The Competition and Inefficiency in Urban Road Last-Mile Delivery

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ABSTRACT

The last-mile delivery market is highly competitive and is saturated with numerous small operators. In this context, the fierce competition between operators, joint with the rapid increase in the demand for home-delivery, resulted in a significant increase in urban freight traffic further worsening congestion and pollution. To tackle these issues, previous research has studied the implementation of collaborative last-mile operations, with organisations sharing resources in the form of inventory space or transportation capacity. However, a common limitation of the proposed models is ignoring time windows and the effects of externalities such as network congestion.

In this work, we propose a framework to quantify the efficiency loss in urban last-mile delivery system by comparing the solutions of a fully-decentralised and fully-centralised last-mile delivery problem. In doing so, we develop a Multi-depot Vehicle Routing Problem with Time Windows and Congestible Network that is solved using a bespoke Parallel Hybrid Genetic Algorithm that accounts for the non-linearities arising from modelling endogenous network congestion. The model is evaluated on a case study based on central London to assess the efficiency gaps of realistic last-mile delivery operations. When time window constraints are not included, our results show that the efficiency loss fluctuates the most with a small number of customers, while it stabilises to less than 15% for instances with over 100 customers. However, time windows could significantly exacerbate this issue, resulting in an additional 25% of efficiency loss.

KEYWORDS

Price of Anarchy; Last-Mile Delivery; Vehicle Routing Problem

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1 INTRODUCTION

Last-Mile Delivery is a crucial component of nowadays logistics systems and has seen substantial growth over recent years, partially as a result of the increasing popularity of e-commerce and home delivery [13]. Worldwide retailers have experienced approximately a 20% yearly revenue growth in e-commerce sales since 2014 [10]. In the UK, the proportion of internet sales has increased to 26% in 2021 from 2.7% in 2006 [12], with over 82% of customers opting for home delivery instead of alternative delivery options [33].

However, the last-mile delivery market is fragmented by thousands of companies and often dominated by small private businesses, resulting in a non-cooperative and decentralised system [16, 17]. Due to customer dynamics and lack of collaboration, the workload among companies tends to be unevenly distributed and resources are not fully utilised. Furthermore, the proliferation of delivery agents, joint with limited coordination, results in a significant freight traffic on the road, which generates significant externalities including congestion, pollution, and traffic accidents. In this respect, the number of registered Light Good Vehicles (LGVs) has increased by 12% during the last five years in the UK [19].

Naturally, congestion and pollution significantly impact the livelihood of inhabitants. In the UK, domestic transport is responsible for approximately a quarter of UK's total green-house gas emissions, with urban and municipal delivery contributing to 50% of the freight sector's total [15].

Amid this backdrop, collaborative supply chains and deliveries could provide the means to substantially reduce the congestion and emissions arising from last-mile delivery. This can be carried out either through horizontal collaboration between the couriers, or through the installment of a mandated governmental body that regulates urban deliveries. It is therefore paramount to evaluate the potential gains arising from collaborative delivery. In this context, the impact of externalities (e.g. endogenous congestion) has not been considered, and is at the core of this work. Specifically, we use the notion of Price of Anarchy (PoA) to evaluate the optimality gap between the status quo, where each company optimises their delivery plan individually, and that where this process is coordinated centrally.

Our analysis of the current literature (see Section 2) reveals that few studies include externalities when evaluating collaborative last-mile delivery, and aspects of endogenous network congestion are disregarded. The latter is of particular importance as it has a

direct effect on delivery travel time, vehicle emissions and citizen's livelihood.

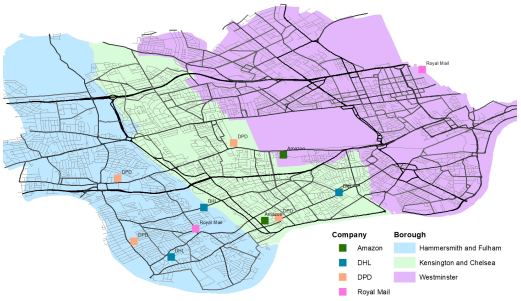


Figure 1: Map of three London boroughs and road network used for our numerical evaluation

This study focuses on urban road last-mile delivery where customers are served by local depots and vehicles are owned by multiple companies. In doing so, we propose a Multi-depot Vehicle Routing Problem with Time Windows and Congestible Network (MDVRP-TWCN) that aims to quantify the inefficiencies arising from non-collaborative delivery. The problem is solved by using a Parallel Hybrid Genetic Algorithm (H-GA) that is validated against well-known Solomon Benchmark scenarios [45]. Additionally, a case study scenario is developed based on the central area of London. Overall, the contributions of this study are three-fold:

(1) We propose a framework based on the vehicle routing problem for measuring the efficiency loss in urban last-mile delivery, which accounts for multiple factors.
(2) We formulate a vehicle routing variant, MDVRP-TWCN, which explicitly considers endogenous congestion effects. And utilise this formulation to estimate the efficiency loss arising from the presence of uncoordinated last-mile delivery.
(3) We find that, in a typical e-commerce scenario, the average efficiency degradation could be as high as 37% and is mainly attributed to excess vehicles, travel cost, and idling time.

