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Hyper-connected Megacity Logistics: Multi-Tier Territory Clustering and Multi-plane Meshed Hub Network Design

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Abstract: *In this paper, we present a dynamic approach for designing a hyper-connected network based on the multi-plane logistic structure proposed by Montreuil, Shannon, et al. (2018). Possible hub candidates are selected based on geographical locations and historic demand volume, and a heuristic solution for large-scale hub location problem (up to 5000 nodes) is presented to reflect different consolidation preference. Moreover, we construct an end-to-end framework for network configuration assessment and update through routing and simulation, allowing optimization of the whole system over comprehensive performance indicators.*

Keywords: *Physical Internet; Hyper-connected Logistics; Large-Scale Hub Location Problem; End-to-End Optimization*

1 Introduction

The parcel logistics industry, as old as this industry is, remains soaring as a result of internet commerce and worldwide trade. On the other hand, the trend also imposes challenges to the industry, pressing for a more reliable system that can offer multiple service levels and tackle with high demand stochasticity.

Currently, most of parcel logistics systems are constructed according to the standard hub-and-spoke network topology, where the term hub denotes a central sorting center (see O'Kelly and Miller, 1994). Although convenient in terms of daily operations and management, this structure suffers from low efficiency in the sense that it is vulnerable to demand peaks and valleys, also unable to prioritize products with the different time limit.

The hyper-connectivity concepts underpinning the Physical Internet (see Montreuil, 2011) aims at transforming the current hub-and-spoke network topology to a logistic web topology based on multi-plane meshed networks interconnecting hubs adapted to each plane (Montreuil, Meller, and Ballot,2013). Compared with the standard hub-and-spoke network, decentralization of the hyper-connected network enables more flexible and adaptable operations based on parcel pickup/delivery locations and service offering.

This paper is positioned as an extension of the works of Montreuil, Shannon, et al. (2018), and it targets a network design that enables max service capability at efficient overall cost via a combination of geographical data analysis and mathematical optimization techniques. The remainder of the paper is organized as follows. In Section 2, we introduce the general idea of the network structure proposed by Montreuil, Shannon, et al. (2018). In Section 3, we present our methods on hub candidate identification. The territory clustering is also included as a necessary step for the identification. In Section 4, we propose an iterative solution for hub location problem with given locations of hub candidates and historic flow data. We also provide an integrated approach for updating the network configurations through routing system.

2 Multi-plane Parcel Logistic Web

The four-tier pixelization of the area covered by the logistics service includes zones, local cells, urban areas, and the overall region (Montreuil, Shannon, et al., 2018). A zone is the most basic tier that the overall region consists of, and it varies in size depending on the managements' estimation of demand. For example, it can be a residential apartment complex or several floors in a sky-rise building in the business area. It can be viewed as a cluster of customers based on geographical location and demand. These zones can be clustered into local cells, and local cell themselves be clustered into areas (see Figure 1).

Figure 1: Four-Tier Pixelization of Service Area from Montreuil, Shannon, et al., 2018

To enable more efficient parcel logistic service corresponding to the four-tier pixelization, Montreuil, Shannon, et al. (2018) present a multi-plane logistic structure, each representing a sub logistics element with different capabilities. As shown in Figure 2, there are four tiers of planes: Plane 0 is the inter-P/D network linking pickup and delivery points; Plane 1 is the inter-zone network linked by access hubs; Plane 2 is the inter-cell network linked by local hubs; and Plane 3 is the inter-area network linked by gateway hubs. Furthermore, from the hub connection perspective, the hyper-connected network characterizes multiple connections between zone and its adjacent access hubs, multiple connections between access hub and its adjacent local hubs, and also multiple connections between local hub and its adjacent gateway hub (see Figure 3, and also Figure 4 for current dominating hub-and-spoke network connections as a contrast).

