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Dynamic resource deployment in hyperconnected parcel logistic hub networks

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Abstract: *With the development of e-commerce, one of the major challenges for many parcel logistics companies has revealed to be designing reliable and flexible scheduling and deployment approaches and algorithms to meet uncertainties of parcel arrivals and resource availability in logistic hubs. In this paper, we want to present models to spatiotemporally adjust the available resource, like workforce and robots, across hyperconnected logistic hub networks using a rolling horizon approach. In most traditional parcel logistic hubs, workers are hired to enable the sorting, consolidation, transshipment, and crossdocking of parcels, and most resource scheduling is periodic (e.g., daily) and limited to single facility, thus the number of required resources in each hub is constrained to meet the peak demand with high variance. We here propose dynamic resource scheduling and deployment mechanisms, that are fed with updated data with sensors and dynamically updated parcel arrival predictions at hubs.*

Keywords: *Physical Internet; Hyperconnected Parcel Logistic Hubs; Dynamic Resource deployment; Dynamic Workforce Scheduling.*

1. Introduction

The increasing global urbanization and the surge of e-commerce underline the necessity for inventive, sustainable, and economically viable strategies in designing, managing, and operating urban logistics systems. Resource allocation in parcel logistic hubs refers to the strategic assignment and scheduling of resources like workforces, robots, and equipment in the logistic networks to achieve the desired service level in the most efficient and effective manner possible. Recently, the COVID-19 pandemic also reveals the significance of designing reliable and flexible resource deployment approaches with swift adjustments for handling the uncertainties and dynamic conditions of unpredictable parcel delivery demands as well as resources availability in logistic hubs.

The shift scheduling problem can be divided into two broad categories based on the type of workload they consider: task-coverage problems and workload-coverage problems [1]. The parcel hub scheduling problem (PHSP) is a scheduling problem that occurs in the parcel delivery industry. Those problems involve allocating resources over time to perform tasks as part of a process, such as sorting, unloading inbound trucks and loading outbound trucks [2]. Smart supply chains incorporate more objects embedded with sensors and better communication technology, along with intelligent decision making and automation capabilities, offer opportunities for cost reduction and improved efficiency [3]. The technologies allow logistics companies to monitor their resources in real-time, detect potential issues early, and make data-driven decisions to optimize resource allocation. Moreover, picking robots, also known as autonomous mobile robots (AMRs), are recently used in the logistic hubs to enhance efficiency, minimize errors, and boost productivity. Since these robots do not have the same physical and mental limitations as humans and can be programmed to respond quickly to real-time changes, they create an opportunity for dynamic resource scheduling and allocation problems. In the past few decades, dynamic scheduling problems have also attracted widespread attention in the literature [4,5,6], including completely reactive scheduling, predictive-reactive scheduling, and robust scheduling problems, which focus on making timely decisions considering real-time system status with uncertainties.

The Physical Internet (PI) was introduced by Montreuil [7] as 'an open global logistics system founded on physical, digital and operational interconnectivity through encapsulation, interfaces and protocols', and thus defines a new opportunity for supply chain design and operations, enabling seamless open asset sharing and flow consolidation [8]. In the context of urban logistics, the PI is realized through a multi-tier urban logistics web that is composed of hyperconnected logistic hubs. These hubs enable the sorting, consolidation, transshipment, and crossdocking of goods. The multi-tier structure consists of access hubs that interconnect unit zones, local hubs that interconnect local cells, and gateway hubs that interconnect urban areas [9,10]. This structure also presents an opportunity for moving workers across these hubs. Some of the hubs are in proximity but on different planes in the network, resulting in different arrival patterns and workforce demand peaks throughout the day. For example, the arrival time of parcels at access hubs depends on customers' pick-up requirements, while the arrival time of parcels at gateway hubs is dependent on transport truck schedules, subway, or train timetables.

