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Optimized Vehicle Routing Problem for The Last Mile E-Commerce Parcels Delivery Using E-Bikes

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Abstract - This research addresses the Optimized Vehicle Routing Problem (VRP) for last-mile e-commerce parcel delivery using e-cargo bikes in a Central London case study setting. The primary objective is to enhance delivery routing efficiency, and reduce operational costs, competition time, and carbon footprints through the application of the Evolutionary Algorithm using the Excel Solver. With the rise of e-commerce, efficient last-mile delivery has become increasingly important to ensure customer satisfaction and sustainability. As an alternative, electric cargo bikes offer promising benefits, capable of navigating congested areas and providing eco-friendly delivery solutions since traditional delivery methods face challenges such as traffic congestion, high fuel costs, and significant carbon emissions. The research begins with a comprehensive literature review, highlighting the various VRP variants and their applications in urban logistics. Existing studies have primarily focused on optimization techniques for conventional vehicles, with limited attention to e-cargo bikes. This study fills that gap by developing the Mixed-integer linear programming (MILP) Mathematical Model specifically for e-cargo bike routes, considering factors such as vehicle capacity, delivery time windows, and distance minimization. Four different scenarios were tested to evaluate the effectiveness of the proposed algorithm. Data for this research was meticulously collected from e-commerce delivery records, urban traffic conditions, and geographical information pertinent to central London's delivery routes. The evolutionary algorithm was implemented to generate and iteratively improve upon feasible routing solutions by setting different parameters of population sizes and mutation rates which led to minimizing the total distance traveled and associated costs. Consequently, the best-optimized routes resulted a substantial reduction in daily logistics costs, from £141 to £112 which reduced the traveling distances from 65.176 km to 29.810 km which underscores the economic viability of e-cargo bikes for last-mile delivery. The research also highlights the substantial potential of e-cargo bikes to lower CO2 emissions, contributing to more sustainable urban logistics. The findings support the integration of e-cargo bikes as a viable alternative to traditional delivery vehicles, promoting both environmental benefits and daily operational efficiency, particularly in metropolitan areas like Central London. This study provides a foundational understanding of the benefits and challenges associated with e-cargo bikes in last-mile delivery, paving the way for further advancements in sustainable urban logistics.

Keywords - Capacitated Vehicle Routing Problem; Last Mile Delivery; Evolutionary Solver; Genetic Algorithm; Electric Cargo Bikes; Logistics Operational Cost; Completion Time; Carbon Footprint; Battery Energy Consumption; Central London Case Study

1 Introduction

1.1 Nature of E-Commerce Booming

The COVID-19 pandemic, the availability of technology gadgets, and the rapid accessibility of the internet have changed the nature of operating businesses, buying and selling behaviors, and pushing humans to adopt flexible approaches to deal with the situations. During the pandemic, people were significantly relying on digital platforms through electronic devices whether to socialize with the outside world or to purchase groceries, commodities, and other parcels of goods both for utilization and convenience living under lockdown and social distancing practices. That period has dramatically continued to push retailers, bankers, and service providers to extend their digital infrastructures from brick-and-mortar businesses as consumers' behaviors were changing based on convenience, accessibility, and time-saving due to online shopping. In addition, the digital platform is not only giving big businesses or retailers the stage but also giving the same open stage of equal opportunities for SMEs which businesses need no physical stores while enhancing bargaining powers to users going nowhere shopping from digital retail websites. The concept of last-mile delivery in e-commerce plays a crucial role as it is the final touch point with end customers and the judgmental service step provided by e-retailers to end customers which determines the success of retailers in the online landscape.

1.2 E-vehicles Demand in Last-mile Logistics

The final destination of delivery parcels in a business operation especially in e-commerce is one of the expensive cost-bearing processes with 40-55% of whole supply chain costs [1] where its efficiency is measured by fast, reliable, and convenient deliveries, leading to customer satisfaction and repeat business. When considering the costs, could be labor costs (parcel handling costs), fuel costs, administration and ordering costs, and vehicle costs where other challenges affect the last mile delivery including traffic congestion in the urban area, routes scheduling problems, infrastructure parking, using narrow lane streets, and drop-off points timing at residential deliveries which slow down the average speed, creating frequently stopped points, long waiting times, prevent productive efficiency and lead to customer dissatisfaction.

Nowadays, retailers in the e-commerce industry are under high competition therefore, they are trying to improve every aspect of their operations starting from picking, packaging, sorting, spacing, and packing to promising customers to transport parcels within one or two days even within one day express delivery. However, the last-mile logistics challenges are not limited but go beyond to sustainable last-mile delivery, therefore to compact traffic congestion, reduce natural fuel consumptions, and decrease carbon emissions considering other cost factors are crucial while increasing delivery efficiency, optimizing for the shortest routes, using less maintained, cost-effective, and eco-friendly vehicles, drones and other advanced vehicles or using shared public transports for delivery could be possible strategies for sustainably dealing the last mile delivery.

1.3 Zero-Emission Target of London

Being the birthplace of the Industrial Revolution, the United Kingdom was one of the historical emitters of the burning of fossil fuels at that time, and global warming, climate change, and environmental pollution are great concerns among the world nations including the UK. In the UK, the domestic transport sector alone accounted for 28% of the nation's net greenhouse gas (GHG) emissions in 2022 followed by other sectors such as buildings and product use (20%), and industrial production (14%) according to the Department for Energy Security and Net Zero [2]. Moreover, the poor air quality particularly in London caused by traffic on the road, especially diesel and petrol cars are key forces impacting residents' health and create environmental hazards that increase the risk of cancer, heart disease, asthma, and many other illnesses, and the last mile delivery carbon footprint was approximately 100 million kilograms equivalent of heating approximately 36,000 homes in London in 2020-21 [3], therefore, needed to address for sustainability in the transportation sector is crucial.

Furthermore, the UK has committed to reducing total greenhouse gas emissions by at least 68% by 2030 under the Paris Agreement as well as regional levels' net zero targets are carried out including for a global city, London's net zero mission forward to 2030 by the mayor brought London [4]. As the United Kingdom is the world's third-largest e-commerce market, it has a forecast market turnover of US\$157,394.7 million by 2023, surpassing South Korea, estimated to contribute to a global growth rate of 8.7% in 2023, and the global e-commerce sales are predicted to rise over the next few years [5]. According to the survey, around 80% of the UK is shopping online due to free shipping, and users strongly prefer the home delivery option in 2022 [6]. Thus, choosing suitable sustainable modes of last-mile delivery shipping is crucial for retailers considering environmental, economic, social, and technological aspects.

Among possible modes, E-cargo bikes offer great potential for last-mile deliveries although having less capacity than traditional delivery methods. They might minimize emissions and operate from tiny hubs or local retailers, eliminating the need for delivery van fleets to drive into cities from out-of-town depots, they are affordable purchased investment, and less maintenance costs while ideal for high-density metropolitan regions and small streets in historically city centers. The trial test in 2018 was carried out by e-Cargobikes.com worked with Sainsbury's market chain under funding from the Department for Transport's Innovation Challenge Fund by accessing the efficiency of e-cargo bikes to deliver grocery orders to consumers' doorsteps living in busy cities [7]. The trials demonstrated 96.7% order fulfillment in a single e-cargo bike drop exceeding expectations for commercial feasibility and efficiency. E-cargo bikes employ cycling and bus lanes performing faster than delivery vehicles, resulting in shorter delivery routes and journey durations meanwhile they may park closer to delivery destinations, resulting in lower 'doorstep' times. However, given the variety of cargo bike options available, certain potential obstacles might need to be overcome. Standardized capacity and speed would need to be restricted or taken into account, taxes and insurance policies would need to be reviewed, and parking and urban infrastructure usage would need to be modified to be able to balance the advantages of e-cargo biking.

In the past few decades, companies have been facing the complexity of planning and managing logistics networks; moving goods within limited capacity, time windows, accessibility of infrastructures, and human capital while using different modes of transport competing for today's global market. The expectations of customers are also changing rapidly with reduced patience, switching quickly with the help of technology to communicate easily and to favor shorter life-cycle products and overnight express delivery continuously pushing to develop the optimal logistics networks to meet those expectations at the right place, on the right time, and in the right condition. Therefore, the classical vehicle routing problem (capacitated vehicle routing problem (CVRP)) is an important problem for both businesses and academics as it is associated with the field of logistics and transportation determining the optimal set of routes to be performed by a vehicle fleet to serve the demand of a given set of customers and ends at the same starting point and could resolve those problems with the help of mathematics formulation and algorithms using suitable advanced software calculators.

