Community Logistics: a dynamic strategy for facilitating immediate parcel delivery to smart lockers

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Abstract

The COVID Pandemic since early 2019 has imposed significant effects towards our life. In the retail and logistics sector, the large-scale national lockdown has drastically driven e-commerce sales because the e-marketplace has become the only sales channel. Whilst the pandemic has accelerated the shift towards a more digital world and led to an irreversible dependence on e-commerce retailing, the pressure is on retailers and logistics service providers to respond to the growing demand for immediate delivery in the e-commerce era. Given the integration of smart lockers into developing a more favorable environment which potentially makes immediate delivery more feasible, this paper introduces a novel, dynamic delivery strategy, namely Community Logistics Strategy (CLS), for formulating and updating the new delivery plan in real-time as new delivery requests to smart lockers arrive. To shed light on the effect of dynamic order arrival towards delivery planning, the CLS attempts to update the delivery plan taking new requests into account in real-time. Simulation results reveal superiority of the proposed strategy in managing e-commerce delivery requests, especially within megacities where consumers are highly dense in a compact geographical area.

1. Introduction

Last-mile delivery in urban logistics has received huge attention from both society and academia due to the on-going developments of e-commerce worldwide (Cardenas et al., 2017; Vakulenko et al., 2018). According to a survey by the United Nations Conference on Trade and Development (UNCTAD), the COVID-19 pandemic has forever changed online shopping behaviors (UNCTAD, 2020). Whilst the pandemic has accelerated the shift towards a more digital world and led to an irreversible dependence on e-commerce retailing, rapid e-commerce growth has resulted in a noticeable increase of parcel delivery volumes, which has accentuated the pressure on last-mile delivery actors (Ferrucci & Bock, 2014) and has created a demand for new solutions (Ducret, 2014). In the last decade, retailers and logistics service providers have wider use of technologies to earn a competitive edge under the fierce competition in the last-mile delivery sector. Mangiaracina et al. (2019) reviewed the innovative solutions dedicated to improving the efficiency of last-mile delivery in B2C e-commerce. Amongst the eight major innovative solutions they summarized, including, to name a few, reception boxes, self-pick-up points, crowdsourced delivery and drones, smart parcel lockers are proven to provide convenience to both couriers and customers by means of eliminating the possibility of failed delivery due to customer absence (Wang et al., 2018), and allowing the aggregation of orders coming from different customers in the same location (Giuffrida et al., 2012). Smart parcel lockers, which can be found under names like parcel kiosks, locker boxes, automated lockers, self-service delivery lockers, and intelligent lockers (Vakulenko et al., 2018), are one of the most widely integrated self-service technologies into the e-commerce last-mile delivery context.

Aside from technological innovations, delivery options are much more dynamic since the past decade. Delivery with specific time windows is a popular delivery mode for last-mile e-commerce environment (Wang et al., 2014). Nevertheless, the wide adoption of smart lockers and collection-and-delivery points (CDP), which allow the absence of consumers in picking up items when they arrive, gradually shifts the trend of delivery with time windows to instant delivery (Klapp et al., 2018). The ever-changing and increasing delivery requirements demanded by end consumers are pushing service providers to deliver items as soon as possible. Consumers are now demanding immediate delivery, such as delivery within two to three hours upon purchase, in lieu of delivery at the selected time slot (Ulmer and Streng, 2019).

In the light of the integration of smart lockers into developing a more favorable environment which potentially makes immediate delivery more feasible, this paper introduces a novel, dynamic delivery strategy, namely Community Logistics Strategy (CLS), for formulating and updating a new delivery plan in real-time as new requests of delivering orders to smart lockers arrive. There is no specific delivery window as couriers strive to perform immediate delivery. The difficulty in formulating a delivery plan under this e-commerce delivery context lies in the fact that service providers are unable to develop a routing plan in advance as orders are arriving at any time. Any newly arriving order requests could be added to the existing delivery plan if its specified delivery location is geographically feasible for inclusion. To shed light on the effect of dynamic order arrival towards delivery planning, the CLS attempts to update the delivery plan in real-time, taking new order requests into account.

The distinguishable differences between the proposed CLS and existing delivery solutions in the mainstream literature lies in two crucial elements: solution format and dynamic customer location clustering. It is worth noting that the investigation of such a dynamic nature under the context of smart locker immediate delivery, has been rarely found in the literature. When considering the dynamic arrivals of delivery orders, most of the dynamic delivery solutions in the literature assume and identify routes of a given fleet of vehicles as the only solution format. In general, these classic solutions attempt to update the routes of a vehicle when a new order arrives. Under the context of smart locker immediate delivery, however, the volume of orders to be delivered to nearby or even exactly the same delivery lockers tends to be large (Xiao et al., 2017). In other words, this implies that a vehicle might only visit just a few locations during its delivery trip to deliver all the orders allocated to the trip, which diminishes the need of generating a route for experienced drivers. In this regard, our proposed CLS treats the vehicle serving region, namely "Delivery Community", as the solution format, rather than the routing of the fleet of vehicles. The similarities and differences of "Delivery Community" with respect to "clusters" in any existing cluster-based delivery models are depicted below.

"Delivery Community" shares similar attributes to customer location clustering in clustered VRPs (Clu-VRPs), in which a sequential decision process is taken place by partitioning customer orders into clusters according to their spatial proximity, following by generating optimal routes in each cluster. Therefore, it is essential to highlight the differences between our "community" and conventional clustering. In Clu-VRPs, customer clustering is a static decision process. Orders are partitioned into clusters solely based on the spatial attributes, i.e. their delivery locations. In contrast, our CLS takes both the spatial and temporal attributes into account by allowing temporal delay of order dispatching from depots. The order dispatching delay is realized by postponing the formulation of community. For example, at time t, if a depot decides to postpone dispatching of the current orders for Δt, the communities formulated at $t+\Delta t$ would potentially be more compact and economic, due to the arrivals of more spatially nearby orders at the depot. In this sense, if a mix of communities was formulated at t, the solution mix would be very different from that at $t+\Delta t$. In fact, whether to introduce Δt, or in other words, the determination of optimal t, has always been a crucial decision in order dispatching. Yet, most of the existing CluVRPs consider a fixed delivery interval. In this study, we attempt to treat this temporal delay possibility as part of the delivery dispatching decision-making process.

The focus of this study is to examine: (1) the potentials of integrating this temporal order postponement consideration into formulating a better delivery community, and (2) the interactions between the temporal and spatial considerations when making a community formulation decision. To yield insightful implications, we develop two solution approaches – Temporal Delivery Postponement (TDP) approach and Spatial Delivery Postponement (SDP) approach. The former emphasizes the temporal consideration of community formulation, that is, delaying the departure of vehicle as a means of generating a more compact community. The latter focuses on the spatial consideration of community formulation, that is, allowing a flexible size of each community to be generated based on real-time order arrivals while disallowing delayed departure. Through assessing the performance of the TDP and SDP approach, this paper justifies the suitability of integrating temporal delay into cluster or community formulation process. Simulated data sets based on large-scale parcel delivery environment under various demand scenarios are used for generating comparative results.

The real-time formulation of dynamic delivery region serves as the core element and solution format of delivery planning denotes the contributions of the proposed CLS in both practical and theoretical standpoints. Practically, locations with high consumer density, like London, New York, Paris, etc., pop up a large number of order requests dynamically on a daily basis, each with a high degree of proximity. A delivery plan which solely governs the delivery region but not the exact route of a vehicle is sensible. In terms of computational requirements, generating a community-type solution on an hourly or even minute-to-minute basis without the need to optimize routes potentially enables logistics practitioners to obtain the solutions in real time more efficiently. Theoretically, the consideration of delivery community, not delivery routing, potentially yields an improved delivery solution in terms of solution compactness. The advantages of the proposed CLS will further be discussed based on the simulation results presented in this paper. Overall, this study delivers a new entry point of model development in facilitating last-mile delivery under the era of e-commerce.

This paper is structured as follows. Section 2 reviews the relevant literature in the e-commerce last-mile delivery context. Section 3 explicitly defines the CLS to deal with the urban logistics problem with immediate delivery to smart lockers. Section 4 provides the problem description and model formulation, followed by the solution approaches. The procedures, results, and discussions of the computational experiments are demonstrated in Section 5, which quantitatively reveals the merits of CLS is in managing immediate e-commerce deliveries. Section 6 and 7 respectively provides the implications of the research, and the conclusions of the study and directions for future research.

2. Literature Review

2.1 Urban logistics in e-commerce era

- *Delivery and pickup requests*

In the era of e-commerce, urban logistics settings requiring efficient vehicle dispatching planning can be categorized into two streams: (i) managing "delivery requests" and (ii) managing "pickup requests". The major differences amongst them are described in Table 1, which include the nature of order, point of origin, and point of destination. In general, delivery requests are those received at depots, requiring to be loaded onto delivery vehicles for delivery to customer's requested locations. That said, without loading designated parcels onto the vehicles, drivers are unable to fulfill the delivery requests. Therefore, a vehicle dispatching plan must be formulated prior to vehicle's departure to fulfill the set of consolidated delivery requests pending at the depot. No further change or update of the vehicle routing plan is possible upon the vehicle's departure, unless the vehicle re-visits the depot to load the new parcels. For pickup requests, they are spatially unknown before actual arrival and pop up dynamically during the day (Ulmer et al., 2018), requiring third-party logistics service providers (3PLs) to timely pick up the parcels from designated pickup locations. Vehicle dispatching in the e-commerce pickup setting falls into the board class of Dynamic Vehicle Routing literature. A vehicle's route can be modified and updated in real-time even during the traveling trip to pick up newly arrived requests.

Savelsbergh and Van Woensel (2016), an invited article discussing the challenges and opportunities of urban logistics, suggest that the aspiration of many companies to offer same-day delivery leads to interesting new optimization challenges for effectively managing the delivery of dynamically arriving orders at distribution hubs. Indeed, online shopping via e-commerce platforms is becoming mainstream for businesses of all sizes. We stress that the continual growth of e-commerce creates an enormous research opportunity to improve the efficiency of outbound delivery operations especially in megacities, which exhibit the features of: (i) High population and consumer density – a large number of fragmented customer requests in a small region, which in turn indicates a close proximity between delivery requests; and (ii) High customer delivery demand – a sufficiently large aggregated volume of parcels for delivery in a small region, which in turn indicates a capacitated vehicle could be fully utilized to serve a compact region.

- *Parcel lockers as part of the last-mile delivery system*

The integration of smart parcel lockers into existing last-mile delivery systems is a promising trend around the globe (Behnke, 2019). This has attracted researchers in recent years to investigate its efficiency (Iwan et al., 2016), usability (Lemke et al., 2016), value to customers (Vakulenko et al., 2018), adoption receptiveness (Tsai and Tiwasing, 2021), and etc. Iwan et al. (2016) suggest that parcel locker adoption is hopeful to be a major direction that shapes the future of urban delivery systems. Zurel et al. (2018) summarize the merits of parcel locker delivery systems from operators, consumers, and environmental perspective. From operators perspective, dropping off multiple parcels at the same time and location, as well as locker's 24/7 availability improve operators' delivery efficiency and save operating costs. From consumers perspective, consumers could enjoy cost savings by choosing parcel locker delivery option as some operators offer a reduced tariff to encourage customers to opt for it. Finally, 24/7 availability of parcel lockers, allowing deliveries and collections at any time, poses positive impact on sustainability and environmental pollution due to traffic congestion in urban areas. In short, parcel lockers have perceived to be not only viable but a preferred delivery mode to home delivery from operators and sustainability standpoints. In operational research perspective, however, optimization models or strategies taking parcel locker delivery options into account have been rare. Deutsch and Golany (2017) consider the problem of designing a parcel locker network as a solution to the last-mile logistics problem by proposing an integer programming model to identify the optimal number, locations, and sizes of parcel lockers facilities. More recently, Schwerdfeger and Boysen (2020) develop exact solution procedures to optimize the changing locations of lockers, such that customers are at some time during the planning horizon within a predefined range of their designated locker. In short, we observe a scarcity of operating strategies and models dedicated to solving delivery problems related to parcel locker immediate deliveries.

