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The feasibility of implementing e-cargo bikes in high density commercial areas of Hong Kong

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Abstract

With the recent attention of transportation researchers looking into alternative transport, this paper address calls in Hong Kong to corporate electric assisted vehicles into the urban road network, as well as regarding city plans looking to enhance walkability and alleviate road loads from motor traffic. By using the logistics sector as a pilot group, this study focuses on the effects of adopting a delivery fleet combined of electric cargo bikes and vans, evaluated by operational costs, performance, and emissions. To achieve this, an agent based model is created based on a small zone in Causeway Bay Hong Kong. Findings suggests that electric cargo bikes could provide a low emission, low cost alternative to alleviate the workload of traditional vans, and full replacement of vans are not practical in the scope of the given area. Finally, as a stepping stone towards the feasibility of legalizing electric assisted vehicles in Hong Kong, the model and design terminology are proposed as a baseline on which future complementary work can expand on using the materials published on Github.

Declaration of Authorship

I, Fung Mei Ki Sophie, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is 11,262 words in length.

Fung Mei Ki Sophie

18 August 2021

Acknowledgement

I would like to express my gratitude to my supervisor, Dr Sarah Wise, for her invaluable advice and assistance during this process. I also want to thank my parents and friends for their patience and mental support during this difficult Covid-19 period.

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Abbreviations

E-CBs Electrical Bicycles

GHG Greenhouse Gases

HGVs Heavy Goods Vehicles

LGVs Light Goods Vehicles

1. Introduction

Sustainable transport is a global and highly controversial topic, there are discussions regarding the impact of motor vehicles on congestion, air quality and climate change (Lelieveld et al. 2015; Stefan, 2020). The emergence of e-scooters first sparked argument for city planners to redistribute space in Europe (Gossling 2020), which along with e-bikes are then categorized as electric transport mode or alternative transportation. Electric transport modes require street space that is occupied by traditional motorized transport, but it is an opportunity for city planners to propose allocating more street space for alternative transportation based on the environmental benefits. It is a global trend and challenge for cities to disentangle transport needs and improve the quality of life (Gossling 2020).

In recent years, innovative vehicles for urban logistics like delivery drones and autonomous robots have been introduced, and the idea of electric cargo bikes received massive attention due to its environmental benefits (Verlinde et al, 2014; Nocerino et al., 2016). Gruber et al. (2014) estimate that up to 42% of courier services can be substituted by electric cargo bikes and reduce externalities that are otherwise caused by motor vehicle used for this purpose. Koning and Conway (2016) verify adopting E-CBs in urban freight helps reducing externalities and has gained rapid momentum between 2001 and 2014. Pilot tests and studies were done in many European places. Furthermore, the issue with vehicle routing problems – urban consolidation, route planning and fleet management has not escaped the attention of researchers and has been studied from a broad variety of perspectives and techniques. Whilst the topic has been previously explored, when it comes to using computer simulation as a technique, many focus on strategically positioning a depot for consolidating items before entering urban zones, route planning and scheduling (Zeimpekis, 2007; Melo and Baptiste, 2017; Hoffman et al., 2017). Only a few works were done around fleet composition and from a commercial perspective.

Geographic factors like population density, narrow streets and regulations for motor vehicles largely affect the viability of adopting cargo bikes (Schliwa et al., 2015). As of 2020, all kinds of electric assisted small vehicles like e-scooters and electric bikes are illegal forms of transport in Hong Kong (Transport Department, 2020). The HKSAR Government is still conducting public consultations and research to test the feasibility of legalizing electric assisted vehicles.

It is important that this research is attempted in the context of Hong Kong because the city population and demand for ecommerce is expanding while struggling with insufficient road space and substandard air quality (Transportation Department, 2020). A simulation in adopting electric assisted vehicles for the logistics sector has the potential to help reduce part of the city's road loads. This topic is therefore very controversial and novel when situated in Hong Kong.

In this study, the feasibility to replace delivery vans with electric cargo bikes will be examined, using the agent-based modelling (ABM) approach to simulate the delivery process in a selected area of Hong Kong. Most studies about traffic or delivery simulation employed various methods like on site field data collection, surveys or using dedicated traffic simulation software. Given the differences in geography and public policies, and the minimal empirical research regarding this topic conducted in Hong Kong and nearby cities like Korea and Singapore, and the lack of updated sector data, it is risky and costly to transfer studies and their methodologies conducted in Europe to Hong Kong. Yet by using ABM, which is purely computer simulations, the study can and will seek to answer specific research questions:

RQ1: The feasibility (and conditions) of adopting electric cargo bikes in business areas of Hong Kong

RQ2: The optimal mixture of big vans and electric cargo bikes for maximum efficiency in terms of monetary costs

With the aim of exploring the topic, Chapter 2 focuses on the need and novelty of this topic in Hong Kong, along with the definition of ABM, methodologies used in similar studies, and explores the potential of Hong Kong to adopt alternative transportation. Chapter 3 is to introduce and explains how the model is designed and built, the terminology behind the agents, calculations that are used as metrics to define success. The selection and method to produce data required for further analysis are documented, as well as the technical challenges stemming from the built model. Chapter 4 presents results and discussion of the project. It provides in detail the conditions where bikes are more favorable over vans, the costs related to the operations, including the tradeoff needed to make when performance is prioritized over costs. Further analysis are also done to identify the factors that have an impact on the costs. Chapter 5 concludes the thesis. Limitations of the present research and model produced are discussed, as well as pointing out areas of interest for future researchers who want to investigate to this topic. Ultimately, this study intends to contribute to the field of traffic study and sustainability research by further examining the possibilities of alternative transportation, and justification to legalize electric assisted small vehicles in Hong Kong.

2. Literature Review

2.1 The logistics sector and e-commerce in Hong Kong

The trading and logistics sector is one of the 4 pillar industries in Hong Kong and contributes to 19.8% of the city's GDP in 2019, at the same time providing 17.5% to the total employment share. In 2019, the city is ranked the 8th in the largest trading economy worldwide, where the Hong Kong International Airport is ranked first in cargo throughput amongst other airports (CSD, 2021). Top items imported by sea include petroleum, fruits and frozen meat; where telecommunication parts, jewelry and motor parts are the main imported items by air (HKLA, 2020). Whether for local retail or exporting, Hong Kong's exposure to foreign imported goods is very large. In light of globalization and strong growth in the cross-border e-commerce boom, the demand for courier services grows, operational challenges lie ahead (Barns, 2016). In Hong Kong, e-commerce only takes up 11% of total retail spending, only a quarter of the 7.5million population currently shop online, there is a huge growth potential and challenge for merchants. The online shopping market is expected to expand at a growth rate of 10.2% in the coming years (J.P. Morgan, 2019). Similar to cities like Singapore, the need to buy things online is unnecessary as physical access to stores is more convenient, resulting in local merchants' low incentive to invest in e-commerce. Eventually, due to a low range of local online shops and the robustness of e-commerce in Mainland China, nearby countries such as Korea and Japan, cross-border e-commerce spending constitutes 60% of Hong Kong's online purchases (J.P. Morgan, 2019). Yet either shopping methods still require courier services for local and overseas delivery.

The e-commerce trend is gaining momentum, demand for its supporting function – intra city deliveries are also growing, but there are challenges regarding delivery time, road load and emission to the environment.

60% of goods vehicles in HK are LGVs, yet 75% of them mostly operate at 40% loading capacity with a mean journey time of 24-25 minutes. (Transport Department, 2011). Assuming the average van speed between 30km/h and 60km/h, those LGVs will have a mileage of around 12.5 to 25km. In a e-bike study done by Gruber et al., the median mileage done by vans are 60km, and that of e-bikes are 40km; a fully charged E-CBs manufactured in recent years can cover a mileage of 80km. The situation of LGVs in HK are under-performing in terms of both loading capacity and mileage covered per trip, there could be potentially fewer emissions, lower operational costs and contribution to congestion if those trips were replaced by E-CBs.