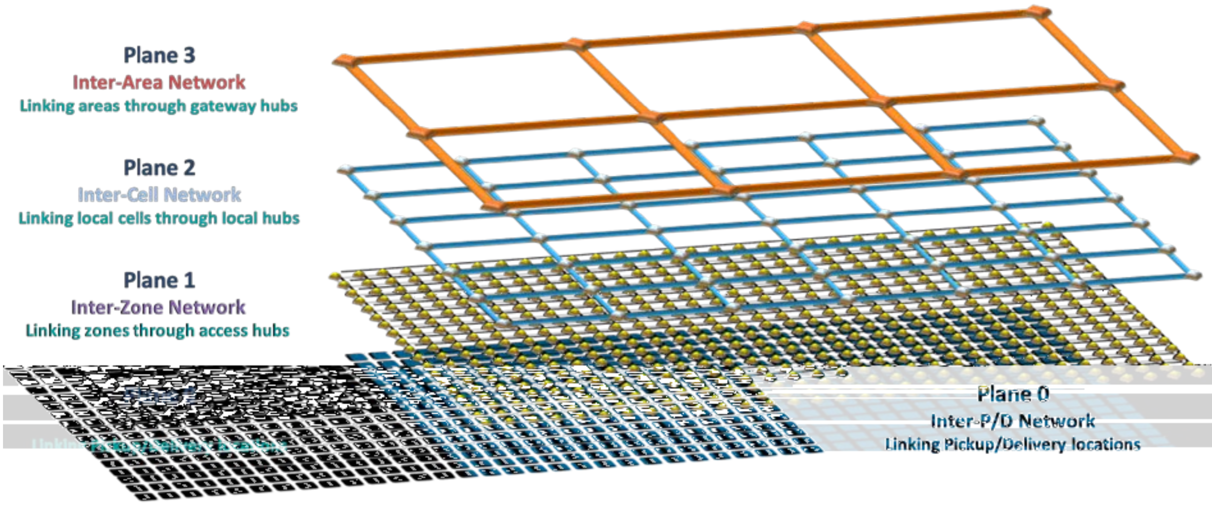

Figure 2: Urban Parcel Logistic Web from Montreuil, Shannon, et al. (2018)

The presented urban parcel logistic web can be extended to higher-plane meshed networks as

well. For example, we could possibly add more planes to allow parcels to flow from city to city or even country to country. In this paper, we shall focus on intra-city network design, i.e., the four-plane network within the urban area, and assume that the zones and gateway hubs are already fixed. Still, the ideas and approaches presented in this paper could be easily applied to a broader scale.

Figure 3: Conceptual Representation of Hyper-connected Network

Figure 4: Conceptual Representation of Hub-and- connected Network Spoke Network

3 Identify Hub Candidates

3.1 Access Hub Candidates

When mapping the pixelized illustration of the service area to the hyper-connected logistics web (see Figure 6), ideal access hub candidates (yellow dots) lie on the intersection of the zones (rectangles). However, the zones in real-world practices, as the smallest logistic unit, are most likely to be in the shape of polygons. In this case, we could consider the vertices shared by multiple polygons as a rough estimate of the intersection point of the zones, and treat them as the ideal access hub candidates. Moreover, any two vertices with a distance below some certain threshold can be merged into one "access hub candidate" if a relatively small number of candidates is preferable (see Figure 7).

Figure 5: Outline for Hub Candidates Identification

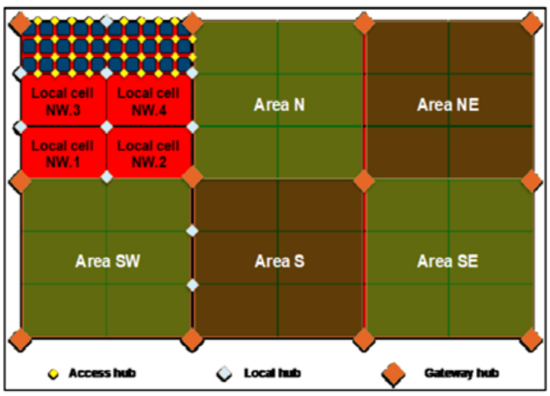

Figure 6: Logistic Web Mapped on Pixelized Urban Area from Montreuil, Shannon, et al. (2018)