In this paper, we propose a dynamic resource deployment system in parcel logistic hubs to match predicted demand with shifts in real-time using heuristic rules to respond quickly to changes of predicted arrivals at hubs and provide guidance for centralized resource assignment. Shifts are scheduled to cover the predicted workloads at hubs and online scheduling problems are solved dynamically based on real-time status including the assigned shifts as well as future tasks. We also rely on a rolling horizon approach to address the presence of uncertainty, which decompose the effect of lookahead into the informational and a processual component [11]. A reactive scheduling method that iteratively solves the deterministic problem by moving forward the optimization horizon in every iteration is proposed; assuming that the status of the system is updated as soon as the different uncertain parameters become known, the schedule can be optimized for the new resulting scenario [12]. We believe that this is the first work that shows the feasibility, efficiency and reliability of the proposed dynamic resource scheduling and allocation system for hyperconnected logistics hubs considering parcels' dynamically predicted arrival time and maximum dwell time in real-world logistics networks.

2. Methodology

2.1 Model preparatory techniques

2.1.1 Demand analysis among multi-tier parcel logistic hubs

To share resources spatial-temporarily in hyperconnected logistics hub networks, data analysis on daily workloads is necessary to identify a set of hubs, which are geographically close and easily accessible to each other, but differ in their demand patterns over time. Methods such as covariance matrix and correlation matrix can be utilized to examine the similarity among several time series demands. Both matrices provide information on the relationships between different time series, with the covariance matrix showing the level of covariance and the correlation matrix showing the strength and direction of the linear relationship. Positive values in the matrices indicate that the time series tend to move together, while negative values indicate that they tend to move in opposite directions. As shown in Figure 1, we select three hubs whose time series demands have comparatively small correlations, which means it is possible that resources could be shared among them over time to perform tasks with demand peaks.

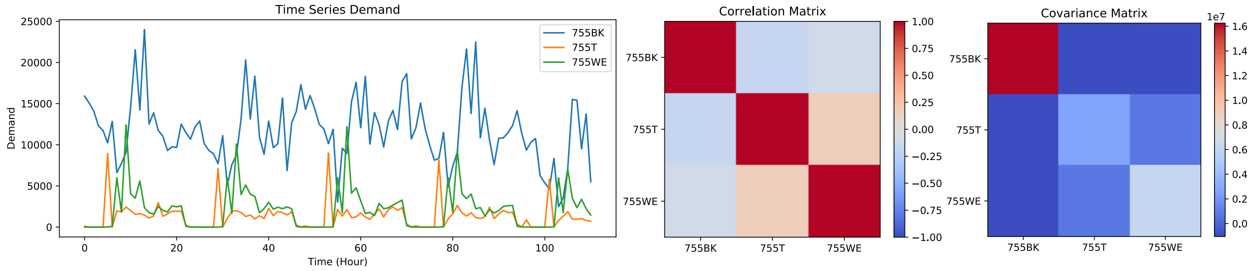


Figure 1: Demand analysis for three hubs in the network

2.1.2 Shift pattern generation

We assume that resources in the system can be classified into four states, namely "in work," "in idle," "in transit," and "off duty" to address the issue of resource allocation in hyperconnected parcel logistic hubs. A combination of the four states, each with a starting and ending time point, constitutes a shift pattern. Different resources may have distinct limitations for shifting patterns, such as maximum working time, idle time, or total time on duty. For example, the workforce may be restricted to an 8-hour workday, while picking robots require recharging after a full working shift. As a result, potential shifting patterns within the planning horizon can be generated for each resource type based on their specific time constraints.

Shift scheduling patterns generation offers several advantages. Firstly, it makes the proposed allocation system flexible enough to accommodate different types of resources. Secondly, it saves time for the subsequent algorithms.

2.2 Dynamic resource deployment and scheduling assignment system

We assume that workload predictions for hubs within hyperconnected logistic networks are provided and can be updated every ϵ minutes. Due to limited capabilities in solving scheduling problems for large logistics networks that contain hundreds of hubs, we propose a reactive scheduling model utilizing a rolling horizon approach to iteratively generate continuous shifts and shift combinations. Additionally, unlike traditional scheduling problems for single logistic hubs, we consider the possibility of labor working sequentially at multiple nearby hubs during daily shifts. The flowchart depicting our developed methodology can be found in Figure 2. Our dynamic resource scheduling and deployment system offers two key benefits: shift assignments within hubs are made while considering maximum dwell time, and resource deployment across hubs is made while considering traveling costs. The overall objective is to cover hub workloads while minimizing costs and associated penalties such as late parcels.