The VRP problem was theoretically researched in 1959 by Dantzig and Ramser with the truck dispatching problem and it is one of the problems in the field of transportation optimization and is the combinatorial optimization problem [8] with the NP-hard problem in real routing for several demand points forming numerous variables under approximate method which are time-consuming while trapped in local optima solving with heuristic methods for VRP routing problems. However, metaheuristic methods can overcome local searches to find the global best optimal as they use explosion and evolution practices by accepting worse moves for VRP routes.

1.4 Problem Statement and Objectives

Over the past years, a number of studies have examined the advantages and disadvantages of using cargo bicycles, both electric and conventional for urban logistics, and some have even suggested decision support models. Research has shown optimization models for sharing truck/van and cargo bike fleets, while few have focused only on electric cargo bike fleets. The research of this study goal focuses on creating effective route schedules for delivering e-commerce packages using the evolution-based metaheuristic Genetic Algorithm (GA) while considering e-cargo bikes capacity limitations while testing under the external force restrictions of weather, road and terrain using the central London case study settings. The deterministic demand points and the micro-depot will be set as part of the parameters while the mixed integer model will be presented in the next chapter. Moreover, using appropriate information sources and geographical target locations a set of delivery locations in central London will be a case while using the Genetic Algorithm model's precision and effectiveness in the optimization of e-cargo bike routes will implement applying the Evolutionary Excel Solver engine. To achieve the optimum e-cargo bike routes in central London the research objective, the following research questions need to be addressed in terms of minimizing travel distances, logistics operational costs and contributing carbon emission using e-cargo bikes.

Therefore, the research paper will be based on following questions:

1. How can the evolutionary solver engine in excel (Genetic Algorithm) solution be effectively implemented to optimize last-mile e-commerce parcel delivery routes using electric cargo bikes (e-cargo bikes) within the central London, with considering vehicle capacity limitations and external forces?

2. How is the evolutionary solver (Genetic Algorithm) model enhancing the accuracy and efficiency of route order scheduling by minimizing travel distance depending on parameters for last-mile e-commerce parcel using e-cargo bikes effecting the daily logistics operational costs and completion time of the delivery operations?

3. To find out how much carbon footprint e-cargo bikes can produce during transportation operations?

2 Literature Review

2.1 Literature of Vehicle Routing Problem (VRP)

Transport optimization, being the final phase in the supply chain, plays a crucial role in optimizing the Vehicle Routing Problem (VRP), which has several variations based on real-life scenarios. Initially, introduced in 1959 by mathematicians Dantzig and Ramser in their work, the vehicle routing problem, an NP-hard combinatorial optimization problem, aims to find the most efficient routes for vehicles that start at a depot, service each client once, and return to the starting location [9]. The first VRP modeling was for the "Truck Dispatching problem" using a fleet of homogeneous trucks to minimize the traveled distance in oil distributing to the number of gas stations from a central hub, in 1964 by Clarke and Wright, the VRP was known widely as the problem was generalized to a linear optimization method by a fleet of trucks with varying capacities to serve a set of customers dispersed around the central depot using the effective heuristic for solving this problem.

Interestingly, variants of VRP have evolved due to the increased complexity and wide ranges of the real-world problems of transportation and logistics industries and the scenarios creating globalization and urbanization using multi-model transportation, multi-depots, and different types of vehicles. Concerning environmental conditions with preparation for emergency crises, changes in consumer behaviors, uncertain demand, and advancements in technology are challenges and opportunities as well as contributing to forming the VRP variants.

Capacitated vehicle routing problem (CVRP) is the classical VRP problem limiting the carrying capacity of goods on the vehicle from the central depot to the known customer locations and demands to determine the optimal routes, shortest distance, minimize the travel cost and number of vehicle utilization for delivering the given demand points. HFVRP heterogeneous fleet VRP also known as the Mixed Fleet VRP and capacitated vehicle routing problem with the time window (CVRPTW) are under the CVRP, and CVRP is common and simple eventually it could be combined with other VRP variants.

The nature of this study is based on the Green Vehicle Routing Problem (GVRP) which is also one of the variants of the classic VRP as it is being attracted by most logistics and transport businesses and governments. The GVRP aims to minimize the negative effects of GHG (greenhouse gases) emissions and pollution considering the environmental impacts while optimizing the transport routes which could be found with other variants in most articles with the multiple objectives' considerations. Although the traditional vehicle routing problem mainly focused on the economic contributions of vehicle routes of organizations when serving distributions, GVRPs are particularly for balancing environmental and economic costs when routed effectively meeting both environmental concerns and financial indexes [10]. The three subclasses of GVRP could be classified according to their nature and objective functions with types of vehicles being utilized since measuring vehicle types, limitations, and functions could not be neglected which are also one of the influence factors calculating the GVRP. According to Lin, Choy, Ho, Chung, and Lam [10] survey research article on the GVRP, Pollution Routing Problem (PRP), Green Vehicle Routing Problem (G-VRP) in the narrower sense, and VRP in reverse logistics are subclasses of the GVRP.

There are two categories based on the engine of the vehicle in the GVRP either the internal combustion vehicles (ICV) using fossil fuel powers or switching to alternative fuel vehicles (AFV), such as electric (EV) and hybrid vehicles (HEVs) when in transportation services. However, electric vehicles (EVs) have some limits compared to conventional vehicles including recharging along the way when transporting delivery or waiting for recharging time with some limited capacities carry, they are versatile in urban routes delivery, eco-friendly, cutting costs whether in investing, maintaining, and avoiding traffic congestion using short cut ways.

On the part of the pollution routing problem (PRP), was introduced by Bektas and Laporte in 2011 [11]. In the PRP problem, an even more expansive and thorough goal function is needed when selecting a vehicle dispatching scheme that reduces pollution, especially carbon emissions, by taking into consideration not only the journey distance but also the amount of greenhouse emissions, fuel, travel times, and prices. A CVRP with environmental criteria was described by Faulin, Juan, Lera, and Grasman [12], who also considered more complicated environmental effects. In addition to the conventional economic cost assessment and the environmental costs resulting from emissions of pollutants, the environmental costs associated with traffic, noise, and infrastructure deterioration were also analyzed.

In a more limited sense, the goal of the Green Vehicle Routing Problem (G-VRP) is to reduce the fleet's fuel usage. These fleets may be ICVs, AFVs, EVs, or HEVs. Since higher fuel usage often translates into higher greenhouse gas emissions, the issue is quite similar to the PRP if the fleet is only made up of ICVs. This particular problem was proposed by Erdogan and Miller-Hooks [13] as vehicles may need to stop at an AFS along the way, thus needing to make sure each one has enough gasoline or power to go to an AFS when needed. In VRP, Erdogan and Miller-Hooks [13] are the first to examine the potential for vehicle refueling or charging along the route. This issue was identified as Green-VRP (G-VRP), wherein (AFVs) alternative-fuel-powered vehicles such as electric vehicles are permitted to refuel during the tour to increase their range. The model aims to reduce the overall distance traveled while eliminating the possibility of running out of gasoline or electric power. They take into account each customer's service time and the maximum duration limit that was placed on each route.

The other variant of the green vehicle routing problem (GVRP) is the reverse logistics vehicle routing problem (VRPRL) as the majority of research focuses on improving garbage collection or recycling old materials, which helps to solve certain environmental problems. In the real world, the operator and how the forward and backward (reverse) flows collaborate impact the system's operating level at the medium level of reverse logistics. Based on the VRPRL study, the problem is separated into four groups: Simultaneous Distribution and Collection, End-of-Life Goods Collection, Waste Collection, and Selective Pickups with Pricing. Reverse logistics has been extensively studied yet the quantity of research on reverse logistics from the angle of vehicle routing is relatively limited [10].