Table 1. A comparison of existing e-commerce city logistics settings

Characteristics	**E-commerce city logistics**	
	First-mile pickup setting	**Last-mile delivery setting**
Associated businesses/services	Return logistics, E-commerce food delivery service, Parcel point-to-point delivery service (requested by individual corporate entities)	B2B/B2C/C2C e-commerce order delivery: - home delivery - delivery to pickup stores -delivery to pickup lockers
Main SOPs (standard operating procedures)	(i) Pick up parcels at the designated location (ii) Deliver them to the requested location	(i) Consolidate consumers' purchased goods at inbound distribution hub, (ii) Deliver packed parcel from the hub to the requested location
Point of origin	Anywhere in the city	Distribution hub or warehouses
Point of destination	Anywhere in the city	Anywhere in the city
Spatial uncertainties	Uncertain pickup locations widespread within the geographical region	Uncertain delivery locations widespread within the geographical region
Temporal uncertainties	Uncertain temporal arrival of pickup requests	Uncertain temporal arrival of delivery requests
Representative models	Dynamic VRP models	Models under the variants of MPVRP, VRPTW, VRPTWS

2.2 *Static approaches for managing e-commerce delivery requests*

The light shed on the last-mile e-commerce delivery setting is limited (Shao et al., 2019; Savelsbergh and Van Woensel, 2016). In the previous literature, the problem is classified into different variants of the vehicle routing problems (VRPs). Due to the NP-hard nature of VRPs (Lenstra, and Kan 1981), a majority of the previous literature proposed the use of heuristics and metaheuristics methods to tackle different variants of the VRPs (Braekers, Ramaekers, and Nieuwenhuyse 2016). The most relevant VRP variants that take into account the temporal consideration for order delivery are multi-period vehicle routing problem (MPVRP), vehicle routing problem with time windows (VRPTW), and vehicle routing problem with time windows and shifts (VRPTWS).

MPVRP conceptually lies between periodic VRP and inventory routing problem (Archetti et al. 2015). However, in MPVRP, there is no periodicity in the service. It considers a planning horizon to serve a set of customers (Wen et al. 2010; Archetti et al. 2015). Customer's delivery requests arrive dynamically over time and must be satisfied before the specified deadline. In the literature, VRPTW further adds more assumptions to reflect the problem nature in real business setting realistically. A complete survey on VRPTW was conducted by Bräysy and Gendreau (2005a; 2005b). In short, the VRPTW can be described as a known set of delivery nodes that must be visited exactly once, each of which can be serviced only within a specified time interval (Kallehauge et al. 2005). As for VRPTWS, the problem further considers the availability of several shifts with non-overlapping operating periods. Each shift has its loading capacity that limits the loading capacity. Dabia et al. (2019) introduce this problem variant with an exact branch-and-bound algorithm to deal with it. Though these problem variants take the specific order delivery requirements, especially the timeliness of servicing the customers and the allocation of delivery requests to designated working shift, into account, none of them studied the possibility of order delivery delay within shifts and several delivery time windows. In reality, particularly in e-commerce delivery environment, the nature of B2C e-commerce delivery requests being frequently, dynamically arriving at the depot gives practitioners a strong motivation to consolidate small lot-sized orders for delivery at the same time, so as to minimize repetitive visits to the same or nearby delivery locations. Dynamic approaches for managing frequent arrivals of delivery requests therefore come into place.

2.3 *Dynamic approaches for managing delivery requests*

Notwithstanding a myriad of algorithms and models developed for a variety of VRP variants, most of the studies in VRP family assume a set of static orders is received days before delivery planning, which ignore the real-time spatial arrival of delivery requests. An exception is Dynamic Vehicle Routing Problems (DVRP), which updates vehicle routing solutions in real time to fulfil newly arrived order requests popped up anywhere around the city at any time. Savelsbergh and Van Woensel (2016) point out that even though there is a vast literature on dynamic vehicle routing, the “demand” invariably refers to “orders to be picked up”, to “orders to be picked up and delivered”, or to “a service performed by the driver". In other words, the origin of the routing is located anywhere around the city, specified by customers. When demand refers to "orders to be delivered", the origin of the routing is the depots, such as warehouses, distribution centres, etc. In such a delivery scenario, the structure of a dynamic vehicle routing problem changes significantly since there are few opportunities to accommodate additional deliveries after a delivery vehicle has left the depot. It makes no sense that the vehicle would have to return to the depot to pick up the additional deliveries to comply with the updated DVRP routing solutions. Therefore, a majority of the existing dynamic vehicle routing literature has limited applicability to scope of e-commerce delivery context (Savelsbergh and Van Woensel, 2016).

Yet, the literature has attempted to tackle the e-commerce delivery problem using the class of DVRP. The most representative variant for solving urban delivery problems is Same-day Delivery Problem (SDDP), which is also related to the work on vehicle routing problem with dynamic and stochastic pickup requests (VRPDSR), and dynamic pick-up and delivery problem (DPDP). According to Voccia et al. (2016), the SDDP for online purchases can characterized by: (i) a fleet of vehicles that serve delivery requests in a service day, (ii) the requests are arrived dynamically, (iii) each request is associated with a delivery deadline or specified delivery time window, (iv) vehicles are loaded and dispatched from the depot to serve the requests. Voccia et al. (2016) use a sample-scenario planning approach to determine the route length based on a consensus function. The function is able to identify if waiting at the depot is beneficial to route optimization. Similarly, Klapp et al. (2018) present an approximate linear programming solution approach to generate dispatching decisions at a fixed interval, with all customer requests on a line, and all requests have the same deadline. Ulmer and Streng (2019) present a policy function approximation approach to decide where and when to dispatch a vehicle and about the corresponding goods to load. Their scope has some similarities to ours, as they consider customers dynamically order goods to a preferred pickup station and expect fast service. The major difference to our study scope is that the goods to be delivered from the depot to the preferred pickup stations are fulfilled by autonomous vehicles. Apart from autonomous vehicles, the use of drones is another emerging trend in last-mile delivery. Recently, Chen et al. (2022) considered the integration of drones to handle the dynamic same-day last-mile delivery operations. They propose a deep Q-learning approach that learns the value of assigning a new customer to either drones or vehicles.

In our approach, the dynamically arriving customer requests are allocated to delivery communities, which are formulated by minimizing intra-traveling distances within the community. Thus, delivery requests with high spatial proximity are more likely to be served first, as a community will be formed with sufficient requests nearby. Similar to Voccia et al. (2016), our CLS allows delay of vehicle departure, so as to maximize the capacity utilization of a vehicle. Instead of integrating new transportation means such as autonomous vehicles and drones, we consider the e-commerce parcel locker immediate delivery problem on the operational planning level, which involves deciding when vehicles are dispatched. When delivery dispatching decisions are concerned, the respective delivery models presented in the literature fall into the vehicle dispatching problem variant. van Heeswijk et al. (2017) address the dispatching problem faced by an urban consolidation center by defining it as a

Markov decision model. Wang et al. (2022) consider urban delivery dispatching problem from workload balancing perspective. They introduce a multi-period workload balancing problem under stochastic demand and dynamic daily dispatching and formulate it as a Markov decision model. Lan et al. (2020) develop a two-echelon city dispatching model that comprises distribution centers located in suburbs and fixed satellites located in urban areas for distribution. A cluster-based variable neighborhood search scheduling algorithm is proposed to determine locations of mobile satellites and dispatching routes of trucks and tricycles. In addition to optimization models for solving the complex urban delivery and dispatching problems, models contributing to the design of urban delivery systems, such as fleet sizing and service region partitioning (Banerjee at al. 2022; Stroh et al. 2021), determine an order cutoff time and combine SDD and overnight order delivery operations (Stroh et al. 2021), can be found.

In summary, evidenced from a vast number of studies in relation to same day delivery and dispatching problems in recent years, last-mile urban delivery and dynamic dispatching have developed as a research area with growing popularity in the transportation field. Nonetheless, though new transportation means, such as autonomous vehicles and drones, have been considered in some studies, sophisticated strategies integrating parcel locker collection points as part of the urban delivery network is rare. This gap in the literature has motivated us to develop community logistic strategy as a solution to the parcel locker-based e-commerce last-mile urban immediate delivery problem.

3. Community Logistics Strategy for solving immediate delivery problems

E-commerce parcel delivery to automated smart lockers are initiated by end consumers, who typically made a purchase online. Upon the receipts of newly arrived orders, they are internally processed at depots and packaged as parcels for deliveries. The delivery scheduling problem faced by practitioners in e-commerce operating environment is about the allocation of parcels to available vehicles. The complexity of this dispatching problem lies in the need to dynamically assign the continuously arriving orders to vehicles in a timely and efficient manner for immediate delivery upon order arrivals. To deal with such a dynamic delivery scheduling problem, the CLS allocate parcels into communities. Each community is to be served by one vehicle. During the formulation of communities, two dimensions are considered: (i) time – temporal delivery postponement and (ii) space – Spatial community adjustment.

Temporal delivery postponement – The availability of non-overlapping delivery periods in each working day, i.e. shifts, in which each shift has a known fixed number of capacitated vehicles, allows pending orders to be allocated to a particular shift and a particular vehicle of that shift. The temporal decision in the process of delivery scheduling is to determine the most appropriate shift for each customer order, taking the allowable delay and delivery location of each order, as well as the vehicle serving community in each shift, into consideration.

Spatial community adjustment – Given a fixed fleet of vehicles in each delivery shift, the geographical distribution and density of the pending orders influence the allocation of shifts and the vehicles of each shift to serve the orders. The spatial decision in the delivery scheduling process is the adjustment of the size of the geographical area served by each vehicle in every shift.

The concept of "intended delivery uncertainty postponement" is realized in the CLS by considering the possibility of delivery postponement in the temporal and spatial dimension. The CLS attempts to determine the degree of temporal and spatial postponement to formulate an appropriate CLS strategy on a daily basis according to the real-time dynamic arrival of geographically diversified e-commerce orders. A complete community logistics solution contains three core elements: (i) Location of communities: the region being identified as a community; (ii) Composition of community: Delivery requests included in the community; and (iii) Delivery requests left in the pending order pool.

To strike a balance between temporal and spatial postponement, the CLS involves a solution update cycle time, which is regarded as the amount of time the depot is allowed to consolidate newly arriving orders before generating a set of communities as the delivery dispatching solution. The determination of the fixed cycle time is purely based on the order arrival frequency. If, for example, a depot historically receives a significant number of discrete and fragmented e-commerce orders in a short period of time, we recommend to set a shorter solution cycle time to generate an updated set of communities at a higher frequency. At each solution update cycle, pending delivery requests geographically widespread across the city will be added into the existing community mix, should their destinations spatially fall into the community. An initial solution consisting of a set of communities is formulated based on the existing delivery requests pending in the pool. Given that a community is served by only one vehicle, a community is determined to be finalized only if the vehicle is fully capacitated or capacitated at a pre-defined utilization rate. The set of spatially compact delivery requests assigned to the "finalized" community will then be removed from the pending order pool, as depicted in Fig. 1. Any unassigned delivery request will be retained in the pool for further community formulation. At the next cycle, same procedure is undergone by continuing the consolidation of newly arrived delivery requests with the unassigned delivery requests still pending in the pool. The dynamic and continuous arrivals of new requests imply that the solution iteration of CLS is indefinite.

The value of community formulation lies not only in the dynamic solution iteration, but the flexibility of either sacrificing space to buy time or sacrificing time to buy space. The former means that the CLS enlarges a community size at the solution update interval to avoid any further delay of a vehicle's departure. In contrast, the latter allows further delay of a vehicle's departure in return for a more compact community size. To fully assess the effect of these inter-related attributes towards community formulation, no upper or lower limit of community size and delivery delay duration is introduced in the experiments to be presented in Section 5. All in all, flexible and dynamic solution formulation under the CLS protocol would empower logistics service providers and retailers to make immediate delivery to smart lockers possible. In the next section, a generic transportation problem for immediate delivery to smart lockers is defined, followed by solution approaches to the problem.