2.2 Policies targeted at mitigating carbon emission

The population density of Hong Kong is 7,140 people per km^2, making the city one of the most densely populated places in the world, ranking behind Macao and Singapore (World Bank, 2020). Road conditions in Hong Kong have been unfriendly for pedestrians due to the high pedestrian volume in limited space within urban areas, hilly topography that are majorly in the form of steep walkways or stepped streets, car-centric street planning, and the subtropical climate that is high in both humidity and temperature during spring and summer (Walk in Hong Kong, 2019). Accompanying global warming and intensified urbanization, a phenomenon where urban temperatures are significantly higher than that of suburban or rural areas is called the urban heat island effects (He, 2018). Amongst other factors like haze, fog, cloud coverage and precipitation, GHG and PM_{10} exerts the largest influence under the air pollution category towards urban heat island effects (He, 2014). To produce better air quality and mitigate the urban heat island effect, the need to reduce GHG emissions cannot be omitted. Studies show that the use of cycle tricycles reduces co2 emissions by at least 40% (Brown et al., 2011; Marujo et al., 2018).

To reach carbon neutrality before 2050, the Environmental Protection Department has been promoting the use of electric vehicles in HK, offering tax reductions for purchasing EVs, profits tax deduction for enterprises, and subsidizations for EV charger point installments (EPD, 2021). However, such measure mainly targets large vehicles such as buses, taxis, light good vehicles (LGV) and private cars. In 2018, 10% of vehicles in HK are goods vehicles and they contribute to 5% of total carbon emissions from vehicles.

In late 2019, the Transport Department listed Central and Shum Shui Po area as the pilot site for enhanced walkability – heavily limit car speed, revitalize alleys as road extension and provide barrier-free access facilities, to maximize pedestrians' share of road space (Walk in HK, 2019). This could mean a favorable operating environment for zero emission vehicles like E-CBS as they are ideal for use in areas that consists of dense narrow streets, with limited car access and high percentages of pedestrian zones. (Schliwa et al., 2015), they can also drive on footpaths, pedestrian zones and cycle lanes (Hertel et al., 2014).

2.3 High Density Commercial Areas and Delivery Demand

There is no explicit definition for high density areas of Hong Kong since the built environment differs from each other across the globe, due to historic and cultural differences. In 2014, the Transportation Department of Hong Kong appointed AECOM to conduct in-depth road studies in 3 zones – Causeway Bay, Admiralty and Mid-Levels Area. The Causeway Bay area of Hong Kong is a "densely built-up area with immense traffic demand" with intense redevelopment plans, whilst also being a business and shopping center (Transportation Department, 2014). The former of the other 2 areas are the central business district and the latter an "administrative moratorium" – an area restricted from developments since 1972, therefore mainly serving residential purposes (Transportation Department, 2010; 2012; 2014), the Causeway Bay area is then selected as a reference to create the simulation environment.

The street of the selected area houses various types of businesses like retailers, food and beverage establishments, in addition to the commercial offices and hotels in high-rise buildings. On top of vehicular traffic issues, the area suffers from heavy crowds in shopping and leisure areas. Narrow footpaths, heavy pedestrian movements, and signalcontrolled crossing led to serious congestions of major roads. Furthermore, there is a small zone that is accessible from main streets and consisted with only narrow one way streets, traffic move in single file. Curb space is very limited and often occupied, and there are even narrow streets that act as a shortcuts between the grid like zone.

Overseeing several junctions to be overloaded in 2021, AECOM suggested long term development of utilizing underground space, and simultaneously increase street space for pedestrians – but never a suggestion in prohibiting vehicles from entering the zone. Their suggestions were based on a car-centric planning concept yet limiting car flow will still hinder the delivery performance of couriers to supply goods to the exotic businesses in the area.

As mentioned previously, a significant growth in ecommerce will bring up the demand for delivery services. Traditionally, vans in Hong Kong serve delivery purposes for maintenance workers (plumbers, carpenters, electrician), retailers, large goods like furniture and building materials. Since maintenance workers often need to carry tools and are already benefitting from electric LGVs via subsidies from the Government. Commercial applications of cargo bikes can be segmented into postal, courier, parcel, home delivery services, service trips and on-site transport (Rudolph and Gruber, 2017). Electric cargo bikes could be an alternative to vehicles that move around a small area whilst carrying limited items. There are limited data that details the number of goods and sectors LGVs and HGVs normally serve, resulting in a conservative estimated number of deliveries that cargo bikes can cover are a portion of retail items.

From a commercial standpoint, there are drawbacks for electric cargo bikes - variabilities like congestion, equipment failures and undesirable weather conditions are factors that affect travel times (Zeimpekis et al., 2007). And longer travel times will result in a higher operational cost. The capacity of E-CBs are only a fraction of that of LGVs, a bike fleet requires more operators to handle the load of only a few van drivers. Available fleet size may vary substantially as vehicles are often operated by freelancers and flexible part-time workers (Gruber et al., 2014; Schliwa et al., 2015), meaning the fleet might not always be able to operate at an optimal level. When integrating E-CBs into an urban distribution schemes, the limited carrying capacity and low operating distance pose optimization challenges in maximizing the number of parcels a bike can carry, yet allow efficiently offloading them in narrow street space (Anderluh et al., 2019). Furthermore, most established electric cargo bike manufacturers are based in Europe, with a few in China, the financial costs of importing and maintaining these items might outweigh the economic and environmental benefits generated (Elbert and Friedrich, 2020).

2.4 Traffic Simulation and Research Gaps

There are many studies that model traffic flow with cargo bikes involved using different software packages and techniques. Specialist software like VISSIM and AIMSUM are designed solely for traffic simulation purposes. Studies that employ such software are often at a larger geographic scale and the focus are macroscopic (Melo & Baptiste, 2017; Ambros et al., 2014; Eisele and Toycen, 2005), ie. Traffic corridor design, junction effects, dedicated lanes design etc… Long term subscription services are required to gain access to the software, posing a threat to further maintenance work and community support as opposed to using open source tools.

Other means of research regarding cargo bikes also include field data collection, surveying and in depth interviewing (Gruber et al., 2014; Marujo et al., 2018; Rudolph and Gruber, 2017), where ongoing trails, equipment like GPS tracking tools and trial bikes, and field time are required. The above methods pose a challenge to this study due to geographical restrictions, cost and time limitations and the availability of industrial partnerships.

Furthermore, in connection with the growing interest in cargo bikes, new forms of consolidation like micro-depots, urban consolidation centers and dynamic depots are introduced (Hoffmann et al., 2017; Pourrahmani and Jaller, 2021; Elbert and Friedrich, 2020). Algorithms targeted at optimizing routing and scheduling for a fleet with bikes

(Letnik et al., 2020; Zeimpekis, 2007; Anderluh et al., 2019) also gained research attention.

Amongst the broad range of previous studies conducted with the involvement of cargo bikes, they differ from the aims of this study in terms of study scope – geographic area size, country of interest and stages of a delivery. Unlike the studies listed above that are conducted in Europe and its nearby countries like Germany, France, Brazil and Portugal – all at a mesoscopic scale, this study is targeted to focus on a zone of approximately 200m^2 in Causeway Bay HK. Previous studies look at the benefits of electric cargo bikes from an environmentally friendly standpoint instead of an entrepreneurial state, yet electric bikes might not be that economically efficient if the training, maintenance and insurance costs are factored in. This study does not focus on traffic simulation nor network analysis about positioning a new depot but rather a behavioral study of couriers when using a different means of transport.

Furthermore, studies that are listed above are very data-centric, despite touching upon the use of cargo bikes, there are no related data available for Hong Kong. Also, the difference in urban geography is very similar yet the impact of congestion is incomparable to the situation of Hong Kong (Transportation Department, 2010).

Studies that explore the sustainability of electricity powered bikes in Hong Kong are not found in local databases as of the date of submission of this piece, as well as literature regarding the courier sector in the city. And most foreign electric cargo bike studies focus on the depot supporting the bikes team instead of discussing a hybrid fleet combining both bikes and vans. A hybrid fleet allows delivering large items as opposed to only small parcels. Whilst most industry related reports are restricted to company subscriptions and related personnel, field data collection or even a survey is a cost intensive and inefficient option.