The remainder of the paper is structured as follows: Section 2 reviews the related work. Section 3 formulates the MDVRP-TWCN. Section 4 presents the H-GA used to solve the routing problem. The results and discussion are presented in Section 5 and 6, respectively. Finally, summary and conclusions are included in Section 7.

2 RELATED WORK

It is well known that, when self-interested agents participate in joint decision making, the resulting outcome could be highly suboptimal from a societal perspective (e.g., selfish routing). In this context, the notion of Price of Anarchy, originally introduced in [26, 38], is often utilised to measure the performance degradation arising from self-interested decision making. This quantity has been thoroughly studied within the realm of congestible traffic networks, where Wardrop's first principle is often used to describe the worst emergent equilibrium flow (user-base equilibrium) [23, 35, 40, 41]. However, few studies have focused on the PoA of supply chains, and only at a macroscopic level. Within this stream of research, [39] measured the efficiency loss of a supply chain containing suppliers, assembly, and retailers, where the efficiency is measured based on the operational profit. This definition was followed and subsequently applied in reverse supply chains [48] and closed-loop supply chains [29]. Instead of using profits, [8] defined a cost-based efficiency for warehouse management operations. Finally, [27] followed this definition and investigated a freight transportation game. However, their analysis was based on an abstract grid map that describes the transportation between different regions.

Reference [6] is one of the first works focusing on collaborative VRP. Therein, authors conducted a joint route planning by single-depot VRP with time windows where orders were served by multiple companies. They introduced the notion of Synergy Value, defined as the cost saving arising from collaboration, and showed that such value could reach 30%. [28] also confirmed this opportunity for cost savings based on the VRP with pickup. Advancing to more realistic settings, [49] formulated a multi-depot VRP to model the multi-player delivery, and results suggested that the synergy value regarding travel costs could reach 18% of initial costs in the grand coalition.

However, several factors affecting the efficiency and utility of delivery were not considered in the cited literature, particularly the effect of time windows in the routing sequence and network congestion. While the VRP with time windows has extensively been studied in the literature [4, 9], the network congestion remains relatively unexplored. The prevailing method of considering real road network in VRP is adopting a time-dependent travel cost matrix and altering the matrix based on real-time traffic data, which converts a common VRP into a Time-Dependent Vehicle Routing Problem (TDVRP) [25, 31, 32]. However, the TDVRP only captures the congestion effect resulted from exogenous traffic.

Our work addresses this gap by accounting for collaboration and the effect of endogenous traffic arising from last-mile delivery. In doing so, we define a utility and cost function that evaluates order fulfillment rate, the total travel time, the total idle time of vehicles, number of vehicles used, and any extra working hours required to complete the delivery for the decentralised and centralised routing strategies. The routing algorithm is also subject to customers' time windows, and any delay of service is computed as a cost.

3 MODEL

Our framework estimates the efficiency loss by modelling and comparing the costs and utilities under two scenarios: a selfish or fully decentralised case where each company is an independent control unit and operates one or several depots to satisfy its own customer orders, and a collaborative or centralised scenario where vehicle fleets and customers are integrated into a single central planner. The distributed case aims to describe an equilibrium allocation arising from real operation, as opposed to an optimum allocation modelling the case of centralised decision-making. Both of them are modelled by vehicle routing problems.

The centralised case resembles the original VRP, where a single entity seeks to minimise the routing cost and ensures all customers are served within their specified time window. In contrast, in the

decentralised case each company seeks to maximise its own profit without concern of potential externalities affecting competition. Thus, companies only consider congestion resulted from exogenous traffic. Furthermore, customers cannot be reallocated across companies, nor they can share resources.

3.1 Definition of System Efficiency

In the context of urban delivery, the benefit and cost are dependent on the routing plans assumed by companies, which specifies the customer visiting sequence of vehicles. Thus, we develop the evaluation functions (1) and (2) which define the overall utility $U(R)$ and total cost $C(R)$ to the company based on its specific routing plan R.

$$U(R) = \beta_q Q(R) - C(R) \tag{1}$$

$$\begin{aligned} C(R) = &\beta_v V(R) + \beta_{TT} TT(R) + \\ &\beta_{DT} DT(R) + \beta_{IT} IT(R) + \beta_{OT} OT(R) \end{aligned} \tag{2}$$

Where $Q(R)$ is the number of orders satisfied, $V(R)$ denotes the number of vehicles utilised, $TT(R)$ defines the total travel time, $DT(R)$ represents the total delay of service, $IT(R)$ is the total idle time of all vehicles, and $OT(R)$ denotes the total overtime of all drivers under route plan R. Parameters $\beta_q, \beta_v, \beta_{TT}, \beta_{DT}, \beta_{IT}, \beta_{OT}$ are coefficients used to convert the above metrics into a monetary value. The rationale for each cost parameter is described below.