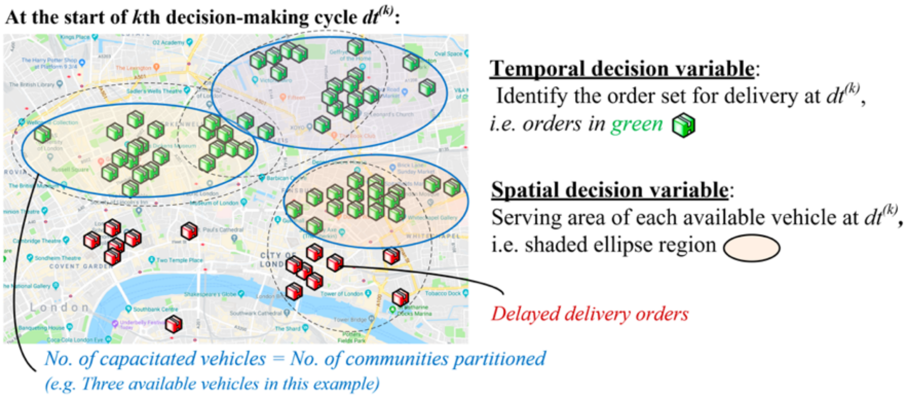

Fig. 1. Spatial and temporal dimensions under the CLS protocol

4. Problem definitions and solution approaches

4.1 Problem description

Considering a depot is responsible for the fulfilment of logistic orders in a square district S. There are $|J|$ identical vehicles with a capacity of Q in the depot. The depot service time is T hours in one day. At the beginning of the operational time, there are already a set of orders waiting to be processed in the depot, including the orders remained from previous operational time and the orders accumulated in the previous night denoted as $V_0 = \{1,2,3,\dots,v_0\}$. During the service time, a set of orders $V_0 = \{v_0+1, v_0+2, v_0+3, \dots, v_0+v\}$ continually arrive at this depot with a certain arrival rate λ or a time-related rate $\lambda(t)$. The arrival time and freight weight of an order i are denoted as t_i and w_i respectively, where $i \in V_0 \cup V$. The relative delivery coordinates to the depot of the order i are (x_i, y_i) whose probability density function is $f(x,y)$. The problem that dispatchers need to solve is how to assign vehicles to fulfil these logistic orders, i.e., what is the departure time of each vehicle and which orders should be delivered by each vehicle, in order to maximize vehicles' usage efficiency and minimize the orders' waiting time. The orders considered in this problem are dynamic and uncertain. Generally, it is more reasonable to make decisions after depots have collected enough number of orders rather than real-time decision because of the limited resources. Therefore, a postponement strategy is introduced in this study to transform the dynamic, uncertain problem into a series of static, certain problems. By so doing, we predetermine K community logistics solution update cycles, denoted as $dt^{(k)}$, where $k = 1,2,3,\dots,K$ and $dt^{(1)} = 0$. During the service time of a business day, the time interval between two adjacent cycles is fixed at Δt. In other words, $\Delta t = T/K$. At the end of each Δt, there is a set of collected orders waiting to be processed, which is denoted as $I^{(k)}$ Dispatchers need to determine $\bar{I}^{(k)}$ and $R^{(k)}$, i.e., the order set for immediate delivery and order set for intended postponement, respectively, where $\bar{I}^{(k)} \cup R^{(k)} = I^{(k)}$. They also need to decide the delivery task $\bar{I}_j^{(k)}$ of each available vehicle according to available vehicle set $J^{(k)}$.

It is noted that for vehicles that are not available at $dt^{(k)}$, they have no delivery task, i.e., $\bar{I}_j^{(k)} = \emptyset$ if $j \notin J^{(k)}$. As aforementioned, the defined CLS problem can be classified as a new optimization category, i.e. postponement first-route optional approach, for managing e-commerce deliveries. In this study, we introduce two alternative approaches in dealing with the question of “how intended postponement can be achieved in spatial and temporal dimension”, namely temporal delivery postponement (TDP) and spatial delivery postponement (SDP) approach. The performance of these approaches serves as the ground to justify the feasibility of the proposed CLS in providing quality real-time delivery scheduling solutions under B2C e-commerce last-mile delivery context. Relevant parameters and decision variables are summarized in Table 2.

An overview of the differences between TDP and SDP is summarized in Table 3. The solution generated by TDP and SDP approaches consists of a set of delivery orders to be fulfilled by a vehicle, in which the possibility of temporal or spatial postponement has been taken into consideration. Therefore, with a static set of orders for delivery, route generation can be performed by conventional VRPs. In this section, solution approaches are formally described, followed by route generation through the Tabu search algorithm. Key performance measurement indices for systematic evaluations of the performance of the proposed approaches are also presented.

Table 2. Notation for parameters and decision variables

Notation	Definition
$\boldsymbol{t}$	time
$\boldsymbol{T}$	Service time of a business day
$\boldsymbol{J}$	Vehicle set
$\boldsymbol{Q}$	Maximum load of a vehicle
$\boldsymbol{S}$	Serving community of a vehicle
$\boldsymbol{V_0}$	Backlog orders collected from the previous days
$\boldsymbol{V}$	Set of orders arriving from $t = 0$ to $t = T$
$\boldsymbol{t_i}$	arrival time of order i
$\boldsymbol{w_i}$	weight of order i
$(\boldsymbol{x_i}, \boldsymbol{y_i})$	relative coordinates of the delivery address of order i from depot
$\boldsymbol{dt^{(k)}}$	kth community solution update cycle (the cycle)
$\boldsymbol{I^{(k)}}$	Order set waiting to be processed at kth cycle
$\boldsymbol{\bar{I}^{(k)}}$	Order set for immediate delivery at kth cycle
$\boldsymbol{R^{(k)}}$	Order set for intended postponement at kth cycle
$\boldsymbol{J^{(k)}}$	Available vehicle set at kth cycle
$\boldsymbol{\bar{I}_j^{(k)}}$	Delivery task for vehicle j at kth cycle
$\boldsymbol{S_{m,n}}$	Service area in community (m,n)
$\boldsymbol{WT}$	Average waiting time of a delivery order
$\boldsymbol{TD}$	Vehicle average traveling distance
$\boldsymbol{CPT}$	Average route compactness vehicle empty space distance

Table 3. An overview of TDP and SDP approach for community logistics

	Temporal Delivery Postponement (TDP)	***Spatial Delivery Postponement (SDP)***
Methodology	Postpone the departure time of vehicle so as to utilize the available capacity of vehicle space	Adjust the service community of each vehicle so as to utilize the available capacity of vehicle space
Fixed parameter	Service community of each delivery vehicle	Departure time of each vehicle
Decision variable	Departure time of each vehicle	Serving community of each delivery vehicle

4.2 Temporal Delivery Postponement approach

For the TDP approach, the whole square area S is prior divided into M by N square communities $S_{m,n}$, where $m = 1,2, \dots, M$, $m = 1,2, \dots, M$, $M = N$. One vehicle is responsible for serving the requests in one community only. At the beginning of each solution update cycle $dt^{(k)}$, depot managers consolidate the collected orders set $I^{(k)}$ into M x N groups denoted as $I_{m,n}^{(k)}$ according to their coordinates and check the number of orders in all communities and number of available vehicles $J^{(k)}$. A vehicle j , where $j \in J^{(k)}$, will be assigned to handle the delivery task in $S_{m,n}$. The orders set $I_{m,n}^{(k)}$ are processed according to the following three rules:

(1) If the total demand of $I_{m,n}^{(k)}$ is less than $\eta \cdot Q$, where $\eta \in (0,1]$ is the threshold, all orders in $I_{m,n}^{(k)}$ will be postponed. Therefore, the delayed order set $R_{m,n}^{(k)}$ in $S_{m,n}$ is $I_{m,n}^{(k)}$;

(2) If the total demand of $I_{m,n}^{(k)}$ is between $[\eta \cdot Q, Q]$, a vehicle $j \in J^{(k)}$ is assigned to serve $I_{m,n}^{(k)}$. Therefore, $\bar{I}_j^{(k)} = I_{m,n}^{(k)}$ and $R_{m,n}^{(k)} = \emptyset$;

(3) If the total demand of $I_{m,n}^{(k)}$ is more than Q, a vehicle $j \in J^{(k)}$ is assigned to serve a part of $I_{m,n}^{(k)}$. The served order set $\bar{I}_j^{(k)}$ is determined based on first in first serve principle until the vehicle capacity is full. Therefore, $R_{m,n}^{(k)} = I_{m,n}^{(k)} / \bar{I}_j^{(k)}$.

The working logic of the TDP approach and its simulation framework are presented in Figs. 2 and 3 respectively. In this simulation framework, $Paras$ contains all parameters needed in the simulation, including: business time T, number of initial order v_0, number of vehicles $|J|$, vehicle capacity Q, order arrival rate $\lambda(t)$, length of time element Δt and probability density functions of w_i and (x_i, y_i). m and n are two variables which influence the performance of TDP approach.

Simulation framework based on TDP approach

Input: $Paras$; m; n.

Output: $\bar{I}_j^{(k)}$; $R^{(K)}$.

$R^{(0)} = V_0$;

$K = T/\Delta t$;

for $k = 1$ **to** K

  Generate arrival orders set from $dt^{(k-1)}$ to $dt^{(k)}$, denoted as $\bar{V}^{(k)}$;

  $I^{(k)} = \bar{V}^{(k)} \cup R^{(k-1)}$;

  for each community $S_{m,n}$

    if $J^{(k)} \neq \emptyset$

      Select a vehicle j in $J^{(k)}$ and determine $\bar{I}_j^{(k)}$ and $R_{m,n}^{(k)}$ based on the proposed three rules;

      Update $J^{(k)}$;

    else

      $R_{m,n}^{(k)} = I_{m,n}^{(k)}$;

    end if

  end for

  $R^{(k)} = \bigcup_m \bigcup_n R_{m,n}^{(k)}$;

end for

Fig. 2. Simulation framework of the TDP approach

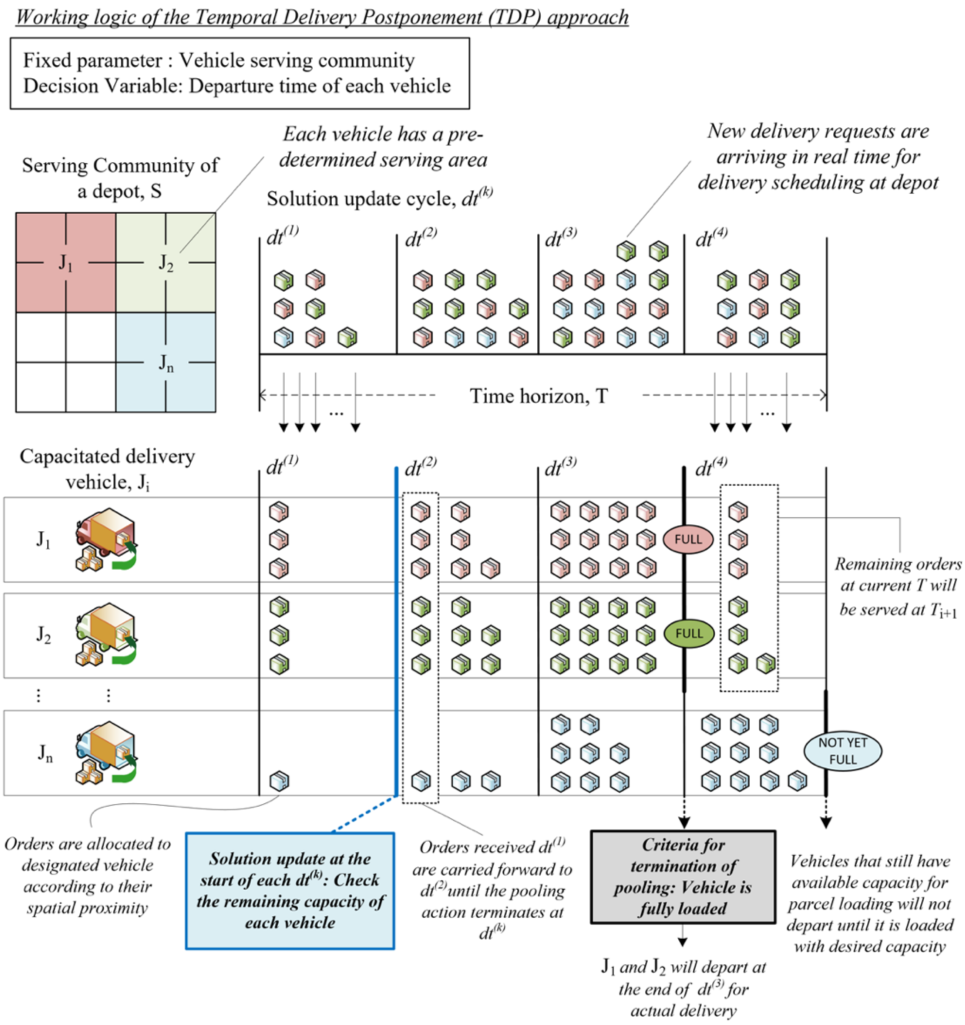

Fig. 3. Working logic of the TDP approach

4.3 Spatial Delivery Postponement approach

For the SDP approach, the departure time is predetermined at each $dt^{(k)}$. The required number of vehicles in *k*th decision can be calculated by:

$$L^{(k)} = \left\lceil \frac{\sum_{i \in I_{m,n}^{(k)}} w_i}{Q} \right\rceil \tag{1}$$