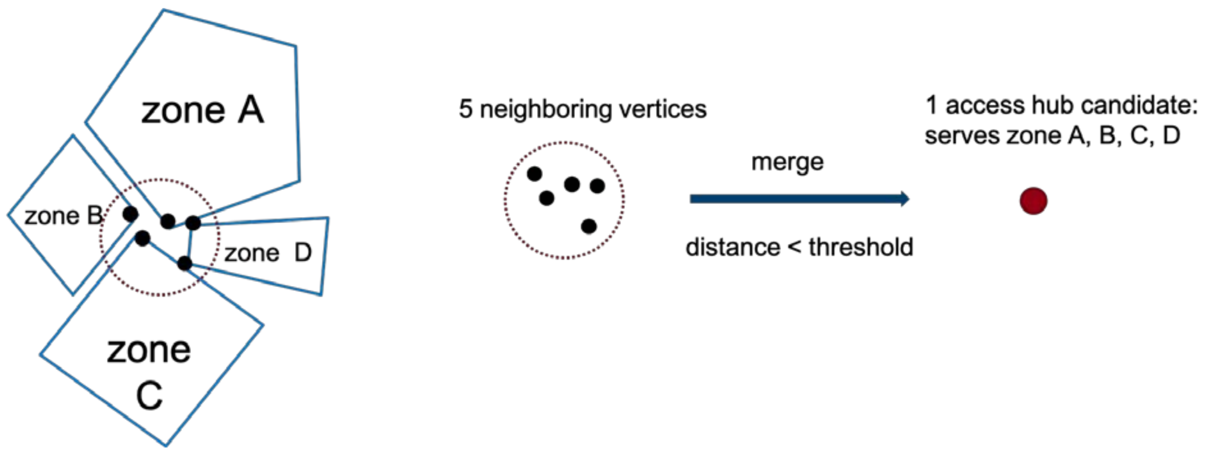

Figure 7: Intersection Point as Access Hub Candidates

3.2 Clustering Analysis: Define Local Cell

As an intuitive illustration, a local cell is depicted as a rectangular cluster covering 3×5 zones in Figure 6. If we assuming the size and demand are equal in each zone, then it is natural to design local cells to be with an equal number of zones, as illustrated in Figure 6. However, in most cases, the zones are different both in size and in demand. As a consequence, the potential benefits we seek from the hyper-connected network such as robustness against stochasticity will be dismissed under an imbalanced design. Therefore, we aim to achieve a clustering that (roughly) balances the demand between different groups.

Obviously, one can apply a classical clustering method, K-means for example, directly to group the zones; and as a result, a cluster would contain neighboring zones that are close to each other. However, as we have previously stated, demand balance should also be taken into consideration while doing clustering. Therefore, inspired by the greedy approach in monotone sub-modular function maximization proposed by Mirzasoleiman et al. (2015), we present a greedy algorithm for identifying clusters as follows.

$$max_{s \subset J} f(S) = \sum_{i \in I} \text{gain}(i) - \beta \sum_{j \in J: y_j = 1} \left(\sum_{i \in I:\, x_{ij}=1} D_i - \frac{\sum_{i \in I} D_i}{|S|} \right)^2 \tag{1a}$$

$s.\ t.$

$$\sum_{j \in J} x_{ij} = 1 \quad \forall\, i \in I \tag{1b}$$

$$\sum_{j \in J} y_j = |S| \tag{1c}$$

$$x_{ij} \le y_j, \tag{1d}$$

$$x_{ij},\ y_j \in \{0,\ 1\} \quad \forall\, i \in I,\ j \in J \tag{1e}$$

where I is the set of zones, J is the set of potential local cell centers, and S is the selected set of local cell center. The demand for each zone i is denoted by D_i, and β denotes the hyper-parameter used to penalize the imbalance in demand. The binary variable x_{ij} indicates whether zone i is assigned to local cell center j or not, and the binary variable y_j indicates if the hub candidate j is selected as a local cell center. To determine the gain function in Eq.

