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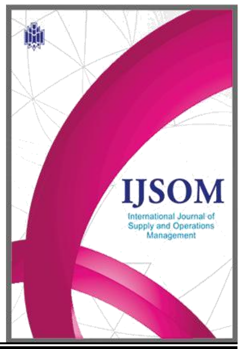

Economic and Ecological Optimization of the London Urban Logistics System Considering Infection Risk during Pandemic Periods

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Abstract

Urban delivery, especially the last-mile delivery, has become an increasingly important area in the global supply chain along with the boom of e-commerce. Delivery companies and merchants can introduce some innovative solutions such as the equipment of autonomous vehicles (AVs) to decrease their operating costs, environmental impact, and social risks during the delivery process. This paper mainly develops a mathematical model to get the best allocation of AVs among city logistics centers (CLCs) as a mixed delivery method. The advantage of the presented model stems from considering the equipment cost, the delivery cost, and the CO_2 emission, which is measured through social carbon cost (SCC). In addition, this paper establishes a risk model considering the impact of seasonal variations to evaluate the infection risk of delivery during pandemic periods for four potential delivery scenarios: customers going to CLCs, ordering online and picking-up at CLCs, delivering by traditional vehicles (TVs), and delivering by the mixed method with the optimal allocation of AVs. The research finds the optimal allocation for a London case, reveals the relationship between the nominal service capacity (NCpa) of CLCs and the optimal number of CLCs equipped with AVs, concludes that the more CLCs are equipped with AVs, the fewer CO_2 emissions and the fewer citizens will be infected, and provides some managerial insights that may help delivery companies and merchants make appropriate decisions about the allocation of AVs.

Keywords: Urban logistics; Cost optimization; CO_2 emission; Infection risk; Net Present value.

1. Introduction

In recent years, the rise of e-commerce has led to a super urban delivery market (Akeb et al., 2018) and an increasing number of logistics service providers (LSPs) who compete over market shares and customer satisfaction (Scherr et al., 2019). Although the development of urban logistics has promoted the prosperity of the world economy, the increasing transportation contributes a lot to greenhouse gas (GHG) emissions (Li et al., 2019). Reducing GHG pollutions, especially CO_2 emissions, is one main challenge face by businesses today to improve economic sustainability (Guerrero et al., 2013). Moreover, there has been an increasing social concern on environmental protection not only among environmental advocacy groups and policymakers but also among enterprises who have begun to consider ecological issues parallel to their economic performance (Abbasi and Nilsson, 2016; Rao et al., 2015). Therefore, LSPs are under pressure to decrease their delivery cost (Palak et al. 2014) and to reduce the impact on the environment (Savelsbergh and Van Woensel, 2016). Furthermore, minimizing the infection risk of both customers and staff is a growing challenge that LSPs are facing in encountering an epidemic situation such as the Coronavirus 2019 (COVID-19) pandemic. This challenge has become an international public health issue because the outbreak of COVID-19 has affected worldwide people and has evoked their vigilance against the infection risk in their daily logistics activities, especially when they contact unfamiliar individuals such as those that they meet during the process of delivering or receiving parcels (Elavarasan and Pugazhendhi, 2020).

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To meet these economic, environmental, and risk-mitigation targets, many LSPs are considering to implement innovative delivery options, such as using autonomous vehicles (AVs) for parcel delivery. Fraedricha (2019) defines delivery AVs as a kind of self-driving vehicle, which can be used by LSPs for goods deliveries to customers' home or to parcel-collection boxes. Masoud and Jayakrishnanb (2017) predicted that AVs would be widely used in the near future because they have considerable advantages conducive to alleviating traffic congestion, improving traffic efficiency and safety, reducing GHG emission, and saving energies (Vahidia and Sciarretta, 2018; Fagnant and Kockelman, 2015; Zhu and Ukkusuri, 2015). Besides, Elavarasan and Pugazhendhi (2020) proposed that new technologies such as delivery robots or AVs can help a lot in mitigating infection and in controlling the situation like the COVID-19 pandemic.

Emerging technologies in smart sensors and communication are making the use of AVs possible in recent years (Wu et al. 2020; Brummelen et al. 2018). And, practically, there has been an increasing worldwide interest in developing robots/vehicles for delivery to increase the efficiency and safety of the whole supply chain. Hoffmann and Prause (2018) stated that Estonia played a leading role in this field with its start-up, Starship Technologies, which focuses on providing a promising solution to solve the last-mile delivery problem. In September 2016, the start-up announced a strategic partnership with Mercedes-Benz Vans, a German truck producer, to develop the 'Robovans' – a truck-based autonomous-robots model for delivery. This model, indeed, realizes the 'hub and spoke' concept – a well-known standard model in logistics – and creates a smart solution for bridging longer distances of delivery. Besides, Xia and Yang (2018) revealed that China was also an important player in the area of autonomous delivery robots, as the largest e-commerce platform by revenue, JD.com, conducted its first trial in autonomous driving vehicles for last-mile delivery on June 18, 2017, at Renmin University, Beijing. The vehicle delivered about 10 packages in approximately six hours. JD subsequently deployed approximately 60 autonomous driving vehicles for last-mile delivery at Beijing, Xian, and Hangzhou for pilot AI-based package delivery. Moreover, a Stanford research conducted by Lee et al. (2016) mentioned that other leading companies developing delivery robots included SideWalk, which has already conducted pilot projects with DHL in Lithuania, and Dispatch, which was formed by MIT and University of Pennsylvania experts. Furthermore, countries like China and India have implemented robots or AVs to deliver foods and medicines in their healthcare supply chain systems to mitigate the infection risk of the COVID-19 epidemic (Elavarasan and Pugazhendhi, 2020).

Scherr et al. (2019) concluded that whether the use of AVs can cause savings to LSPs depends on their costs relative to TVs. Although, theoretically, AVs have advantages such as lower GHG emissions and the higher degree of safety, the weakness of AVs derives from their apparent inability to completely substitute manned vehicles and from their significantly high manufacturing cost primarily resultant from the added cost of various sensors they need to be equipped with (Duarte and Ratti, 2018; Masoud and Jayakrishnanb, 2017). These problems can be solved along with technical development in the future. With the widespread use of AVs for delivery, customers will gradually accept this model because they will be increasingly impressed with the high efficiency and low risk of AVs rather than with the mechanical and indifferent interactions with these robots. Burn (2013) predicted that the AVs will be widely used for logistics activities and will greatly change the transportation systems in the future.

City Logistics Centers (CLCs) are an essential part of the modern urban logistics system, and the selection of the location of a CLC has become a critical challenge in logistics and supply chain management (Rao et al., 2015). This paper, aiming at finding the optimal allocation of a mixed delivery fleet including both AVs and TVs, highlights a research perspective of urban logistics that is very different from the traditional perspectives of scholars who focus on comparing the economic or environmental impacts of only using AVs with those of only using TVs. In this study, the main objectives are to optimize the allocation of delivery vehicles among all CLCs in terms of the total cost and environmental impact and to evaluate the advantage of AVs in reducing infection risk during pandemic periods.

This paper, for the first time, mainly develops an optimization model to get the best allocation of AVs among city logistics centers (CLCs) as a mixed delivery method. The advantage of the presented model stems from considering the equipment cost, the delivery cost, and the CO2 emission, which is measured through social carbon cost (SCC). In addition, this paper creatively establishes a risk model considering the impact of seasonal variations to evaluate the infection risk of delivery during pandemic periods for four potential delivery scenarios: customers going to CLCs, ordering online and picking-up at CLCs, delivering by traditional vehicles (TVs), and delivering by the mixed method with the optimal allocation of AVs. The research finds the optimal allocation for a London case, reveals the relationship between the nominal service capacity (NCpa) of CLCs and the optimal number of CLCs equipped with AVs, concludes that the more CLCs are equipped with AVs, the fewer CO2 emissions and the fewer citizens will be infected, and provides some managerial insights that may help delivery companies and merchants make appropriate decisions about the allocation of AVs.

This research develops in the following outline. It first briefly introduces the background of the autonomous vehicles used in urban logistics and lists the research objectives. Following that, the literature-review section presents the current research achievements about autonomous delivery vehicles and the urban-logistics optimization considering delivery cost, pollution, and social risk. In light of these previous studies, the paper then moves into the proposed mathematical model to design a logistics network equipped by autonomous vehicles with measuring the total infection risk. The results are summarized and analyzed in the 'results and analysis' section. Then the following 'discussions and managerial implications' section discusses the key findings and proposes some business suggestions from a practical perspective. Finally, the conclusion section reviews the whole study and discusses the implication of the findings to future research in the area of urban logistics.