If the available vehicle capacity is sufficient, i.e., $L^{(k)} \leq |J^{(k)}|$, all orders $I^{(k)}$ collected before $dt^{(k)}$ will be delivered, i.e., $\bar{I}^{(k)} = I^{(k)}$. Otherwise, orders in $I^{(k)}$ will be delivered as first-in-first-serve to meet the capacity limitation and remained order set $R^{(k)}$ is postponed to the next solution update cycle $dt^{(k+1)}$. After identifying the delivered order set $\bar{I}^{(k)}$, a tailored capacitated k-means clustering algorithm is proposed to generate the $\bar{I}_j^{(k)}$ in the community served by vehicle $j \in J^{(k)}$. The simulation framework based on the SDP approach and its working logic are presented in Fig. 4 and 7, respectively. In this simulation framework, $Paras$ contains all parameters needed in the simulation which is same as the parameters in the simulation based on TDP approach. Δt is the variable which impacts the performance of the SDP approach.

The capacitated K-means clustering algorithm, as detailed in Fig. 5, has a similar procedure with conventional K-means clustering algorithm, which assigns each observation to the nearest centroid and update all centroids subsequently. The difference is that our algorithm contains a component to handle the capacity constraint. If a predetermined community $\tilde{l}$ is full when we allocate order i to this community, our approach to handle the capacity is not simply reallocate i to the other nearest community where the total demand is less than Q. Instead, our approach will insist on allocating order i to the community $\tilde{l}$. However, another order i' will be transferred to a near cluster to ensure the capacity constraint is satisfied. Lines 9-16 in Fig. 5 are introduced to select the order i'. For ease of understanding, we also present Fig. 6 to illustrate our community's capacity handling process.

Simulation framework based on SDP approach

Input: $Paras$; Δt.

Output: $\bar{I}_j^{(k)}$; $R^{(K)}$.

$R^{(0)} = V_0$;

$K = T/\Delta t$;

for $k = 1$ **to** K

Generate arrival orders set from $dt^{(k-1)}$ to $dt^{(k)}$, denoted as $\bar{V}^{(k)}$;

$I^{(k)} = \bar{V}^{(k)} \cup R^{(k-1)}$;

if $L^{(k)} \le |J^k|$

$\bar{I}^{(k)} = I^{(k)}$, $R^{(k)} = \emptyset$;

else

Select $\bar{I}^{(k)}$ from $I^{(k)}$ as first in first serve until the total vehicle capacity $|J^{(k)}| \cdot Q$ is full;

$R^{(k)} = I^{(k)} \backslash \bar{I}^{(k)}$;

$l^{(k)} = |J^k|$

end if

Partition $\bar{I}^{(k)}$ into $L^{(k)}$ sets $(\bar{I}_l^{(k)})_{l=1,2,\ldots,L^{(k)}}$ by using capacitated K-mean clustering algorithm;

Assign sets $(\bar{I}_l^{(k)})_{l=1,2,\ldots,L^{(k)}}$ to vehicles in J^k to obtain $(\bar{I}_j^{(k)})_{j\in J^{(k)}}$;

end for

Fig. 4. Simulation framework of the SDP approach

Capacitated K-means clustering algorithm

Input: $\bar{I}^{(k)}$, $L^{(k)}$, Q.

Output: $(\bar{I}_l^{(k)})_{l=1,2,\ldots,L^{(k)}}$;

Randomly initialize $L^{(k)}$ centroids $(c_{l,0}^{(k)} = (x_{l,0}^{(k)}, y_{l,0}^{(k)}))_{l=1,2,\ldots,L^{(k)}}$ in S;

$\bar{I}_l^{(k)} = \emptyset$, for $l = 1,2,\ldots,L^{(k)}$;

$n = 0$;

while 1

for $i \in \bar{I}^{(k)}$

$\tilde{l} = \mathrm{argmin}_l\ ((x_{l,n}^{(k)} - x_i)^2 + (y_{l,n}^{(k)} - y_i)^2)^{0.5}$

$\bar{I}_{\tilde{l}}^{(k)} = \bar{I}_{\tilde{l}}^{(k)} \cup \{i\}$;

while $\sum_{i\in \bar{I}_{\tilde{l}}^{(k)}} w > Q$

for $q = 1$ to $L - 1$

Denote the number of the qth nearest centroid to centroid $c_{\tilde{l},n}^{(k)}$ as l';

$i' = \mathrm{argmin}_{i\in \bar{I}_{\tilde{l}}^{(k)}}\ ((x_{l',n}^{(k)} - x_i)^2 + (y_{l',n}^{(k)} - y_i)^2)^{0.5}$;

if $\sum_{i\in \bar{I}_{l'}^{(k)} \cup \{i'\}} w \le Q$

$\bar{I}_{l'}^{(k)} = \bar{I}_{l'}^{(k)} \cup \{i'\}$, $\bar{I}_{\tilde{l}}^{(k)} = \bar{I}_{\tilde{l}}^{(k)} \cap \{i'\}$

break

end if

end for

end while

end for

Compute new centroids $(c_{l,n+1}^{(k)} = (x_{l,n+1}^{(k)}, y_{l,n+1}^{(k)}))_{l=1,2,\ldots,L^{(k)}}$;

if $c_{l,n+1}^{(k)} = c_{l,n}^{(k)}$ for each $l = 1,2,\ldots,L^{(k)}$

break

end if

end while

Fig. 5. Proposed capacitated K-means clustering algorithm in the SDP approach

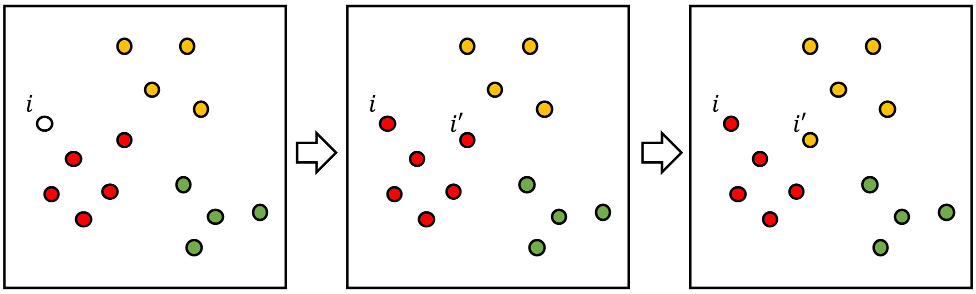

Fig. 6. An illustration of the community capacity handling process

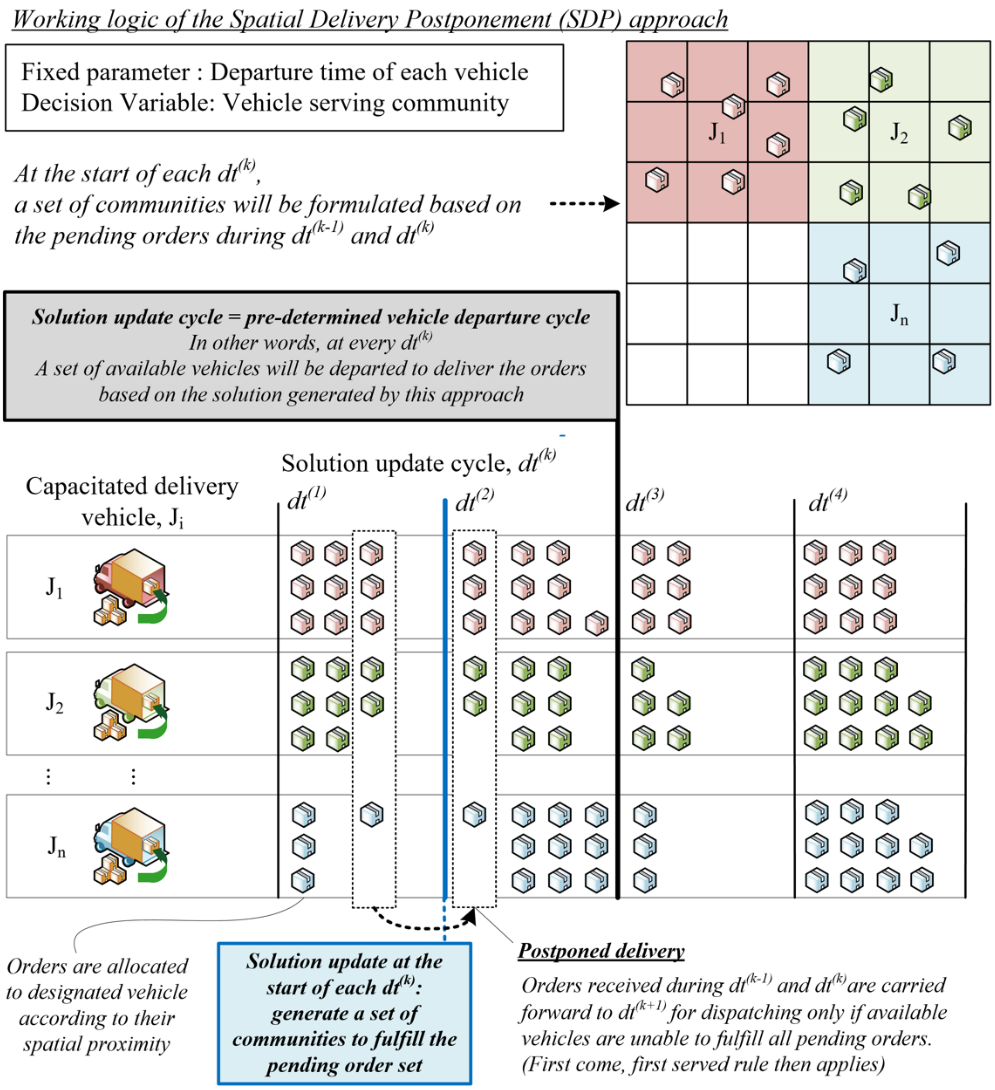

Fig. 7. Working logic of the SDP approach

4.4 Performance measurement for TDP and SDP approach

To evaluate the effectiveness of the above two approaches and identify appropriate parameter combinations, we propose three key performance indicators (KPIs). The first KPI is average postponement duration of an order (WT), which is a measure of the amount of time delivery is pending in the depot upon actual delivery. It is calculated by:

$$WT = \frac{\sum_{k} \sum_{i \in \bar{I}^{(k)}} dt^{(k)} - t_i}{\sum_{k} \left| \bar{I}^{(k)} \right|} \tag{2}$$

The second KPI is the average route compactness of a vehicle's trip (CPT). The route compactness is an intuitive concept and can be defined unequivocally (Rossit et al. 2019). Generally, the higher proximity amongst the destinations of the community, the more compact this route is. In this study, we use the definition proposed in Poot et al. (2002) to measure route compactness, which is formulated as:

$$CPT = \frac{\sum_{k} \sum_{j} \sum_{i \in \bar{I}_j^{(k)}} dist\left(i, c_j^{(k)}\right)}{\sum_{k} \sum_{j} \left| \bar{I}_j^{(k)} \right|} \tag{3}$$

where *dist(a,b)* is a function to calculate the Euclidean distance between point *a* and point *b*. $c_j^{(k)}$ is the geometric center of the location in the order set $\bar{I}_j^{(k)}$. Smaller value of CPT indicates a more compact solution.