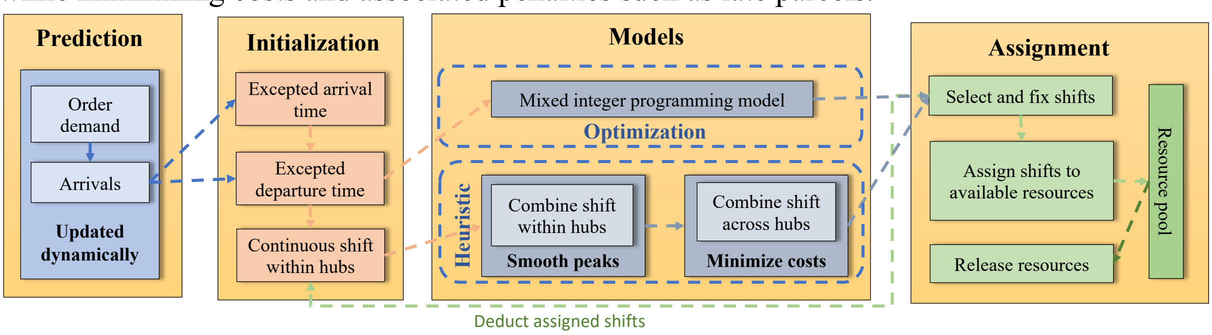


Figure 2: Flowchart of the developed dynamic resource scheduling and deployment system

2.2.1 Smoothing demand peaks

The dwell time of parcels at logistics hubs refers to the amount of time that a package or shipment spends at a hub or sorting center before it is dispatched to its next destination. The duration of this dwell time can vary depending on several factors, including the shipping service selected, the schedule of the following transportation method and the size and weight of the package. The duration of parcels' dwell time at a logistic hub is closely linked to the level of demand and the allocation of resources at the facility. Essentially, if the departure time for parcels is predetermined by the chosen service level, it may be possible to optimize resource usage by prioritizing emergency shipments and handling less urgent packages later.

An Integer Programming (IP) model can be used to demonstrate the idea. The optimization problem involves allocating resources to shift scheduling patterns in order to reduce overall scheduling costs and minimize lateness penalties. The objective is to flatten demand peaks, considering the parcels' dwell time at logistic hubs. Let I indicates the set of resources, S indicates the set of all possible shifting patterns and T indicates the set of time units in the planning horizon. For every shift pattern $s \in S$, according to the number of working and waiting time units in the shift pattern, we define C_s as the payment if a resource be assigned the shift pattern s. Specially, a shift with no working time units would cost 0. We define $x_{i,s}$ equals to 1 if the resource i is assigned to the shift pattern s, and 0 otherwise. Integer variables y_t and z_t is defined to be the number of parcels being processed and late at time unit t. We also assume that parcels' dwell time at the hub is pre-decided and could not be changed, therefore, we could calculate the number of parcels need departure the hub according to their arrival time, we define A_t and D_t to be the number of parcels arrive and need to depart the hub at time unit t. We assume parcels could be processed by a resource with the working efficiency λ. Then, the problem can be formulated as follows:

$$Min \sum_i \sum_s C_s x_{i,s} + +\delta \sum_t z_t \tag{1}$$

s.t.

$$\sum_s x_{i,s} = 1 \qquad \forall i \in I \tag{2}$$

$$y_t \leq \lambda \times \sum_{s:t \in Q_s} x_{i,s} \qquad \forall t \in T \tag{3}$$

$$\sum_{0 \leq c \leq t} y_c \leq \sum_{0 \leq c \leq t} A_c \qquad \forall t \in T \tag{4}$$

$$z_t \geq \sum_{0 \leq c \leq t} y_c - \sum_{0 \leq c \leq t} D_c \qquad \forall t \in T \tag{5}$$