2. Literature review

The rapid urbanization and the development of e-commerce stimulate the social demand for an efficient transportation and logistics system (Çolak et al., 2016). However, this demand is increasingly difficult to be satisfied due to the growing urban problems such as congestion and pollution (Batty, 2008; Bettencourt, 2013). Therefore, in recent years, scholars in logistics and transportation areas have focused a great deal of attention on evaluating the advantages and impacts of using autonomous vehicles (AVs) for urban logistics in more detail by taking account of three aspects: economy, environment, and society (Mohammed et al. 2017; Chanchaichujit 2016).

Decreasing the environmental burden while minimizing total cost is a critical objective of logistics managers and relative scholars (Sherafati et al., 2020). Guerrero et al. (2013) proposed a Trucking Sector Optimization (TSO) model to evaluate the impact of different decisions made by truck operators on life-cycle GHG emissions. This model simulates the transitional dynamics of the truck-delivery industry in responses to changes in the business environment and time-dependent governmental interventions, and these scholars analyzed the optimal decisions considering the change of policies, GHG emissions, and the costs usually observed in this industry, such as fuel cost, capital cost, human-resource cost. Some other scholars also built this kind of optimization model to evaluate the different decisions about vehicle fleets considering environmental issues, especially GHG emissions. For instance, Figliozzi et al. (2011) used an integer program to find the optimal composition of the personal vehicle fleet that minimizes the total cost that includes the cost of GHG emissions. Similarly, Stasko and Gao (2010) used an integer programming model to determine the optimal management of a bus fleet. They held that bus operating companies should equip buses with more energy-efficient propulsion technologies to satisfy governmental regulations. Furthermore, some studies considered the properties of both cost and time efficiency of the logistics system. The time efficiency mainly refers to minimize total time or distance from CLCs to customers. Wong et al. (2018) proposed a comprehensive carbon-driven multi-criteria truckload utilization model to optimize the loading of consolidated cargos from multiple customers with different sizes, weights, and destinations into a fleet of trucks with minimum distance, GHG emissions, and fuel consumption. Their results show that the model can be used to improve the operational efficiencies and minimize the carbon emitted from trucks. Other scholars, instead of only considering the properties of vehicles, aimed to optimize the number, location, and capability of logistics centers such as CLCs. Alho et al. (2018) focused on parking optimization to improve mobility by optimizing the location, number, and usage of loading/unloading bays for urban freight vehicles. Besides, Tsao and Thanh (2019) developed a multi-objective mixed robust possibilistic flexible programming (MOMRPFP) approach to optimize the design of a sustainable dry port network. Their results show that the total network cost and CO_2 emissions will greatly decrease by optimization.

Different form scholars such as Chabot et al. (2018) who developed optimization models to minimize the costs and GHG pollutions based on current manned vehicles, some scholars have begun to study the advantages of AVs. Wu et al. (2020) modeled a mixed traffic network with non-autonomous streets and special expressways for AVs to achieve the system optimum, considering user cost, travel time, and travel distance. Feng (2021) studied the time and cost efficiency of AVs based on a case study at Coventry city in UK. He concluded that using AVs will improve the time efficiency and the long-term cost efficiency. Masoud and Jayakrishnan (2017) proposed an optimization model for AVs to minimize total travel time and concluded that a central shared AVs service provider could achieve the highest environmental benefits. The shared AVs model is also analyzed by Lokhandwala and Cai (2020), who found that shared AVs generated by electricity can greatly reduce daily CO_2 emission. Besides, Lopez et al. (2020) demonstrated that using shared AVs can have lower costs than using privately-driven cars.

It is also necessary to study the influence of using delivery AVs from a social perspective. Wang and Zhao (2019) evaluated the risk preference of adopting AVs among different socioeconomic groups considering two kinds of social risks – economic risk and psychometric risk. Considering the infection risk during pandemic periods such as the worldwide pandemic COVID-19, Elavarasan and Pugazhendhi (2020) proposed a hospital supply chain system integrating AVs for the distribution of products to mitigate the infection risk. They held that technologies such as Artificial Intelligence (AI), Internet of things (IoT), AVs, and drones could help the whole society to control epidemic situations.

Table 1. A summarized comparison of previous studies on urban logistics optimization considering delivery cost, pollution, and social risk

Reference	Optimal model	Using AVs	Time efficiency	Equipment cost	Delivery cost	CO_2 emission	Pandemic situation	Delivery type
Chabot et al. (2018)	✓				✓	✓		Intercity
Masoud and Jayakrishnanb (2017)	✓	✓	✓					General
Wu et al. (2020)		✓	✓		✓			Intercity
Scherr et al. (2019)	✓	✓	✓	✓	✓			Urban
Guerrero et al. (2013)	✓			✓	✓	✓		Intercity
Tsao and Thanh (2019)	✓			✓	✓	✓		Seaport
Lokhandwala and Cai (2020)		✓				✓		City travels
Lopez et al. (2020)		✓		✓	✓	✓		General
Anderhofstadt and Spinler (2020)		✓	✓	✓	✓	✓		Intercity
Alho et al. (2018)	✓		✓		✓			Urban
Wong et al. (2018)	✓		✓		✓	✓		Intercity
Govindan et al. (2020)							✓	Healthcare
Elavarasan and Pugazhendhi (2020)		✓					✓	Healthcare
Feng (2021)		✓	✓	✓	✓		✓	Last-mile
This research	✓	✓		✓	✓	✓	✓	Urban

Table.1 summarizes the previous related studies and the comparison with this research. This research is devoted to filling the following three research gaps that can be extracted from Table.1.

The first research gap lies in the insufficient study of the advantage of AVs used in urban logistics activities through quantitative comparison with traditional vehicles (TVs). Although most scholars, such as Masoud and Jayakrishnanb (2017); Wu et al. (2020); Lokhandwala and Cai (2020); Lopez et al. (2020); Wang and Zhao (2019), studied the advantage of AVs for general transportation, few of them considered using AVs for urban logistics activities. To our knowledge, only Anderhofstadt and Spinler (2020) revealed that freight companies are generally open to switching to innovative trucks including AVs because these vehicles will lead to fewer costs and GHG emissions, by conducting a qualitative choice-based conjoint (CBC) analysis be questioning employees from freight companies in Germany.

The second research gap is that few scholars consider the total economic and environmental impact of a mixed delivery fleet of AVs and TVs. Only Scherr et al. (2019) proposed a service network with a mixed delivery fleet of AVs and TVs without considering the ecological impacts. The fact that many previous studies considered the AVs only a kind of innovative tool that could totally substitute TVs, a practice that overlooked the advantages of TVs especially for CLCs with low delivery frequencies and few customers and for those in developing countries where the traditional delivery cost is low, led to a de-emphasizing of the role of TVs in a mixed delivery fleet that is more available and efficient in the near future.

The third research gap is the lack of study on the relationship between delivery AVs and the infection risk. Although scholars such as Elavarasan and Pugazhendhi (2020) proposed that hospitals can use new technologies such as AVs for the distribution of foods and medicines to mitigate infection risk, there is a lack of research about the relationship between using AVs for urban delivery activities, instead of the supply chain inside hospitals, and the infection risk during long-term pandemic periods such as the COVID 19 broke out at the beginning of 2020, a risk that worldwide people are worried about because of the tremendous lasting effect caused by this contagion (Govindan et al. 2020).

For filling these three defined research gaps, this research proposed a mathematical model to optimize the allocation of AVs and TVs among the CLCs owned by one LSP by minimizing the total cost of equipment cost, delivery cost, and social cost of CO2 emissions. Besides, this research evaluates the infection risk of the optimal allocation and compares it with the risk under the other three common logistics patterns.

3. Problem description and assumptions

In this section, two mathematical models are proposed. The first model focusses on total discounted cost (TDC), the sum of three main costs: namely, the total cost of equipment (TCE), the total accumulated discounted cost of delivery (TDCD), and the total discounted social cost of CO_2 pollution (TDCP). One objective of this research is to find the optimal allocation of AVs and TVs, the allocation through which the total cost is minimum, among all CLCs under certain nominal/maximum service capacity (NCpa) of these CLCs.

The second risk model is proposed for another research objective – evaluating the infection risks, during pandemic periods, of potential urban logistics activities categorized into four patterns, as shown in Fig.1. The optimal allocation in the first pattern is that under the most reasonable NCpa value defined in the first model.

