotted line shows routings when all customer destinations are assigned to the nearest DC.

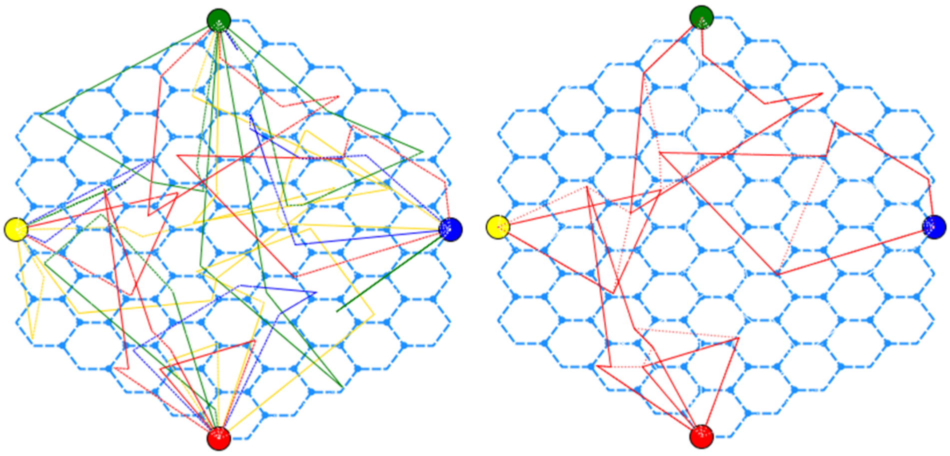

Figure 5: Sample Daily Routes of Scenario 2 for All Retailers (left) and for Retailer 2 (right)
(Actual Routes in Solid Line and Routes with Order-based Overnight Deployment in Dotted Line)

As stated in previous sections, two inventory deployment policies are tested separately. On average, more customers can be assigned to nearer DC with overnight deployment.

4.3 Scenario 3: Open shared storage and delivery with minimum information disclosure

In scenario 3, delivery is shared through a third party logistic company in addition to open shared storage space of DCs. Under minimum information disclosure policy, retailers first assign customers to each DCs based on a distance and inventory availability and delivers the information of DC assignment and customer order to the third party logistic company. Based on the given information, the third party logistic company determines routes and makes delivery. Note that one delivery route can include deliveries for multiple retailers in this scenario. Sample daily delivery routes are shown in Figure 6. Unlike figures for previous scenarios where routes are colored by retailers, routes are colored by departing DCs because routes are not belong to a specific retailer when delivery is shared. Both of inventory deployment policy is tested in this setting as well.

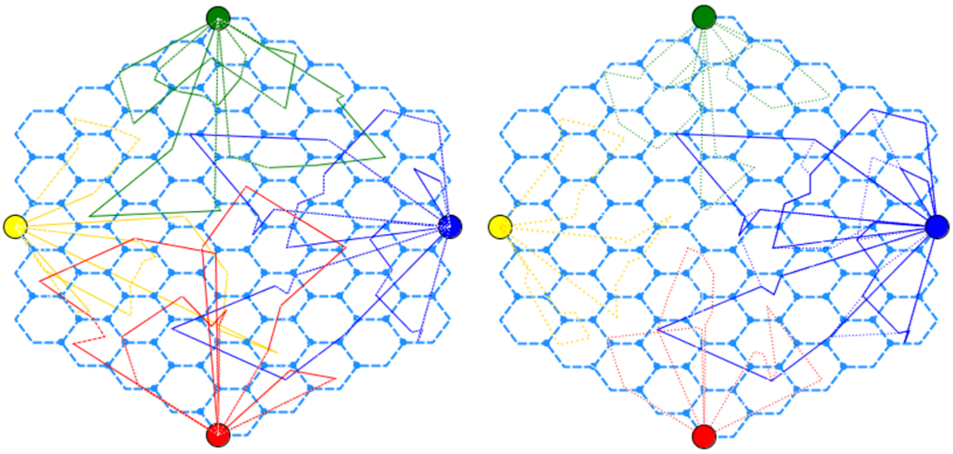

Figure 6: Sample Daily Routes of Scenario 3 from All DCs (left) and from DC 4 (right)
(Actual Routes in Solid Line and Routes with Order-based Overnight Deployment in Dotted Line)

4.4 Scenario 4: Open shared storage and delivery with selective information disclosure

Scenario 4 is identical to Scenario 3 except the level of information disclosure to the third party logistic company. Under selective information disclosure policy, retailers share the necessary information of inventory status of requested products with an urban deliverer but not share all the information. For example, if 2 units of a product are requested and the retailer has 1, 2, 3 and 4 units of the product at each DC, then the retailer will inform the third party logistic company that there are 1, 2, 2 and 2 units of the products at each DC. Note that the retailer will not share the additional information, that they have more than 2 units in the third and the forth DC, since it does not make any difference on routing performance. Sample daily delivery routes are shown in Figure 7 which is similar to Figure 5 without surprise.