Objective (1) minimize the sum of total shifting cost and the lateness penalty. Constraint (2) ensures that every resource is assigned to one shift pattern while constraints (3) – (5) are put in place to guarantee that the number of processed parcels never exceeds the number of arrived parcels at any given time, and that the number of late parcels equals the number of parcels that need to depart minus the number of processed parcels. This optimization model works well within one hub but could not incorporate shared resources among multiple hubs. Also, the optimization model could not return a near optimal solution for a large-scale resource allocation problem of hyperconnected logistic networks within limited time.

2.2.2 Heuristic algorithms for large-scale multi-hub resource allocations

Our approach for optimizing workforce allocation and smoothing demand peaks involves using dynamically updated workload predictions to initialize shifts with the maximum possible length at each hub. Algorithm 1 is used to estimate resource demand in each time unit, based on predicted parcel arrivals and assumed working efficiency. The list $x = [x_0, x_1, x_2, \dots, x_n]$

indicates current the labor demand in each time unit that need to be assigned shift patterns. Additionally, we select the most cost-effective shift scheduling pattern components with possibly maximum working time during this step.

Algorithm 1: Initialization with labor demand and efficient shifts

```
Input: a list of integers x representing resource demand, the maximum
       working hour ρ, the length of the list n
Output: a list of tuples representing initialized shifts

start ← 0;
shifts ← ∅;
while start < n do
    if x[start] = 0 then
        start ← start + 1;
    end
    x[start] ← x[start] − 1;
    end ← start + 1;
    /* find the shift with the maximum possible length*/
    while end < n and x[end] > 0 and end − start ≤ ρ do
        x[end] ← x[end] − 1;
        end ← end + 1;
        shifts ← shifts ∪ {(start, end)};
    end
    start ← end;
end
return shifts;
```

Our model assumes a specified maximum dwell time ζ for each parcel at the hub, during which it can be processed and prepared for departure. This allows us to combine shorter shifts into longer ones, without resulting in workforce demand peaks. To accomplish this, we use Algorithm 2 is used to identify potential scheduling pattern components based on demand predictions, and utilize the dwell time to smooth out demand peaks, so as to find the minimized number of shifts and maximized shift total length.

Algorithm 2: Within Hubs: Combine Scheduling Pattern Components with Minimized Number of Shifts and Maximized Shift Length

```
Input: a list of integers x representing resource demand, the maximum
       working hour ρ, a list of tuples representing possible shifts
       shifts
Output: a list of tuples representing combined shifts

Combined ← ∅;
for shift in shifts do
    if shift[end] − shift[start] = ρ then
        Combined.append(shift);
        x[shift[start] : shift[end]] ← x[shift[start] : shift[end]] − 1;
    end
end
start ← 0;
while start < n do
    if x[start] = 0 then
        start ← start + 1;
        continue;
    end
    end ← start + 1;
    while end < n and end − start < ρ do
        Find next non-zero hour and add to shift;
        if x[end] = 0 and x[end − 1] ≠ 0 then
            /* smooth labor demand by moving count to next
             time unit */;
            Move count from end − 1 to end;
        end
        end ← end + 1;
    end
    Combined ← Combined ∪ {shifts};
    x[shift[start] : shift[end]] ← x[shift[start] : shift[end]] − 1;
    start ← end;
end
return Combined;
```

Algorithm 3 is utilized to merge shifts across nearby hubs, considering both transportation modes and cost. The algorithm operates by considering shifting components at different hubs and greedily combining them, provided that their shift hours do not overlap, and transportation time falls within the specified requirements. We continue merging shifts between hubs until the cost of traveling becomes greater than the cost of utilizing a new resource.