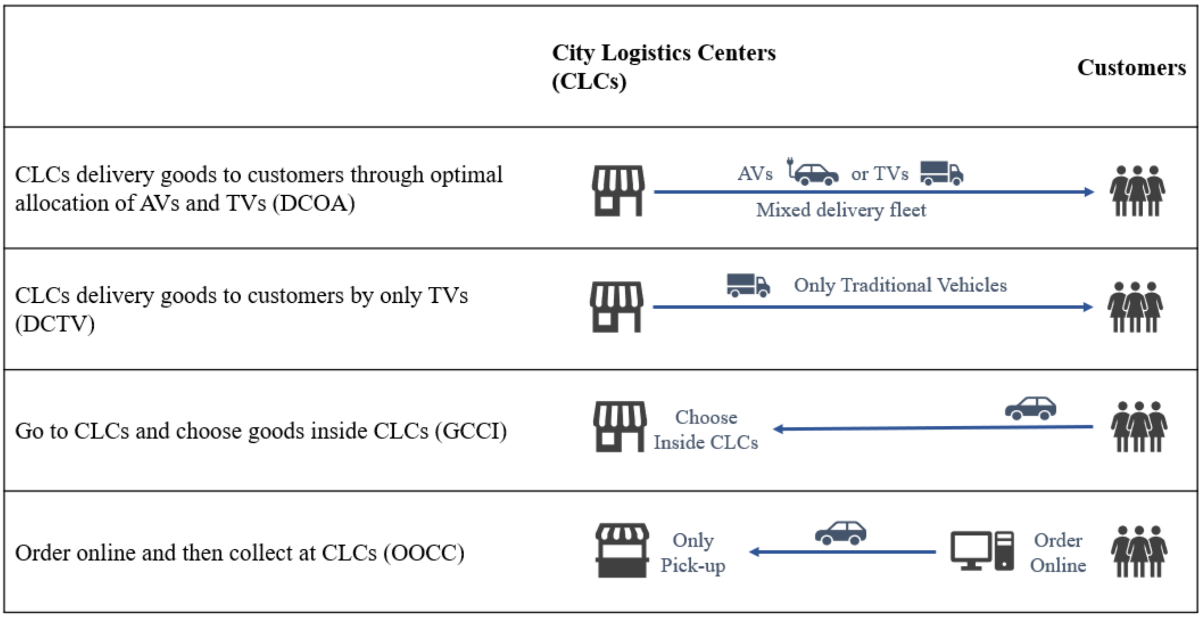

Figure1. An illustration of four potential patterns of logistics between CLCs and customers

In this research, the optimization model integrates the objectives of minimizing both the economic costs and the environmental impact. The economic costs include TCE, which is incurred due to initial investment on vehicles, and TDCD, which is the accumulated discounted value of all the delivery costs during the service life of these vehicles. The environmental impact, which refers to CO_2 pollution in this research, is usually measured in tons of emission. In this research, the CO_2 emissions are multiplied by the trade price of CO_2, and the results represent the social cost of carbon (SCC). In this way, the accumulated CO_2 pollution is represented as a kind of cost that can be added directly with the economic expenses. The concept of SCC is prevalently used to measure environment costs among scholars such as Hänsel and Quaas (2018); Hepburn (2017); Ricke et al. (2018).

Another advantage of the optimization model is that it uses the discounted cash flow (DCF) method to reflect the time value of money. This method, discounting each cost that will happen in the future to the initial time of equipment, makes it more reasonable and acceptable to add the delivery costs and pollution costs incurred in different years and the initial TCE together.

In the infection risk model, the infection risk is evaluated by the accumulated infected population (AIP), which depends on the probability of being infected for any individual when a customer meets another person within a certain society (IP_w^*). The calculation of AIP is based on the assumption made by Kissler et al. (2020) that the pandemic period will last in the long term. The accumulated infected risk, represented as the accumulated probability of being infected, cannot be directly calculated through the continued product of the infected probability/risk per week, because people who have the risk of being infected in one week are not those already infected in any previous weeks, but those survivors uninfected in all previous weeks. In this research, the problem is solved by calculating the accumulated infected risk by one minus the continued product of the uninfected probability per week. Another merit of this model is that it considers the value of IP_w^* varies in any year due to seasonal variation in virus transmission. As suggested by Kissler et al. (2020), the risk or probability of being infected is assumed to be seasonal with a period of 52 weeks.

This research is based on the following main assumptions:

- Each CLC is equipped with the same number of only one kind of delivery vehicles – AVs or TVs.
- AVs and TVs are assumed to be homogenous with the same capacity.
- All AVs are energized by electricity, and for CLCs equipped with AVs, the main delivery cost is the energy cost.
- All TVs are energized by traditional fuel energy, and for CLCs equipped with TVs, the main delivery cost included fuel cost and driver-based cost.
- Each CLC serves at least one customer zone, and each customer zone is only served by one CLC.
- The impact of pandemic risk is in the long term.
- The discount rate is constant in the long term.

The following nomenclature collects all the abbreviations used in this paper and all the sets, parameters, and decision variables that are considered for the mathematical formulae and models.

Sets:

I	Set of CLCs, $i \in I$, N is the number of CLCs
J	Set of customer zones, $j \in J$, M is the number of customer zones
T	Set of periods (in years), $t \in T$, NT is the number of total years in this study
W	Set of periods (in weeks), $w \in W$, NW is the number of weeks

Parameters:

Cod_{Aij}	Per delivery cost from CLC i to customer zone j using autonomous vehicles.
Cod_{Tij}	Per delivery cost from CLC i to customer zone j using traditional vehicles.
Cop_{Aij}	Cost of CO2 pollution per delivery from CLC i to customer zone j using autonomous vehicles.
Cop_{Tij}	Cost of CO2 pollution per delivery from CLC i to customer zone j using traditional vehicles.
EC_{Ai}	Equipment cost of autonomous vehicles for CLC i.
EC_{Ti}	Equipment cost of traditional vans/vehicles for CLC i.
Pop_j	Population of customer zone j.
$NCpa$	Nominal capacity – maximum average population each CLC can serve.
d_{ij}	The distance (in km) from CLC i to customer zone j.
IP_w^*	Average probability of being infected for each customer when he or she meets one another person at week w.
nc	Number of people contacted by each customer per time whenever he or she goes to CLCs or is delivered.

Constants

Nd	Number of deliveries per year for each vehicle
Nv	Number of autonomous or traditional vehicles equipped by each CLC
$ACpa$	Actual capacity (actual average population that each CLC serves)
$price_A$	The unit price of each autonomous vehicle
$price_T$	The unit price of each traditional manned vehicle/van
$price_e$	Electricity price per kWh
$price_{CO2}$	Social cost of CO2 emission per ton
cpk_T	Delivery cost per km per traditional manned vehicle including fuel and diver costs
epk_A	Electricity consumption per km for autonomous vehicles
pl_T	CO2 emission/pollution per km for traditional manned vehicles/vans
pl_A	CO2 emission/pollution per km for autonomous vehicles
$TPop$	Total population of Great London including all customer zones
IP^*_{min}	Minimum probability of being infected for each customer when he or she meets one another person
IP^*_{max}	Maximum probability of being infected for each customer when he or she meets one another person
f	Average frequency of going to CLCs or being delivered for each customer per week

Integer decision variables:

k	The number of CLCs equipped with autonomous vehicles (TAAV)
nc	Number of people contacted by each customer per time whenever he or she goes to CLCs or is delivered (0 for using autonomous vehicles, 1 for delivering by traditional manned vans, 20 for normal shopping, and 5 for ordering online and picking-up)

Binary decision variables:

X_{ij}	1 if autonomous vehicles are used for delivery from CLC i to customer zone j, otherwise 0.
Y_i	1 if CLC i is only equipped with autonomous vehicles, 0 if CLC i is only equipped with traditional manned vehicles/vans
Z_{ij}	1 if traditional manned vehicles are used for delivery from CLC i to customer zone j, otherwise 0.

3.1 Total cost optimization model
3.1.1 NPV (Net Present Value) Method

Net present value is calculated as the sum of the initial cost (CF_0) and all the future discounted annual cash flows over a period (Brealey et al., 2010) and is an important indicator of investment (Gilchrist and Himmelberg, 1995).

$$NPV_{cost} = CF_0 + \sum_{t=1}^{NT} \frac{CF_{out}}{(1+r)^t} \tag{1}$$

As defined in Eqs. (1), this research focuses on the NPV of the total cost, and, therefore, the annual cashflow only includes annual cash outflow (CF_{out}), i.e., the annual cost.

$$CF_0 = \sum_{i=1}^{N} EC_{Ai} \times Y_i + \sum_{i=1}^{N} EC_{Ti} \times (1 - Y_i) \tag{2}$$

where

$$EC_{Ai} = Nv \times price_A \tag{3}$$

$$EC_{Ti} = Nv \times price_T \tag{4}$$

$$CF_{out} = \sum_{i=1}^{N}\sum_{j=1}^{M}\left(Cod_{Aij} + Cop_{Aij}\right) \times Nd \times Nv \times X_{ij} + \sum_{i=1}^{N}\sum_{j=1}^{M}\left(Cod_{Tij} + Cop_{Tij}\right) \times Nd \times Nv \times Z_{ij} \quad (5)$$

where

$$Cod_{Aij} = d_{ij} \times epk_A \times price_e \quad (6)$$

$$Cod_{Tij} = d_{ij} \times cpk_T \quad (7)$$

$$Cop_{Aij} = d_{ij} \times pl_A \times price_{CO2} \quad (8)$$

$$Cop_{Tij} = d_{ij} \times pl_T \times price_{CO2} \quad (9)$$

In this paper, the NPV of cost is an important indicator for LSPs, such as delivery companies and merchants, which own some CLCs equipped with delivery vehicles and aim at minimizing their NPV of cost through optimizing the allocation of service zones and delivery methods – AVs or TVs – for each CLC. For these LSPs, this research assumes that CF_0 is only comprised of the equipment cost of delivery vehicles, as defined by Eqs. (2)-(4), and that the annual CF_{out} in future years only includes the delivery cost and social cost of CO_2 emission, as defined by Eqs. (5)-(9). CF_0 and the accumulated discounted CF_{out} together comprise the total cost to these LSPs. The objective of this research is to minimize the NPV of the total cost.