2.4.1 Agent based modelling

ABM is a kind of simulation modeling technique, where a collection of agents makes decisions as coded, their interactions and behavior patterns will then be studied. ABM excels in areas that explain a phenomenon as a result of aggregating the behaviors of the agents within the model (Bonabeau, 2002). Examples of ABM is the Sugarscape model, sugar agents respawn at a given rate and eater agents will keep hunting sugar agents whenever they are 'hungry'. This model has many variations available to test the behavior when the conditions of the environment changes. The earliest ABM was published in 1993 to use in water resource modeling, agriculture and forestry. Another early application of ABM is traffic simulation about the size frequency distributions of traffic jams, which later due to the nature of geographically distributed - extended into the use of transportation scheduling and management (Chen, 2012).

ABM systems are built bottom up, where the behaviors of its constituent units – the agents, will be studied (Chen, 2012). The outcome from their interactions are the object to study. However, the amount of autonomy given to agents to interact nonlinearly leads to collective behaviors that might evolve into a self-organization (Gilbert, 2008). Interactions between agents are called 'social', where they interact with each other to complete their tasks and help others with their activities. Agents are also designed to operate and make decisions independently. These 2 features separate ABM from object-oriented programming and distributed computation that are dependent on each other (Chen, 2012).

Application areas of such technique include evacuation planning, traffic flow planning, customer behavior simulation and stock market dynamics. ABM is suitable for topics that compost of complex interactions, heterogeneous populations, topological complexity and flexibility (Bonabeau, 2002). Following the aims of this study and the special capabilities of ABM, ABM is therefore, an ideal technique to help answer the research questions.

3. Methodology

3.1 Model Design and Details

The aim of this study is to evaluate the feasibility of using cargo e-bikes to replace LGV vans, and finding the better of a fleet combining the 2 car types to form a fleet or a full replacement of vans. Based on the reasons clarified in the last section, an agent based model will suit the problem well, and the availability of well-documented open sourced tools makes reproducibility and transparency for future developments at ease. An environment resembling a real street structure in Hong Kong is designed using the Mesa library in Python, which is a popular coding language.

The model contains a square grid with 5 main roads, shops along the road, and different settings that allow users to test, and will be further addressed in later sections. The impact of traffic flow and parcel load will be accessed, additionally the average speed and greenhouse gas emissions will be monitored as a key metric to determine feasibility.

Link to model: https://github.com/sophie-sdsv/abm_dissertation

3.1.1 Overview (Following ODD protocols)

Purpose

The model's purpose is to evaluate the effectiveness of cargo e-bikes in a small network of roads. Cargo e-bikes has its own limitation of having only a fraction of LGV's carrying capacity, yet their small size allows parking on curbs that can potentially mitigate effects from parking on the road or even double parking. Also, their limited capacity means multiple bikes are required to replace one van, therefore the effects of having multiple bikes in the network will be examined using metrics in emissions and traffic density.

Entities, state variables, scales

There are two types of agents used in the model – environmental and car agents, they each has their own variables and moving rules, which will be detailed below.

	Entity	Type	Description
1.	Curb	Environment	The road patch between buildings and the road, mainly responsible for road-side parking, each curb cell allows multiple agents to park on.
2.	Building	Environment	There are 2 types of buildings, the ones that are destinations of delivery and those that are not. Each target buildings will receive one parcel list and expect deliveries.
3.	Road	Environment	The tracks where vehicles move along, it is a single road with fixed walking direction
4.	Electric cargo bikes	Cars	A electric cargo bike agent, have fixed and limited cargo carrying capacity
5.	Vans	Cars	A van agent, have 4 times the carrying capacity of bikes
6.	Other cars	Cars	All kinds of road users except for the 2 mentioned above, contributes to traffic level

Table 1 Entity Summary

Curb Agent

Curb agents are located between buildings and road agents, their main purpose is to let bike agents park on, and carries the parcel list that the target building behind this agent is expecting. The bike agents will need to confirm with the curb agent that they arrived at the right destination.

Variable/State	Type	Description
Deliveries	List	2 lists containing the parcels to be received by this curb agent respectively from bike and van agents
Delivery Time	List	2 lists to store the time taken to complete a delivery circuit for all agents, to be submitted to the <data collector> class for calculations

Table 2 Curb Agent Attribute Summary

Building Agent

The building agents are divided into 2 types, ones that will be expecting parcels called 'target buildings' and the other type a normal building to fill the road. This is currently hard-coded due to technical limitations. Building agents have a parcel limit of 11, and will be allocated parcels by the scheduler.

Variable/State	Type	Description
Deliveries	List	A list containing the parcels to be received by this agent from both bike and van agents
Pos	tuple	The coordinates of the building on the grid

Table 3 Building Agent Attribute Summary

Road Agent

Road agents serve a simple purpose of holding the information of which section in the grid belongs to which road. This information will be passed to car type agents to move around the world.

Electric Cargo Bike Agent

Electric cargo bike agents (Bike agents) travels along the roads and arrive at a destination to deliver the parcels.

Variable/State	Type	Description
Pos	tuple	The coordinates of the agent on the grid
State	Integer	Represents driving or parking state, will perform further actions based on the state
Deliveries	List	The list of parcels to be delivered by this agent
Delivered	List	The list of parcels delivered
Speed monitors	Integer	Counters that increment when the agent moves one step, for data collection purposes
Road checkpoints	Boolean	Make sure agents moved along all roads in one lap
Delivery Time	List	Counter that increment after each step the agent has taken, will then be passed to curb agent for storage
Wait Time	Integer	Counters that decrement per step to indicate the time taken to deliver the parcel

Table 4 Bike Agent Attribute Summary

Van Agent

Van agents travels along the roads and also deliver parcels. Van agents cannot park on curbs but instead park on roads. Only the bottom 2 roads in the world allows vans parking.

Variable/State	Type	Description
Pos	tuple	The coordinates of the agent on the grid
State	Integer	Represents driving or parking state, will perform further actions based on the state
Deliveries	List	The list of parcels to be delivered by this agent
Delivered	List	The list of parcels delivered
Speed monitors	Integer	Counters that increment when the agent moves one step, for data collection purposes
Road checkpoints	Boolean	Make sure agents moved along all roads in one lap
Delivery Time	List	Counter that increment after each step the agent has taken, will then be passed to curb agent for storage
Wait Time	Integer	Counters that decrement per step to indicate the time taken to deliver the parcel, is double the time for bike agents

Table 5 Van Agent Attribute Summary

Other Cars Agent

Other cars agents will move down the road without stopping unless blocked and contribute to the traffic level.

Variable/State	Type	Description
Pos	tuple	The coordinates of the agent on the grid
State	integer	Represents the state of driving or parked
Speed Monitors	Integer	Counter that increments after each step the agent has taken, for data collection purpose
Wait Time	Integer	A random number created to represent the time the agent stays parked in a spot

Table 6 Other Cars Agent Attribute Summary

The Model Scale

The model is a 30 x 30 grid created to represent an area of around $200m^2$ in Hong Kong, each cell represents 6 meters of distance. A whole number is used because the average speed of vehicles in Hong Kong Island is 21 km/h (ie. 5.97m/s) (Transport Department, 2021). Simulations are designed to run until there are no more delivery agents present in the map, as agents will be removed after completing all deliveries.