The third KPI is the average traveling distance of a vehicle's trip (*TD*), which is used to describe vehicles travel efficiency and is computed by:

$$TD = \sum_{k} \sum_{j \in J^{(k)}} D(\bar{I}_j^{(k)}) \tag{4}$$

where $D(\bar{I}_j^{(k)})$ is the minimum distance for the vehicle *j* to deliver all orders in $\bar{I}_j^{(k)}$. This figure can be obtained by solving the traveling salesman problem (Lawler, 1985) using Tabu search algorithm. In this study, we suggest that route optimization is an optional decision. The route is identified solely for the purpose of the numerical experiments and analysis detailed in Section 5.

5. Numerical studies

In this section, we present our numerical experiments to assess the performances of TDP and SDP approach in dealing with general e-commerce last-mile delivery scheduling problems. The numerical analysis is based on real data sets extracted from a logistics service provider, whose distribution centers handling e-commerce logistics orders for last-mile delivery are based in two different geographical locations. Section 5.1 describes the data set used in our simulation experiments, followed by a detailed explanation in Section 5.2 regarding the parameter setting. We then present the results of each solution approach and compare their performance respectively in Section 5.3 and 5.4.

5.1 Data Sets

The problem discussed in this paper is based on a real-world case in a third-party logistics service provider in the mainland China. One of the depots of the 3PL located in Beijing is selected for this case study. Each depot serves as the B2C distribution hub for last-mile delivery to local end consumers within a 5km by 5km area. Currently, the case company handles outsourced last-mile delivery operations of an omni-channel and online shopping platform. There are two delivery options for end consumers: home delivery or in-store pickup. Upon receiving delivery requests from the end consumers, the 3PL is required to schedule the daily delivery operations by determining the despatching B2C e-commerce orders timely to the entire smart lockers network within the region served by the depot, with the trade-off between minimizing the number of daily delivery trips and the postponement time of each delivery order.

The uncertainties of the daily last-mile e-commerce delivery scheduling problem lies in the dynamic arrival of delivery requests and fluctuating demand of smart lockers within the network. A typical operating scenario in scheduling for last-mile e-commerce delivery is the arrival of an enormous number of delivery requests in depots during both operating and non-operating hours. At the beginning of each working day, each depot receives an aggregated, initial delivery backlog orders. During the service time, i.e. from 8:00 to 18:00, new delivery requests are received in real-time. As delivery requests are randomly distributed across the 5km*5km area served by the distribution hub, operators of each depot are required to justify the serving community of the delivery vehicles and to allocate delivery orders to each vehicle accordingly. Currently, in the absence of decision support tools, decisions regarding the possibility of spatial postponement of delivery vehicle (i.e. adjusting the serving community of a vehicle's trip) and temporal postponement of delivery order (i.e. determining the duration of consolidating orders) cannot be made. FIFO strategy is applied to allocate the delivery orders to available vehicles for last-mile delivery.

In the literature, the well-known VRPTW instances by Solomon (1987) comprise 56 instances, each of which contains 100 customers located in a 100 by 100 square. The set is divided into six classes so as to distinguish the difference in terms of the time window and vehicle capacities. However, the Solomon instance lacks generality as it does not demonstrate different demand distributions (Bianchessi et al. 2019). Further, in the e-commerce environment, orders exhibit more characteristics other than time windows constraints and vehicle capacities. For example, e-commerce orders have varying arrival rate at the depot 24/7 during operating and non-operating hours. The same day or next day delivery promise makes the time window constraints more or less fixed. To realistically reflect the business nature of today's e-commerce delivery sector while taking reference of the standard Solomon benchmark, we extract a real data set from the 3PL and obtain the historical real order arrival patterns. Based on the real data set, we identify the essential parameters as discussed in the next section.

5.2 Parameter settings

Adapted from the Solomon benchmark, we consider a 5km*5km square area served by the depot. The order distribution within the area tends to be evenly distributed, as delivery requests are widespread (the green and yellow region in Fig. 8) across the populated areas. The remaining parameters are classified into four categories: vehicle-related, order pattern-related, serving community-related, and experiment-related. A one-year delivery order data for the depot concerned in this simulation study are collected for determining the first two categories of parameters. In particular, the distributions for order arrival rate during operating and non-operating hours, the spatial distribution of the arrived orders, and the weight of an order, are calculated based on real data patterns. To examine the feasibility of integrating the *Temporal delivery postponement* and *Spatial community adjustment* features identified in Section 3, experiments of TDP and SDP needs to be conducted in a controlled simulation environment where vehicles are assumed to have immediate availability to perform delivery tasks, similar to the case of crowdsourced delivery. By so doing, the intended temporal delay of order dispatching will not be resulted from vehicle unavailability. To reflect the real operating scenario in the depot, the maximum available number of vehicles for daily delivery operations is limited to be 10 and is always sufficient to handle the changing delivery demand. Idling vehicles remain at the docking area of the depot waiting for order releases for loading and last-mile deliveries. Each truck has an identical capacity of 500 kg for loading B2C e-commerce orders. Considering the time required for unloading parcels at each delivery point and perform actual delivery, the speed of the truck is fixed at 5 km per hour. A summary of all parameters concerned is presented in Table 4.

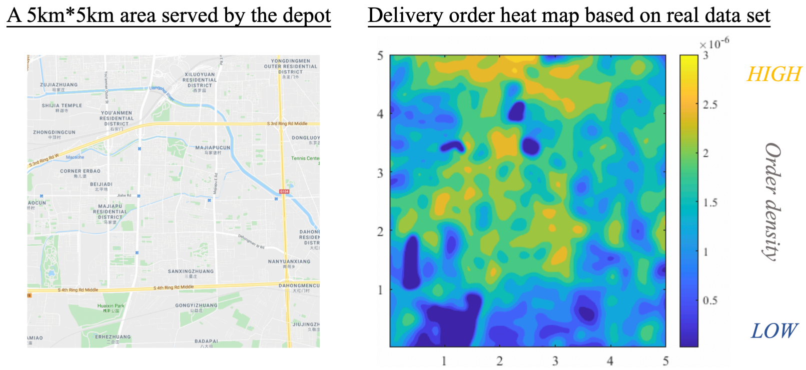

Fig. 8. Heat map reflecting order distribution and density of the real data set

Table 4. A summary of the parameter settings

Parameters	Setting
Vehicle-related parameters	
Number of trucks	10
Truck capacity	1000 kg
Truck speed	5 km per hour
Order pattern-related parameters	
Order arrival rate during operating hours	A. Low demand – 0.75 min per order B. Normal demand – 0.5 min per order C. High demand – 0.35 min per order D. Peak demand – 0.25 min per order
Order arrival rate during non-operating hours	A. Low demand – 2.5 min per order B. Normal demand – 2 min per order C. High demand – 1.7 min per order D. Peak demand – 1.5 min per order
Order distribution within the smart locker network	Uniform distribution
Weight of a delivery order	Gamma distribution (20, 1)
Size of order set	20 kg per order set
Community-related parameters	
Serving size of a community	5 km * 5 km

Number of communities	1*1/ 2*2/ 3*3/ 4*4/ 5*5/ 6*6/ 7*7
Community partitioning method	Unit squares
Experiment-related parameters	
Operational time length	10 hours (i.e. 600 minutes)
Solution update cycle	TDP approach: every 10 minutes SDP approach: Equivalent to the pre-defined vehicle departure cycle
Simulation time	10 days

5.3 Results of the solutions generated by TDP, SDP and VRP approach

Based on the parameter settings as defined in section 5.2, the city logistics problem is simulated for 10 days, with the operational time being 10 hours per day, i.e. 600 minutes. Experiments are performed through MATLAB 2019 on an x64-PC with an Intel dual Core i7-6700 3.40GHz CPU and 16GB of RAM. Results using our proposed mechanism, i.e. TDP and SDP approach, and using VRP approach, are presented as follows.

5.3.1 CLS solutions generated by TDP approach

Using the TDP approach, the 5 km by 5 km serving community of the depot is partitioned evenly using M by N squares, where $M = N$. Fig. 9 depicts four solution examples when $M = N = 3$, under high demand scenario. A total of nine fixed communities implies that there exist nine individual order pools for consolidating delivery orders. Each pool is served by at least one vehicle. For a predetermined solution update cycle ($dt^{(k)}$) of 10 minutes, every 10 minutes the TDP approach checks if the orders consolidated in each community reach the desired loading capacity of the vehicle. The solution examples presented in Fig. 9 indicates that the vehicle departure time in each community differs in accordance with the actual order pooling situation in each community. For example, four vehicles depart at the 1st cycle ($dt^{(1)}$), i.e. 8:00 am, followed by another community fulfilling the vehicle loading requirement at the 15th cycle ($dt^{(15)}$), i.e. 10:30 am, and so on. Under the scenario of "high demand", simulation results reveal that TDP approach performs well in terms of traveling distance and route compactness. As for an order fulfillment rate of 98.8%, this figure depicts a very satisfying order throughput progress across the 10 simulation days. Only an insignificant number of backlog orders (less than 2%) remain undelivered.

(i) Effect of community partitioning towards traveling distance and route compactness

CLS solutions generated by TDP approach under all demand scenarios (low, normal, high and peak) are presented in Appendix I. Solutions with seven community partitioning sizes are developed, which demonstrate the sensitivity of community partitioning towards the three KPIs introduced, i.e. order postponement duration, traveling distance and route compactness. When M = N = 1, no sub-community partitioning is applied to the entire serving community. The effect of sub-community partitioning towards order postponement duration, traveling distance and route compactness, as shown in Fig. 10, shows that solutions without applying sub-community partitioning give the worst results under all demand periods. The finding makes sense as vehicles have to travel across many districts for delivery, which in no doubt reduces the compactness of route, increases the traveling distance and time, thereby delaying the delivery of other pending orders in the depot delivery time given a fixed number of available vehicles. When serving community partitioning is applied, the more the number of sub-community partitioned, the smaller the actual serving community of a vehicle. Hence, it is not difficult to comprehend that partitioning serving community would reduce traveling distance and at the same time generate a more compact route, which is reflected in Fig. 10. A drastic reduction of average traveling distance and route compactness of a trip is found when the number of serving communities is partitioned up to 16, i.e. M = N = 4. While these two KPIs continue to improve for M = N = 5 and onwards, there is a noticeable decrease in the rate of improvement.

(ii) Relationship between order arrival frequency and community partitioning

As for the average postponement duration of an order, the figure is substantial under all demand scenarios (except for low demand period) when no serving community is applied. Moreover, it is revealed that the higher the order arrival rate (i.e. demand), the larger the duration of order delivery delay. This finding reflects the crucial need to perform serving community partitioning mainly when the depot receives an enormous number of orders. Using the same fleet of vehicles to fulfil such a considerable number of delivery requests by allocating each vehicle to overlap their delivery destinations with other vehicles does not make sense. Besides, Fig. 10 provides another essential indication about serving community partitioning. Under low demand scenario, the average postponement duration of an order reaches its minimum when M = N = 1, which indicates the fleet of vehicles works well in fulfilling the delivery requests even if no serving community partitioning is applied. Under normal and high demand scenario, the average postponement duration of an order reaches its minimum when M = N = 2 (i.e. 4 communities). As for peak demand scenario, its minimum is reached when M = N = 3 (i.e. 9 communities). There is a gradual shift in the optimal number of communities in order to achieve the minimum duration of delivery delay with the increase of order arrival rate. Hence, this provides a clear indication that more communities should be introduced to deal with greater demand.