(1a), let d_{ij} be the distance from the center of zone i to the hub candidate j, and the gain from current assignment is defined as:

$$\text{gain}(i) = \max(0, \text{ distance cutoff } - \min_{j \in J} d_{ij}) \tag{2}$$

where the distance cutoff is the maximum allowed distance between zone i and its assigned hub candidate. Moreover, the imbalance in demand between each local cell is in the form of mean square error, which is the last term in Eq. (1a):

$$\sum_{j \in J: y_j = 1} \left(\sum_{i \in I:\, x_{ij} = 1} D_i - \frac{\sum_{i \in I} D_i}{|S|} \right)^2 \tag{3}$$

Next, we conduct the clustering analysis via greedy selection algorithm. Let S initially be an empty set. In each iteration, we aim at finding one hub candidate j from J which maximizes the function value of f in Eq. (1a), and then add this point j into S. In summary,

$$j = \text{argmax}_{j \in J} \big(f(S \cup \{j\}) - f(S) \big) = \text{argmax}_{j \in J} f(S \cup \{j\}) \tag{4}$$

$$S := S \cup \{j\} \tag{5}$$

Similar to ideal access hub locations, ideal local hubs should also lie on the intersection of local cells, with each local hub serving multiple local cells. Therefore, after selecting local cells through the above clustering analysis, we set the local hub candidates to be those access hub candidates that lie on the intersection of local cells.

Furthermore, the techniques for clustering zones as local cells can also be extended to a multi-tier setup. For example, we can apply the above process to cluster local cells as urban areas, and even cluster urban areas as some broader regions, if needed.

4 Network Design Optimization

In this section, we present a flow optimization model for selecting hubs out of all the hub candidates identified through the process we discussed in the previous section. To solve the flow optimization problem, we construct a graph with all hub candidates as nodes and their connections as edges.

Figure 8: Global v.s. Local Edges

Figure 9: Vertical v.s. Flat Edges

Based on different criteria, we will classify the edges in the network into two groups, as illustrated in Figure 8 and Figure 9.

- Based on vehicle usage, we divide the edge into global edges and local edges. Local edges contain the edges between a customer and an access hub, between access hubs, and between an access hub and a local hub; while global edges are between local hubs, between a local hub and a gateway hub, or between gateway hubs. Hence, in practice, small vehicles like motorcycles and small vans are commonly used for local edges, and the transportation on the global edges usually rely on large vans and trucks (see Figure 8).

- Based on the utilization of hyper-connection, we have vertical edges and flat edges. A vertical edge (blue in Figure 9) connects nodes in different tiers, and a flat edge (brown in Figure 9) connects two hubs within the same tier. So preferably, when pickup and delivery locations are close enough, in the hyper-connected network, flat edges should be fully utilized, since directly sending all packages to hubs at higher layer not only slows down delivery, but also increases the capacity pressure for hubs at a higher layer as well.

Additionally, for the flow optimization model, there are two types of flow for the network within urban area level.

- Intra-city flow: this is the flow from a customer within an urban area to another customer within the same urban area. The flow between source and destination can be viewed as a *(customer, customer)* pair.
- Inter-city flow: the package either originates outside the urban area and the destination of which is within the area, or it originates from a customer within the area, and the destination is outside the urban area. From the perspective of network design, these flows can be viewed as either *(gateway hub, customer)* or *(customer, gateway hub)* pair.

With the above classifications, next we discuss the problem of determining hub locations.