- $Q(R)$: Orders may not be fulfilled by a company due to lack of resources in the decentralised scenario. However, these can be reallocated to companies with spare capacity if collaboration is allowed.
- $V(R)$: The number of total vehicles used can be reduced by collaboration, increasing the vehicle occupancy rates.
- $TT(R)$: In collaboration, customers can be assign to the closest depots. Furthermore, companies will avoid the congestion resulted from the fleets of other companies.
- $DT(R)$ and $IT(R)$: When the temporal distribution of customers is uneven, the customers can be reallocated to another company to reduce the delay of service and idling time due to early arrival.
- $OT(R)$: In some cases, the courier must work overtime due to excessive demand and dispersed time slots. This can be resolved by orders reallocation.

Based on the cost and utility functions, two complementary definitions of PoA, utility-based PoA (3) and cost-based PoA (4), are proposed. They are both variables ranging from 1 to infinity. A larger value of these two variables indicates a larger efficiency loss. Compared with the utility-based definition, the cost-based one ignores the number of sales and could lead to an underestimated value. However, when the system is profitable in the collaborative scenario while unprofitable in the non-collaborative scenario, the utility-based one yields a negative value and becomes invalid, but the cost-based PoA still works. Therefore, although the utility-based PoA is preferred, it should be only used for a profitable delivery system.

$$PoA_U = \frac{U(R_c)}{U(R_d)} \tag{3}$$

$$PoA_C = \frac{C(R_d)}{C(R_c)} \tag{4}$$

Where R_c is the collaborative route plan optimising the total utility of all companies, and R_d defines the integrated route plan of all companies under decentralised scenarios.

For a given delivery system, (3) and (4) are computed by the following 4 steps: (1) Formulate separate MDVRP-TWCN instances for each company in the system. Combining the solutions of all these instances provides the optimal selfish routing plans R_d. (2) All the customers and depots are integrated into a single instance and formulated as a centralised MDVRP-TWCN. The solution R_c of this instance yields the optimal collaborative routing plan. (3) The utilities and costs of the collaborative and selfish cases are recalculated by applying equations (1) and (2). (4) Calculate the efficiency ratio or PoA based on equations (3) and (4).

3.2 Vehicle Routing Formulation

A Multi-depot Vehicle Routing Problem with Time Window and Congestible Network (MDVRP-TWCN) is proposed to model the two scenarios. This formulation is a variant of MDVRP-TW in which a set of orders are served by capacitated vehicles from multiple depots within booked time slots. The modification is that the travel cost of each link is dependent on the vehicle flows. The formulation is subject to the following assumptions: (1) The number of customers, number of depots, and their location are predetermined; (2) The vehicle fleet is heterogeneous; (3) Each customer can only be visited once; (4) A vehicle can only be assigned one route and should start and end at the same depot; (5) The beginning of service at customer i should be within the time window $[e_i, l_i]$. If the vehicle arrives earlier than e_i, it will wait and the idle time is recorded. Conversely, if it arrives after l_i, a penalty of delay will be added for this service.

Obtained from regression analysis based on substantial traffic survey data, the Bureau of Public Roads (BPR) function is commonly employed to relate travel time, traffic flow and link capacity [36]. To capture the externalities of traffic flows in congestible networks, the following modified BPR function that explicitly models both freight traffic flow and passenger traffic flow is adopted to estimate the travel cost of routing plans [11].

$$t_a(v_a^f) = t_a(0)\left[1 + \alpha_f \left(\frac{v_a^f}{C_a}\right)^{\beta_f}\right]\left[1 + \alpha_p \left(\frac{v_a^p}{C_a}\right)^{\beta_p}\right] \tag{5}$$

where $t_a(v_a^f)$ denotes the total travel time of link a subject to freight flow v_a^f, $t_a(0)$ is the free-flow travel time, v_a^f represents the freight traffic flow on link a, v_a^p denotes the passenger traffic flow on link a, and C_a is the capacity of link a. Parameters $\alpha_f, \beta_f, \alpha_p, \beta_p$ need to be calibrated by realistic data.

During routing, the freight traffic volume of the route plan R is loaded into network by the following steps: (1) Take a node pair (i, j) in routes plan R; (2) Find all the links used by the shortest path between i and j based on static travel cost $t(0)$; (3) For each link used, add traffic volume of $1/\delta T$ unit to this link where δT is the time interval modelled in the vehicle routing problem; (4) Repeat the above three steps until all node pairs in routes plan R are executed.