2.2 Last Mile Logistics Under Electric Cargo Bikes Literature Review

Various government agencies, as well as private organizations and businesses, have started utilizing AFVs (alternative fuel vehicles) to proactively lessen the harmful impact of fossil fuels on the environment or to comply with energy laws or environmental rules [13]. The green routing problems tend to be concentrated in certain areas to mitigate the negative influences of CFFVs (combustion fossil fuel vehicles) by converting truck fleets to AFVs using hydrogen and electricity as energy sources which is clean and environmentally friendly. Therefore, the market share of EVs (electric vehicles) for personal and commercial use has grown rapidly over the past decade with the encouragement of state regulations and government policies to utilize EVs in both the private and public transportation sectors [14].

Operations research has conducted most of the study on the use of cargo bikes and delivery vehicle combinations [15]. Comparing cargo bikes to motorized delivery trucks, the following are their advantages since they are electric-assisted vehicles, they do not emit noise or direct emissions, secondly, they are smaller, making it easier for them to navigate narrow streets and find parking spots faster and closer to the recipient; and then labor costs are roughly the same but vehicle purchase and maintenance costs are lower [16-17]. On the other hand, Cargo bikes are limited in range by their batteries and have much lower capacities. Cargo bikes can pose a risk to driver tiredness, and their top speed is often lower than that of conventional vehicles [18-19].

Zhang et al. [20] claimed that for transport clients, virtually entirely replacing vehicles with cargo bikes might result in a 28% and 28% decrease in costs and emissions associated with package distribution. However, the research conducted by Arnold et al. [21] discovered that cargo bikes have higher operating expenses for providers, and this might encourage providers to provide self-pick-up services, wherein they pass along a portion of the cost to their customers. Substantial decreases in the distance driven by electric motorized bikes were also found in a simulation conducted for a limited region in Munich by Niels et al. [22]. Previous studies [20-21, 23] indicated that cargo bikes could carry 10–25 packages, which is equivalent to 5–15% of light trucks, and can go at a speed of about 10–25 km/h. With a replacement rate of around three bikes per truck, the usage of cargo bikes in Seoul, South Korea's densely populated area may save expenses by 14.1% while also reducing carbon pollution emissions by 10% and lengthening service times by reducing walking distances from the vehicle to the consumer.

In terms of technology, deliveries can presently be made using electric cargo bikes, and this is becoming even more realistic with increasingly sophisticated battery packs. Electric tricycles, quadricycles, and bicycles can carry 50–250 kg of freight, and their battery packs may extend their transit range to 50–80 km, as suggested by Schier et al. [24]. According to Gruber et al. [18], electric freight bikes can cover between 19% and 48% of the distance that conventional vehicles can.

According to operation costs aspects, different methods are used to determine operating expenses including wheel-to-wheel energy usage, CO2 emissions, traffic volume, average speed, average delay, and external expenses about electric cargo bikes are determined as alternatives to delivery trucks in Seattle case study by Sheth et al., [17]. The study was based

on four distinct delivery scenario models to assess the potential effects of the following independent route parameters on delivery route costs, such as the number of stops, the distance between each stop, and the number of packages per stop. The outcome suggested that EA (electric-assisted) cargo bikes are more economical than delivery trucks under deliveries in three of the four modeled routes that are close to the DC—less than two miles for the observed delivery route with 50 parcels per stop at which there is a high density of residential units.

The monitoring of traffic key performance indicators, well-to-wheel energy, CO2 emission reductions, and other factors were analyzed to evaluate the impacts of using cargo cycles on urban logistics in Melo and Baptista's research paper in 2017 [19]. With specifying the study area located in Porto (Portugal), several scenarios about the introduction of electric cargo bikes replacing conventional vans were reviewed and evaluated. Considering the restricted availability of cargo bikes, the simulation is run and the whole cost of transportation is estimated including labor, transport, and pollution costs when the vehicle is moving as well as while it is idle. The key finding was that, in regions where horizontal distances are limited to around 2 km, cargo bikes could take over up to 10% of traditional vans without affecting the overall efficiency of the network. Furthermore, it is possible to minimize the well-towheel (WTW) CO2 emission impacts of urban logistics by up to 73%, or 746 kg of avoided emissions. Moreover, implementing electric cargo bikes in urban logistics operations yields benefits for all vehicle types and situations, with a potential 25% decrease in external expenses. Choubassi et al. [23] examined urban postal delivery. The net present values of the different methods of delivery are provided by the authors, who examine the economic effects of switching from US Postal Service cars to electric cargo bikes in three urban regions. A comparison of various vehicle depot arrangements is made, and suggestions are made for where cargo-bike vehicle depots should be located within the operational area.

2.2.1 Proposed Papers Using Exact Algorithm Approach

In 2021, Caggiania, Colovica, Prencipea, and Ottomanellia [25] presented a new approach to the Two-Echelon Capacitated Electric Vehicle Routing Problem with Time Windows and Partial Recharging (2E-EVRPTW-PR), building on the work of Keskin and Çatay [26]. The approach emphasizes the use of zero-emission technologies for last-mile deliveries, specifically e-cargo bikes and e-vans with the comparison between the EVRPTW-PR model (Case 2.a) and the 2E-EVRPTW-PR model (Case 2.b) intending to reduce the overall expenses and minimize the total distance for city distribution. As they expanded the mathematical model to include the two-echelon problem, the model seeks to minimize the overall expenses of two echelons while taking into account the costs of micro-depots, drivers' salaries, initial vehicle investment, and travel. The suggested approach draws attention to the energy and investment cost reductions that come with utilizing e-cargo bikes in restricted traffic areas whereas adopting the mix integer formulations used the exact solution method in CPLEX 12.10. As the result of the study, the green logistics solution (Case 2.b) may be advantageous to logistics organizations employing e-cargo bikes in limited traffic zones while minimizing total cost and distance.

2.2.2 Proposed Papers Using Heuristic Approaches

A mathematical optimization model and heuristic that can be used to estimate the ideal number of vehicles based on delivery demand, as well as the best routes for electric cargo cycles had been studied by Lee, Han, et al. [27]. This strategy assesses effectiveness with an emphasis on examining its impact on the economy and environment to reduce the overall cost of all economic expenses spent in providing services. It is made up of the overall labor cost, fuel expenses incurred when operating the vehicle, and fixed costs incurred when vehicles are available while processing, constraints are determined including weight and loading capacity, volume and volume capacity, working duration, and battery capacity. A

case study will also be used to examine social concerns including equitable allocation of courier service across vehicles and the prioritization of deliveries for electric cargo bikes according to speed restrictions. This makes to evaluate the social consequences thoroughly.

2.2.3 Proposed Papers Using Metaheuristic Approaches

Papaioannou, Iliopoulou, and Kepaptsoglou's (2023) [28] research paper proposes an optimization model for dealing with the e-cargo bike routing problem for urban deliveries taking into account road grade and workload balancing for couriers. Their developed model used 25 delivery places that are part of four different municipalities in the city center of Athens's southwest, Greece. The packages being transported are homogeneous, meaning they are identical in size and weight, like parcels or typical delivery boxes. The objective is to reduce the amount of energy that electric cargo bicycles use for a particular set of delivery requests and the significance of road incline concerning electric bike (e-bike) usage. It suggests that steepness affects e-bike suitability and energy consumption. To address this, planners exclude routes with unsuitable inclines and adjust for incline impact on energy use when planning routes. This ensures that recommended routes are both feasible and energy-efficient for e-bike riders. Distributing delivery requests among bike couriers equally is known as driver workload balance. Specifically, to guarantee equal task distribution among bike couriers, the number of delivery locations unaffected by package quantity and the total distance covered by each courier should be equivalent. The issue is presented as a Capacitated Vehicle Routing Problem (CVRP), in which e-cargo bikes begin in a depot, go to delivery nodes, and then end up back there with a mathematical model using Genetic Algorithm (GA) for finding optimal routes within short times. Enthoven, et al. (2020) [29] proposed the two-echelon vehicle routing problem with covering choices (2E-VRP-CO) for e-commerce and city distribution. Trucks move goods to two different destinations in the first echelon, leaving from a single depot. Customers can pick up products personally at covered areas, such as parcel lockers. Goods are loaded into zero-emission vehicles (such as cargo bikes) at satellite locations and driven to clients. The attempt is to discover ways to minimize costs by choosing routes and places to satisfy every consumer. Adaptive large neighborhood search heuristic was being approached that solves the 2E-VRP-CO problem which is simultaneously vehicle routing and facility location without duration constraints. According to Lee, Chae and Kim (2019) [30] focuses on integrating electric bicycles (e-bikes) into courier services, exploring their economic and environmental benefits in the case study in Seoul. They find that e-bikes have emerged as a viable alternative in urban areas, offering advantages such as maneuverability in congested zones and access to areas off-limits to larger vehicles. Compared to traditional automobiles, e-bikes are more environmentally friendly and can efficiently handle last-mile deliveries, despite their limitations in carrying capacity and load weight. Moreover, the case study also examined the integration of e-bikes into a major courier company's fleet, using a truck-bike mixture model. The study employed simulated annealing to address the complex heterogeneous fleet vehicle routing problem. Data from the courier company were analyzed across 15 scenarios with varying demands and restricted areas. Results showed that the mixed fleet model significantly reduced operating costs and carbon emissions. Costs decreased in all scenarios, and carbon emissions dropped by approximately 10%. This demonstrates the potential of e-bikes to enhance urban courier services' sustainability and efficiency.