4.1 Hub Location Problem

Hub location problem is a classic topic in the area of integer programming, and has been studied extensively (one can see Farahani et al., 2013 for a good review of the topic). In our study, given the number of nodes and connection variables in the network, it is infeasible to seek an exact solution, and thus most heuristic approaches employ the Benders decomposition technique. However, most large network solved via Benders decomposition contains no more than 3000 nodes (for example, one can see the paper of Fischetti, Ljubić, and Sinnl, 2016). On the other hand, adding the effect of the economy of scale to the hub location model, as first proposed by O'Kelly and Bryan (1998), results in a prohibitively large number of variables, which also poses an obstacle in finding solutions. Therefore, we propose a novel, iterative approach to the hub location problem by solving a weighted shortest path problem for each zone. The weight on the edges are adjusted in each iteration to reflect current preferential attachment, and they decrease exponentially every time the edges are utilized because of the effect of the economy of scale. We will describe our approach for the remainder of this section.

Let N be the set of customer nodes, and K the set of hub candidate nodes, including access hub candidates, local hub candidates, and fixed gateway hubs. The union of N and K is the set of all the nodes in the network, denoted as V, and note that N and K do not overlap. In each iteration, given a customer (i.e., an origin zone), we solve the following shortest path problem:

$$\min \ \sum_{i,j\in N} \sum_{v\in V, u\in\delta(v)} f_{ij}(u,v)\cdot \mathrm{dist}(u,v)\cdot \mathrm{cost}(u,v) \qquad (6a)$$

$s.t.$

$$\sum_{k\in\delta(i)} f_{ij}(u,k) = \sum_{k\in\delta(i)} f_{ij}(k,u), \quad \forall\, i,j\in N, k\in K,\ u\in V \qquad (6b)$$

$$\sum_{k\in\delta(i)} f_{ij}(i,k) = Demand(i,\ j),\quad \forall\, i,j \in N \tag{6c}$$

$$\sum_{k\in\delta(i)} f_{ij}(k,j) = \ Demand(i,\ j),\quad \forall\, i,j \in N \tag{6d}$$

Our objective function in Eq. (6a), similar to most hub location problems, at the network planning phase, is to identify hubs from the set of hub candidates over the hub-customer links and the inter-hub links. The constraint (6b) follows the conservation of flow at each hub, and constraints (6c) and (6d) require that all outflow from zone i must route through its hub first and all inflow to zone j must pass its hub first.

The major innovative part in our approach is that in each iteration, the weight of previously used edges are updated to reflect consolidation preference. More specifically, in each iteration the weight is calculated as follows.

$$\text{weight}(u,\ v) = \min(\gamma \cdot \text{weight}(u,\ v),\ \ \beta) + \delta \tag{7}$$

where β is the consolidation threshold, δ is the hop penalty, and γ is the cost decay factor, which promotes reusing edges/consolidation of flow. Note that smaller β promotes the reuse of previous edges, and larger δ promotes fewer hops on each path.

Moreover, we could also set different proportional weight on different types of edges. Here we define two consolidation ratios according to vehicles usage and flat edges utilization:

- global consolidation ratio $= \frac{\text{cost on global edges}}{\text{cost on local edges}}$
- vertical consolidation ratio $= \frac{\text{cost on vertical edges}}{\text{cost on flat edges}}$

Note that in definitions above, the exact number of weight on edges are not required. Instead, it is crucial to use the ratio itself as an agent to reflect the desired usage of different types of edges. Higher global consolidation ratio promotes more global flow, while higher vertical consolidation ratio promotes more usage on vertical edges.

4.2 Network Validation and Update

The objective of the hub location model described above is to minimize the flow cost, which is not a very representative performance indicator in practice. To address this problem, we introduce a simulation system to assess the quality of the network produced by the optimization model. On the other hand, the hyper-parameters in the iterative model needs some fine-tuning, so we need to build a Bayesian optimization model to learn the function mapping between different weight parameters and more comprehensive performance indicators provided by the simulation system. The Bayesian method is commonly used when no exact functional form for integrated parameter evaluation is available. It proceeds by maintaining a probabilistic belief and designing an acquisition function to select the next point to query, learning a surrogate model over time, as described by Shahriari et al. (2016). Overall, this end-to-end optimization scheme allows for large-scale, in-the-loop models to directly optimize the whole system for target performance indicators.