3.1.2 Total cost optimization model

$$\begin{aligned} Minimize\ NPV_{cost} &= \sum_{i=1}^{N} EC_{Ai} \times Y_i + \sum_{i=1}^{N} EC_{Ti} \times (1 - Y_i) \\ &+ \sum_{t=1}^{NT}\sum_{i=1}^{N}\sum_{j=1}^{M} \frac{\left(Cod_{Aij} + Cop_{Aij}\right) \times Nd \times Nv \times X_{ij}}{(1+r)^t} \\ &+ \sum_{t=1}^{NT}\sum_{i=1}^{N}\sum_{j=1}^{M} \frac{\left(Cod_{Tij} + Cop_{Tij}\right) \times Nd \times Nv \times Z_{ij}}{(1+r)^t} \end{aligned} \quad (10)$$

Constraints:

$$\sum_{i=1}^{N} Y_i = k \quad (11)$$

$$\sum_{i=1}^{N} X_{ij} + \sum_{i=1}^{N} Z_{ij} = 1, \forall\, j = 1, \dots, M \quad (12)$$

$$\sum_{j=1}^{M} X_{ij} \le M \times Y_i, \forall\, i = 1, \dots, N \quad (13)$$

$$\sum_{j=1}^{M} Z_{ij} \le M \times (1 - Y_i), \forall\, i = 1, \dots, N \quad (14)$$

$$\sum_{j=1}^{M} X_{ij} + \sum_{j=1}^{M} Z_{ij} \ge 1, \forall\, i = 1, \dots, N \quad (15)$$

$$\sum_{j=1}^{M} Pop_j \times X_{ij} + \sum_{j=1}^{M} Pop_j \times Z_{ij} \leq NCpa, \forall i = 1, \ldots, N \tag{16}$$

$$X_{ij}, Y_i, Z_{ij} \in [0,1] \tag{17}$$

Eqs. (10)-(17) defines the optimization model for the NPV of the total cost. The objective function (10) seeks to minimize both the delivery cost and the social cost of CO_2 emission. Eq. (11) regulates the number of CLCs equipped with AVs. According to Eq. (12), each customer zone must be served by one CLC using only one type of delivery vehicles – AVs or TVs. Constraints (13)-(15) ensure that each CLC needs to serve at least one customer zone and no more than all zones. Eq. (16) defines that the accumulated population each CLC serves cannot exceed the maximum capacity of one CLC. Finally, the type of variables is determined by constraint (17).

3.2 Model of evaluating infection risk

$$AIP_w = \sum_{j=1}^{M} Pop_j \times [1 - \prod_{w=1}^{NW} (1 - f \times nc \times IP_w^*)] \tag{18}$$

where

$$IP_w^* = \frac{IP_{max}^*}{2} \times \cos\left(2\pi \times \frac{w+12}{52}\right) + \left(\frac{IP_{max}^*}{2} + IP_{min}^*\right) \tag{19}$$

Eqs. (18)-(19) defines the risk model for evaluating the accumulated infected population (AIP) until week w in urban logistics activities during pandemic periods. Eq. (19) defines that the probability of being infected for each customer when meeting one another person (IP_w^*) is a seasonal parameter, whose value varies among 52 weeks within each year – high in autumn and winter with a peak at late autumn and low in spring and summer with a trough at the late spring. The idea that IP_w^* is a seasonal parameter and can be represented as a cosine function derives from the dynamic transmission model proposed by Kissler et al. (2020), who studied the transmission dynamics of two previous contagions – HCoV-OC43 and HCoV-HKU1 happened in the United States.

4. Results and analysis

This section discusses remarkable observations related to the optimal allocation generated according to the proposed mathematical model. Two comparative sensitive analysis is conducted to demonstrate the impacts of different number of CLCs equipped with AVs and different NCpa on the optimal allocation. Then the infection risk model is used to calculate the accumulated infected population (AIP) in the long term for four patterns of urban logistics. The more use AVs for delivery, the fewer people will be infected.

The proposed optimization formulations are solved using the MATLAB software. An Intel Core i5-8250U CPU (1.60 GHz) laptop with 8 GB RAM is applied for carrying out all the computations.

In this research, geographical data of 91 customer zones and 20 CLCLs in Great London are used as inputs for the mathematical model and for the risk calculation. London, the capital of the UK, is one of the largest cities garnering attention as new hubs of logistics activities for LSPs, and it has various factors such as social, economic, and environmental factors worth to be considered for research (Nakamura, 2020). Therefore, the analysis results based on the information of the Great London have reference significance in the similar projects in metropolitan cities worldwide. Great London is made up of 32 boroughs, which are evolved from the original 91 districts before the enactment of the London Government Act 1963 (Self, 2002). The original city map of 91 districts is more detailed than the current one and, thus, the 91 original districts are more appropriate to be defined as the 91 customer zones in this research. Besides, this research selects the largest 20 distribution centers of a leading glossary brand within the Great London to represent 20 CLCs for analyzing urban logistics activities.

A schematic city map, as shown in Fig. 2, is generated through MATLAB according to the latitude and longitude of each CLC and the center of each customer zone, showing the number and positions of all these locations. It should be noted that the approximate geographic center of each customer zone is used as the population center of this zone to represent the whole zone.

The assumed default values of some constants and the datasets used in the paper are presented as follows.

First, the service life for each vehicle, no matter AV or TV, is assumed to be 8 years, i.e., NT = 8 and NW = 416 for 8 years.

Second, this research supposes that each CLC equips 20 AVs or TVs, i.e., Nv = 20, and that the establishment cost for each CLC equals the product of the price per vehicle and Nv.

Third, Nd is assumed to be 500 – 250 working days per year and 2 deliveries per day.

Fourth, the discounted rate used in this research is 3.5%, as defined by Price (2018).

Fifth, the value of ACpa is defined as the result of the total population of Great London ($TPop$) divided by the number of CLCs (N=20).

Sixth, for evaluating infection risk, this research assumes that IP^*_{min} = 0.01%, IP^*_{max} = 0.1%, and f = 1.

Besides, all datasets are available on the website https://github.com/bashirimahdi/AV_Delivery.

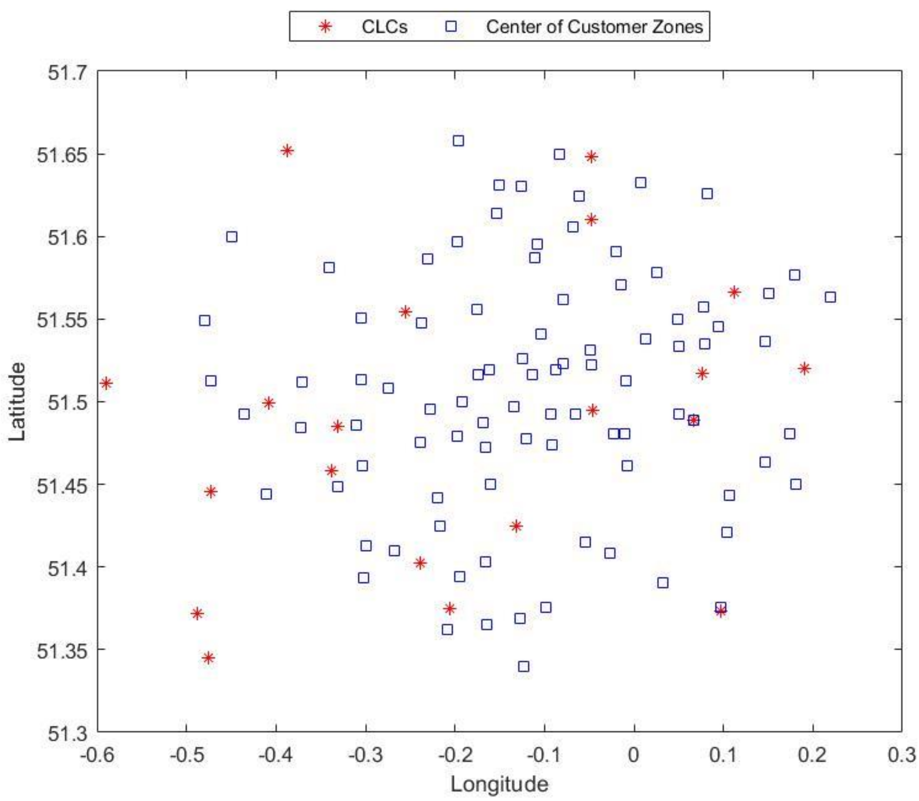

Figure 2. A schematic map of the Great London including CLCs and customer zones for the selected case study