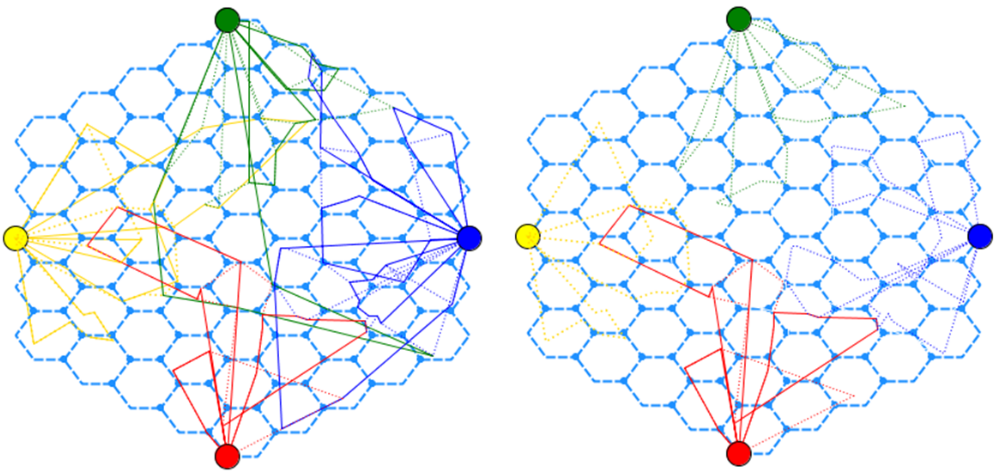

Figure 7: Sample Daily Routes of Scenario 4 from All DCs (left) and from DC 3 (right)
(Actual Routes in Solid Line and Routes with Order-based Overnight Deployment in Dotted Line)

4.5 Scenario 5: Open shared storage and delivery with inventory borrowing

In Scenario 5, storage and delivery are openly shared and inventories can be partly shared under specific condition. The inventories are borrowed through the urban deliverer to improve delivery efficiency. As mentioned previously, retailers borrow inventories if the other retailer has the product on hand but only in DCs located far from the customer who requested it and they do not share their inventories if the other retailer has no on-hand inventory. Following situation describes how this inventory sharing policy works: *Product A is sold by both retailer i and j. One day, retailer i needs to deliver a product A to customer C located near DC 1 but only has product A's in DC 3, when retailer j has extra on-hand inventory in DC 1. The third party logistics company can 'borrow' the inventory of retailer j. That is, it can satisfy order of customer C with retailer j's stock and fill it with retailer i's inventory overnight. This allows the last mile delivery during operation hours to be more efficient and let the logistics company to utilize less congested time to balance inventories of the retailers.*

This scenario is similar to vendor managed inventory (VMI), but not identical to it. Unlike VMI, risk of lost sales is not pooled and total inventory level remains unchanged. Also, deployment decision is made independently by each retailer. Only efficiency of last mile delivery during congested hours is improved at a cost of inventory rebalancing operation overnight. Therefore, this policy can be advantageous when travel during congested hours is considerably more costly than travel during night time.

Sample daily delivery routes are shown in Figure 8.