In the following experiment, we aim at tuning two parameters: the global consolidation ratio and the vertical consolidation ratio. For simplicity purpose, the consolidation threshold β and the hop penalty δ will be fixed at 0.1 and 5 for all tested

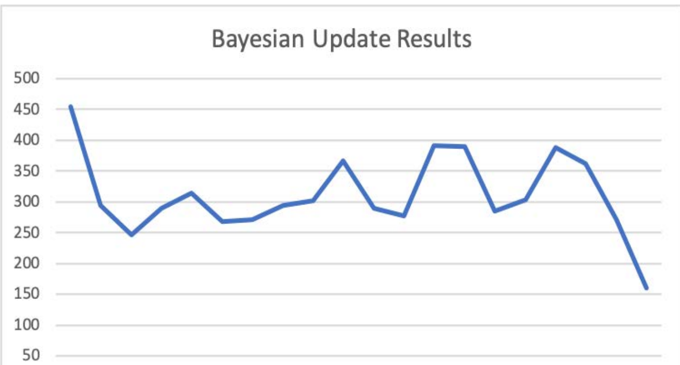

Figure 10: The Resulting Total Lateness per Iteration

networks. Our target is to minimize the total time (in minutes) of delivery lateness in the system. In each iteration, the Bayesian optimization model selects different combinations of the global consolidation ratio and the vertical consolidation ratio. As illustrated in Figure 10, the Bayesian method shows a clear decreasing trend in terms of the total lateness time.

5 Summary

To improve efficiency and flexibility in logistic service, this paper develops the methodology of designing a hyper-connected network. We first conduct a clustering analysis to identify possible hub candidates by using a greedy algorithm to balance the demand in different zones, and then propose a novel, iterative approach to solving large-scale hub location problems. Furthermore, to fine-tune the hyper-parameters in our iterative model, we build a Bayesian optimization model and demonstrate the effect of Bayesian techniques in terms of updating network configurations according to specific performance indicators.

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References

- Farahani, R. Z. et al. (2013). "Hub location problems: A review of models, classification, solution techniques, and applications". In: Computers & Industrial Engineering 64.4, pp. 1096–1109.
- Fischetti, M., I. Ljubić, and M. Sinnl (2016). "Redesigning Benders decomposition for large-scale facility location". In: Management Science 63.7, pp. 2146–2162.
- Mirzasoleiman, B. et al. (2015). "Lazier than lazy greedy". In: Twenty-Ninth AAAI Conference on Artificial Intelligence.
- Montreuil, B. (2011). "Toward a Physical Internet: meeting the global logistics sustainability grand challenge". In: Logistics Research 3.2, pp. 71–87.
- Montreuil, B., R. D. Meller, and E. Ballot (2013). "Physical Internet Foundations". In: Service Orientation in Holonic and Multi Agent Manufacturing and Robotics. Ed. by T. Borangiu, A. Thomas, and D. Trentesaux. Vol. 472. Springer Berlin Heidelberg.
- Montreuil, B., B. Shannon, et al. (2018). "Urban Parcel of Logistics Hub and Network Design: The Impact of Modularity and Hyperconnectivity". In: 15th IMHRC Proceedings. Savannah, Georgia. USA.
- O'Kelly, M. E. and D. Bryan (1998). "Hub location with flow economies of scale". In: Transportation Research Part B: Methodological 32.8, pp. 605–616.
- O'Kelly, M. E. and H. J. Miller (1994). "The hub network design problem: a review and synthesis". In: Journal of Transport Geography 2.1, pp. 31–40.
- Shahriari, B. et al. (2016). "Taking the human out of the loop: A review of bayesian optimization". In: Proceedings of the IEEE 104.1, pp. 148–175.