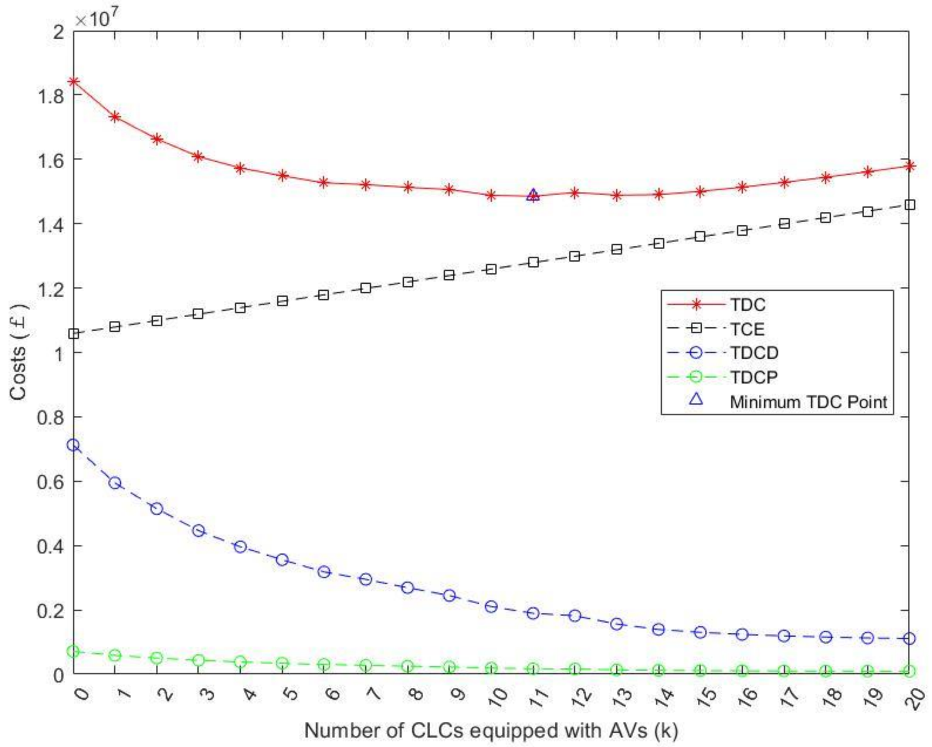

Figure 3. The optimization results when ACpa/NCpa = 60%

4.1 Economic and ecological optimization

4.1.1 The optimal TDC

The optimization result in Fig. 3 is generated when ACpa/NCpa = 60%, i.e., the actual capacity (ACpa), a constant decided by the city population and number of CLCs, occupies 60% of the nominal capacity (NCpa). The larger NCpa is, the more extra spare capacity CLCLs will have. The extra spare capacity is a kind of resource waste because it cannot create any benefits after the delivery demands of the whole population are satisfied. NCpa should be greater than ACpa because the sum of the nominal/maximum capacity of all CLCs should satisfy at least the whole population of the city. However, in reality, each CLC has more or less extra spare capacity, which leads to ACpa/NCpa to be less than 1. In this research, 60% is assumed as reasonable value of ACpa/NCpa.

Fig. 3 illustrates the change of TCE and the optimal result of TDC, TDCD, and TDCP when there are a different number of CLCs equipped with AVs, with each point represents the most optimal allocation when a certain number of CLCs equipped with AVs. TCE has a simple positive linear relationship with the number of CLCs equipped with AVs. While both TDCD and TDCP decrease when increasing the number of CLCs equipped with AVs at a diminishing rate of decrease. From the perspective of minimizing TDC, the most optimal allocation emerges when there are 11 CLCs equipped with AVs. At this time, the higher equipment cost and lower delivery and pollution cost of AVs than TVs achieves a balance, and more or fewer than 11 CLCs equipped with AVs will lead to a higher total cost. It can be seen from the vertical intercept that the optimal total cost is the highest when none of CLCs are equipped with AVs, even higher than when all CLCs are equipped with AVs. This result confirms that the cost advantage of AVs thanks to lower delivery and pollution costs will gradually overcome their disadvantage due to the higher equipment cost than TVs in the long term and that, after a certain point – 11CLCs with AVs, the marginal utility of equipping more CLCs with AVs will diminish.

4.1.2 The comparative sensitivity analysis of the optimal TDC under different values of NCpa

When increasing the nominal/maximum capacity (NCpa) of CLCs, the value of ACpa/NCpa decrease. This sensitivity analysis of optimal cost is conducted under three ACpa/NCpa values: 60%, 50%, 40%.

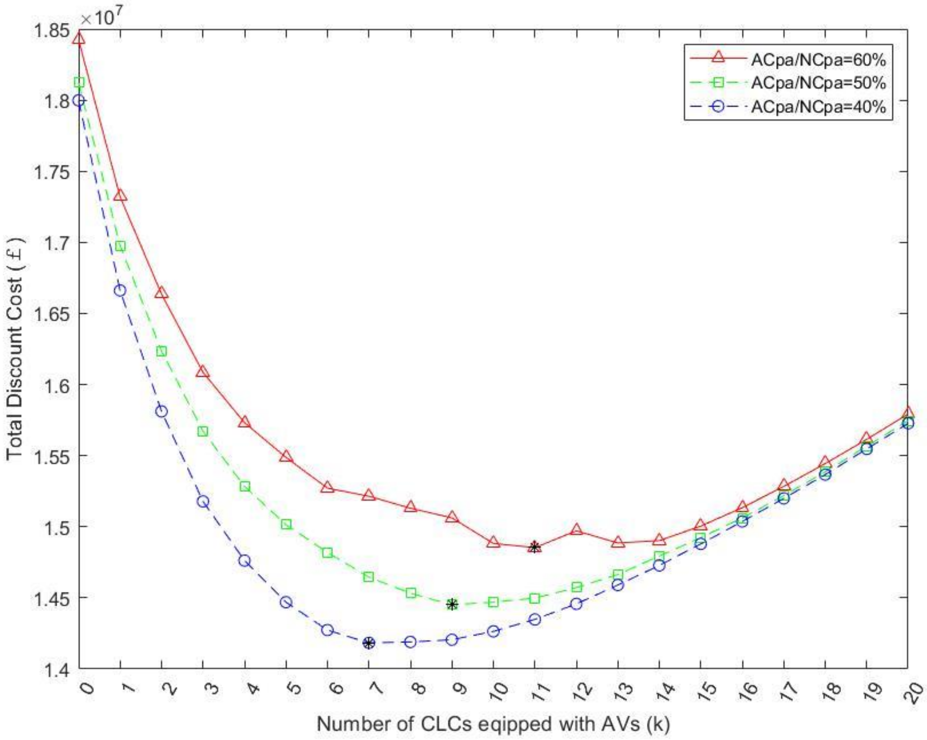

Figure 4. Optimal total cost curve under three different values of NCpa

The result in Fig.4 shows that, in order to minimize TDC, the most optimal number of CLCs equipped with AVs decrease as the NCpa increase. This move can be explained away as the average nominal/maximum capacity limits the customer number of some CLCs. If the maximum service capacity is increased, some CLCs will attract more customers who are allocated to other CLCs where the delivery distance and ensuing cost are disfavored by these customers, and the loss in customers makes it less attractive for those disfavored CLCs to equip AVs than to equip TVs because a CLC equipped with AVs enjoys cost advantage only when it serves enough customers. Although equipping AVs has lower delivery and pollution cost than equipping TVs per delivery, the difference is so small that only with enough customers and corresponding deliveries can the accumulated saving cost of equipping AVs offsets the excess cost of doing so caused by the significantly higher unit price of AVs than that of TVs.

In Fig.5, the value of the most optimal TDC also decreases as the NCpa increases. This movement agrees fairly well with the fact that the disfavored CLCs have fewer customers when NCpa is high than when NCpa is low and that the equipment cost of TVs is significantly lower than that of AVs, a cost advantage that will make equipping TVs more attractive for a CLC, especially when this CLC only serve limited customers, than equipping AVs.

4.2 Infected risk evaluation

In this section, the effect of nc is evaluated. So, four scenarios of the customers' behavior are considered. The four scenarios are considered as GCCI, OOCC, DCTV, and DCOA according to the nc values of 20, 5, and 1 for the first three scenarios, respectively. GCCI represents that a customer goes to CLCs and choose goods inside CLCs, OOCC means that a customer orders online first and then collects the parcels at special collection zones of CLCs, DCTV represents that CLCs deliver goods to customers by only using TVs, and DCOA is the optimal allocation mixed AVs with TVs when ACpa/NCpa = 60%. In the DCOA scenario, nc equals 0 for only using AVs and 1 for only using TVs. Therefore, the AIP for DCOA pattern is calculated as the sum of the AIP among customers who receive deliveries by AVs and the AIP among those who receive deliveries by TVs.