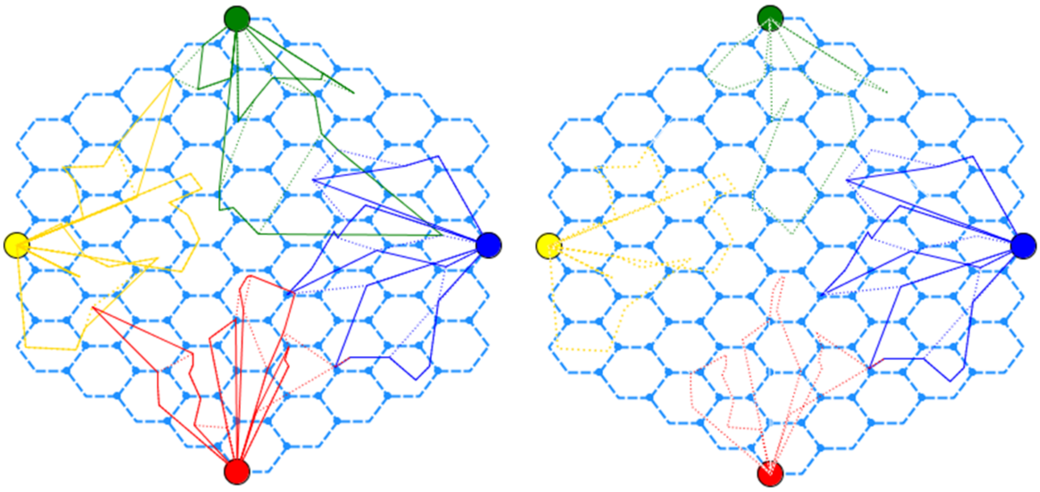

Figure 8: Sample Daily Routes of Scenario 5 from All DCs (left) and from DC 3 (right)
(Actual Routes in Solid Line and Routes with Order-based Overnight Deployment in Dotted Line)

5 Experimental results

At the simulation run of each scenario, selected performance measures are estimated: the average daily travel distance for delivery and the average number of vehicles used per day. Figure 9 demonstrates the graphs of performance measures over time from Scenario 1 and Scenario 2a.

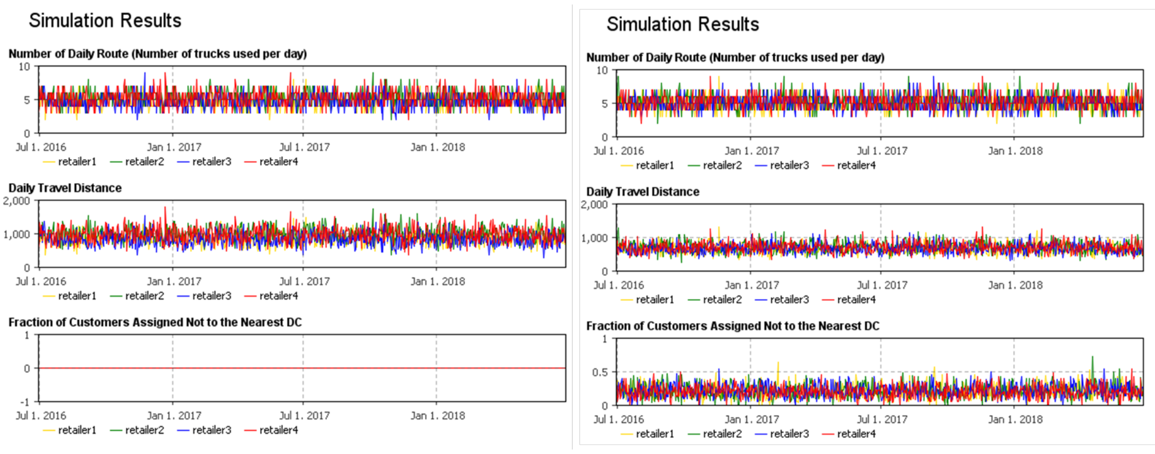

Figure 9: Simulated Performance Measures over Time from Scenario 1 (left) and Scenario 2a (right)

Figure 10 shows the reduction in average travel distance in the *Physical Internet* inspired scenarios compared to the average travel distance in Scenario 1. For Scenario 2a and 2b, distance from each DC represents the distance travelled by each retailer. In other scenarios, distance from each DC is the sum of the length of routes departing from the DC. At all *Physical Internet* inspired scenarios, average daily travel distance for delivery is reduced dramatically. The result corresponds with the findings of Goyal at el. (2016). Note that, in this study, the reduction in average daily travel distance for delivery is not identical in every DC as the location of DCs and demand density in the city are not symmetrical. For instance, customer destination tends to be located near DC 3 since demand density near DC 3 is high and, as a results, reduction in daily travel distances departing from DC 3 is the smallest.