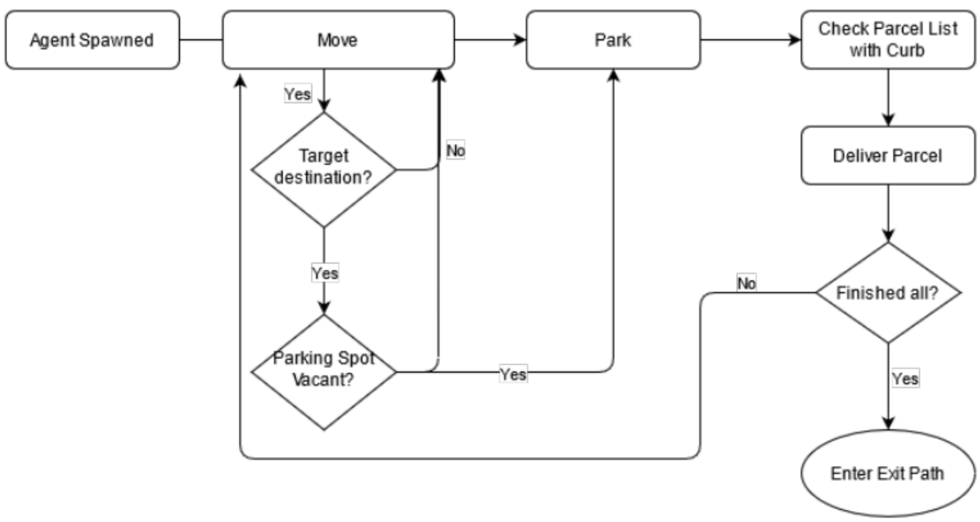


Figure 1 Flow Chart of Delivery Agents

Process overview and scheduling

The model will start by activating (initializing) the different classes of agents and submit the items to a scheduler. There will be a agent list holding the information of all agents that will be spawned. The Random Activation class in MESA's library will randomize the order of agents of that list and spawn them. In each step, agents with a move function will check if the cell ahead is occupied or not, if not, it will move one step along the road. Moving agents like bikes, vans and cars will keep moving and constantly checking with the curb agent whether they have arrived at the right spot to deliver, curb agents must be directly in front of the destination building. If yes, the agent will proceed to park on the curb agent instead of the road.

After the agent is parked, their state will change and continue into the countdown process of the timer resembling delivery actions, which is 5 steps for bike agents, and 10 for van agents. After delivering, the agents will move forward diagonally onto the road and continue to move along the road.

During each step, delivery data at a model level are collected and reflected on the live charts if the model is running in a browser tab which is the interactive mode. Agents will move along the roads to complete the deliveries and will exit the map located in the bottom right corner once they completed all deliveries, the agent will be removed from the scheduler, and the model will stop if the list that records the agents removed equals the list of agents to be spawned.

3.1.2 Design Concepts

Basic Principles

The model aims to look at the viability of replacing LGV delivery vans with electric cargo bikes. Electric cargo bikes provide flexibility in packed urban areas due to its slim shape and the ability to walk on pedestrian roads, cycle lanes and traditional car lanes, and parking cycles occupy less space compared to LGVs which cannot be parked on pavements. Despite having less flexibility moving around the city, LGVs have the biggest advantage of high carrying capacities that is often 4-5 times that of cargo bikes. However, the cost to use either vehicle have different equations, therefore this model will test the efficiency of deliveries against operational costs.

Emergence

A baseline scenario will be created (at R=0 and T=0) so that newer cases can be measured against the different parameters. The costs of completing deliveries are measured as a key criterion for viability.

Adaptation

The design of the environment is based on the actual street state of this area in Causeway Bay, Hong Kong. It is a small area constructed of 5 single lanes, and double parking is prohibited. Given the restriction of single lanes and no stopping in any spot along the roads, vans must park in the curbside. If in the first attempt an agent cannot park the car because the spot is occupied, it will complete the lap and go back to the same spot in the second lap and try to park. The checkpoint feature for both bike and van agents ensure they visit every road on the map.

Sensing

Moving agents detect if cells ahead are empty before moving onto it, and when attempting to park, they will check whether the cell ahead and diagonal is empty.

Interaction

Moving agents all require interacting with the curb agent to verify a matching parcel ID in both agent's entity before a parcel is marked as delivered. As agents move around the map, agents interact with the road entity located at the bottom right corner, if they finished delivering all parcels they will enter the exit route instead of going back to the starting point.

There are 2 types of data collection scope, agent and model level. Due to the limitations of the MESA library, the same ID cannot be reused for naming agents – there are 3 classes of moving agents but their ID all start from 0, which crashed the program when the ID's need to be submitted in the backlog. To tackle this, model level monitoring was adopted.

Stochasticity

The emergence of agents are randomly scheduled using the Random Activation class. Agents are defined by classes, and submitted to the scheduler in the last stage of assembling the model (also a class).

Observation

If the model is running in interactive mode, there are live graphs that update per step, showing deliveries completed by both agents types, speed, and time taken to complete the delivery process. For systematic observation, the Batch Runner class will collect labeled variables at the end of each run, stepwise collection is not possible.

3.1.3 Details

Initialization

The world is created using a external file that marks different cell type (curbs, buildings, roads…etc) using different numbers. The 30x30 grid is then colored according to the text file. However, the exact number of agents to be spawned depends on the information from model parameters. The model parameters are as follows:

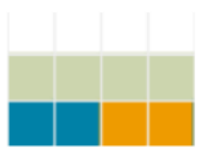
1. Number of parcels to deliver
2. The carrying capacity of each light goods vehicle and electric cargo bikes
3. The ratio of bikes to vans
4. Traffic flow

The above parameters will be used to create the agents. Since the nature of this MESA library creates each agents as a class, and the model itself as another class, some agents need to be created first in order for the following agents to use attributes from existing classes. At the initialization stage, the complete parcel list to be delivered using either method will be generated, and then distributed to agents. The spawning order of agents on the map is random (refer to previous section).

Input data

The only input file required for this model is a text file that stores a dataframe of 30 x 30 numbers. Each cell in the grid except for road agents is assigned a number to represent them, ie. 1 represents road agents, 2 for curbs etc… a 30x30 dataframe will translate into a grid of 30 blocks on each side.

1	1	1	1
2	2	2	2
3	3	4	4



Submodels

As users choose parameters in the interactive mode or console mode, it will alter the number of agents in the simulation.

Variable	Description
N	Number of Parcels
R	Ratios of Vans to Bikes
C_v	Van Capacity
C_b	Bike Capacity
T	Traffic Level Multiplier

Table 7 Model Parameters

The van capacity and bike capacity are key determinators to calculate the exact number of agents to be spawned to deliver the specified number of parcels, formulas are as follows:

$$\text{Number of bikes required } = [\frac{N}{C_b + (R * C_v)}]$$

$$\text{Number of vans required } = R[\frac{N}{C_b + (R * C_v)}]$$

The level of traffic is denoted by T, it has a range of 1-5 and will determine how many car agents will be spawned. It is calculated by multiplying T with 20, ie. If T is set to 2, the cars to be spawned will be 40. The total circuit length of the environment is 321 blocks, but there are only 160 blocks of road, 20 is a acceptable number because spawning in ratio to any road length will overload the environment and all moving agents will be unable to move.

The cost of completing deliveries by either method is a crucial monitor to answer the research question. A formula created by Marujo et al is referenced and numbers are localized into Hong Kong dollars. The formulas and table of cost conversion are as follows:

$$\text{Cost of delivery }_{Bikes} = d(C_{bike}^{km} + \frac{C_{bike}^{hour}}{v_{bike}}) + C_{bike}^{hour} t_{bike}^{stop} n_{stops}$$

$$\text{Cost of delivery }_{Vans} = d(C_{van}^{km} + \frac{C_{van}^{hour}}{v_{van}}) + C_{van}^{hour} t_{van}^{stop} n_{stops}$$

Item	Calculation (in HKD)	Source
CPI change between 2020 and 2011 in Hong Kong	135.031/105.277 = 1.2826	World Bank, 2021
LGV operation cost from 2011 in 2020's term	Operation cost + Salary costs = $105,380 + $178,500 * 1.2826 = $364,105	HKSAR Transport Department, 2011
Costs of LGV		
Cost per km of LGV	364,105/31,200 = $11.67	HKSAR Transport Department, 2011
Hourly cost of operation	364,105/46.8/7/24 = $46.31	HKSAR Transport Department, 2011
Costs of E-CB		
Cost per km	0.043EUR * 9.2 = $0.396	Elbert and Friedrich, 2020 Bloomberg, 2021
Hourly cost of operation	Operation Cost + Salary Costs = (9.02/24 EUR)* 9.2 + $37.5= $40.96	Elbert and Friedrich, 2020 HKSAR Labour Department, 2021

Table 8 Costs Related to Calculating Delivery Costs

3.2 Technical Specification and Challenges

The model was built using the MESA library, all codes were written in a Jupyter Notebook. The design of Jupyter Notebook is a interactive console so users can run one set of code in one cell first, and proceed to write code in other cells based on the output of the previous cells.