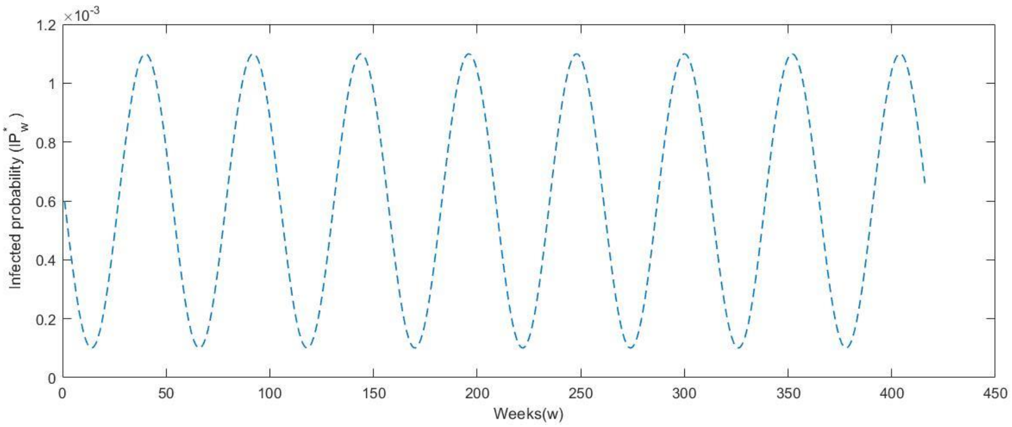

Figure 5. The curve of IP with seasonal values

According to Eq. (19), the IP_w^* is a seasonal parameter. As shown in Fig. 5, the curve of IP_w^* has a peak at nearly week 40, the end of autumn, and a trough at nearly week 14, the end of spring. In the periods of peak virus transmission, that is, in the late autumn and in the winter, Kissler et al. (2020) recorded the maximum weekly transmission rate for two virus – HCoV-OC43 and HCoV-HKU1 – that once broke out in America.

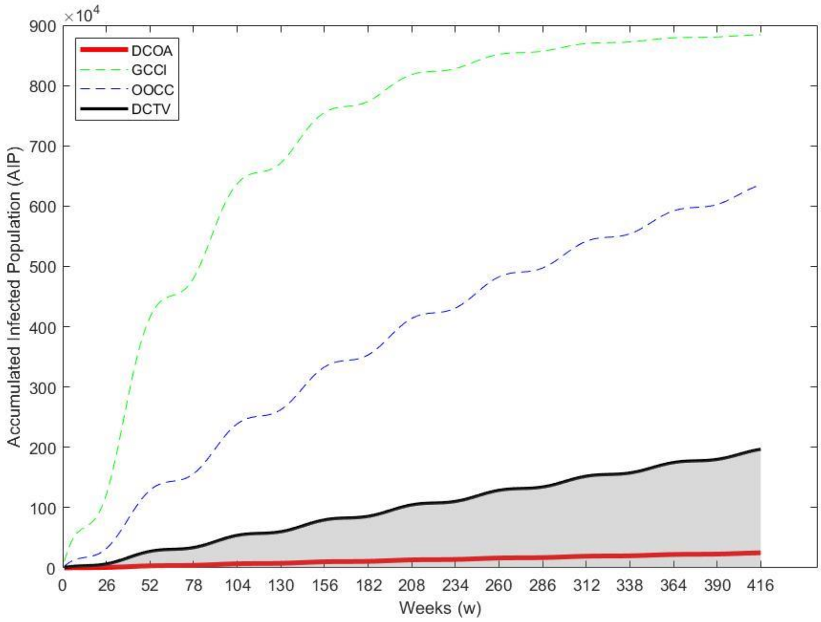

Figure 6. Comparison of the AIP of four urban logistics patterns

Fig.6 presents the growth trend of AIP of four urban logistics scenarios – GCCI, OOCC, DCTV, and DCOA. The red curve shows the trend of AIP of the optimal pattern - DCOA. It can be seen from Fig.6 that AIP increases the most fast in the GCCI pattern, then in OOCC pattern, while most slow in the optimal DCOA pattern. The increasing rates of GCCI and OOCC are significantly higher than those of another two patterns. This result can be explained away as the AIP and its increasing rate is positively correlated with the parameter nc – the number of people a customer meets in urban logistics activities.

It is worth to be noted that all the four AIP curves in Fig. 6 are zigzag lines with their slopes, the increasing rates of AIP, vary with time because the infected probability per week is a seasonal variable that changes periodically over time. The grey area in Fig.6 represents the AIP curves when a different number of CLCs equipped with AVs.

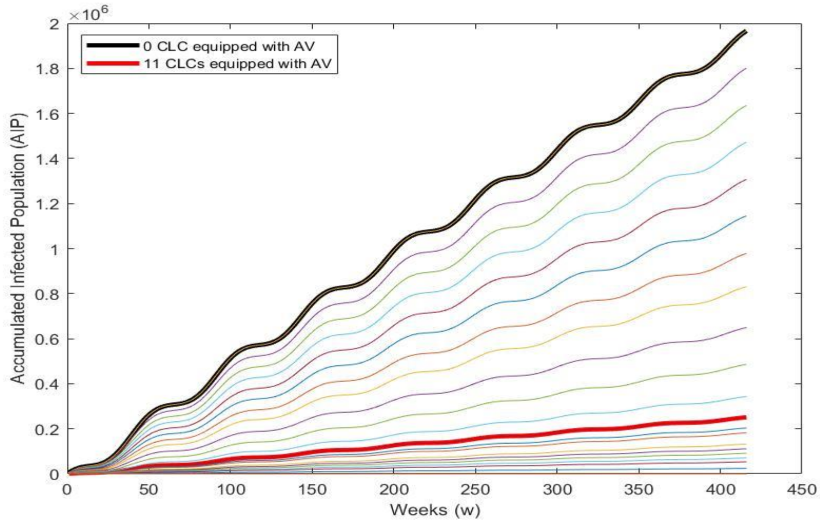

Figure7. AIP curves when a different number of CLCs equipped with AVs

Fig. 7 shows the details of the grey area in Fig.6. In Fig.7, curves from top to down are the AIP curves when the number of CLCs equipped with AVs increases from 0 to 20 separately. It is concluded that the more CLCs are equipped with AVs, the less AIP and its growth rate are, because using AVs to deliver goods to a customer can lead to no contact with another person and, therefore, zero infection risk.

5. Discussions and Managerial implications

This section discusses the implications of the research results on real-life managerial decisions. The findings of this research can be useful for many stakeholders enrolled in urban logistics activities. For example, the optimization results can help LSPs minimize cost through the appropriate allocation of AVs and TVs. Besides, minimizing pollutions such as CO_2 emission can also help these LSPs build better reputations and attract impact investors who, focusing more on the intention to shift the future of the world, proactively use their investments to generate a tangible social or environmental impact alongside a financial return (Chatzitheodorou et al. 2019). The infection risk evaluation is conducive to predicting the social risk caused by urban logistics activities during pandemic periods.

5.1 Least-cost frontier

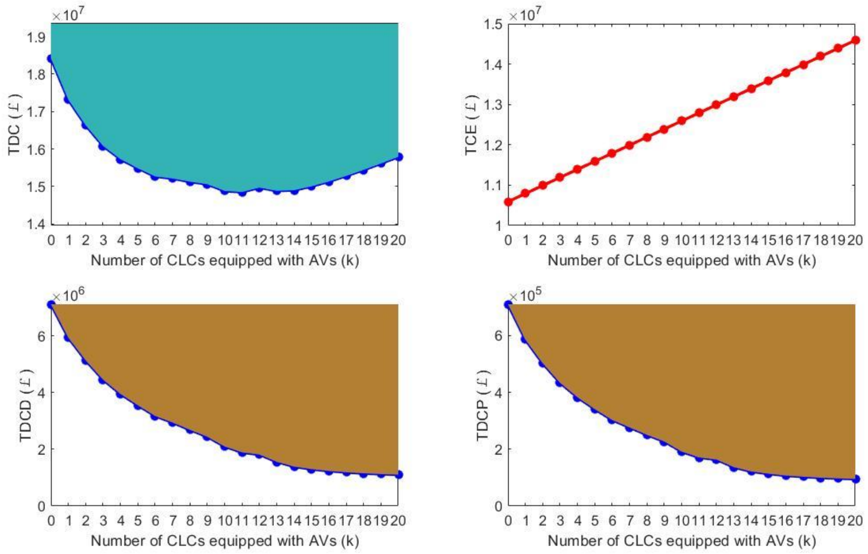

Figure 8. Cost curves of the optimal allocation when ACpa/NCpa = 60%

In Fig. 8, the dark areas separately mean the potential cost sets of TDC, TDCD, and TDCP. The frontier lines of these areas are the optimal cost curves when ACpa/NCpa = 60%, with each point on the lines representing the optimal cost-minimum allocation when there are a certain number of CLCs equipped with AVs. Any point in the dark area above the frontier lines represents a relatively ineffective allocation that cannot achieve minimum cost. Although, according to the TDC frontier curve, the most optimal point is when there are 11 CLCs equipped with AVs, other points on the frontier line are meaningful because, in real practice, the LSPs may lack enough funds to purchase as many AVs as required by the most optimal point. Therefore, based on their affordable number of AVs, the LSPs can find the most optical allocation on the least-cost frontier curve of TDC.