2.2.4 Proposed Papers Using Hybrid Approaches

A selection of research-integrated optimization and simulation models had been implemented for cargo bikes in hybrid delivery systems. By comparing a delivery distribution system run by cargo cycles with mobile hubs versus a truck-only system, Dall Chiara et al. (2020) [31] simulated the system's performance under various demand and parking scenarios. Two alternating bin-packing problems—one for each delivery request priority

level—were solved to allocate a vehicle. With coordination operated at urban consolidation centers, Fikar et al. (2018) [32] created a decision support system for urban food delivery using a fleet of cargo bikes and conventional vans. To assess how various scheduling strategies might affect the results, a dynamic agent-based simulation was coupled with local search and best-insertion heuristics. To handle package delivery in metropolitan areas, Perboli and Rosano (2019) [33] established a simulation–optimization decision support system tool for analyzing mixed-fleet policies taking into account conventional, diesel, and electric cars as well as cargo bikes. To optimize routes, the simulation was combined with an adaptive neighborhood search metaheuristic. In the setting of parcel delivery, Llorca and Moeckel (2020) [34] evaluated cargo bike deployment under various modal shares between cargo bikes and vans, demand circumstances, and micro-depot densities using MATSim in conjunction with an open-source metaheuristic routing solver. In Hesselmans [35] thesis project, the case study in the research on routing electric cargo bikes focuses on Utrecht, a city in the Netherlands. This study examines the unique challenges and advantages of using electric cargo bikes for last-mile delivery in an urban setting, considering factors such as load-dependent travel times and the impact of road slope and weight on travel speed. The hybrid solution method proposed in the study combines column generation and local search, incorporating elements like constant wind and stochastic travel times to more accurately reflect real-world conditions. While this approach aims to improve the efficiency and sustainability of urban delivery services using electric cargo bikes. Based on the computational experiments using real-life instances from Utrecht confirmed the model's viability, showing that it could effectively handle the complexities of urban delivery with electric cargo bikes.

3 The Problem Definition and Mathematical Formulation

3.1 The Case Study Description of Target Area Central London Congestion Charge Zone (CCZ)

The model geography is based in the center of London where the micro-consolidation depot is located in Greater London and transports parcels to the targeted customers' locations in central London for last-mile delivery. Central London is restricted called the Congestion Charging Zone (CCZs) managed by Transport for London (TfL) to lower the number of vehicles in the city center. The CCZs are designated for every vehicle that emits 76 grams of CO2 per kilometer or more and is obligated to pay the £15 daily cost to operate a vehicle within those zones [36], however, exemptions are given for certain categories of vehicles while e-cargo bikes also are under "cleaner vehicle discount" which exempt them from charging until 2025. Within London's CCZs, e-cargo bikes provide an attractive alternative for last-mile deliveries that are both affordable and sustainable and which are used in this case model for transporting parcels. Compared to conventional vans, E-cargo bikes can easily operate through small narrow streets, and crowded streets, increasing delivery efficiency in densely populated locations while e-cargo bikes occupy less space in parking areas, thus they lessen the effect of parking shortages. Since e-cargo bikes run on electricity, they contribute to creating a more sustainable urban environment and cleaner air which classified them as generally free from congestion fines and parking fees, which saves financial substantially. In this study research, the parcel delivery operation model is carried out starting from 8 AM from the micro-consolidation depot hub near the central London and begins with loading segregated parcel boxes by the rider into the front-line flight case of the electric cargo bike and departing to customers' delivery locations in the central London. This is an example of the operation model of the third-party delivery service provider for last-mile e-commerce parcel deliveries. Therefore, the number of deliveries of parcels can fluctuate according to the order received by the third-party provider in real business operations. Thus, we will assume the termination of the delivery operation model is based on all parcel deliveries being successfully transported by riders of electric-cargo bikes to the final destinations and returning to the same micro-consolidation depot hub.

3.2 Understanding Electric Cargo Bike and Parcel Size

In this study, the average weight of the e-commerce parcel is limited to 4.5 kilograms [34] with a standard size, weight, and packaging assumption. Most of the e-commerce parcel categories to be delivered are clothing, fashion accessories, books, gaming gadgets, and consumer electronics under 4.5 kg as these categories are in higher demand purchased by e-shoppers in the United Kingdom in 2023 [37]. In central London, the average bike speed is limited to 15km/hour and 16.4km/hour in the inner London areas [38]. For the electric cargo bike infrastructure, we will use the Urban Arrow Flight-case cargo L model which bike weight is 50 kg, uses a Bosch battery capacity 500 Wh, can carry 125 kg cargo at the front loading (300 Liters) equivalent of 4-euro containers (60 x 40), has 94 x 70cm platform size and can resist carrying 275 kg overall [39-40].



Figure 1: Electric Cargo Flightcase Cargo L by Urban Arrow [40].

The bike can travel a maximum range of 50 km on a full battery with a 15.5 mph (25 km/hour) top-assisted speed by charging for 4 to 5 hours meanwhile the e-cargo bike's cost of transport per mile in fuel is estimated at 0.3p (pence) according to Urban e-bikes and Urban Arrow service center [40]. Moreover, the market value for the regular Urban Arrow Flight-case cargo L model starts around £5,700 at Urban e-bikes trading, apart from that the leasing of the bike for business purposes would start from £129 / month excluding VAT in the market. In this study, we will use electric bikes with a lease of £154.8 including VAT for 3 years however, no mileage limitation could be found from the source, so we estimate the limited mileage per year be 10,000 miles maintained.

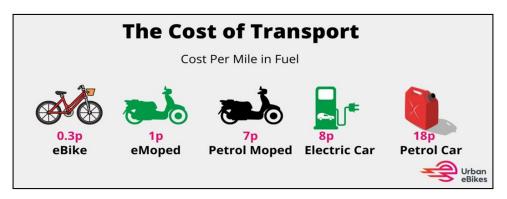


Figure 2: The transportation cost per mile in fuel of e-bike, e-moped, and petrol moped [39].

Based on the research paper of Llorca, and Moeckel [34], they assumed the carrying capacity of one electric-cargo bike could be 20 parcels and on the other hand, Niels, Hof, and Bogenberger [22] research paper assumed a cargo bike carried up to 30 packages. However, in this study, the e-cargo bikes here can carry more parcels therefore, we assume an e-cargo

bike can carry up to 25 parcels. In real circumstances, the size and weight of the parcel can vary if all parcels are not homogeneous items.