Sets:

D	The set of depots
C	The set of customers
N	The union of C and D
K	The set of vehicles
K_d	The set of vehicles at depot d

Parameters:

e_i	The earliest starting time of service at customer i
l_i	The latest starting time of service at customer i
$c_{ij}(x)$	The travel cost from node i to node j subject to route plan x
s_i	The duration of service at customer i
d_i	The demand of customer i
v	The price of a unit of demand
t_k	The maximum working hours of vehicle k
q_k	The capacity of vehicle k
$\|K_d\|$	The number of vehicles at depot d

Decision Variables:

x_{kij}	Boolean: equals 1 if vehicle k directly travels from node i to node j, otherwise, 0

Auxiliary Variables:

a_{kn}	The actual arrival time of vehicle k at node n
b_{kn}	The beginning time of service at node n for vehicle k
w_k	The working duration of vehicle k

$$\text{maximise} \sum_{i\in C} vd_i \sum_{j\in N}\sum_{k\in K} x_{kji} - \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} c_{ij}(x)x_{ij} \tag{6.1}$$

$$\sum_{i\in C}\sum_{k\in K} x_{kdi} \le |K_d| \;\; \forall d \in D \tag{6.2}$$

$$\sum_{j\in C} d_j \sum_{i\in N} x_{kij} \le |q_k| \;\; \forall k \in K \tag{6.3}$$

$$\sum_{d\in D}\sum_{j\in C} x_{kdj} = \sum_{d\in D}\sum_{i\in C} x_{kid} \le 1 \;\; \forall k \in K \tag{6.4}$$

$$\sum_{k\in K}\sum_{i\in N} x_{kij} \le 1 \;\; \forall j \in C \tag{6.5}$$

$$\sum_{i\in N} x_{kij} - \sum_{i\in N} x_{kji} = 0 \;\; \forall j \in N, k \in K \tag{6.6}$$

$$\sum_{i\in R}\sum_{j\in R} x_{kij} \le |R| - 1 \;\; \forall R \subseteq C, k \in K \tag{6.7}$$

$$\sum_{i\in D}\sum_{j\in D} x_{kij} = 0 \;\; \forall k \in K \tag{6.8}$$

$$x_{kij}(b_{ki} + s_i + c_{ij}(x) - a_{kj}) = 0 \;\; \forall i, j \in N, k \in K \tag{6.9}$$

$$b_{ki} \ge a_{ki} \ge 0 \;\; \forall i \in C, k \in K \tag{6.10}$$

$$e_i \le b_{ki} \le l_i \;\; \forall i \in C, k \in K \tag{6.11}$$

$$w_k \le t_k \;\; \forall k \in K \tag{6.12}$$

$$x_{kij} \in 0, 1 \;\; \forall k \in K, i, j \in N \tag{6.13}$$

$$w_k = \sum_{i\in C} x_{kid}(b_{ki} + s_i + c_{id}(x)) - \sum_{i\in C} x_{kd'i}(a_k i - c_{id'}(x)) \;\; \forall k \in K, d, d' \in D \tag{6.14}$$

The MDVRP-TW formulation is presented above for the centralised case. In the decentralised case, each company optimises the operation using this same problem irrespective of the other's routing plan.

The objective (6.1) maximises the utility of the routing plan. Constraint (6.2) limits the number of vehicles available to each depot, with (6.3) ensuring vehicle capacity is not exceeded. Constraint (6.4) present that the start and end of a route should be the same depot. Constraint (6.5) forces each customer to be visited no more than once. Subtour elimination constraints are specified by (6.7) and (6.8). Constraints (6.9)-(6.11) specify the limitation of time windows. Constraints (6.12) present the limitation of working hours. Note that constraints (6.11)-(6.12) will be relaxed and converted to penalty terms in the objective function in GA-based solving.

4 SOLUTION ALGORITHM

While the VRP-TW problem has been previously solved to optimality in a small or medium scale, incorporating the non-linear congestion (5) results in a much more challenging problem. In this context, Genetic Algorithms (GAs) are a widely used family of metaheuristics for large-scale VRPs, especially owing to their solution time scaling linearly with the problem size [7]. Their performance have been shown to be close to the best-known solutions recorded [2, 20, 24].

For this reason, we develop a bespoke Hybrid Genetic Algorithm (H-GA). Its structure (shown in Figure 2) consists of a generation stage which creates the initial population of solutions, a selection stage that discards under-performing solutions, and a modification stage that alters the solution structure through mutation, crossover and education. These key processes are described in the following subsections.

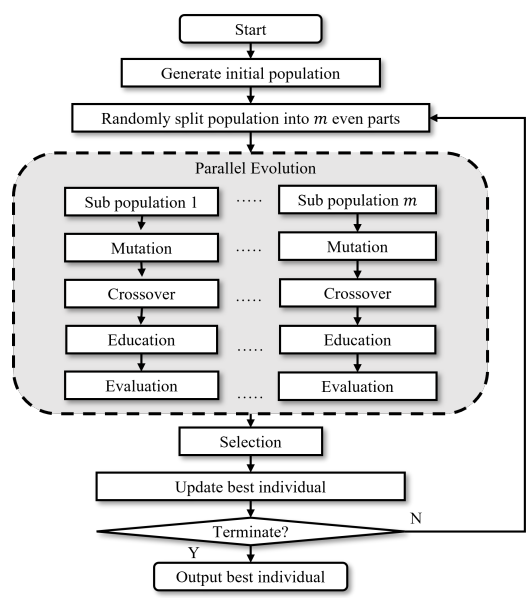


Figure 2: Execution flow of H-GA

4.1 Solution Representation and Chromosome Decoding

Every feasible route plan is encoded into a chromosome, which is a permutation of customers and depots. Using a two-step decoding algorithm based on Split Algorithm [3], each chromosome can be decomposed into depot routes and vehicle routes: the former denotes a sequence of customers served by a depot, while the latter defines a sequence of customers served by a vehicle. The two-step decoding algorithm is described in Algorithm 1.