Because of this feature, some entities must be created first in order to become a callable object in latter cells. For example the functions for calculating parameter requirements and the functions for all moving agents to move, park and depart are made sharable by multiple classes, hence they are first created. And to reduce code redundancy, information like road section definitions are stored in the road agent, and is then callable for all latter cells after making it a global variable.

All agents are created by naming them a class object and they all have their own notebook cells, and it led to problems with data collection. To retrieve the delivery time taken for each agent, the counter is implemented into the agent's class. To illustrate with an example, a new van agent with ID 1 of the same class will spawn whenever the step function is called in the model class, causing the stored data of the previous van agent with ID 0 to be reset - only the delivery time of the latest spawned van will be stored. To tackle this, a list to store the delivery times of each agent is created to the curb class, because the curb class will never be reinitialized throughout the whole run. So agents will interact with the curb agent located at the bottom left corner to communicate their delivery time, and proceed to leave the environment.

4. Simulation Results and Analysis

The parameters used in the simulations and their results will be explained in this section.

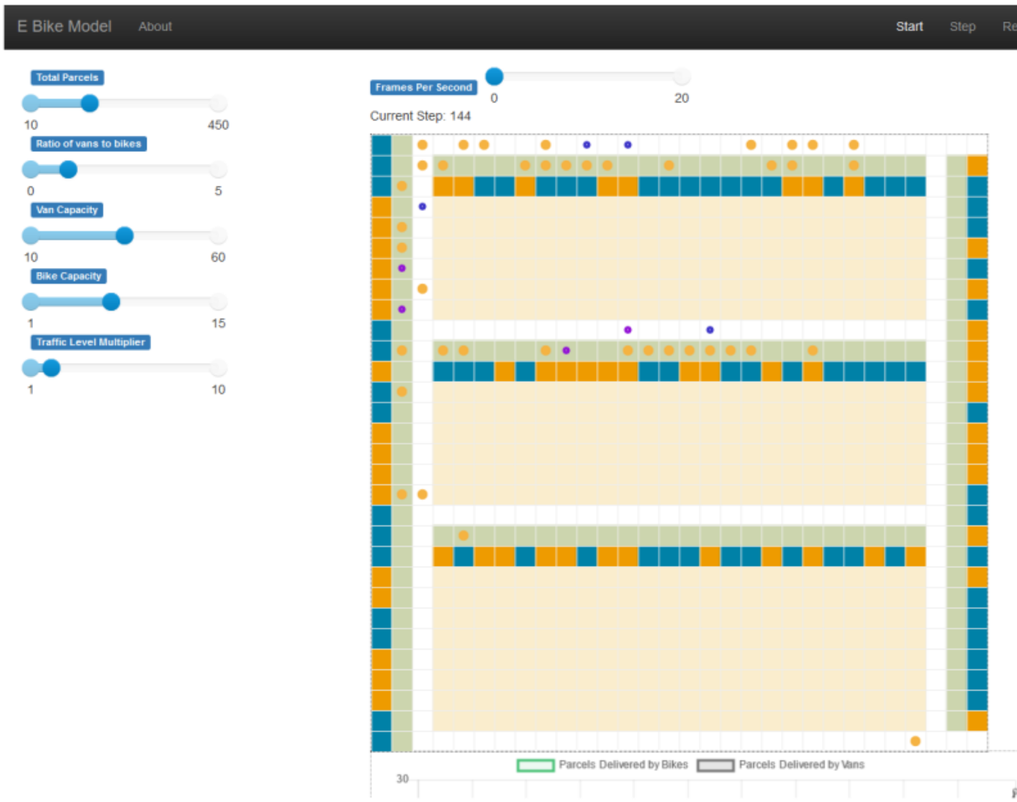


Figure 2 Model Running in Interactive Mode

4.1 Simulation Details

To systematically investigate the impact of parameter combinations on the cost of delivery, a parameter sweep is performed using the Batch Runner class in the MESA library. Every combination was tested 5 times and averaged. Information about the total parcels delivered, the cost of delivery and average speed were collected.

Parameter	Variable	Range Simulated
Number of Parcels	N	[100, 200, 300]
Ratios of Vans to Bikes	R	[0, 1, 2, 3]
Van Capacity	C_v	[35]
Bike Capacity	C_b	[7]
Traffic Level Multiplier	T	[1, 3, 5]
Element Monitors		Remarks
Cost per parcel for Vans	P_v	
Cost per parcel for Bikes	P_b	
Failed to deliver parcels	f	
Total Cost of Delivery for Vans	TP_v	
Total Cost of Delivery for Bikes	TP_b	
Total Delivery Time for Vans	D_v	Time in terms of model steps
Total Delivery Time for Bikes	D_b	Time in terms of model steps

Table 9 Parameter Sweep summary

4.2 Results and Analysis

The process was hugely resource consuming, with each iteration taking around 13-15 minutes to complete. Initial runs were conducted on my computer, yet it took more than 10 hours to complete one tenth of the amount required, after through calculations, ranges to be simulated are reduced.

From the simulations, measures were taken to speed up the batch runner process. Originally, a few calculations were set so that in the end of the batch run, metrics like mileage and emission can be recorded in the output data frame. But it was discovered this will greatly affect the computation time. Metrics can always be calculated in a latter stage as long as the key values are selected to be mined out of the simulation. Adjustments to the model monitors were made and eventually, the cloud computing platform Faculty AI was used to handle the large number of computations even after a reduction in metric ranges. Faculty AI provides CPU power that is equivalent to 3 times that of my computer. Therefore with multiple Python notebooks running different segments of the required simulations at the same time, finally a total of 108 simulations were conducted.

	N	R	T	C_b	C_v	P_b	P_v	f
mean	200	1.5	3	7	35	0.563741	2.352146	34.58819
std	82.80787	1.133893	1.656157	0	0	0.370793	2.355254	18.34941
min	100	0	1	7	35	0.172906	0	1
25%	100	0.75	1	7	35	0.297951	0.943069	18.875
50%	200	1.5	3	7	35	0.408114	2.244029	36.68333
75%	300	2.25	5	7	35	0.779239	2.930329	51.1
max	300	3	5	7	35	1.350933	10.80746	64.33333

	TP_b	TP_v	D_b	D_v
count	108.00	108.00	108.00	108.00
mean	97.44	341.20	5591.22	2518.76
std	77.43	302.00	6722.42	1903.29
min	32.09	0.00	577.00	0.00
25%	48.53	0.00	1508.50	0.00
50%	63.53	273.74	2177.00	2296.00
75%	111.38	493.95	7437.50	4093.50
max	405.28	1151.65	31197.00	6515.00

Table 10 Simulation Summary

The delivery success rate and time taken are then averaged because each set of parameters were ran for 5 times to record a more precise model behavior. Costs are also normalized by dividing the total cost by the number of parcels to be delivered.

4.2.1 Delivery Success Rate

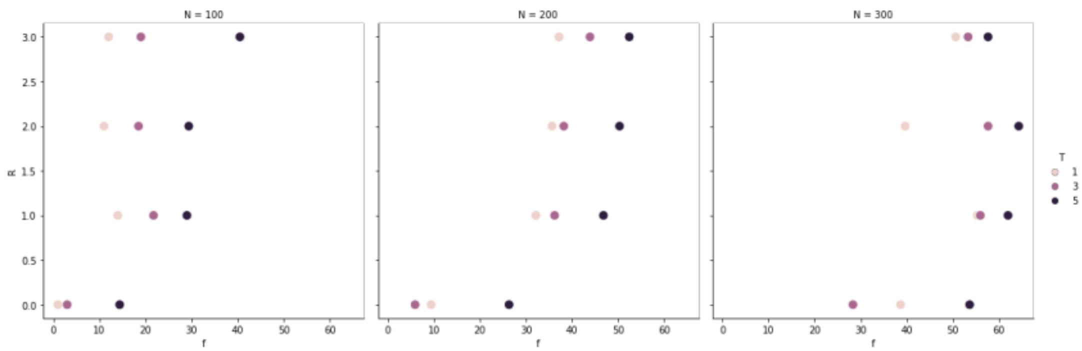


Figure 3 f-value comparison

The given duration for agents to complete deliveries are all set to 800 steps during the batch simulation process, and it results in parcels that failed to be delivered. The f-value in percentage is evaluated against the N and T value. According to the formula to spawn both vehicles, there are more vans compared to bikes as R rises.