3.3 Mathematical Formulation

The model is based on (CVRP) capacitated vehicle routing problem for delivery of ecommerce parcels to near customers' locations at the counter click and collect service stores within the Central London from the micro-consolidation hub using e-cargo bikes with capacity constraints, and it is also based on the paper of Papaioannou, Iliopoulou, and Kepaptsoglou [28]. Parameters are:

- V = Set of predetermined customer delivery points, stores $V = \{1, ..., n\}$
- $A = \text{Set of arcs where } A = (i, j), \forall i, j \in V$
- *D* = Distance matrix between all nodes (*i*, *j*)
- *Q* = Set of predefined parcel demands
- *B* = Set of electric-cargo bikes
- C = Maximum parcels carried by each e-cargo bike (C = 25 parcels)
- V_0 , V_{N+1} = Start and end at the same micro-consolidation hub depot

Decisional Variable

Let X_{ij} be a binary variable where:

- $X_{ij} = 1$ if an e-cargo bike travels from node *i* to node *j*
- $X_{ij} = 0$ otherwise
- b = Number of electric-cargo bikes, $b \in B$

$$\min \sum_{b \in B} \sum_{i \in V_0, N+1} \sum_{j \in V_0, N+1} D_{ij} X_{ij}$$
(1)

Subject to:

$$\sum_{i \in V} X_{0j,b} \le 1, \quad \forall b \in B, i \neq j$$
(2)

$$\sum_{i \in V} X_{i0,b} \le 1, \quad \forall b \in B, i \neq j$$
(3)

$$\sum_{b\in B} \sum_{i\in V} X_{ij,b} = 1, \quad \forall j \in V_{N+1}, i \neq j$$

$$\tag{4}$$

$$\sum_{b\in B}\sum_{j\in V}X_{ij,b} = 1, \quad \forall i \in V_{N+1}, i \neq j$$
(5)

$$\sum_{i,j\in V} Q_i X_{ij,B} \le C, \quad \forall b \in B$$
(6)

$$\sum_{i \in V} X_{ij,B} = \sum_{j \in V} X_{ij,B}, \quad \forall i, j \in V, \forall b \in B$$
(7)

$$1 \le \sum_{b \in B} \sum_{i, j \in V} B \le 4, \quad \forall b \in B, i \ne j$$
(8)

$$X_{ij,B} \in \{0,1\}, \quad \forall i, j \in V_0, N+1, \forall b \in B, i \neq j$$
 (9)

Hence, the fitness function is the equation (1) to minimize the total distance traveled by e-cargo bikes. In the constraints function equations (2) and (3) ensure that each e-cargo bike leaves the depot and returns to the same depot creating a tour route for each e-cargo bike going to the depot again. Constraints equations (4) and (5) enforce that each customer node is visited exactly once by the single e-cargo bike to eliminate tour again to delivery points. Constraint equation (6) limits the demand parcels of the customers carried by each e-cargo bike depending upon the maximum capacity of each e-cargo bike. Constraint equation (7) enforces that the number of e-cargo bikes that enter each customer node and leave from the distribution center should be equal. Constraint equation (8) represents that the set of e-cargo bikes has been limited to four bikes are used for the delivery operation satisfying all parcels demand visiting all delivery points on their respective routes. Constraint equation (9) states the binary condition of decision variables.

3.4 Daily Logistics Operational Expenses Calculation

For the calculation of daily logistics operational cost, the following formula is used:

- Delivery time = Total distance traveled / Average speed (km/h)
- Total loading/unloading time = number of parcels carried by an e-cargo bike × loading/unloading minutes/parcel
- Total logistics operational completion time = Delivery time + Loading/unloading time
- Total Labor (rider) cost for one day delivery operation = hourly wages paid × total logistics operational completion time
- Lease cost of electric-cargo bikes = number of e-cargo bikes × lease contract price per bike/month
- Average kilometers traveled per full battery charge under 15 km/hour force = motor support setting, the terrain and weather conditions operate by a ride with a vehicle load [41]
- Estimated Power consumption (kWh) by e-cargo bikes during total traveled distance = (Total Distance traveled by e-cargo bikes × full Battery capacity kWh) / Average kilometers traveled per full battery charge under 15 km/hour force
- Electricity consumption cost per bike in kilometers traveled = Electricity cost per kWh x estimated power consumption (kWh) by e-cargo bikes during total traveled distance [42]
- Total e-cargo bikes CO2 emission (kg) = Estimated Electricity Power consumption (kWh) by e-cargo bikes during total traveled distance × CO2 emission factor 0.23104 kg CO2 per kwh [42]

3.5 Model Assumptions and Limitations

1. Uniform Parcel Size: For simplicity's sake, the model assumes that every parcel has the same dimensions and weight.

2. Fixed Delivery Locations: It assumes that delivery locations are predetermined and fixed, not accounting for ad hoc pickups or changes in delivery destinations.

3. Optimal Operating Conditions: The model is assumed to be performed in situations with general traffic congestion, with flat terrain, the city road condition with ideal weather is summer having moderate wind blowing while carrying overall weight of 275 kg.

4. Uniform Energy Consumption: It assumes that irrespective of rider behavior, terrain, and

payload, all e-cargo bikes have the same energy consumption per kilometer.

5. Centralized Depot: All e-cargo bikes are assumed to have one centralized microconsolidation depot where packages are gathered, delivered, and reloaded onto the bikes.

6. Complete Battery Capacity: This assumes that all e-cargo bikes have fully charged batteries when they begin delivery duties; it does not consider partial charge levels mid of the tour.

7. Homogeneous Fleet: The model operates under the assumption that there is a single fleet of e-cargo bikes, all of which have the same features, capacities, and performance metrics with the same electric assistant motor and support pedal force by rider must be a constant average traveling speed of 15 km/ hour with carrying limitation of 25 parcels per bike.

8. Riders Efficiency: All riders are assumed to be proficient in riding electric-cargo bikes while familiar with the geographic location of the target central London area.

9. Real-world Variability: The model might not adequately capture the variability of realworld elements that can impact delivery operations, such as traffic patterns, weather-related delays, and unforeseen disasters and accidents.

10. Dynamic Routing: It doesn't take into consideration the need to modify a route dynamically in response to unforeseen circumstances or current events, like delivery time windows or traffic congestion.

11. Operational Constraints: It might not take into account all operational factors that could affect the effectiveness and efficiency of delivery, such as rider fatigue, vehicle maintenance, and legal requirements.

12. Data Availability: The quality and quantity of data inputs, such as road network data, parcel information, and e-cargo bike specifications, have a significant impact on the model's accuracy and dependability.

13. Technological Restrictions: Software capabilities for routing optimization, GPS accuracy, and communication dependability are a few examples of technological restrictions that could limit the model's effectiveness.

14. Payload weight: In reality, the payload weight would be differ depending on the weight or size of the parcels which would impact on the range speed power producing by the rider and battery motor which is considered the maximum capacity weight in the model but somehow it can vary in real operation.

4 Data Collection

4.1 Parcel Demand Estimation and Distances Measure

The rising popularity of online shopping has had a substantial influence on urban logistics and delivery patterns. According to the Office of National Statistics [43], the sales proportion of the digital platform of 2022 was 26.6% of the total revenue of the retail industry whereas the non-food online sales percentage accounted for 20.3% in the UK. Additionally, the B2C (Business to consumer) e-commerce merchandise sales share in 2022 was \$ 289.9 billion according to Research and Markets data (2023) [44], and in Global Data's latest report [45] the click & collect service was worth 9.6-billion-pound revenue (13.9%) of the total online sales which now possesses the higher preferences by e-shoppers along with home delivery and parcel Lockers options. In understanding the ideal central London location, London's central sub-region is comprised of boroughs including Kensington and Chelsea, Westminster, Camden, Islington, City of London, Southwark, and Lambeth while the region is made up of 11,144 people per km2 in population density which is the highest level as compared to the rest sub-regions, and East London such as 5,640 and 6,184 people per km2 respectively [46]. According to the 2011 census of the Office of National Statistics, it was 1,435,500 estimated population living in the central sub-region.

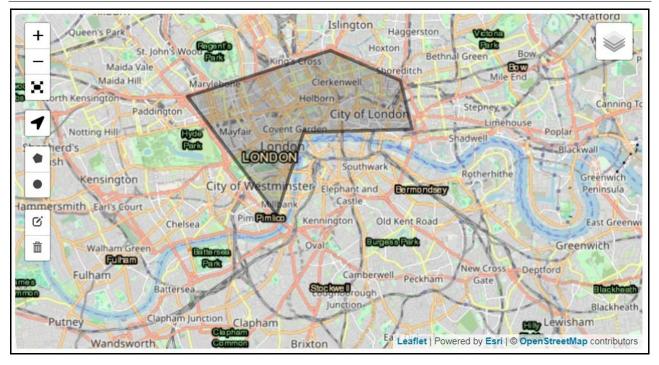


Figure 3: Targeted Central London in Grey shape [47].