Algorithm 1 Two-step decoding method

1: Break the chromosome into $m + 1$ slices from the locations of depot nodes
2: Assign the first m-1 slices to the first m-1 depots in sequence, and the combination of the mth and $(m + 1)^{th}$ slices to m^{th} depot to construct depot routes
3: Apply a modified Split Algorithm that uses vehicle-specific capacities as constraints to split each depot route to several vehicle routes

Figure 3 demonstrates the conversion process where 0,1 are depots and the number in green dashed box is demand. The chromosome, [2,3,4,0,5,6,1,7,8,9], is divided into two depot routes: [2,3,4] for depot 0 and [5,6,7,8,9] for depot 1. The latter is then split into [5,6],[7],[8,9] for three vehicles.

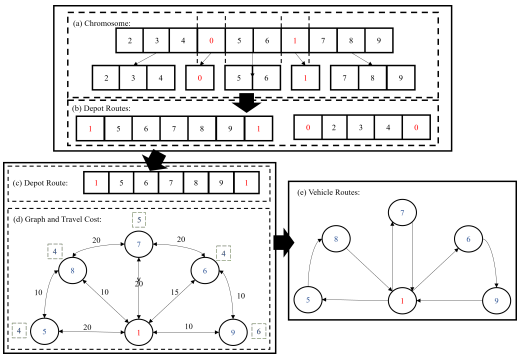


Figure 3: Simple decoding example

4.2 Initialization

The population is initialized through either a random permutation or the Nearest Neighbourhood Search (NNS) heuristic as in Algorithm 2. A parameter r_{NNS} denotes the probability of individuals to be generated from the latter method.

4.3 Genetic Operations and Education

During each iteration, a chromosome (i.e., individual) can be modified by any of the following mutation mechanisms: swap, insertion and inversion. Swap randomly changes two genes, insertion randomly selects a gene and moves to a randomly selected location in the chromosome, and inversion reverses the sequence of genes between two randomly selected bounds. A two-point crossover mechanism further combines the solutions of two randomly selected chromosomes in the population.

Algorithm 2 Initialization

function INIT(r_{NNS},n) ▷ n is population size
  for $i \leftarrow 1$ to $n * (1 - r_{NNS})$ **do**
    randomly generate an individual
  end for
  for $j \leftarrow 1$ to $n * r_{NNS}$ **do**
    assign customers to the nearest depot
    do NNS with randomly selected start for each depot route
  end for
  return population
end function

In addition to mutation and crossover, our algorithm employs a simplified 2-opt heuristic in the education stage to further improve the quality of solutions. Differing from the original 2-opt heuristic which checks all possible combinations until no improvement is made [5], this one only performs a single pass through the chromosome. Its important to note that all the individuals created from mutation, crossover and education are treated as offspring and added into population without affecting origin individuals.

4.4 Selection and Termination

The fitness of an individual is evaluated by the utility function (1). After each iteration. all the individuals are sorted and individuals with the lowest fitness are eliminated until the current population size equals the initial population size.

5 EXPERIMENTAL RESULTS

This section presents the results obtained from the methodology described in Sections 3 and 4. The H-GA above is coded in Python 3.9 and executed in a PC with Intel(R) Core(TM) i7-9750H CPU@2.60GHz processor and 16 GB RAM.

5.1 Algorithm Validation

The H-GA algorithm is first tested using Solomon's benchmark scenarios. These are a series of well-known VRPTW instances that have been used in the literature to compare the performance of several algorithms [21, 46]. We solve three scenarios with 100 customers and one depot: one where customers are randomly arranged (R101), another with clustered customers (C101), and a mixed scenario where customers are distributed using both patterns (RC101). Table 1 compares the results (optimised travel costs) found by our H-GA (50 samples) and the best-known solutions collected by [43]. Table 1 also reports the number of customers not served in given time slots, which is denoted by TW Violation, as well as their standard deviations. These results show that our HGA performs well in the clustered pattern and slightly less so in the random pattern, due to our simple mutation and deterministic selection. Nonetheless, our case study follows a similar pattern to the C101 instance, as customers are generated only within residential areas.