5.2 The impact of different maximum capacities

The result in this research shows that the larger the NCpa for each DC, the lower the optimal total cost and the fewer CLCs equipped with AVs. However, this philosophy faces many challenges in real business practice because NCpa, the maximum capacity of a DC, is always limited and because the number of CLCs equipped with AVs is subject to the financial capability of the LSPs. In addition, it needs to be considered that a large NCpa may cause a loss in customers to some CLCs because these customers prefer to choose other nearby CLCs – if they have extra service capability.

Table 2. CLCs equipped with AVs in three optimal allocations with three different values of NCpa

No. of CLCs	ACpa/NCpa = 60%	ACpa/NCpa = 50%	ACpa/NCpa = 40%
1			
2	✓		
3		✓	✓
4	✓		✓
5		✓	
6	✓	✓	
7	✓	✓	✓
8	✓	✓	✓
9			
10	✓	✓	✓
11			
12			
13	✓	✓	✓
14	✓	✓	
15			
16			
17	✓	✓	
18			
19	✓		✓
20	✓		

In this research, the CLCs that need to be equipped with AVs to optimize total cost under three values of NCpa are listed in the Table. 2. It can be seen that the 7^{th} ,8^{th} ,10^{th}, and 13^{th} CLCs keep attractive to customers when NCpa increases and that the 2^{nd}, 5^{th}, 6^{th}, 14^{th}, 17^{th}, and 20^{th} CLCs lose customers when NCpa increases. LSPs who want to enter a city can conduct such sensitivity analysis to plan potential CLC locations and to avoid the waste of service capabilities of some CLCs before establishing them.

5.3 The impact of infected risk

The COVID-19 broke out at the beginning of 2020 has dramatically influenced the urban logistics industry and made people more worried about their safety when contacting other individuals in logistics activities, such as going shopping and receiving deliveries. The result of the risk model in this research shows that using AVs for delivery can greatly decrease the infection risk. Therefore, LSPs should equip more AVs than TVs to reduce social risk and to protect the health of their own employees. If building a delivery fleet fully equipped with AVs is not available or not cost-efficient, the LSPs can allocate more TVs for delivery in spring and summer when the infection risk is low and allocate more

AVs in autumn and winter when the infection risk is high, because the infection risk is a seasonal variable whose value varies within each year.

5.4 Managerial implications

Based on the findings of this research, some managerial implications for LSPs in London are presented as follows.
First, this research fills the research gap – optimizing the allocation of AVs and TVs among the CLCs to minimize costs, GHG emissions, and infection risk. This achievement can help managers in LSPs to establish a sustainable logistics system by maximizing profits, minimizing CO_2 emissions, and reducing public health risks simultaneously.
Second, this research rules out that the use of AVs can greatly reduce the CO_2 emissions in logistics activities. Companies such as LSPs can consider equipping AVs to reduce GHG pollutions and to satisfy the increasingly strict environmental requirements in many countries.

Third, the substantial initial cost and the gradually diminishing marginal utility of equipping AVs suggest that, on the one hand, LSPs need to evaluate their financial budgets and cost structures to find the optimal number of AVs, while on the other hand, LSPs can invest funds in research of developing low-cost AVs to promote the mass application of AVs.

Fourth, according to the seasonal characteristic of infection risk, LSPs, especially those that cannot equip AVs for all deliveries in the short term, can allocate more AVs for delivery when this risk is high and more TVs for delivery when it is low.

Finally, the proposed multi-objective optimization model considering fixed equipment cost, delivery cost, and social cost of CO_2 emission can be used by any companies or policymakers when they make decisions under the pressure of maximizing profit and minimizing environmental impact, simultaneously.

6. Conclusion

In this paper, an adequate literature review is firstly presented with identified knowledge gaps. Then an optimization model is presented to fill the identified gaps, considering the equipment cost, delivery cost, and the cost of CO_2 emissions at the same time. Using the data of 20 selected supermarkets as CLCs and 91 customer zones in Great London, this research obtains the optimal cost curve and conducts a sensitivity analysis to study the impact of the service capacity on the optimal result by comparing the optimal curves under three values of NCpa. The results show that the optimal cost and the number of CLCs equipped with AVs are less when the NCpa of each CLC increases. Finally, this research takes account of the delivery risk of infection during pandemic periods and calculates the accumulated infection population under four logistics patterns. The calculation result of the infection risk shows convincingly that the wide use of AVs can discourage the transmission of viruses, a social risk that challenges public health, especially during pandemic periods.

The results of this research are helpful for LSPs, operators of warehouses, supermarkets, and even restaurants, to make decisions about whether it is necessary to equip AVs for delivery and how to allocate them among subbranches. These LSPs need to make a balance between different considerations. From the perspective of the total cost, there exists a breakpoint of the minimum total cost, and more CLCs equipped with AVs than the number required at this point will increase the total cost. However, from the perspective of infection risk, the more AVs, the less infection risk. Furthermore, it is very important for any LSP to make its allocation strategies based on its own managerial, economic, environmental, and social considerations. Joerss et al. (2016) argued that the use of AVs for delivery can reduce the total cost in developed countries where the labor cost is high, however, in developing countries, labor costs are more likely to remain low enough to impede any new technology changes in the next five to ten years. Besides the labor cost, James and Katsuaki (1984) found that the cost of introducing pioneer technologies is usually underestimated due to uncertainty, instability, and unrecognized problems. Therefore, the profitability of using autonomous delivery would depend on many factors and would need to be assessed on a case-by-case basis. Although a small ACpa/NCpa ratio leads to lower optimal total cost than a large one does, that ratio will be favored that maximizes the useable capability of each CLC and hence minimizes the waste due to excess service capability. In addition to the cost and risk perspectives in this research, other managerial factors need to be concerned when equipping AVs. For example, some CLC managers under pressure to maximize cost-cutting may resist innovation because they worry that more fundamental changes in the current delivery system will, especially in the short term, wreak havoc with the performance results on which they are measured. Therefore, only when a delivery system associates the AVs and TVs within it with the real economic, environmental, and risk demand may the entire system be considered sustainable.

This research provides some useful guides for delivery companies or distribution centers like supermarkets to develop their delivery methods. These companies can use the model in this paper to explore the optimal hybrid delivery allocation between traditional vehicles and AVs. As this research did, these entities need to consider the environmental cost and infection risk when make management decisions. For example, they can refer to the optimazition model and the infection risk model used in this research.

This study has several limitations in need of further research. For instance, this research optimizes the allocation of AVs among all CLCs under the assumption that each CLC can only equip one kind of delivery vehicles – AVs or TVs. While, in practice, one CLC can equip AVs and TVs at the same time, and it would be interesting to optimize the allocation of AVs and TVs in each DC. Besides, this study evaluates the infection risk without considering stochastic parameters for uncertain situations that are popular in pandemic periods. So, evaluating this risk in a two-stage stochastic programming framework will be valuable and can be considered as a direction for future study. Furthermore, another possible area of future research would be to evaluate the advantage of AVs according to different development periods, because the manufacturing cost and technical risks of AVs will significantly decrease as the development of technology in the long term.

References

Abbasi, M., and Nilsson, F. (2016). Developing environmentally sustainable logistics: Exploring themes and challenges from a logistics service providers' perspective. *Transportation Research Part D: Transport and Environment*, Vol. 46, pp.273-283.

Akeb, H., Moncef, B., and Durand, B. (2018). Building a collaborative solution in dense urban city settings to enhance parcel delivery: An effective crowd model in Paris. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 119, pp.223-233.

Alho, A., Silva, J., Sousa, J., and Blanco, E. (2018). Improving mobility by optimizing the number, location and usage of loading/unloading bays for urban freight vehicles. *Transportation Research Part D: Transport and Environment*, Vol. 61, pp.3-18.

Anderhofstadt, B. and Spinler, S. (2020). Preferences for autonomous and alternative fuel-powered heavy-duty trucks in Germany. *Transportation Research Part D: Transport and Environmen*t, Vol. 79, p.102232.

Batty, M. (2008). The size, scale, and shape of cities. *Science*, Vol. 319(5864), pp.769-771.

Bettencourt, L.M. (2013). The origins of scaling in cities. *Science*, Vol. 340(6139), pp.1438-1441.