Since, the paper has focused on the central London (CCZ) zone with the boroughs of Westminster, Camden, Islington, and the City of London, which has a geographically approximate 14.10 km2 total area or a distance of around 12.21 miles measuring from the global positioning system (GPS) using Google Map [48]. All distances are measured using Google Maps' cycling route in kilometers between every delivery point and the distance measured at each delivery point from the micro-consolidation depot is also counted for further calculation.

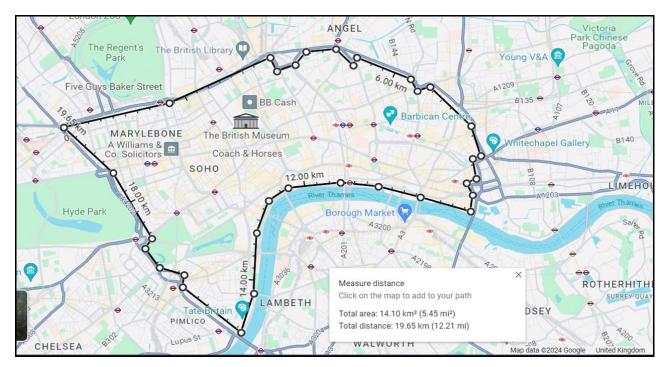


Figure 4: Targeted Central London Total Area Measurement from Google Map.

Under the Agile Urban Logistics project by the Greater London Authority, the Mayor's Smart London Demonstrator program was carried out with aims to improve congestion, emissions, and market sector of transport with the usage of light-weighted electric vehicles

for consolidating deliveries of multiple retail and non-retail clients using a single carrier (Gnewt Cargo) in a single van trial in the central London congestion charges zone (CCZ) under-supported by the University of Westminster for processing and analyzing data collections by trials [49]. Gnewt Cargo logistics provider implemented many case study trials for retails (e-commerce) and non-retailers separately to achieve aims and benchmark data collected from July 2015 to 30 June 2016 of each round-trip distribution, number of parcels per van, emission reduction rate contribution and congestion impacts. The study found that the total parcels delivered within the year by Gnewt Cargo carrier from the base line case trial for retails (e-commerce) was delivered 2,005,728 parcels average weekly 38,572 and 151 per day delivered driven a total of 148,545 miles per year.

Total parcels delivered	2,005,728
Parcels per week	38,572
Average number of parcels per van per day	151
Max parcels/day	668
Min parcels/day	1
Total miles driven in one year during deliveries	148,545
Average miles per van per day	11
Average metres per parcel	119
Average completion	87%

Figure 5: Gnewt Cargo Client A's key performance indicators [49].

Using the benchmark data from Clarke and Leonardi [49], the average estimation of 151 parcels of both retail (e-commerce) and business-to-business digital trading demands were delivered for the targeted central London (CCZ) zone within a year of survey however, the business-to-business trading on the digital channels is 46% occupied in 2023 [50]. Therefore, the average number of parcels demanded in the central London congestion charged zone carried out by a single carrier logistics provider share of parcels for e-commerce business to customers would be estimated taking close numbers 80 parcels per day for targeted central London 14.10 square kilometers area.

4.2 E-commerce Customers Distribution

The delivery points for the central London Congestion Charge Zone (CCZ) are targeted randomly near residential housing where targeting counter click and collect service stores where e-commerce shoppers can collect, send or return online parcels. Using the Google Maps satellite view, 15 delivery points of click-and-collect counter service store shops are identified and pinned after searching them using from the independent website named collect+parcel.co.uk [51] which shows nearest collect service giving stores inserting post code. The click-and-collect service cannot be neglected since they are widely used by e-commerce retailers and e-shoppers as a second option in transporting parcels which has recently high potential to grow in coming years since it offers quick delivery, with convenient options of stores to pick up parcels for shoppers when if they are not home, while e-shoppers have several pick up points to choose conveniently within their areas [52].

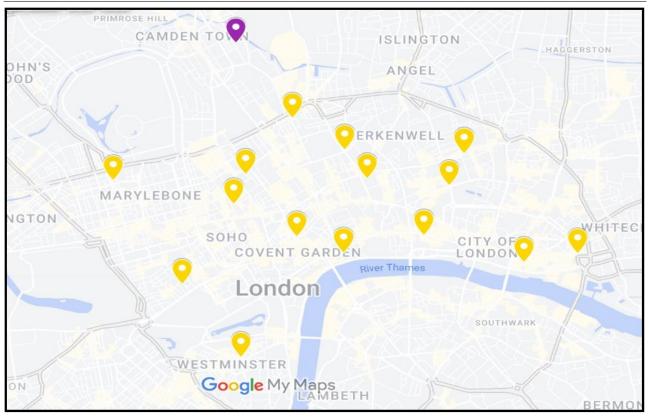


Figure 6: Click-and-collect counter service stores (yellow), and the micro-consolidation hub depot (purple).

4.3 Micro-consolidation Hub Depot

The micro-consolidation hub depot is situated outside of the Central London congestion charge zone (CCZ) which is 1.28 km away from the nearest delivery point within central London and 7.4 km from the farthest point. The micro-consolidation hub depot was chosen from the Google Maps Satellite as the ideal depot on the ground in the north part of Central London within the borough of Camden which is in the Ultra Low Emission Zone (ULEZ) within inner London. Central London is more highly populated than the rest of the UK as mentioned above, it would be difficult to choose the depot with limitations within that zone as it is the heart of the United Kingdom where residential areas with tourist attraction sites are plenty around with official buildings where spaces are limited, and social environmental factors are highly concerned by London government and authorities [53].

4.4 Electric-cargo Bike Specification

4.5 Data Collection Parameters for Daily Logistics Operational Expenses

In the daily operational cost analysis, we will use the important parameters which are related to each other, and operation calculations can be obtained depending on those parameters. For the total completion time calculation, all electric-cargo bikes operate on the average speed of 15 km per hour which is the average speed ride of city traffic, and peak hours congestion in bustling central London according to research taken by Pedal Me [38] since the delivery operation starts from 8 o' clock in the morning. Therefore, an e-cargo bike could not operate parcel delivery operations at the full speed of 25 km per hour that it can go. The loading and unloading time of a parcel is assumed to be more or less 4 minutes long for the rider since it can be time consuming when unloading parcels especially at stores' locations such as for taking out, checking, arranging parcels, and deliver into stores than in loading time at the depot. However, the e-cargo bike can park at pavements, in front of stores or do convenient park which is just near the store location in most circumstances. For the electric-cargo bike's

Specification	Details
Bike Model	Urban Arrow Flight Case Cargo L
Drive	Cargo Line with Pedal Support
Power Mode	Bosch Ebike System 2 (BES2)
Maximum Capacity	125 kg, 4 (60×40) euro containers
Bike Weight	50 kg
Battery Capacity (Bosch)	500Wh or 0.5 kWh
Front Load Capacity	125 kg
Volume Capacity	300 Liters
Maximum Range Speed	25 km/h
Maximum Travel	50 km
Charging Time	4 to 5 hours
Overall Capacity (Bike + Rider + Load)	275 kg

 Table 1: The Electric-cargo Bike Specification.

lease operational cost, we use the market lease price per month of the Urban Arrow electric cargo L bike model with £154.8 including VAT at Urban eBikes dealer [39]. For the Labor (rider) cost, the average wage for the e-cargo bike delivery rider is £24,375 per year or £12.50 per hour in the United Kingdom [54]. For the electricity cost per kilowatt hour (kWh), we use the average electricity rate of £0.245 per kilowatt hour paid by direct debit under the Energy price cap rates 1 April to 30 June 2024 by The Office of Gas and Electricity Markets (Ofgem) [55].