In the figure, as R and N get bigger, the delivery performance starts to stabilize, the range of failure rates reduces, where the impacts of the traffic level were not as volatile as that in a smaller N.

The design of the environment allows multiple bikes to park on the same curb because of their slim shape, this is a feature that vans do not share. For vans, if the destination's parking lot is occupied, they will have to move down the road and come back in the next lap to attempt parking again. The effect of this setting is amplified when the traffic level gets higher. As a result, the bikes-only fleet lineup performs the best with a low failure rate of under 10% when N is under 200 and the traffic level is under 3. However, the performance is greatly affected by traffic beyond that point, this is because it requires a minimum of 42 bikes to deliver 300 parcels, under T=1 there will be 62 vehicles present in the environment that only has 160 blocks of road, suggesting heavy congestion. It is observable from the left most chart that any fleet combination will not work efficiently, so that would be the maximum capacity of the environment.

4.2.2 Cost of Delivery

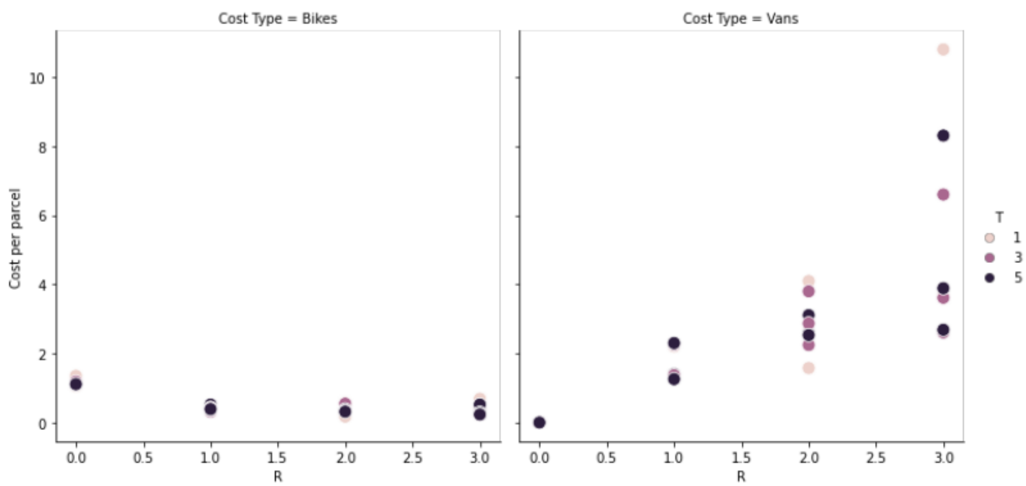


Figure 4 Cost per parcel for both types of vehicles

Model monitors were embedded when creating the agents to track their performance during the iteration. The cost of delivery was calculated using the formulas referenced in previous sections, localized to local currencies. The cost is then normalized using N (number of parcels to be delivered) instead of the successfully delivered number of parcels.

It can be observed that bikes have a narrow range of cost, not heavily affected by traffic. This can be explained by the ability to park together instead of having to find a parking lot in the next run. Also, the cost per parcel seems to be slightly lower as R goes up.

The cost for vans are higher than that of bikes, and goes up alongside R, with the effects of traffic widening the range of costs. Therefore linear regression was used to evaluate the effect of R and T.

OLS Regression Results

Dep. Variable:	Vans	R-squared:	0.734
Model:	OLS	Adj. R-squared:	0.709
Method:	Least Squares	F-statistic:	29.42
Date:	Mon, 09 Aug 2021	Prob (F-statistic):	2.52e-09
Time:	21:22:13	Log-Likelihood:	-57.581
No. Observations:	36	AIC:	123.2
Df Residuals:	32	BIC:	129.5
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
N	-0.0103	0.003	-3.956	0.000	-0.016	-0.005
R	1.6131	0.189	8.517	0.000	1.227	1.999
T	-0.0388	0.130	-0.299	0.767	-0.303	0.225
BC	0.0115	0.004	2.843	0.008	0.003	0.020
VC	0.0577	0.020	2.843	0.008	0.016	0.099

Omnibus:	31.901	Durbin-Watson:	1.450
Prob(Omnibus):	0.000	Jarque-Bera (JB):	78.240
Skew:	2.108	Prob(JB):	1.02e-17
Kurtosis:	8.863	Cond. No.	3.02e+17

OLS Regression Results

Dep. Variable:	Vans	R-squared:	0.733
Model:	OLS	Adj. R-squared:	0.717
Method:	Least Squares	F-statistic:	45.34
Date:	Mon, 09 Aug 2021	Prob (F-statistic):	3.41e-10
Time:	23:13:07	Log-Likelihood:	-57.632
No. Observations:	36	AIC:	121.3
Df Residuals:	33	BIC:	126.0
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
N	-0.0103	0.003	-4.011	0.000	-0.015	-0.005
R	1.6131	0.187	8.637	0.000	1.233	1.993
BC	0.0109	0.003	3.203	0.003	0.004	0.018
VC	0.0545	0.017	3.203	0.003	0.020	0.089

Omnibus:	33.209	Durbin-Watson:	1.454
Prob(Omnibus):	0.000	Jarque-Bera (JB):	86.824
Skew:	2.169	Prob(JB):	1.40e-19
Kurtosis:	9.250	Cond. No.	3.17e+17

Figure 5 Regression Results for Van's delivery cost

From the regression results, T has a very high p-value so it will be rejected under 0.005 significance level. And in the second run, T is not included as a variable, but the R^2 value did not change significantly. It can be concluded that the cost is not affected by the traffic level, and the R value is the biggest determining factor of the cost.

4.2.3 GHG Emissions

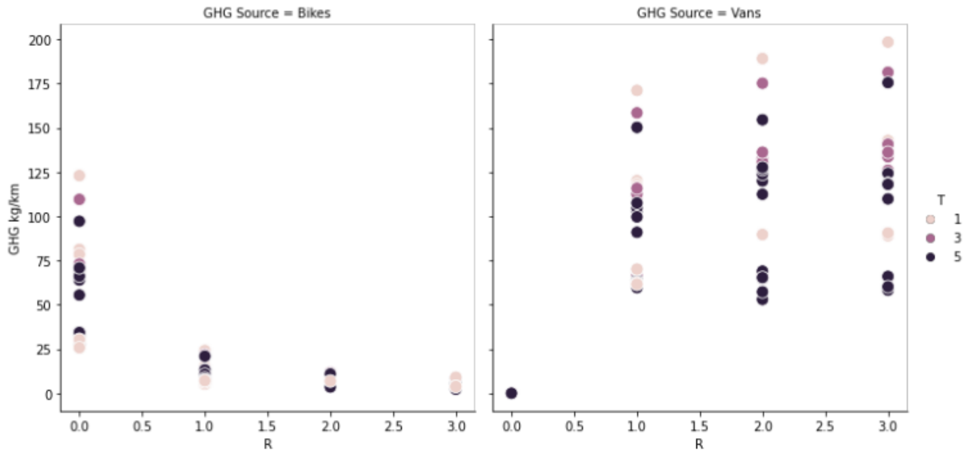


Figure 6 Greenhouse Gas Output by Vehicle Type

The total output of GHG emitted by both vehicle types are also compared. The relevant GHG emission estimations were referenced from Marujo et al. (2018), the GHG gas and atmospheric pollutants from both medium sized cargo trucks and tricycles were documented. The GHG gas created by trucks are 0.85 kg per km, and 0.11 for bikes. The output is calculated using the total steps taken for entities to complete a delivery journey. From Figure 5, the emissions are very different for both vehicles. Like the results in comparing the cost of delivery per parcel, the amount of GHG emissions from bikes decreases as R increases, but it is the opposite to vans. The emission from vans has a very large range that is dependent on traffic level, yet does not fluctuate with R as significantly as observed in bikes. For R 1-3, once there are vans in the environment, there will be a minimum of 50kg GHG emitted to the environment, such fixed cost is not observed in bikes.