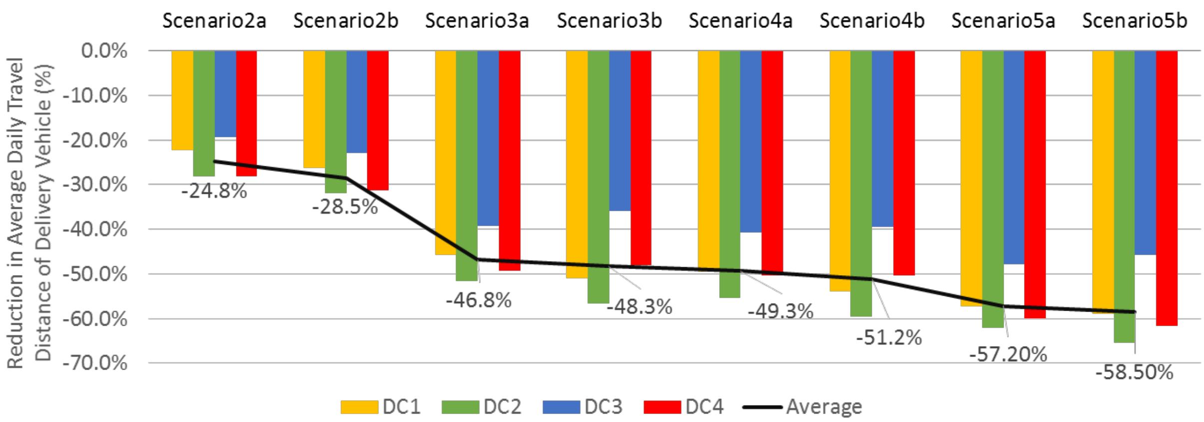

Figure 10: Reduction in Average Daily Travel Distance for Delivery on the Basis of Scenario 1

The impact of overnight deployment on delivery miles varies by scenarios but, at all scenarios, about 2% of additional reduction is achieved. Table 3 shows the average and marginal reduction in travel distance by inventory deployment strategy. Order-based overnight deployment is included as well. The additional reduction in travel distance achieved by sharing inventories is marginal compared to the reduction by sharing storage and vehicle. However, it must be noted that this additional reduction comes from extra flexibility in the routing decision by information disclosure, not from structural change in logistic operations. This implies that information disclosure would be a cost efficient strategy for retailers. Lastly, allowing inventory borrowing leads to sizable additional reduction in travel distance.

Table 3: Average Reduction in Travel Distance for Delivery on the Basis of Scenario 1 with Marginal Reduction in Parentheses and Average Fraction of Misassignment by Inventory Deployment Strategy

Scenario ID	One-time Placement	Forecast-based Overnight Deployment	Order-based Overnight Deployment
1	0%	-	-
2	-25%	-29% (-5%)	-41% (-17%)
3	-47%	-48% (-3%)	-63% (-29%)
4	-49%	-51% (-4%)	-64% (-25%)
5	-57%	-59% (-3%)	-64% (-13%)
Average Fraction of Misassignment (Scenario 2-4 / Scenario 5)	*21% / 9%*	*17% / 7%*	*0%*

The average fraction of misassignment, which seems to be correlated positively to the average travel distance, is also shown in Table 3. Here, the fraction of misassignment is the fraction of customers not assigned to the nearest DC due to inventory availability at first. Note that the final assignment can be different from the first assignment due to the routing heuristics in Scenario 2, 4, and 5, but not in Scenario 3 where retailers fix the assignment and the urban deliverer cannot change the decision. The reduced misassignment rate by balancing DCs every night seems to contribute to the additional reduction in travel miles. This further implies that with better prediction on future demand and better inventory placement strategy, more reduction in travel distance can easily be achieved. On the other hand, under same inventory deployment policy, sharing inventories as described in the study can reduce the average fraction of misassignment considerably.

Along with the average travel distances for delivery, the average number of delivery vehicles used per day is estimated and the result is shown in Figure 11. As in Figure 10, the number of vehicles from DC k represents the number of vehicles used by retailer k in Scenario 1 and 2, and the same represents the number of vehicles departing from DC k in Scenario 3, 4, and 5.