Algorithm 3: Across hubs: Combine Scheduling Pattern Components with Minimized Travelling Cost

Input: a list of hub pairs H, the maximum working hour ρ
Output: a list of tuples representing combined shifts

$Combined \leftarrow \emptyset$;
for *hub in H* **do**
    for *shifts in hub* **do**
        if *shift hours do not overlap and moving time* $\leq$ *shifts gap* $\leq$ *maximum gap and total working time* $\leq \rho$ **then**
            $Combined \leftarrow Combined \cup \{shifts\}$;
            Remove *shifts* from *hub*;
        end
    end
end
return *Combined*;

Finally, we select and assign shift patterns to available candidates from the resource pool, with the option to incorporate individual preferences. When their resting or maintenance shifts are complete, resources are released back into the pool. Further details can be found in Algorithm 4.

Algorithm 4: Assigning Scheduling Patterns to Resources

Input: a list of tuples representing combined shifts, a threshold γ, a pool of available workers
Output: a list of tuples representing assigned shifts

$Assigned \leftarrow \emptyset$;
for *shift in Combined* **do**
    if *Value(shift)* $\geq \gamma$ **then**
        Assign an available worker in the pool to *shift* according to preference if possible;
        $Assigned \leftarrow Assigned \cup \{shift\}$;
    end
end
return *Assigned*;

2.3 Rolling horizon approach

To address the uncertainty present in demand prediction, a rolling horizon approach is employed. This involves iteratively assigning cheap and efficient shifts to workers by advancing the planning horizon with updated demand predictions at each iteration. The selection of shifts within each planning horizon is crucial, as fixing shifts too early may result in overstaffing in the presence of significant demand prediction intervals, while selecting shifts too late may lead to high emergency penalties and leave insufficient time for crew planning. Therefore, we evaluate shifts using the value function outlined below:

$$Value = \alpha \times \frac{\text{Duration threshold } \tau \text{ to fix a shift}}{\text{Shift start time } - \text{ Current time } t} + \beta \times \frac{\text{Working time}}{\text{Maximum working time } \rho} + \gamma \times \frac{\text{Working time}}{\text{Resting time}}$$
$$\alpha + \beta + \gamma = 1$$

The rolling horizon approach is employed to iteratively assign efficient and cost-effective shifts to workers using updated demand predictions. To evaluate shifts, a value function is utilized, and a continuous shift or combination of shifts with a value greater than a threshold δ $(0 \leq \delta \leq$

1) is fixed and assigned to an available worker. The parameters α, β, γ, δ and τ can be adjusted to minimize costs under different prediction scenarios. After a resource's assigned shifts are finished, they are released back to the workforce pool and become available for their next day shifts. Additionally, as workload predictions are updated and shifts are assigned, the corresponding workload is subtracted from the new predictions to be used in the next planning horizon.

3. Experimental results

To assess the benefits of our proposed heuristic model for shared resource allocation in the hyperconnected logistic networks, we also conduct experiments using logistics networks from the logistics company in China, leveraging an urban logistics simulator to dynamically collect parcels' arrivals at hyperconnected hubs. In our experiments, 52 local hubs and gateway hubs from the company's logistics networks in Shenzhen, China are included. We set the planning horizon to be 24 hours and there exist 1,173,253 parcel arrivals at hubs during a day. We assume the maximum dwell time $\zeta = 1$ hour and the working efficiency $\mu = 150$ parcels/hour, and our models to be run every $\epsilon = 60$ minutes utilizing updated predictive results. It takes about a minute to run the methodology for a whole day with the rolling horizons.

We consider various types of resources that can be utilized in hyperconnected logistics networks, including human workforce and picking robots. The key distinguishing factor among them is the maximum allowable working duration during a day. Specifically, contracted employees are restricted to working for a maximum of 8 hours, whereas robots can operate continuously until their batteries are depleted. Hence, we categorize resources into three types in the experiment, each with a distinct daily working hour limit of 8, 15, and 22 hours, respectively.