(iii) Conversion between the "Cost of Postponement" and the "Value of Postponement"

When comparing the performance of postponement duration, traveling distance and route compactness as a whole, the delay of order delivery serves as a practical trade-off of improving the vehicle routing solution in terms of both traveling distance and route compactness. This validates our proposed concept of postponement first-route second in facing today's e-commerce last-mile delivery problems where delivery requests are arriving at the depot at a high frequency for timely fulfillment. Nevertheless, we should be aware of the selection of the degree of community partitioning. As shown in Fig. 10, after reaching the minimum duration of order delivery delay, this figure continues to increase gradually when a higher degree of community partitioning is imposed. However, such an increase in delivery delay does not provide a significant improvement in terms of the traveling distance and route compactness, as the rate of reduction of these KPIs is decreasing when more communities are introducing. In other words, the value of postponement might not be able to offset the cost of postponement. Therefore, while 3PLs could strategically sacrifice a more significant degree of delivery delay in exchange for better delivery planning and execution in terms of improved traveling distance and visual attractiveness of route, they are recommended to strike a balance between the value and cost of postponement by identifying the "optimal" degree of community partitioning based on their depots' demand and supply, that are, respectively, the order arrival frequency and delivery vehicle availability.

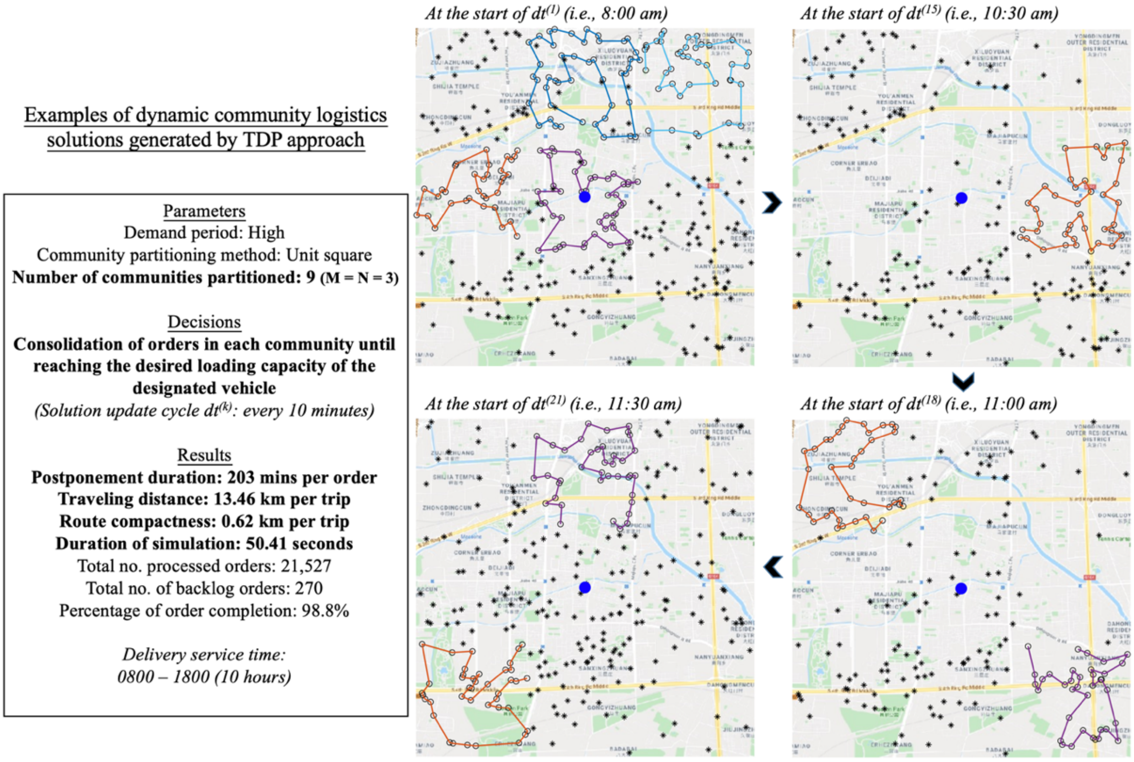

Fig. 9. Community logistics solution update using TDP approach – a graphical example

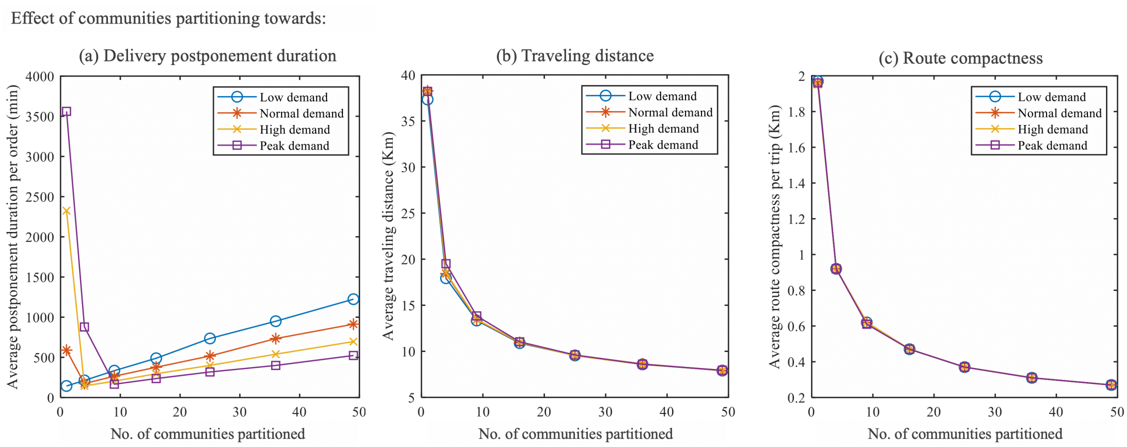

Fig. 10. Effect of community partitioning towards (a) delivery postponement duration, (b) traveling distance and (c) route compactness using TDP approach

5.3.2 CLS solutions generated by SDP approach

Under the SDP approach, vehicles are departed at a pre-determined interval (say 60 minutes) to fulfil the pending orders. By restricting the departure time of each vehicle, the SDP approach is able to generate a more flexible community in terms of its size, depending on the spatial distribution of the pending order set. Fig. 11 depicts four solution examples extracted under high demand scenario with vehicle departure cycle is fixed at 60 minutes. At each $dt^{(k)}$, once a set of community logistics solution is generated, the formed communities must be fulfilled by the available vehicles. For example, at the 1st departure cycle, i.e. 8:00 am, a total of 10 communities are formed, which therefore implies that 10 vehicles are to be departed after loading the corresponding order set. It is noted that any additional orders cannot be served at the current $dt^{(k)}$ will be postponed to $dt^{(k+1)}$, if the pending order set exceeds the capacity constraint of the available vehicles. With fluctuating arrivals of orders at distribution centres, it can be observed in Fig. 11 that each $dt^{(k)}$ has a flexible set of vehicles to depart. For example, a total of 6, 3 and 5 communities are formed at $dt^{(18)}$ $dt^{(36)}$ and $dt^{(54)}$ respectively.

Under the "high demand" scenario, simulation results shown in Figs. 9, 11 and 12 reveal that solutions generated from SDP approach with 60-minute vehicle departure cycle perform as good as those from TDP approach with nine communities partitioned. However, more investigations are required to justify which approach is better under different demand scenarios due to a variety of parameter settings regarding vehicle departure cycle and community partitioning. As for the order fulfillment rate, only 0.1% of orders remain undelivered. This demonstrates the appropriateness of adopting this approach.

CLS solutions generated by SDP approach under all demand scenarios (low, normal, high and peak) are presented in Appendix II. Solutions with seven variations of vehicle departure cycles are developed, which are used for testing the sensitivity of the variations of vehicle departure cycles towards the three KPIs introduced, i.e. order postponement duration, traveling distance and route compactness. As both SDP and VRP approach have a fixed vehicle departure cycle, the solutions generated by SDP approach are presented and compared with those generated by VRP approach in Section 5.4.

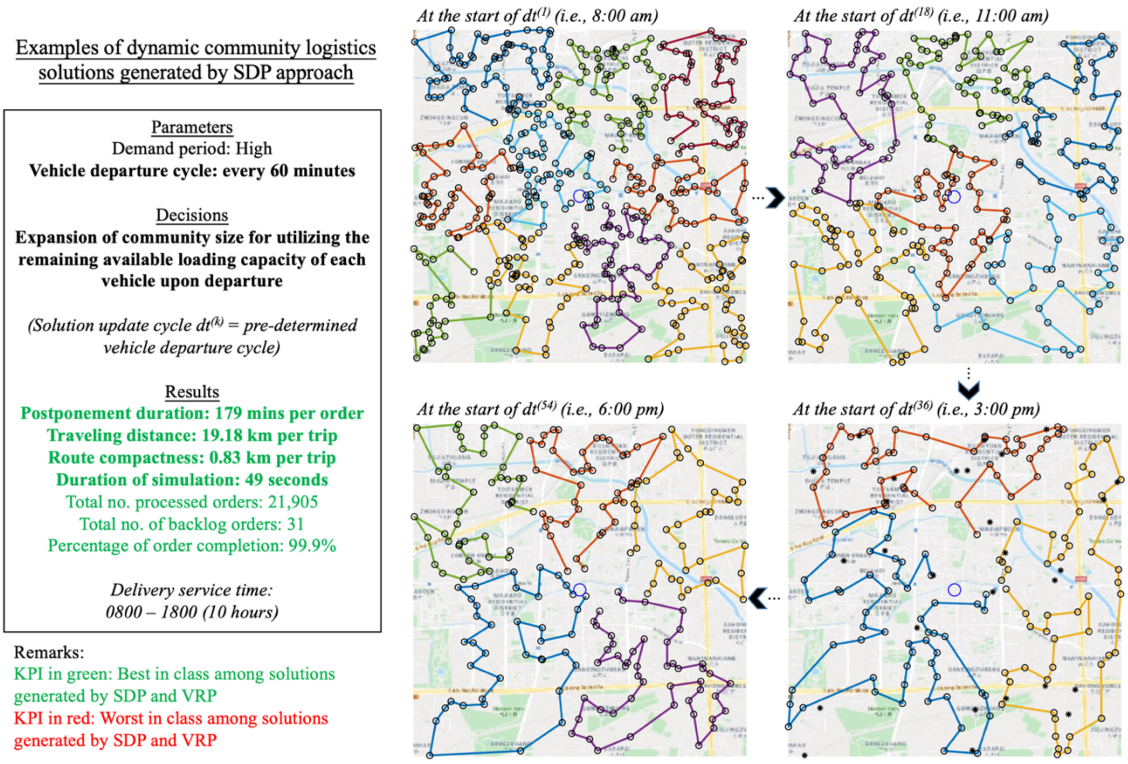

Fig. 11. Community logistics solutions update using SDP approach – a graphical example

5.3.3 *Vehicle routing solutions generated by VRP approach*

To validate the appropriateness of the proposed TDP and SDP approach in solving city logistics problem, the same set of parameters is replicated for use in VRP modelling. The simulation process of using VRP approach is similar to the simulation process of using SDP, where the available vehicles are dispatched at a set of predetermined departure times. The difference is that VRP approach determines the customers served by each vehicle through solving the VRP. The aim of VRP approach is to minimize the total vehicle traveling distance. By contrast, SUP approach focus on narrowing the service area of each vehicle. In this study, we use an adaptive large neighbourhood search algorithm proposed by Hemmelmayr et al. (2012) to solve the VRP at the end of each departure cycle. An example of a set of vehicle routing solutions is presented in Fig. 12. Under high demand period, VRP solutions give a comparatively poor performance in all the KPIs considered. The reason is that solving the large scale VRP within an acceptable time is extremely difficult even using powerful solution algorithms. Specifically, when comparing with SDP under the same parameter setting as depicted in Figs. 11 and 12, i.e. high demand period and 60-minute vehicle departure cycle, the average delay of an order for actual delivery is 2,160 minutes (equivalent to 36 hours or 1.5 days), while that of SDP is only 179 mins (equivalent to 2.98 hours). The average traveling distance and route compactness of a trip using VRP is respectively 31.04 km and 1.66 km, while that of SDP is only 19.18 km and 0.83 km. Vehicle routing solutions generated by VRP approach under all demand scenarios (low, normal, high and peak) are presented in Appendix III. A more comprehensive discussion and comparison of the results obtained from SDP and VRP approaches is provided in Section 5.4.