Table 1: Validation results of H-GA

Benchmark Instances	R101	C101	RC101
Benchmark Results (travel cost)	1650.80	828.94	1696.95
H-GA Results (travel cost)	1628.85	839.24	1873.03
H-GA Standard Deviation	212.07	19.37	138.96
TW Violation	62.00	4.00	19.67
TW-Violation Standard Deviation	3.18	1.80	2.02

Table 2: Calibrated parameters

Para.	Value	Para.	Value	Para.	Value
β_q	2	β_v	22	β_{TT}	10.25
β_{IT}	10.25	β_{DT}	10.25	β_{OT}	21.25
α_f	0.715	β_f	2.480	α_p	0.683
β_p	2.890	r_{NNS}	0.5	r_m	0.8
r_c	0.6	r_e	0.8		

5.2 Case Study Design

We develop a case study based on the implementation of last-mile delivery of e-commerce in central London where customers order goods from online platforms and the commodities are delivered from local depots to their homes within given time slots. Every company operates its own local depots and aims to maximise its profits by expanding orders, reducing operation costs, and improving service quality (e.g., reduce the delay of services).

The study area considered consists of three boroughs in central London —Hammersmith & Fulham (H&F), Kensington & Chelsea (K&C), and Westminster (W), as shown in Figure 1. The road network is obtained from Open Street Map (OSM) and filtered to remove roads inaccessible to delivery vehicles [1, 37]. A total of 11 service points assigned by 4 companies serve as local depots. For the purposes of this study, 5 vehicles of 100 parcel capacity are available at each depot, with each driver being able to work a maximum of 8 hours. Customers are randomly generated in residential areas, each with a demand of 10 parcels and a random time window between 9:00 AM to 18:00 PM. The service duration at each customer is configured at 5 minutes.

25 problem instances are designed to assess the range of PoA and its relationships with different factors. 15 instances are under relaxed time windows (i.e. without constraints (6.11)) with the customer number ranging from 10 to 150. 10 instances are under tight time windows (i.e. with constraints (6.11)) with the customer number ranging from 10 to 100.

5.3 Model Calibration

The parameters of the utility function, cost function, latency function and H-GA are calibrated based on real-word data or realistic assumptions.

(1) Utility/Cost Function

As it is not possible to calibrate the coefficients in the cost and utility function using real route plans (this data is proprietary), the values of these coefficients are configured based on available information. The values are summarized in Table 2 and justified as follows.

- Q: According to Royal Mail annual report [30], the volume of UK parcels delivered in 2021 is 1,735 million while the annual revenue from UK parcels is 3,518 million. Therefore, the coefficient β_q is set to £2 per parcel.
- V: A vehicle costs £8,056 per year to operate on average if the cost of acquisition is excluded [44]. Therefore, the coefficient β_v quantifying the unit cost of vehicle operations is assumed £22 per day per vehicle.
- TT, IT: The largest component associated with driving time is the labour salary. Therefore, β_{TT} and β_{IT} are set as the average salary for a delivery driver in London, which is £10.25 per hour [22].
- DT: The unit cost associated with delay of service is highly subjective. In experiments, £11 per hour, which is approximately the average hourly pay in London [42], is adopted.
- OT: To impose the penalty on overtime, the coefficient of OT is set to the sum of β_{TT} and β_{IT}.

(2) Latency Function

Based on real-road data, α_f, β_f, α_p and β_p are set to 0.715, 2.480, 0.683, 2.890 respectively as given by [11]. The static travel time $t_a(0)$, capacity C_a and passenger (exogenous) traffic flow v_a^p are calculated and imputed as follows.

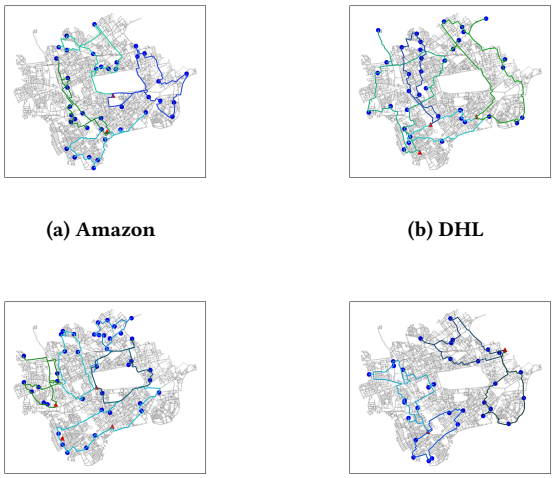
- $t_a(0)$: It equals to the ratio of link length over free-flow speed. The free-flow speed is approximated and replaced by the maximum speed provided from OSM [37]. For the cases where the value of the maximum speed is not provided, a typical value of 38km/h for central urban roads in London is used instead as recommended by [14].
- C_a: The maximum realistic value of capacity per lane for central urban roads in London is 800 veh/h/lane [14]. Therefore, the capacity of each link is calculated by the production of this value and the number of carriageways of that link which is provided by OSM [37]. If no value is provided, a single lane is assumed as a default.
- v_a^p: Traffic flow in Passenger Car Equivalent, which is 40% of link capacity, is loaded on the network to simulate the effect of exogenous traffic.