Since the prediction of parcels' arrival time at hubs can be dynamically improved as they approach to the hubs, in the experiment we assume that the prediction of number of arrivals p of time t_1 conducted at time t_0 can be written as

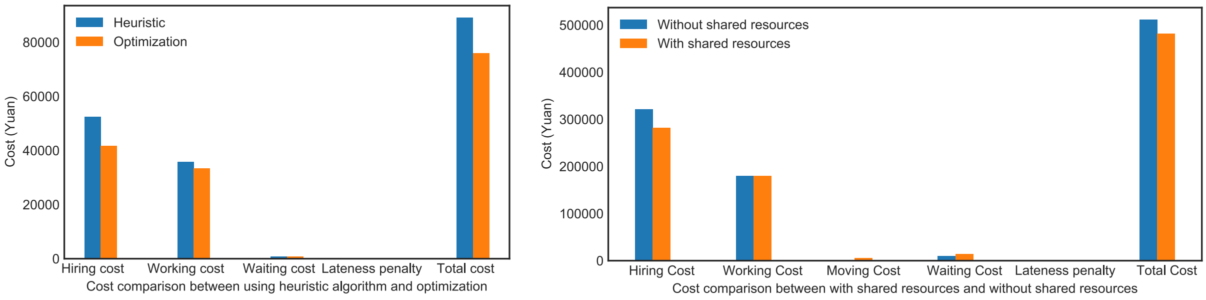
$$p = C * e^{r*(t_1 - t_0)}$$

where $r \sim normal[\mu, \sigma^2]$ and C is the actual number of arrivals at time t_1. μ and σ is set to be 0 and 0.01 in the simulation to generate prediction scenarios. The parameters to fix combined shifts during the rolling horizon are tuned like $\alpha = 0.4$, $\beta = 0.3$, $\gamma = 0.3$, $\delta = 0.9$ and $\tau = 4$. As these influence performance, different settings may be further tested.

3.1 Scheduling and allocation costs

In the proposed dynamic resource deployment and scheduling assignment system, the costs we consider include hiring cost, working cost, waiting cost and transportation cost if resources move from one hub to another hub. We also take lateness penalty into consideration if parcels could not be processed before their departure deadline. As mentioned in section 2.3.1, we utilize parcels' maximum dwell time to smooth demand peaks and reduce resource allocation costs. We also proposed two methods for resource allocation within hubs, including one Integer Programming model and heuristic algorithms 1&2. Figure 3 shows the allocation cost comparisons for resources with the 8-hour maximum daily working hour limit using optimization and heuristic methods. As shown in Figure 3(a), the heuristic algorithms can achieve near-optimal solution but takes less time for allocations given arrivals of one selected large gateway hub from the logistic company.

Also, given the scheduling and allocation results utilizing updated predictive parcel arrivals of the logistic networks, we could reduce total allocation costs, especially hiring cost, by allowing shared resources moving among the 52 local hubs and gateway hubs, as shown in Figure 3(b).