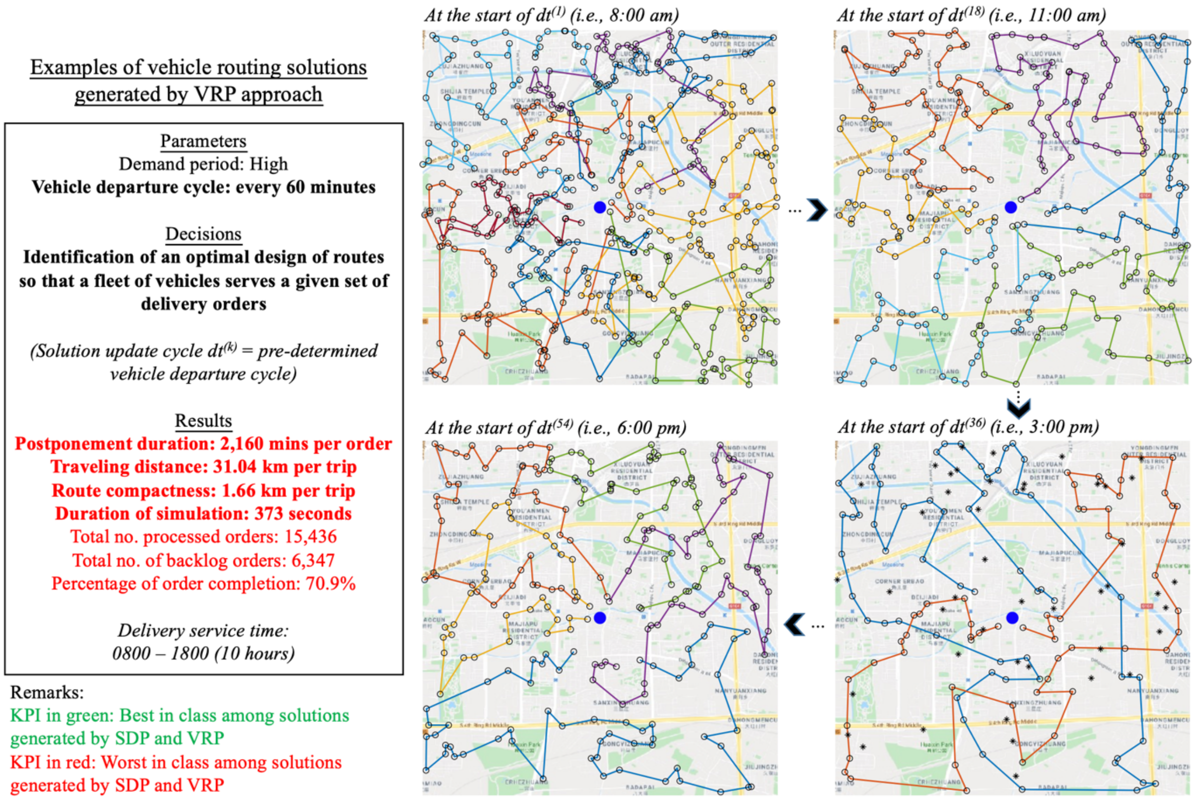

Fig. 12. Vehicle routing solutions generated by VRP approach – a graphical example

5.4 Comparisons between TDP, SDP and VRP approach

Based on the above results obtained individually using TDP, SDP and VRP approach, we present some major comparisons among their solutions with respect to simulation time, order fulfillment rate and vehicle departure cycle.

5.4.1 Simulation time comparison

According to Appendix I – III, the simulation time for solution generations using TDP, SDP and VRP approach is, on average, 40.9, 40.4 and 299.4 seconds, respectively. The reason for requiring almost five minutes to generate a single routing solution for a fleet of vehicles by VRP approach is the existing of a large set of order nodes for each vehicle routing solution generation. In contrast, the postponement first- route second operating strategy adopted in TDP and SDP separates a broad set of order nodes into many clusters based on the objective of temporal and spatial postponement. In this sense, the subsequent routing generation using Tabu search algorithm is a much smaller set of order nodes. Therefore, the TDP and SDP approach under the scope of CLS gives a significant reduction of time for generating a solution. In the long run, as solution generation process is performed frequently throughout the operating hours, the simulation time reduction using TDP and SDP approaches drastically minimizes a decision-maker's waiting time for obtaining a delivery postponement or scheduling solution.

5.4.2 Order fulfillment rate comparison

Order fulfillment rate can be an essential indicator for the selection of solution approach. Such a comparison enables practitioners to justify which approach works best under a particular demand period. As presented in Fig. 13, the order fulfillment rate using TDP approach achieves over 90% under all demand scenarios when serving community partitioning is applied (M = N >1). More importantly, a comparison of order fulfillment rate under different demand scenarios reveals that the TDP approach gives an even higher order fulfillment rate under high and peak demand period. This suggests that partitioning serving community is an effective uncertainty postponement strategy, especially during high demand seasons.

For the SDP approach, it is worth noting that it works well in peak demand period. The maximum order fulfillment rate in peak demand period is about 80% when the vehicle departure time is fixed at every 100 minutes. Nevertheless, the approach performs very well and is the best amongst three solution approaches in low, normal and high demand scenarios when the vehicle departure cycle is respectively fixed at 200, 150 and 100 minutes or below. When considering low and normal demand period, a comparison between TDP and SDP reveals that the latter achieves higher order fulfillment rate.

For the VRP approach, it is observed that the approach performs well only under low demand scenario. When order arrival frequency is getting higher, it is unlikely that the approach can guarantee an order fulfillment rate of 80% or above. In other words, more backlog orders will be accumulated at the depot due to unsatisfying routing solutions (in terms of both traveling distance and route compactness as shown in Appendix III). This finding serves as strong evidence of the need to develop a postponement first-route-second solution approach for solving today's city logistics problem where there is significant B2C customer demand in a small geographical area within a short duration.

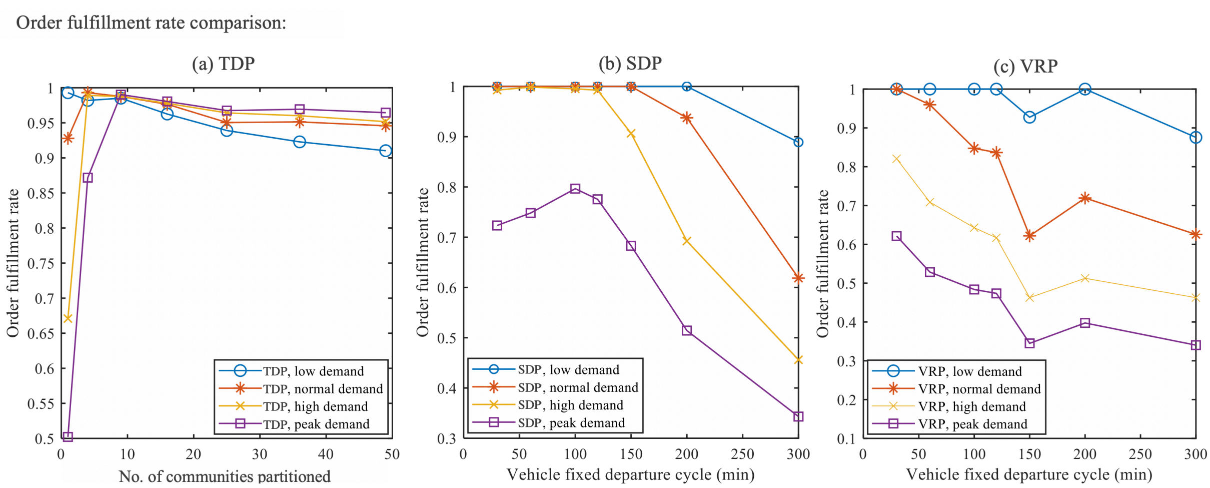

Fig. 13. Order fulfillment rate comparison between (a) TDP, (b) SDP and (c) VRP solutions

5.4.3 Effect of vehicle departure cycle for SDP and VRP approach

As both SDP and VRP approach employs fixed vehicle departure cycle for order delivery, pairwise comparison can be conducted for these approaches regarding the effect of the variations of vehicle departure cycle towards order delivery delay, traveling distance and route compactness. For order delivery delay, Fig. 14 shows that the delivery delay of each order is getting more severe for both approaches when the vehicle departure cycle is increasing. However, when the vehicle departure cycle is below 150 minutes, the rate of change of delivery delay using SDP approach is insignificant. When considering the traveling distance and route compactness of SDP approach, we could also observe a significant rate of reduction of these KPIs when vehicle departure cycle is below 150 minutes. This suggests that order delivery delay serves as the “Cost of postponement” to generate the “Value of postponement” in terms of traveling distance and route compactness. This finding aligns with that of TDP approach discussed in section 5.3.1, indicating that both SDP and TDP approaches are managed to deliver the value of postponement through the idea of "intended postponement" in the dimension of spatial and temporal respectively.

As for the VRP approach, though the duration of order delivery delay continues to increase, the traveling distance and route compactness have a positive correlation with order delivery delay. Such contrasting outcome in comparison with the SDP approach shows that the delay of order delivery from VRP approach should be regarded as “unintended postponement”. The order delivery delay in VRP is originated from the inefficiencies of the generated solution to deal with city logistics problem where a large number of order nodes exist. Again, this provides a sharp indication of the appropriateness of introducing postponement first-route second typology in solving today's city logistics problem. Further, as TDP and SDP approaches generate a solution with short traveling distance and high route compactness, this suggests that the order set served by a vehicle is mostly within a small geographical region. That said, an experienced delivery person should have the adequate capability of determining the delivery sequence within such a small region. Hence, a relaxation of the assumption of requiring "route second" is worth consideration.

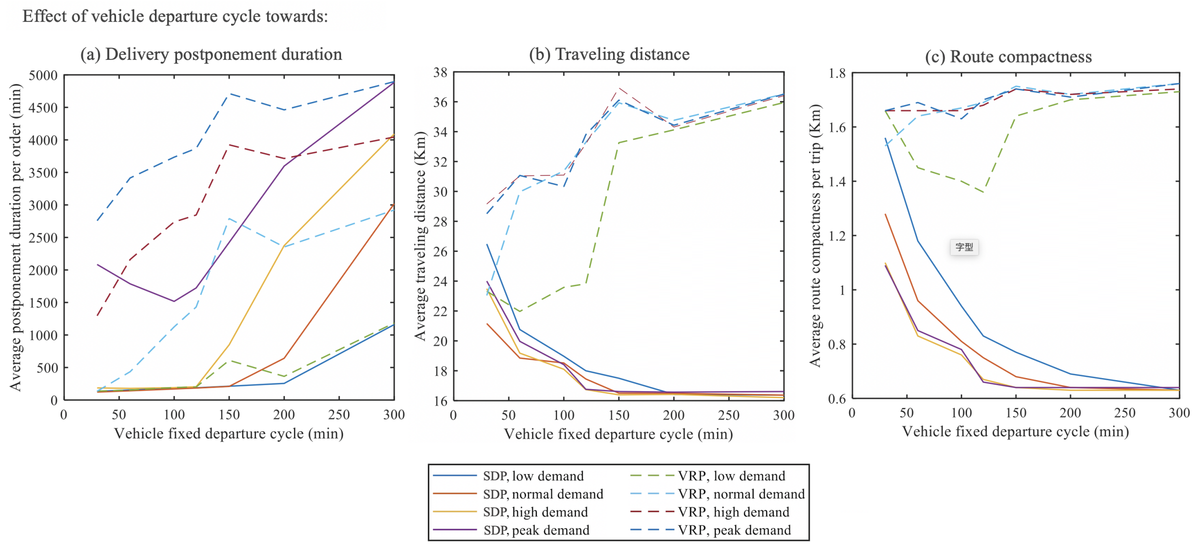

Fig. 14. Effect of vehicle departure cycle towards (a) delivery postponement duration, (b) traveling distance and (c) route compactness using SDP and VRP approach

6. Implications of this study

To provide implications for the interests of future scientific research in the area of last-mile delivery postponement problems, implications are discussed in two aspects: (i) interaction between the CLS and VRP, and (ii) applicability of the CLS in a wider spectrum.