(3) H-GA

The values of parameters are determined by manual parameter tuning. To balance the diversity and quality, r_{NNS} is set to 0.5. Mutation rate r_m, crossover rate r_c and education rate r_e are tested from 0.2 to 0.8 with step 0.2. Given the average performance (10 runs), the process yields a r_m,r_c and r_e of 0.8, 0.6, 0.8 respectively. The population is of 100 size and with 4 sub-populations.

5.4 Results

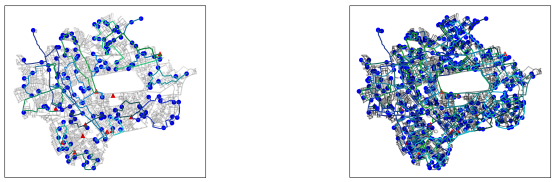
Figures 4 and 5 show the decentralised and centralised route plans for the instance with 150 customers and relaxed time windows, which is taken as an example for illustration. The utilities, costs and corresponding PoA are summarized in Table 3 where MD and MD-TW indicate whether time windows are relaxed or tight, respectively.



(a) Amazon (b) DHL

(c) DPD (d) Royal Mail

Figure 4: Decentralised route plans of four companies (MD150)



(a) Centralised (b) Decentralised

Figure 5: Centralised and decentralised route plans (MD150)

As shown in Figure 6, with the increase of the scale of the problem, the value of PoA stabilises between 1.05 and 1.50. One can also see that when the customer number is less than 50, the efficiency degradation of instances with tight time windows is significantly larger than that of instances with relaxed time windows. This part of inefficiency will not be captured by the purely travel-cost-based efficiency measurement.

Figure 7 plots the absolute gaps of performance indicators between two scenarios, which are the differences between the terms in equation (1) and (2). The results suggest that:

- On average, the major resource that undermines the degree of efficiency is vehicle operations. However, this effect declines as the number of customers increases.
- The contributions from overtime and travel time due to congestion are not significant within the scale of our experiments.
- With the increase of problem scale, the effect of the travel cost on the overall efficiency becomes more significant.
- Idle time also accounts for a significant part of inefficiency. Sometimes it mainly comes from early arrivals, which can be alleviated by a collaborative routing plan. However, limited by this delivery pattern, when major is from waiting for the customer to pick up, it is not avoidable. One possible solution is to adopt the other delivery patterns, such as self-collection.

Table 3: Estimated results for all problem instances. MD - Relaxed Time Window Instances. MDTW - Tight Time Windows Instances.

Instance	$C(R_d)$	$C(R_c)$	$U(R_d)$	$U(R_c)$	PoA_U	PoA_C
MD10	130.08	53.84	69.92	146.16	2.09	2.42
MD20	157.76	98.55	242.24	301.45	1.24	1.60
MD30	183.50	144.71	416.50	455.29	1.09	1.27
MD40	231.04	190.87	568.96	609.13	1.07	1.21
MD50	323.82	234.30	676.18	765.70	1.13	1.38
MD60	348.01	277.20	851.99	922.80	1.08	1.26
MD70	398.25	322.49	1001.75	1077.51	1.08	1.23
MD80	440.70	386.71	1159.30	1213.29	1.05	1.14
MD90	489.50	430.15	1310.50	1369.85	1.05	1.14
MD100	524.46	472.35	1475.54	1527.65	1.04	1.11
MD110	559.12	517.05	1640.88	1682.95	1.03	1.08
MD120	624.01	558.89	1775.99	1841.11	1.04	1.12
MD130	644.35	600.62	1955.65	1999.38	1.02	1.07
MD140	724.86	673.06	2075.14	2126.94	1.02	1.08
MD150	765.48	685.96	2234.52	2314.04	1.04	1.12
MDTW10	165.94	81.42	34.06	118.58	3.48	2.04
MDTW20	296.12	124.68	103.88	275.32	2.65	2.38
MDTW30	339.89	157.51	260.11	442.49	1.70	2.16
MDTW40	423.13	236.91	376.87	563.09	1.49	1.79
MDTW50	417.29	268.70	582.71	731.30	1.25	1.55
MDTW60	453.05	330.23	746.95	869.77	1.16	1.37
MDTW70	515.23	417.18	884.77	982.82	1.11	1.24
MDTW80	549.28	481.58	1050.72	1118.42	1.06	1.14
MDTW90	611.77	476.74	1188.23	1323.26	1.11	1.28
MDTW100	641.37	536.71	1358.63	1463.29	1.08	1.19

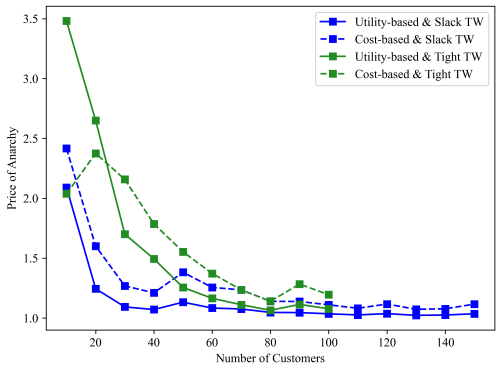


Figure 6: The values of PoA under different problem sizes.