4.6 The Average Kilometers traveled Range Search Using Bosch System Range Calculator

The average kilometers range speed traveled of the electric cargo bike is important not only to calculate the operational cost but also planning routes, especially for longer trips or deliveries meanwhile it helps to understand how far the bike can travel on a single charge at different speeds. Due to the increased effort placed on the motor to maintain the higher speeds, the power consumption of an electric bike increases as its speed increases, the traveled distances of an electric-cargo bike could be less. However, to know the average kilometers traveled under 15 km per hour speed with loading 275 kg weight under the city road traffic with moderate wind with flat terrain using cargo line with pedal support, the range simulation model is necessary to calculate. Therefore, to generate km travel range estimation that closely align with real-world performance, the impact of various factors on an electric cargo performance needs to be analyzed including battery capacity, vehicle weight, aerodynamics, driving conditions, and environmental factors, motor configurations, regenerative braking systems, and energy management system on providing the reliable and efficiency estimation of potential kilometers travel in the real-world conditions. For the simulation model calculator, we use the Bosch range calculator [41] because of its accuracy and reliability with free of charge which leverage its extensive knowledge and experience in automotive technology by utilizing precise data and advanced modeling techniques to generate travel range estimates that closely align with real-world performance. The Bosch itself is the customized battery provider partner with numerous manufacturers in the battery industry. Therefore, in the simulation model, we set the riding mode as "Eco" which is low level support with maximum efficiency for the greatest range and in rider category, we use 15 km/ h average speed with 275 kg total weight as in below Figure (7).

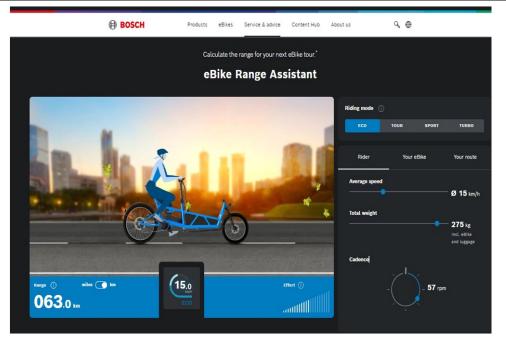


Figure 7: Configuring the riding mode and rider category in Bosch range calculator.

Then, the Bosch eBike system 2 which has already been used in Urban Arrow cargo L e-cargo bike is configured in "Your ebike" category with cargo line drive, 500 Wh battery capacity and hub shifting system with hybrid bike tires in Figure (8).

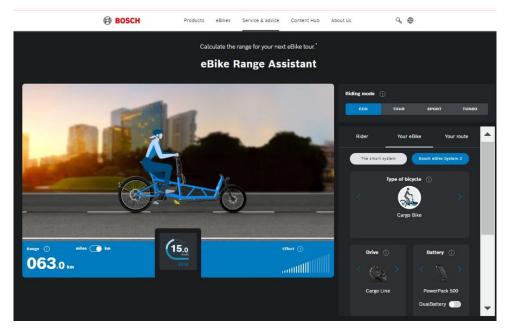


Figure 8: Configuring the systems, drive and battery in Bosch range calculator.

Next, the configuration is made in "Your route" category by selecting flat terrain, good road surface, light breezes in summer with city traffic condition be the real-world setting of central London in Figure (9).

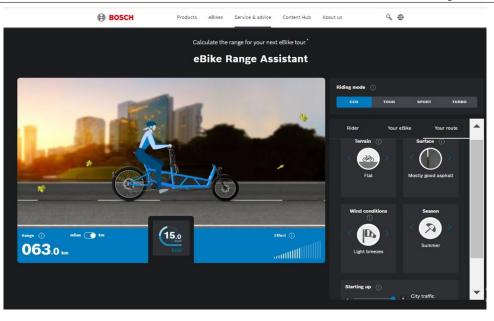


Figure 9: Configuring the terrain, road, traffic and weather conditions in the Bosch range calculator.

After making the configuring using those settings, the Bosch range calculator showed the average kilometers range of 63 kilometers (km) is traveled with the average speed of 15 km/h with weight 275 kg, 500 Wh battery with pedal support by the rider in the central London setting in Figure (10).

Range () miles () to 063.0 km			effect ©	Tire tread () Hybrid bike tires Shifting system () Deraillear Hub gear			
	n overview of your rgo Line + PowerPack 500	settings					
به ۱۵ ۱۵	Cargo Diae Drive & battery Cargo Line + PowerPack 500 Starting up City traffic Terrain Flat	rłu Shriting system Hub gear system 15 15 km/h 15 275 kg Surface Mostly good asphalt	ି ମଧ୍ୟ ଜନ ସେ ସେ ସେ ଅବ ସେ ଅବ ସେ	re tread fybrid bike tires ding mode 20 adence 7 pm asson asson ammer			

Figure 10: Generating the average kilometers range by the Bosch range calculator.

4.7 Contribution Carbon Footprint By E-cargo bikes

According to the energy saving trust [42], the amount of carbon generated per kWh of electricity is 0.23104 kg (2020) which is indirect emission for the electricity supplied to the grid that organizations purchase. However, they do not include the emissions associated with the transmission and distribution of electricity source from the Department for Energy Security and Net Zero UK. We use this number to calculate the carbon footprint of e-cargo bikes during delivery operations.

5 Model Implementation

5.1 Solution Method

In the solution method, the genetic algorithms solution is used which is Inspired by natural selection and genetics, it is a subset of meta-heuristic optimization techniques. The genetic algorithm is adopted from Darwin's principle of natural selection by creating an environment where possible solutions of a problem compete with one another and only the fittest survive. Each solution passes along its good 'genes' through 'offspring' solutions so that the entire population of solutions will continue to evolve better solutions from local optimum space to the nearest global optima. They work especially well at resolving complicated optimization issues like the capacitated vehicle routing problem (CVRP) and its variations, the green vehicle routing problem (GVRP), and the vehicle routing problem (VRP). When utilizing e-cargo bikes for last-mile e-commerce parcel delivery, genetic algorithms provide a practical method for identifying nearly ideal routes that minimize travel time, distance, and expense while considering the vehicles' capacity limitations and the requirement to lower carbon emissions.

5.2 Model Implementation

In the model implementation, we will use the evolutionary excel solver engine since it has a higher chance of locating a globally optimal solution, the evolutionary algorithm is more reliable than the GRG Nonlinear of solver solution even though the approach is slow [56]. The Theory of Natural Selection, upon which the evolutionary method is predicated, which also falls under genetic algorithm (GA) and begins with a random "population" of input value sets. A second population of "offspring" is created by selecting the sets of input values that produce a solution that is closest to the target value. A "mutation" of that optimal set of input values is what the offspring are. This process continues until the objective function varies very little between populations. The user can therefore select the population size and mutation rate from the Solver options to possibly shorten the solution.

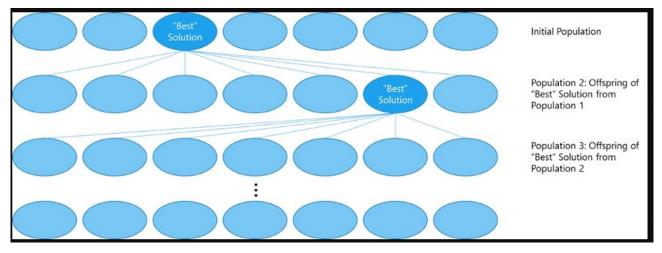


Figure 11: The Evolutionary Nature of Genetic Algorithm [56].

Once the solver is run after meeting constraints, we will compare the original value and improve values and will continue to calculate the operational costs of the last-mile delivery. In the operational cost, the electricity consumption by each bike rider's wages for delivery, carbon footprint and the estimated monthly lease cost of the electric cargo bike will be calculated depending on the total distance kilometers travelled experimented using the evolutionary excel solver. Afterward, we will continue to calculate the estimated total completion time for the whole operation as we assume the experiment is for one typical delivery operation of a single carrier transport for the last mile logistics in central London.

5.3 Evolutionary Algorithm parameters

The optimization is performed on the "hp laptop" the processor intel(R) core i7-8550U CPU @ 1.80GHz with 8 GB RAM memory. When using the evolutionary excel solver solution, setting appropriate parameters for population size and mutation are crucial for achieving effective and efficient optimization. Since, mutation preserves genetic diversity in a population by introducing random changes to individual solutions. It aids in escaping local optima and keeps the population from worsening. We will do our experiments on parameters such as setting different population sizes of 300, 200, 100 with mutation rate (MR) (values of 0.15, 0.35, 0.45). The system termination depends on searching for the best solution and will terminate if no best solution is found.