6.1 Interaction between CLS and VRP – "Delivery uncertainty postponement" serving as a mean of generating order pooling effect

In the mainstream literature, we have seen VRP solution approaches that adopt the idea of cluster first-route second. Nevertheless, the districting algorithms of these VRPs only attempt to perform capacitated clustering based on the geographical delivery locations of orders. The possibility of pooling delivery orders based on both the spatial and temporal considerations has not been studied. Under the scope of CLS, capacitated districting of delivery orders is performed with an objective of "intended delivery postponement", so that the duration of postponement of each order serves as an effective "cost" of reducing traveling distance and improving the visual attractiveness of a delivery trip. Simulation results based on real data patterns validate the appropriateness of implementing the concept of postponement first-route second strategy where a large number of delivery requests are received at a high frequency within a compact region. The assumption of requiring the subsequent route generation can even be relaxed at a practical standpoint.

6.2 Applicability of CLS in a wider spectrum

The applicability of the proposed dynamic spatiotemporal-based order pooling mechanism, comprising temporal and spatial postponement through TDP and SDP solution approach, is validated through the sensitivity analysis with respect to VRPs as presented in the previous section. Nevertheless, the applicability of the proposed CLS can be examined further by considering a wider variety of delivery scenarios, such as different geographical patterns and nature of orders.

The simulation experiment performed in this study adopts a real order arrival data set with the orders distributed quite evenly across the 5km*5km area as delivery requests are widespread across most of the locations with populations. The geographical area considered is a flat land without high elevation of land surfaces. For coastal area, mountainous region and large hilly area, the undulation of its surface relief might affect the performance of the TDP solution approach as communities are partitioned based on a square shape. Similarly, most previous transportation studies taking city logistics into account disregard the integrated effects of geographical patterns and order nature towards last-mile order dispatching. Therefore, these parameters should be considered to design and determine an appropriate community partitioning method.

In the perspective of order nature, last-mile city logistics problem should be explicitly categorized into two streams: order delivery and order collection problem domains. The former considers a set of orders with specified delivery locations to be distributed by a delivery person, whereas the latter considers a set of orders with specified collection locations to be collected by a delivery person. We stress the need to integrate real-time order arrival features into city logistics model development. For example, the dynamic spatiotemporal-based order pooling mechanism introduced in this study deals with the last-mile order deliveries where orders are continuously arriving and intervenes the formulations of dispatching solutions. In addition to dynamic order arrivals, crowdsourced delivery options – a large pool of citizen workers to perform the final leg of delivery and collection, should also be further investigated in the design of any spatiotemporal-based order pooling mechanisms that attempt to jointly or individually tackle the order delivery and order collection problems under the last-mile city logistics context.

7. Conclusive remarks

A dynamic strategy, namely Community Logistics Strategy, is introduced in this study. Numerical studies reveal its superiority in managing the dynamic arrivals of e-commerce delivery requests without generating route decisions. While this paper applies the CLS into particularly dealing with instant parcel delivery to smart lockers located around every corner of the city, it should be highlighted that there is potentially a wide range of practical delivery scenarios which is feasible for transformation of their existing order fulfilment operations through CLS deployment. To name a few, they include the joint pickup-and-delivery environment, e-commerce delivery with tight time windows, etc. This study demonstrates the essence of managing the uncertainty of delivery requests through taking both “time” and “space” into consideration – On one hand, delaying delivery fulfilment as a means of “buying time” for consolidating more delivery requests is one good tactic. Nevertheless, enlarging vehicle serving community would, on the other hand, reduce the potential over delayed deliveries. Striking a balance between these factors is therefore crucial in real practice.

From the operational standpoint, relaxing the need for route optimization by shifting the focus onto community partitioning based on real time arrivals of orders yields some noticeable benefits. First, less reliance on computational requirements can be achieved as the grouping of orders into order sets, rather than the visiting sequence of delivery locations, is treated as the solution format under the CLS methodology. Second, applying it into city logistics contexts where numerous small orders exist in compact regions with high rise commercial and residential buildings decentralizes the visiting sequence decision-making to delivery persons. This increases the degree of flexibility for them to perform delivery operations especially when traffic issues arise in megacities. Managerially, the delegation of routing decision-making also creates rooms for the management to focus on the real-time formulations of delivery communities that are operationally easy to execute, thereby indirectly addressed the difficulties and inabilities of including the real-time requests in the delivery route of the vehicle in real practice.

The limitation of this study lies in the spatial and temporal considerations being individually considered, as represented by the proposed SDP and TDP approach. Future research directions therefore include the integration of these attributes in the development of CLS-based dynamic delivery strategy in city logistics context. To develop executable real-time delivery dispatching models, future studies should also consider the practical issues arising from the delivery system, such as delivery security, drivers' work time, etc. Given the steady growth of last-mile logistics becoming more apparent than ever, we call for greater research emphasis on the innovation and development of new methodologies to meet the demand under this ever-changing and dynamic delivery environment, especially in the e-commerce era.

Data availability statement

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

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Appendices

Appendix I – CL solutions generated by TDP approach under various demand scenarios

No. of communities partitioned	***Average postponement duration*** *(mins per order)*	***Average traveling distance*** *(km per trip)*	***Average route compactness***	***Total no. of processed orders*** *(in 10 days)*	***Total no. of backlog orders***	***Order fulfillment rate***	***Average simulation time*** *(seconds)*
Low demand scenario							
1	143.5	37.33	1.97	11257	80	*99%*	23.9
4	212.9	17.93	0.92	11210	206	*98%*	24.9
9	334.2	13.34	0.62	11197	169	*99%*	25.2
16	488.7	10.89	0.47	10711	417	*96%*	24.5
25	735.1	9.55	0.37	10708	695	*94%*	24.2
36	949.7	8.58	0.31	10386	868	*92%*	24.1
49	1223.9	7.91	0.27	10385	1024	*91%*	24.6
Normal demand scenario							
1	589.8	38.26	1.96	14743	1146	*93%*	30.6
4	174.0	18.43	0.92	16121	113	*99%*	34.4
9	265.3	13.42	0.62	15543	195	*99%*	34.9
16	377.0	10.95	0.47	15561	374	*98%*	34.0
25	517.0	9.56	0.37	15218	793	*95%*	34.4
36	733.6	8.63	0.31	15224	779	*95%*	33.7
49	913.3	7.90	0.27	15199	871	*95%*	35.1
High demand scenario							
1	2325.9	38.07	1.95	14811	7266	*67%*	35.5
4	144.0	18.54	0.92	21591	235	*99%*	46.5
9	203.9	13.46	0.62	21527	270	*99%*	50.4
16	295.6	10.97	0.47	21421	488	*98%*	50.3
25	399.8	9.52	0.37	21056	782	*96%*	46.7
36	539.4	8.57	0.31	21175	879	*96%*	49.5
49	696.2	7.93	0.27	20703	1051	*95%*	47.2
Peak demand scenario							
1	3561.2	38.21	1.96	14769	14646	*50%*	41.0
4	878.2	19.51	0.92	25839	3800	*87%*	55.2
9	165.9	13.84	0.61	29261	289	*99%*	61.3
16	236.1	11.03	0.47	28624	569	*98%*	61.6
25	318.1	9.60	0.37	28452	957	*97%*	62.1
36	399.4	8.60	0.31	28809	909	*97%*	64.1
49	523.1	7.94	0.27	28541	1050	*96%*	63.6
						Average:	*40.9*

Appendix II – CL solutions generated by SDP approach under various demand scenarios

Vehicle fixed departure cycle (mins)	*Average postponement duration (mins per order)*	*Average traveling distance (km per trip)*	*Average route compactness*	*Total no. of processed orders (in 10 days)*	*Total no. of backlog orders*	*Order fulfillment rate*	*Average simulation time (seconds)*
Low demand scenario							
30	132.7	26.48	1.56	11,273	0	*100%*	27.7
60	155.1	20.76	1.18	11,270	0	*100%*	25.9
100	179.2	18.97	0.94	11,233	0	*100%*	24.5
120	187.7	18.00	0.83	11,411	0	*100%*	25.0
150	212.1	17.50	0.77	11,323	0	*100%*	25.7
200	255.4	16.42	0.69	11,368	0	*100%*	24.8
300	1159.9	16.37	0.63	10,058	1,257	*89%*	22.7
Normal demand scenario							
30	122.2	21.16	1.28	16,344	0	*100%*	40.1
60	141.7	18.85	0.96	16,175	0	*100%*	36.9
100	170.0	18.52	0.81	16,106	0	*100%*	37.0
120	183.9	17.45	0.75	15,913	0	*100%*	35.0
150	209.2	16.50	0.68	15,991	0	*100%*	35.9
200	641.8	16.49	0.64	15,050	1,003	*94%*	33.6
300	3018.1	16.37	0.63	10,078	6,213	*62%*	25.9
High demand scenario							
30	186.0	23.49	1.10	21,672	158	*99%*	46.1
60	178.8	19.18	0.83	21,905	31	*100%*	49.0
100	190.2	18.10	0.76	21,565	103	*100%*	46.8
120	203.9	16.74	0.67	21,479	162	*99%*	48.4
150	848.5	16.39	0.64	19,782	2,037	*91%*	45.6
200	2374.5	16.42	0.63	14,999	6,667	*69%*	38.3
300	4090.7	16.20	0.63	9,994	11,919	*46%*	29.0
Peak demand scenario							
30	2084.2	24.00	1.09	21,339	8,163	*72%*	53.4
60	1786.6	19.97	0.85	22,014	7,412	*75%*	55.9
100	1516.8	18.41	0.78	23,354	5,966	*80%*	68.3
120	1723.3	16.76	0.66	22,744	6,587	*78%*	74.2
150	2423.7	16.61	0.64	19,948	9,267	*68%*	64.4
200	3597.1	16.57	0.64	15,069	14,234	*51%*	50.8
300	4884.0	16.61	0.64	10,026	19,194	*34%*	39.5
						Average:	40.4

Appendix III – Vehicle routing solutions generated by VRP approach under various demand scenarios

Vehicle fixed departure cycle *(mins)*	***Average postponement duration*** *(mins per order)*	***Average traveling distance*** *(km per trip)*	***Average route compactness***	***Total no. of processed orders*** *(in 10 days)*	***Total no. of backlog orders***	***Order fulfillment rate***	***Average simulation time*** *(seconds)*
Low demand scenario							
30	137.8	23.32	1.66	11,266	0	*100%*	534.8
60	152.3	21.97	1.45	11,311	0	*100%*	346.4
100	192.3	23.58	1.40	11,089	0	*100%*	277.8
120	200.3	23.82	1.36	11,240	0	*100%*	255.7
150	610.0	33.26	1.64	10,391	813	*93%*	212.1
200	363.7	34.12	1.70	11,398	0	*100%*	236.0
300	1184.6	35.95	1.73	9,983	1,419	*88%*	196.2
Normal demand scenario							
30	135.1	23.04	1.53	16,049	0	*100%*	516.0
60	435.3	29.97	1.64	15,388	647	*96%*	362.7
100	1124.8	31.37	1.67	13,663	2,461	*85%*	305.4
120	1430.0	33.29	1.69	13,496	2,637	*84%*	283.2
150	2790.4	35.93	1.75	10,017	6,090	*62%*	199.5
200	2353.8	34.76	1.72	11,620	4,534	*72%*	237.0
300	2921.3	36.52	1.76	9,955	5,958	*63%*	193.7
High demand scenario							
30	1296.0	29.16	1.66	18,013	3,940	*82%*	479.0
60	2160.9	31.04	1.66	15,436	6,347	*71%*	372.9
100	2738.3	31.09	1.66	14,066	7,812	*64%*	312.9
120	2844.8	33.18	1.68	13,444	8,349	*62%*	282.8
150	3924.2	36.93	1.74	10,138	11,774	*46%*	195.7
200	3714.3	34.31	1.72	11,183	10,636	*51%*	235.9
300	4044.4	36.41	1.74	10,042	11,665	*46%*	198.4
Peak demand scenario							
30	2757.7	28.51	1.66	18,140	11,052	*62%*	510.5
60	3414.6	31.07	1.69	15,560	13,879	*53%*	366.4
100	3734.4	30.33	1.63	14,158	15,111	*48%*	321.0
120	3868.7	33.80	1.70	13,998	15,556	*47%*	293.7
150	4712.8	36.11	1.74	10,175	19,327	*34%*	214.0
200	4461.9	34.43	1.71	11,611	17,606	*40%*	242.8
300	4895.7	36.51	1.76	10,015	19,416	*34%*	201.4
						Average:	299.4