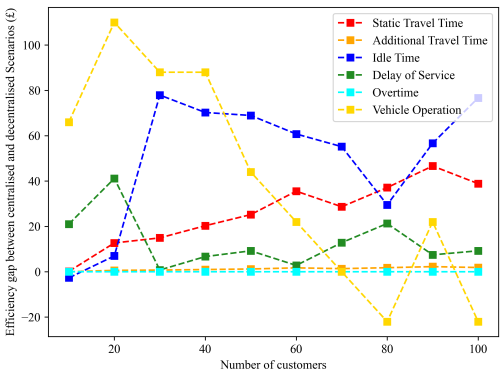


Figure 7: Absolute cost gaps between the worst and optimal cases.

6 DISCUSSION

Our results with relaxed time windows are consistent with prior observations that collaborative routing could result in a substantial reduction of travel cost [6, 28]. When the time windows are considered, this reduction of travel cost decreases and is compensated by the reduction of vehicle operation cost and delay of service. Nonetheless, the reduction rate of generalised cost is still considerable for instances with less than 100 customers. Although the PoA stabilises in instances with over 100 customers, its value is highly sensitive to the coefficients and therefore, is more meaningful in comparison analysis.

Our case study also shows that congestion travel time is the lowest contributing cost factor. This, however, can be attributed to several assumptions and case study design decisions. There are over 3.2 billion LGVs in traffic in London every year in 2021: i.e. over 34,000 LGVs every hour in three boroughs [18]. However, to control the complexity of VRP and get robust estimation, our experiment only considers 5 vehicles each depot, which means a maximum of 55 freight vehicles on the road. Furthermore, in our study, 10 parcels are aggregated in one stop point and couriers can only do a maximum of 10 stops in 8 hours. This deviates from the fact that a real-life courier could have 200 parcels to deliver per day and 1-2 parcels per stop [34], and could amplify the effect of idle time. Moreover, the traffic in the inner city involves large temporal and spatial fluctuations and could be highly congested. Given the flow-delay relationship (5), the increase of exogenous flow will exacerbate the congestion effect resulted from the freight traffic flow. This challenges our assumption of uniformly loaded passenger traffic. Nonetheless, our study provides a complete framework that can be easily generalised to a larger scale by reducing the time span and increasing customer size. Further work is required to develop large case studies of sufficient size and various exogenous traffic conditions, which represent reality more faithfully.

Our formulation assumes a limitless sharing of resources and customer orders, which idealises the optimal cases. In reality, companies are not willing to share all their orders and even try to occupy the market share of other companies [47]. This means that the efficiency of the routing operation would worsen if unregulated. In this case, it is expected to regulate and promote the coordination by government-mandated actions, which can maintain a more sufficient competition by avoiding the monopolization of a platform (e.g., Amazon) and prompt the integration of resources from the urban planning level (e.g., Urban Consolidation Centres)

The deployment of incoming technologies, such as drones and autonomous vehicles (AVs), could further affect the PoA. E.g., drone-delivery can mitigate the congestion externalities by avoiding traditional traffic networks. The lead time will also decrease by virtue of its high velocity. Similarly, AVs can alleviate the congestion through real-time responses to traffic conditions and reduce the emission of pollutants and carbon by electrification. The existence of these new devices needs to be incorporated in future work and our framework could serve as a basis of their effectiveness assessment.

7 CONCLUSION

In this study, a framework based on the MDVRP-TWCN for evaluating the degree of inefficiency in urban last-mile delivery is proposed. Furthermore, a parallel hybrid genetic algorithm is designed for solving the problem instances, which is validated using several well-known benchmarks. Finally, several elaborated experiments are conducted. The results suggest that: (1) Efficiency estimated is highly dependent on the parameters in utility/cost function; (2) When the number of customers is small, the degradation of efficiency is larger and stabilises with larger problem instances; (3) The static travel time, which is determined by exogenous traffic flow, accounts for a considerable part of the degradation of inefficiency; (4) The presence of time windows could significantly worsen the efficiency, and therefore, cannot be ignored during policy making.

On the other hand, there are still limitations needed to be addressed in future work: (1) The VRP-based formulation introduces significant computational complexities to overcome when modelling large fleets of vehicles; (2) This study assumes the allocation of orders is predetermined, which simplifies the interaction between companies and customers, and future studies can employ an auction mechanism to carry out the order assignment; (3) Due to the lack of realistic route plan data, the utility function and cost function are calibrated manually based on the fragmented information. This limits the generalisation of the results of our experiments because the value of coefficients has a great impact on the range of value of the estimated PoA.

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