Brealey, R.A., Myers, S.C., and Allen, F. (2010). *Principles of Corporate finance*, 10th ed., USA: McGraw-Hill/Irwin.

Brummelen, J., O'Briena, M., Gruyerb, D., and Najjaran, H. (2018). Autonomous vehicle perception: The technology of today and tomorrow. *Transportation Research Part C: Emerging Technologies*, Vol. 89, pp.384-406.

Burns, L.D. (2013). Sustainable mobility: a vision of our transport future. *Nature*, Vol. 497(7448), pp.181-182.

Chabot, T., Bouchard, F., Legault-Michaud, A., Renaud, J., and Coelho, L. (2018). Service level, cost and environmental optimization of collaborative transportation. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 110, pp.1-14.

Chanchaichujit, J., Saavedra-Rosas, J., Quaddus, M. and West, M. (2016). The use of an optimisation model to design a green supply chain. *The International Journal of Logistics Management*, Vol. 27(2), pp.595-618.

Chatzitheodoroua, K., Skouloudisb, A., Evangelinosb, K., and Nikolaoua, I. (2019). Exploring socially responsible investment perspectives: A literature mapping and an investor classification. *Sustainable Production and Consumption*, Vol. 19, pp.117-129.

Çolak, S., Lima, A., and González, M.C. (2016). Understanding congested travel in urban areas. *Nature communications*, Vol. 7(1), pp.1-8.

Duarte, F. and Ratti, C. (2018). The impact of autonomous vehicles on cities: A review. *Journal of Urban Technology*, Vol. 25(4), pp.3-18.

Elavarasan, R.M. and Pugazhendhi, R. (2020). Restructured society and environment: A review on potential technological strategies to control the COVID-19 pandemic. *Science of The Total Environment*, Vol. 725, p.138858.

Fagnant, D.J. and Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, Vol. 77, pp.167-181.

Feng, X. (2021). Time and Cost Efficiency of Autonomous Vehicles in the Last-Mile Delivery: A UK Case. *International Business Research*, Vol. 14(3), pp.1-26.

Figliozzi, M.A., Boudart, J.A. and Feng, W. (2011). Economic and environmental optimization of vehicle fleets Transportation Research Record. *Journal of the Transportation Research Board*, Vol. 2252(1), pp.1-6.

Fraedricha, E., Heinrichs, D., Bahamonde-Birkeb, F., and Cyganskib, R. (2019). Autonomous driving, the built environment and policy implications. *Transportation Research Part A: Policy and Practice*, Vol. 122, pp.162-172.

Gilchrist, S. and Himmelberg, C.P. (1995). Evidence on the role of cash flow for investment. *Journal of monetary Economics*, Vol. 36(3), pp.541-572.

Govindan, K., Mina, H., and Alavi, B. (2020). A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). *Transportation Research Part E: Logistics and Transportation Review*. Vol. 138, p.101967.

Guerrero, S., Manadat, S., and Leachman, R. (2013). The Trucking Sector Optimization Model: A tool for predicting carrier and shipper responses to policies aiming to reduce GHG emissions. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 59, pp.85-107.

Hänsel, M.C. and Quaas, M.F. (2018). Intertemporal distribution, sufficiency, and the social cost of carbon. *Ecological Economics*, Vol. 146, pp.520-535.

Hepburn, C. (2017). Climate change economics: Make carbon pricing a priority. *Nature Climate Change*, Vol. 7(6), pp.389-390.

Hoffmann, T. and Prause, G. (2018). On the Regulatory Framework for Last-Mile Delivery Robots. *Machines*, Vol. 6 (33), pp.1-16.

James, Q., and Katsuaki, T. (1984). Sample selection and cost underestimation bias in pioneer projects. Working Papers 512, California Institute of Technology, Division of the Humanities and Social Sciences

Joerss, M., Neuhaus, F., and Schröder, J. (2016). How customer demands are reshaping last-mile delivery. Travel, Transport & Logistics October (2016), Mckinsey & Company

Kissler, S.M., Tedijanto, C., Goldstein, E., Grad, Y.H. and Lipsitch, M. (2020). Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science*, Vol. 368(6493), pp.860-868.

Lee, L.H., Chen, Y., Gillai, B., and Rammohan, S. (2016). Technological Distribution and Innovation in Last-mile Delivery. White Paper (2016), Stanford Graduate School of Business

Li, Y., Du, Q., Lu, X., Wu, J., and Han, X. (2019). Relationship between the development and CO2 emissions of transport sector in China. *Transportation Research Part D: Transport and Environment*, Vol. 74, pp.1-14.

Lokhandwala, M. and Cai, H. (2020). Siting charging stations for electric vehicle adoption in shared autonomous fleets. *Transportation Research Part D: Transport and Environment*, Vol. 80, p.102231.

Lopez, N., Soliman, J., Biona, J., and Fulton, L. (2020). Cost-benefit analysis of alternative vehicles in the Philippines using immediate and distant future scenarios. *Transportation Research Part D: Transport and Environment*, 82, p.102308.

Masoud, N. and Jayakrishnanb, R. (2017). Autonomous or driver-less vehicles: Implementation strategies and operational concerns. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 108, pp.179-194.

Mohammed, F., Selim, S.Z., Hassan, A. and Syed, M.N. (2017). Multi-period planning of closed-loop supply chain with carbon policies under uncertainty. *Transportation Research Part D: Transport and Environment*, Vol. 51, pp.146-172.

Nakamura, H. (2020). Evaluating the value of an entrepreneurial city with a spatial hedonic approach: A case study of London. *Socio-Economic Planning Sciences*, p.100820.

Palak, G., Eksioglu, S., and Geunes, J. (2014). Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: An application to a biofuel supply chain. *International Journal of Production Economics*, Vol. 154, pp.198-216.

Price, C. (2018). Declining discount rate and the social cost of carbon: forestry consequences. *Journal of Forest Economics*, Vol. 31, pp.39-45.

Rao, C., Goh, M., Zhao, Y., and Zheng, J. (2015). Location selection of city logistics centers under sustainability. *Transportation Research Part D: Transport and Environment*, Vol. 36, pp.29-44.

Ricke, K., Drouet, L., Caldeira, K. and Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, Vol. 8(10), pp.895-900.

Savelsbergh, M. and Van Woensel, T. (2016). 50th anniversary invited article—city logistics: Challenges and opportunities. *Transportation Science*, Vol. 50(2), pp.579-590.

Scherr, Y., Saavedra, B., Hewitt, M., and Mattfeld, D. (2019). Service network design with mixed autonomous fleets. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 124, pp.40-55.

Self, P. (2002). The Evolution of the Greater London Plan, 1944-1970. *Progress in Planning*, Vol. 3(57), pp.145-175.

Sherafati, M., Bashiri, M., Tavakkoli-Moghaddamc, R., and Pishvaee, M. (2020). Achieving sustainable development of supply chain by incorporating various carbon regulatory mechanisms. *Transportation Research Part D: Transport and Environment*, Vol. 81, p.102253.

Stasko, T.H. and Gao, H.O. (2010). Reducing transit fleet emissions through vehicle retrofits, replacements, and usage changes over multiple time periods. *Transportation Research Part D: Transport and Environment*, Vol. 15(5), pp.254-262.

Stoiber, T., Schubert, I., Hoerler, R., and Burger, P. (2019). Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households. *Transportation Research Part D: Transport and Environment*, Vol. 71, pp.265-282.

Tsao, Y. and Thanh, V. (2019). A multi-objective mixed robust possibilistic flexible programming approach for sustainable seaport-dry port network design under an uncertain environment. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 124, pp.13-39.

Vahidia, A. and Sciarretta, A. (2018). Energy saving potentials of connected and automated vehicles. *Transportation Research Part C: Emerging Technologies*, Vol. 95, pp.822-843.

Wang, S. and Zhao, J. (2019). Risk preference and adoption of autonomous vehicles. *Transportation Research Part A: Policy and Practice*, Vol. 126, pp.215-229.

Wong, E., Tai, A., and Zhou, E. (2018). Optimising truckload operations in third-party logistics: A carbon footprint perspective in volatile supply chain. *Transportation Research Part D: Transport and Environment*, Vol. 63, pp.649-661.

Wu, W., Zhang, F., Liu, W., and Lodewijks, G. (2020). Modelling the traffic in a mixed network with autonomous-driving expressways and non-autonomous local streets. *Transportation Research Part E: Logistics and Transportation Review*. 134, p.101855.

Xia, H. and Yang, H. (2018). Is Last-Mile Delivery a 'Killer App' for Self-Driving Vehicles?. *Communications of the ACM*, Vol. 61(11), pp.70-75

Zhu, F. and Ukkusuri, S.V. (2015). A linear programming formulation for autonomous intersection control within a dynamic traffic assignment and connected vehicle environment. *Transportation Research Part C: Emerging Technologies*, Vol. 55, pp.363-378.