In addition to the fixed cost observed in vans, there is a large range of emitted gases especially for cases with vans involved. Linear regression results show a R^2 of 0.73 for vans, where T has a 0.063 p-value, only barely over the 0.05 significance value. Whereas for bikes, a R^2 of 0.632 is produced with T having a p-value of 0.895. Comparing the results of both regression results, T value has a higher impact to vans compared to bikes.

OLS Regression Results

Dep. Variable:	Vans	**R-squared:**	0.730
Model:	OLS	**Adj. R-squared:**	0.722
Method:	Least Squares	**F-statistic:**	93.72
Date:	Fri, 20 Aug 2021	**Prob (F-statistic):**	1.90e-29
Time:	00:03:00	**Log-Likelihood:**	-520.48
No. Observations:	108	**AIC:**	1049.
Df Residuals:	104	**BIC:**	1060.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-24.9000	10.841	-2.297	0.024	-46.398	-3.402
N	0.3572	0.046	7.795	0.000	0.266	0.448
R	37.4921	2.695	13.913	0.000	32.148	42.836
T	-3.3945	1.805	-1.881	0.063	-6.974	0.185

Omnibus:	6.748	**Durbin-Watson:**	0.426
Prob(Omnibus):	0.034	**Jarque-Bera (JB):**	4.610
Skew:	-0.360	**Prob(JB):**	0.0998
Kurtosis:	2.289	**Cond. No.**	686.

OLS Regression Results

Dep. Variable:	Bikes	**R-squared:**	0.632
Model:	OLS	**Adj. R-squared:**	0.621
Method:	Least Squares	**F-statistic:**	59.52
Date:	Fri, 20 Aug 2021	**Prob (F-statistic):**	1.75e-22
Time:	00:03:20	**Log-Likelihood:**	-452.65
No. Observations:	108	**AIC:**	913.3
Df Residuals:	104	**BIC:**	924.0
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	20.6039	5.785	3.561	0.001	9.132	32.076
N	0.1491	0.024	6.098	0.000	0.101	0.198
R	-17.7354	1.438	-12.333	0.000	-20.587	-14.884
T	-0.1280	0.963	-0.133	0.895	-2.038	1.782

Omnibus:	10.637	**Durbin-Watson:**	0.445
Prob(Omnibus):	0.005	**Jarque-Bera (JB):**	10.765
Skew:	0.731	**Prob(JB):**	0.00460
Kurtosis:	3.506	**Cond. No.**	686.

Figure 7 Regression Results Regarding GHG Emission for Both Vehicles

This can be explained by several factors: availability of parking and parking capacity. The setting of the model requires 10 steps for vans to park, and 5 steps for that of bikes. But when vans struggle to find a parking space and had to go over the lap again, factoring in the effect of traffic level, the time taken to park will eventually be way larger than that of bikes.

4.2.4 R Rate

From the previous batch tests of using whole numbers for R, the maximum capacity of the environment is found, but detailed performance difference required more detailed R values. According to the equation to spawn the 2 types of vehicles, bikes will be spawned first, and the ratio will scale according to the number of bikes. There are many possible fleet combinations to complete the case of 100 parcels.

R	**0**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
N	100	100	100	100	100	100	100	100	100	100	100
Number of bikes	15	10	8	6	5	5	4	4	3	3	3
Number of Vans	0	1	2	2	2	3	3	3	3	3	3

Table 11 Different Fleet Combinations for 100 Parcels

As seen in Table 11, the number of vans increase by 1 when R equals to 0.2, 0.4, 0.6, the cost of delivery and emissions will then be compared for these combinations.

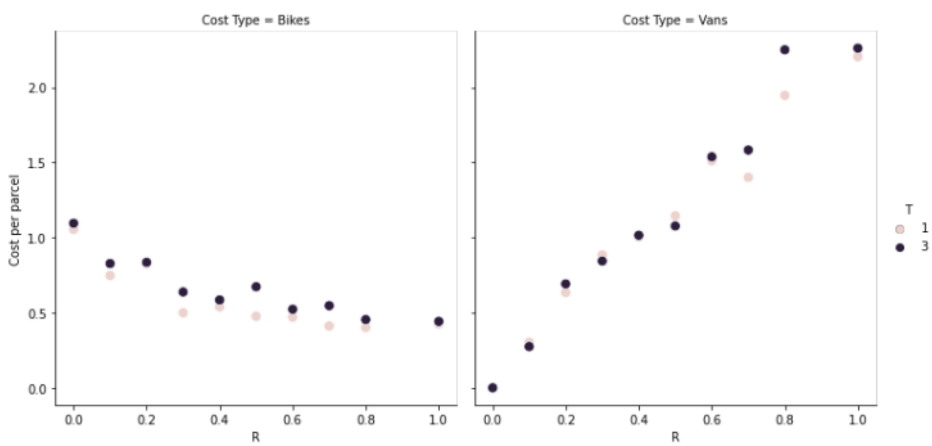


Figure 8 Cost per Parcel for small R-value

Much like the trend of costs seen in the broader scope using parameters of R from 0 to 3 in previous sections, van's cost does not scale with an increasing R. More precisely, there are 3 vans for R from 0.5 to 1, yet the costs rise significantly as compared to the decreasing costs as seen in bike. As less bikes are involved in the fleet as R increases, the parcels allocated to vans increases, and so is their utilized capacity. The optimal R value or fleet combination occurs when the least number of bikes are required for every unit of increase in vans required ie. R=0.4, 0.8.

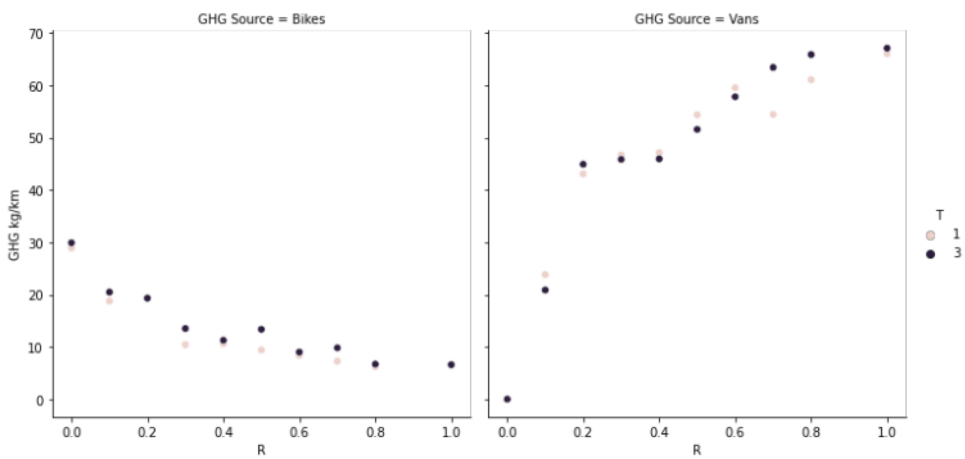


Figure 9 GHG Emission Comparison under small R-value

As seen in Figure 9, GHG emissions decreases as R rises for bikes, and the opposite for vans. For R=0 to 0.2, there is a jump from 0 vans required to 2 vans, hence the significant increase. The steady increase in emissions for vans as R rises can be explained by its utilized capacity. As mentioned before, the number of vans only increase by 1 at 0.2 and 0.5, because fewer bikes are involved in latter R until an extra unit of vans are added, vans will be operating at a higher capacity during this transition. And a van operating at high carrying capacity will require more road time to finish deliveries, hence the increase in emissions.

From an economic standpoint, vans operating at its highest capacity, requiring the least number of bikes is the optimal combination. This happens when R is at 0.4 and 0.8, but at the cost of high delivery cost for vans. From an environmental standpoint, it is more ideal to involve more bikes to complete the same number of parcels. Tradeoffs exist between maximum efficiency and environmental friendliness on whether to involve more bikes in the fleet, because vans are inevitable to form a fleet to deliver the unallocated parcels.