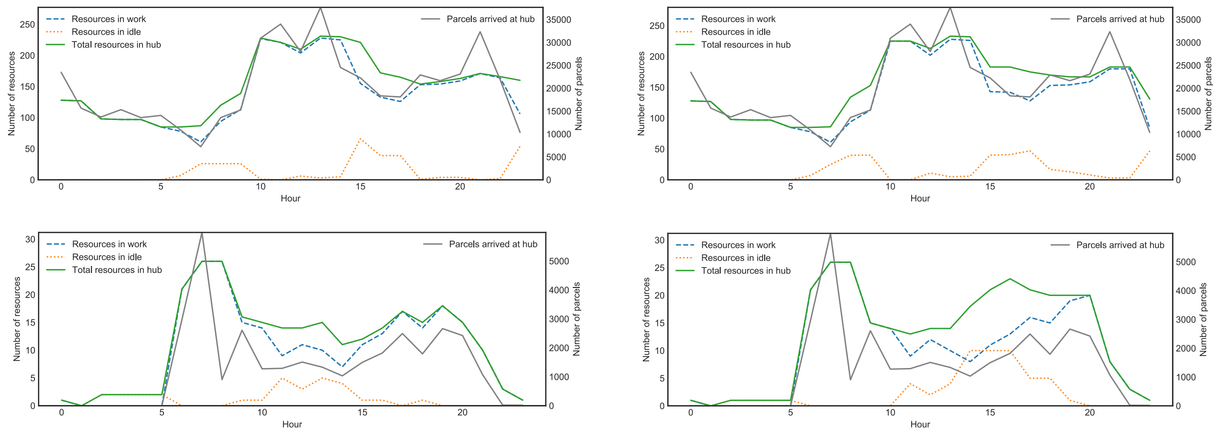


(a). Allocation within hubs (b). Allocation across hubs

Figure 3: Cost comparisons

3.2 Parcel arrivals and resources assigned at hubs

To illustrate the dynamic assignment of shifts and resource allocations based on workload prediction, figures displaying the evolution of parcel arrivals, and the number of working and resting resources at one gateway hub and one local hub throughout a day are provided. As depicted in Figure 4, the actual number of parcels arrived at the hubs is represented by black lines, while the total number of resources at hubs is depicted in green lines, with blue and orange dashed lines indicating working and resting resources, respectively. Also, we compare two types of resources with 8-hour working limit (workforces) and 15-hour working limit (robots), shown in Figure 4(a) and 4(b) respectively. We can see that the number of resources at hubs follows a similar pattern to that of parcel arrivals, but the arrival peaks are flattened. Also, resources tend to take rest during arrival valleys. Moreover, the working hour limit does not have large influence on the number of resources assigned at hubs, but resources with larger working limit tend to have more resting time at hubs.

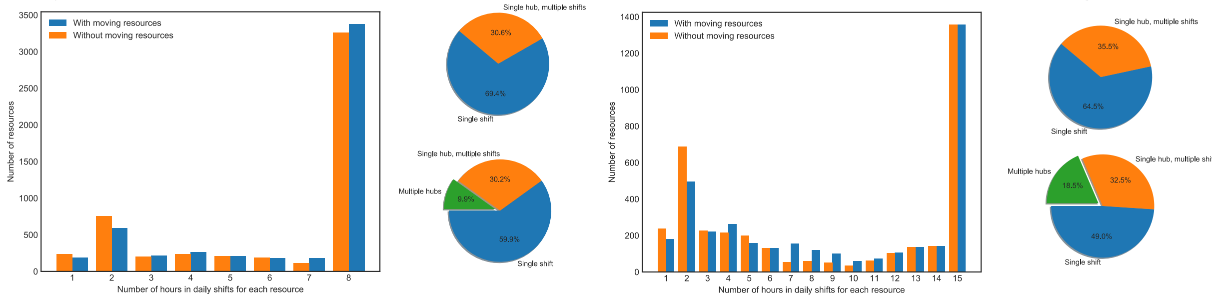


(a). Workforces (8-hr limit) (b). Robots (15-hr limit)

Figure 4: Parcels arrived and resources assigned at one larger gateway hubs (above) and one smaller local hubs (bottom)

3.3 Complexity of assigned shifts

In this section, we show the complexity of assigned shifts to workforce and robots with 8 working hours and 15 working hours limit. By allowing movements across hubs, we assign 9.9% of total shifts for workers and 18.5% of total shifts for robots moving across nearby hubs, as shown in Figure 5. In addition, even though most of the shifts assigned within hubs have maximum allowed duration, allowing movements across hubs improve the average working duration by combining short shifts into a long shift. The comparison of the number of hours in daily of shifts between with and without movements across hubs is also shown in Figure 5.