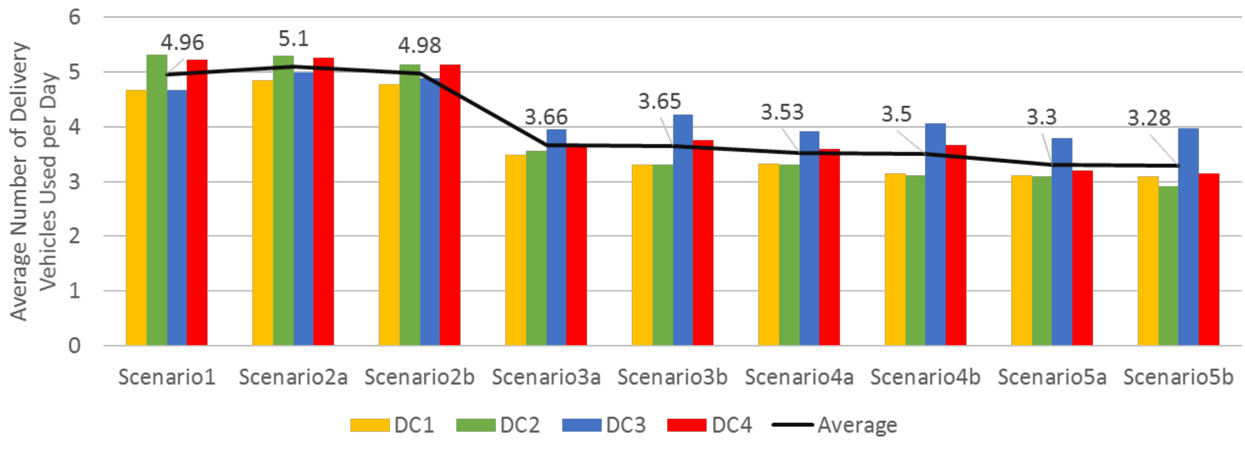

Figure 11: Average Number of Delivery Vehicles Used per Day by Scenario

There is no decrease, or even a slight increase, in the number of vehicles in Scenario 2 compared to Scenario 1 whereas the travel distances decreased significantly. That is, each vehicles travels shorter distances while almost same number of vehicles are used by each retailers. On the other hand, in the other scenarios, the number of vehicles decreased significantly as delivery density increased with shared delivery. The volume and weight constraints are weaker constraints than time for the routing and this let delivery per mile rate increase with the increase of delivery density. This reduction is important for operational purposes because the number of drivers needed is proportional to the number of vehicles used. Furthermore, when many retailers in furniture and large appliances industry experience shortage of drivers (Terry, 2013), the gain is more than just a labor cost savings. Interestingly, only slight decrease in the number of vehicles is observed by overnight inventory deployment.

Another interesting trend is that, in scenarios 3-5, more vehicles departing from DC 3 and 4 than from DC 1 and 2 and the gap is larger with overnight deployment and with more flexibility is given for routing. It is because DC 3 and 4 are preferred over DC 1 and 2 as demand density near those DCs are higher and it is likely for customers to be assigned to DC 3 and 4 when inventory is available in all DCs. This preference among shared DCs are observed in delivery travel distances as well. However, in Figure 11, it is also observed that the difference between the number of vehicles departing from preferred DCs and the others is further enlarged by overnight deployment. From this, it can be seen that savings from open asset sharing is not equal for all retailers there would be a game between retailers. To implement *Physical Internet* based logistic model successfully in real world, the conflicting interests of participants must be considered and coordinated carefully.

6 Conclusion

In this paper, we demonstrated the impact of inventory policy on potential gains of open logistics asset sharing for last mile delivery in a city, in focus of furniture and large appliances industry through simulation-based scenario analysis. First of all, sizable reductions in travel distance was shown to be still achieved when taking inventory into consideration as estimated ignoring inventories as shown by Goyal at el. (2016). As expected, significant difference is observed in savings in average travel distance for delivery by inventory strategies. Compared to one time deployment of inventories, the results shows that the last mile travel distance can potentially be reduced by more than 20% with smart inventory redeployment and maximum 64% total reduction in travel miles can be achieved by open sharing storage and delivery. We also observed different preference on the open shared DCs due to asymmetric demand distribution and DC locations. This implies unequal gains for participating retailers, which can lead to conflicts between retailers. Although this study is focusing on the last mile delivery of furniture and large appliance in urban setting but the results can be generalized easily.

Meanwhile, there is huge potential to improve this study and provide more sophisticated measure of the benefit of the *Physical Internet*. Only several major limitations of this study are to be listed here. First and foremost, this study only concentrates on the efficiency of last mile delivery and ignores the cost of inventory redeployment. This can be justified if the travel during day time is so costly that the additional travel for inventory redeployment at night becomes ignorable due to heavy traffic in the city. However, in general, to demonstrate and compare the net gains of these inventory policies properly, such costs must be taken into account. However, the operational settings are carefully determined to estimate the cost of inventory deployment as it differs significantly by the type of packaging and handling at DCs. Also, although openly sharing logistic assets can be an effective first step toward hyperconnected supply chain, more *Physical Internet* oriented scenarios can further devised and examined instead of restricting shared assets to the already existing ones. Lastly, pricing strategy for DC spaces or cost allocation strategy can be designed to address the asymmetric gains of participating retailers. The asymmetric gains may be critical obstacles when sizes of the retailers vary significantly. Obviously, there are more limitations of this study not listed here. In other words, however, there is considerable potential for future study in this topic.

To sum up, although the benefits of hyperconnected logistic system can be easily seen, the actual gain and success of such system are not obvious as each party participating in the system pursues its own interests. Overall, the results stress the points that, when implementing hyperconnected supply chain in real worlds, behavior of participating companies must be predicted and analyzed carefully to structure the system which can successfully utilized and maximize efficiency of logistics operation.

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