5. Discussion

<u>Delivery Success Rate and Costs</u>

As seen in figures in previous sections, the fail to deliver percentages fluctuates alongside factors like traffic level, bike to van ratio and delivery load. A high delivery success rate means less monetary loss of failing to deliver, the costs incurred to transit the parcel back to the depot and attempt to deliver again could be detrimental to a courier. In the delivery success rate standpoint, it is best to run a bikes-only fleet for delivery loads of under 200 parcels and traffic level below 3, the success rate is the highest. But if LGVs are inevitable, it is still ideal to operate under 200 parcels, and a T and R range of below 2. The range of success rate for the hybrid fleet gets bigger as R >= 3, which is not ideal for operational planning because of the volatility traffic level has against the delivery success rate.

In terms of monetary costs, both vehicles performed very differently. The costs per parcel to bikes do not fluctuate a lot against rising traffic and fleet combination, but that of vans rises with R, unaffected by traffic levels. Despite LGVs having almost 5 times the carrying capacity of electric cargo bikes, the operational cost is inversely correlated with that of bikes as R increases, suggesting van's operational costs do not scale well with operating conditions. Further investigation even revealed within a fleet, vans operate at higher loaded percentage by pairing with the minimum number of bikes needed to complete a delivery run. Meaning if the allocation process starts with maximizing van's capacity first and let bikes take up the remaining load, it will result in the most efficient fleet in terms of money and emission costs. However, the effect of traffic on delivery cost using vans widens the range of delivery costs, making financial planning for operations under that situation hard to manage.

Furthermore, factoring in the emissions produced by vehicles in an array of scenarios, it is discovered bikes are more environmentally friendly when R gets larger, ie. More vans in the fleet. There is a tradeoff between low costs of delivery and emission levels, yet from an entrepreneurial standpoint, considering vans have a stable range of emissions under scenarios from R 1-3, and a fixed emission output no matter how loaded they are - combining the benefits of bike's low cost of delivery and success rates, bikes are still a preferable option.

The optimal fleet combination is a bikes-only fleet, even if a courier tries to scale up the delivery capabilities using other combinations, it will result in a heavy tradeoff. For example, in the N=100 stage, the delivery success rate does not improve significantly even when R increases, but the cost of doing so will be double or triple the van cost for a 1-2% success rate improvement. Hybrid fleets are a suboptimal option, at R below 0.5, the costs for both vehicles are very similar, and the success rate is also acceptable at maximum of 20% fail.

Cargo Bike Behavior

The design of the model with only single laned roads negated the ability of bikes to maneuver in small areas like move on curbs and overtaking traffic. The contribution to the traffic level from the number of bikes are abundant as opposed to real world scenarios. Despite bikes will deliver all parcels regardless of their order in the parcel list that belongs to one single curb in one go, bikes will move and park at the target building just next to the previous building, when it could have been parking in the middle of the target building cluster and complete the delivery process, further reducing the time spent in moving (and affected by congestions) and parking.

6. Conclusion

6.1 Limitations and Future Work

There are several limitations in this work, in the library nature and model completeness aspect. The former limited the ability of the model to resemble reality, whilst the latter can be tackled by endeavoring more effort into building the model, and this section will look at how these features affected the outcomes of the simulations.

The decision to use MESA is based on the availability of open-sourced tools, coding language and ease of use for the scope of a dissertation. However, unlike other popular Python libraries like Keras and Tensorflow, MESA does not support any kind of hardware acceleration, nor is the parallel simulation tool well built, which caused tremendous operational bottlenecks when choosing the scope of simulations to run.

6.1.1 Model Nature

The MESA library built the model in a grid form, the movements are all bind to a value of one step and one cell. This cannot reflect the real-world situation as all buildings and cars have a different dimension, speed that is not proportional to a cell's width, and movements in time that do not scale with one step's value in terms of seconds. When entities are presented as one of the many blocks of the model, their size and movement are unified. In terms of size, the block/grid form cannot reflect the difference in physical sizes between bikes and vans, even if a dual lane system is introduced, it cannot reflect the situation when bikes overtake cars using the narrow space between the curb and the cars just like what a real-life cyclist will attempt. In terms of movement, entities cannot move unless the block ahead is clear, and even if they move, it will be at the maximum speed of 21km/h, which is unrealistic because real life drivers will accelerate when nothing is ahead and decelerate to maintain a safe driving distance.

Model Completeness

On path finding, the model cannot fully resemble real world scenarios. Looking at how densely located the target buildings are, a real-life delivery serviceman will tend to park in the middle of that building cluster and deliver by walking a few steps instead of returning to the vehicle and park 1 cell away from the last parked spot. And due to how the grid is set out and the heavy demand it would cost for computing resources to recalculate the proximity for around 20 agents at every step, agents should have been able to prioritize destinations based on the proximity to the next delivery instead of being set to revisit the path just to reach the target destination. Whilst there could be a lot of workarounds such as unsupervised learning models to mimic a pathfinding decision, it is currently a challenge to systematically portray the micro-behaviors of agents.

6.2 Future Work

As mentioned in the limitations detailed above, the current model is in a prototype stage that opens up many future development ideas, there are still a lot of room for improvement in several aspects. Despite each idea seem very minor, it is a small step to take to resemble real world situations. The following is a list of possible adjustments:

Targeted at model scale

There are several things to adjust so that the environment resembles more closely to the real world.

The number of bikes that can be parked in one cell should be limited to around 6-10, much like what a bike rack can hold. Currently there is no upper limit, but to implement this it will require interactions between curb and bike agents. Bikes will need to register their ID with the curb agent, and once the counter of a curb agent's parking capacity reaches maximum it needs to tell the incoming agents it is full. But first there must be a way to fix the ID allocation in the library scale because all agent's ID start from 0 and cannot be altered by any calculations to separate them from each other.

Also, to mimic a more realistic behavior of a driver, they usually park in the center of a point where they have access to several delivery spots by only parking once. A center point of a target building cluster as the parking spot is needed. This will save up the time used to park and deliver.

Buildings should have different number of parcels to receive. It is currently fixed at 11 for all buildings because a dynamic number is not accepted during the creation of the building entities. Creating a list of random numbers within a range and allocate it to the building just like the parcel allocation method did not work.

The original plan was to only allow parking in the bottom 2 lanes to resemble the suggestions from AECOM regarding reducing the area traffic, so van agents are expected to walk to destinations. But it did not work because of the lack of distance-based calculation and agents need to physically reach the curb agent in order to register the delivered parcel.

One last thing is to include more variety of parcels and delivery agents. There could be differences in delivery time for paper box parcels versus frozen items.

Targeted at libraries supporting ABM

The MESA library is still underdeveloped, there are so many features the user base is anticipating. And one of them will be to allow users to specify lane widths, or a flexible table instead of a grid. This would enable users to create bus lanes, dual lanes, cycle lanes to better resemble real world situations.

Also, regarding the tedious work put onto batch simulations, it is discovered unlike other popular Python libraries like Tensorflow and PyTorch, hardware support is not a feature in MESA, and in other ABM libraries in general. Hardware support for parallel processing to speed up systematic investigations is crucial if studies of a larger scale with more agents are produced. Studies discussed the viability of using CUDA-enabled GPUs support for ABM (Kosiachenko, 2018) and is highly anticipated.

Despite beyond the scope of this research, more attributes of the economic viability should be investigated. The costs associated with adopting an electric bike fleet also involve work planning and staff training to suit the operational constraints of cargo bikes. This research did not consider large parcels such as furniture, expensive, frozen or perishable items, but it is a tradeoff to couriers whether they want to use a fleet that is environmentally more friendly but at the cost of forgoing profits from delivering high value adding products like the ones listed above.

6.3 Conclusion

In conclusion, the agent based simulation model produced for this dissertation verified that electric cargo bikes are indeed a feasible option to replace LGVs, and outlined the conditions where this replacement is optimistic. One of the strongest advantage of bikes are the ability to be unaffected by traffic levels, which is crucial in reducing road load but at the cost of pedestrian’s road space. The costs associated with delivery on bikes are only a fraction of that of vans, with a relatively more consistent performance under congestion and heavy load pressure, ultimately making bikes a highly favorable alternative to traditional delivery vans. This positive outcome is a great inspiration towards legalizing electric assisted bikes and scooters in Hong Kong.

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