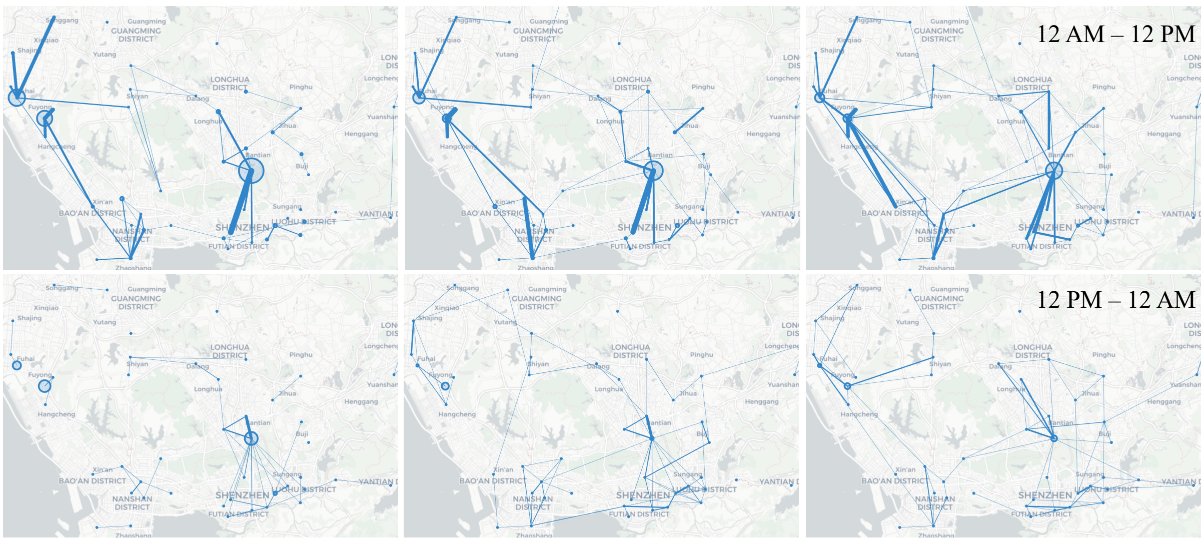
(a). Workforces (8-hr limit) (b). Robots (15-hr limit)

Figure 5: Complexity of assigned shifts

3.4 Resources in hub and flow across hubs

We also plot the locations of hubs as well as how workers appear and move across hubs during a day. As shown in Figure 6, the size of the circles indicates the number of shifts assigned in each hub while the width of lines signifies the number of workers transported from one hub to another hub every 12 hours with 8, 15 and 22 working hour limit. The three large circles in each picture mean that many shifts are assigned to the three gateway hubs to cover comparatively large quantities of arrivals, many resources move between gateway hubs and local hubs from 12 AM to 12 PM because of their different parcel arrival patterns during this time span. Also, more resources tend to move from one hub to another hub with larger working hour limit.

We have also visualized the hub locations and resource movements throughout a day with 8, 15, and 22 working hour limits. Figure 4 illustrates the number of shifts assigned in each hub with circle size and the number of workers transported from one hub to another every 12 hours using the line width. The three larger circles in each image correspond to the three gateway hubs, where more shifts are assigned to cover larger quantities of arrivals. The workers are observed to move between gateway hubs and local hubs from 12 AM to 12 PM due to the different parcel arrival patterns during this time frame. Additionally, there is a higher frequency of worker movement between hubs with larger working hour limits.



(a). Workforces (8-hr limit) (b). Robots (15-hr limit) (c). Robots (22-hr limit)

Figure 6: Resources in hubs and flow across hubs

4. Conclusion and Future Research

In this paper, we propose a novel reactive scheduling and allocation model with rolling horizons for efficient and reliable resource management in the hyperconnected logistic hubs. First, the paper demonstrates the feasibility and cost-effectiveness of incorporating mobile resources among nearby hubs, particularly for logistics networks operating in urban regions. Second, the paper highlights the impact of shared mobile resources with different daily working limit. Lastly, the paper highlights the usefulness of the proposed rolling horizon method, which utilizes updated predictions to manage workload uncertainty.

In addition to the resources allocated for in-hub activities, the scheduling and allocation system could also incorporate resources for transporting goods across hubs, such as trucks, trailers and containers. Moreover, to enhance the overall performance and swiftly respond to dynamic situations, future research may involve exploring diverse predictive scenarios for dynamic decision-making and employing stochastic optimization models for robust scheduling that combines long-term planning with short-term adjustments. The paper also suggests investigating sequential decision-making to enable dependable and informed decision-making under stochastic conditions.

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