5.4 Distances Between Customers' Delivery Points and the Micro-Depot

For distance measurement, the bicycle lane mode distance travel option from Google Maps is chosen to measure distances from the micro-depot and between customer delivery points which also counts the twist and turn measure of each point. Google Maps software estimates possible accurate distances in real circumstances with more options provided rather than using the "Euclidean distance" x and y coordinates which only measure straight-line distances. Therefore, we used the actual distances as close as to the real ground scenario while the distance matrix assumes to be symmetric. Moreover, there is no restriction that could be found that e-cargo bikes could not be used in the bicycle lane in the central London since the advantages of e-cargo bikes are to use narrow lanes, could avoid traffic while no expenses for parking lots [48].

1	А	В	С	D	E	F	G	Н	1	J	К	L	М	N	0	Р	Q
2	Distance Matrix in Kilometers (km) between The Micro Depot and Click-and Collect Service provider Stores																
3	In Kilometers	Depot (0)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
4	Depot (0)	0	1.28748	2.25331	3.05775	4.184	4.774	6.678	5.793	4.345	4.55	7.402	5.95	4.02	2.89	4.34	2.574
5	1	1.28748	0	0.965606	1.77028	2.89682	3.21869	5.31084	4.50616	2.89682	2.73588	4.98897	3.86243	3.37962	2.09215	2.57495	1.28748
6	2	2.253308	0.965606	0	0.64374	1.93121	2.25308	4.18429	3.37962	1.93121	2.41402	4.6671	4.02336	3.54056	1.93121	2.25308	1.60934
7	3	3.05775	1.77028	0.64374	0	1.44841	1.28748	3.86243	3.05775	1.60934	1.77028	4.34523	3.70149	4.18429	2.25308	1.93121	2.25308
8	4	4.184	2.89682	1.93121	1.44841	0	0.64374	2.73588	2.09215	1.28748	2.09215	4.6671	4.82803	5.31084	3.21869	2.73588	3.21869
9	5	4.774	3.21869	2.25308	1.28748	0.64374	0	3.05775	2.41402	1.93121	2.73588	5.31084	4.6671	5.1499	3.05775	2.89682	3.21869
10	6	6.678	5.31084	4.18429	3.86243	2.73588	3.05775	0	0.80467	2.09215	3.21869	5.47177	6.92018	8.85139	4.98897	4.50616	5.1499
11	7	5.793	4.50616	3.37962	3.05775	2.09215	2.41402	0.80467	0	1.28748	2.41402	4.6671	5.79364	6.11551	4.18429	3.70149	4.34523
12	8	4.345	2.89682	1.93121	1.60934	1.28748	1.93121	2.09215	1.28748	0	1.12654	3.70149	4.50616	4.82803	2.89682	2.09215	3.05775
13	9	4.55	2.73588	2.41402	1.77028	2.09215	2.73588	3.21869	2.41402	1.12654	0	2.57495	2.57495	4.02336	2.09215	0.80467	2.25308
14	10	7.402	4.98897	4.6671	4.34523	4.6671	5.31084	5.47177	4.6671	3.70149	2.57495	0	2.89682	4.34523	3.05775	2.41402	3.70149
15	11	5.95	3.86243	4.02336	3.70149	4.82803	4.6671	6.92018	5.79364	4.50616	2.57495	2.89682	0	2.41402	2.09215	1.77028	2.73588
16	12	4.02	3.37962	3.54056	4.18429	5.31084	5.1499	8.85139	6.11551	4.82803	4.02336	4.34523	2.41402	0	2.09215	3.54056	2.09215
17	13	2.89	2.09215	1.93121	2.25308	3.21869	3.05775	4.98897	4.18429	2.89682	2.09215	3.05775	2.09215	2.09215	0	1.28748	0.80467
18	14	4.34	2.57495	2.25308	1.93121	2.73588	2.89682	4.50616	3.70149	2.09215	0.80467	2.41402	1.77028	3.54056	1.28748	0	1.44841
19	15	2.574	1.28748	1.60934	2.25308	3.21869	3.21869	5.1499	4.34523	3.05775	2.25308	3.70149	2.73588	2.09215	0.80467	1.44841	0
20																	

Figure 12: Distance Matrix in Kilometers (km) between The Micro Depot and Click-and Collect Service provider Stores.

5.5 Parcel Demands

Parcel demands of the click-and collect counter service stores are included.

Parcel Collection Stores	Parcel Demand
	1 5
	2 7
	3 6
	4 5
	5 6
	6 4
	7 6
	8 5
	9 4
1	.0 5
1	.1 6
1	.2 4
1	.3 6
1	.4 5
1	.5 6
Total Demand	80

Figure 13: Service Stores with Parcel Demands.

5.6 Electric Cargo Bike Pay Load Capacity and Number of Bikes Limitations

Parcel demands of the click-and collect counter service stores are included.

Number of E-cargo Bikes	4
Demand Carrying Capacity	25
Total Number of Parcel Demand	80

Figure 14: Electric-Cargo Bikes and Their Carrying Capacity Limitations During Last Mile Delivery.

5.7 Defining The Model in Excel Solver Software

For e-cargo bikes, several procedures and functions are used to design routes, compute distances, and define restrictions in order to simulate the vehicle routing problem using Excel Solver. Initially, the route for every store is mentioned, which includes the depot (ID "0"). The e-cargo bikes have numbers ranging from 1 to 4, and the "IF" feature is used to identify their routes.

Subsequently, the distance matrix table is utilized to calculate the overall distance traveled using the "INDEX" function. Using the "IF" and "VLOOKUP" functions, parcel demands are established for each shop. Each e-cargo bike's total distance traveled, and the package boxes it holds are compiled using the "What-if" function connected to the "T1" cell. This information makes each bike's accomplishments in terms of distance covered and delivery packages.

From a drop-down list, users may choose how many e-cargo bikes they want to examine, along with detailed route plans, total mileage, and package load on each bike number. Ultimately, the Excel Solver is set up to reduce the total distance covered by every e-cargo bike.

2	a Que	ries &	Conne	ections	5		Data	Types		Sort & Filter					
	fx	=INDE	EX(\$B\$4	:\$Q\$19	,U6+1,U	17+1)									
	K	L	М	N	0	P	Q	R	S	т	U	V	W	х	Y
						\sim	_		E-cargo Bike	3					
									Capacity	25					
9)	10	11	12	13	14	15								
	4.55	7.402	5.95	4.02	2.89	4.34	2.574		Route	E-Cargo Bike	Route trip Bike	Total distance	Parcels of Stores		
Ì			0.00		2.000		2.07.1				_				
	2.73588	4.98897	3.86243	3.37962	2.09215	2.57495	1.28748		0)		0			
	2.41402	4.6671	4.02336	3.54056	1.93121	2.25308	1.60934		1	1)	D	
	1.77028	4.34523	3.70149	4.18429	2.25308	1.93121	2.25308		2	2 1		0 0		D	
	2.09215	4.6671	4.82803	5.31084	3.21869	2.73588	3.21869		3	3 1		0 0		D	
	2.73588	5.31084	4.6671	5.1499	3.05775	2.89682	3.21869		4	1		0 0)	D	
	3.21869	5.47177	6.92018	8.85139	4.98897	4.50616	5.1499		5	j 2		0 0)	D	
	2.41402	4.6671	5.79364	6.11551	4.18429	3.70149	4.34523		6	5 2		0 0)	D	
	1.12654	3.70149	4.50616	4.82803	2.89682	2.09215	3.05775		7	2		0 0)	0	
	0	2.57495	2.57495	4.02336	2.09215	0.804672	2.25308		8			0 0)	0	
	2.57495	0	2.89682	4.34523	3.05775	2.41402	3.70149		9	2		0 0)	D	
	2.57495	2.89682	0	2.41402	2.09215	1.77028	2.73588		10) 3	1	0 7.402	2	5	
	4.02336	4.34523	2.41402	0	2.09215	3.54056	2.09215		11	3	1	1 2.89682	2	6	
	2.09215	3.05775	2.09215	2.09215	0	1.28748	0.804672		12	2 3	1	2 2.41402	2	4	
ſ	0 904670	2 41402	1 77000	2 54056	1 00740	0	1 44941		10	2	1	2 00216			

Figure 15: The "Index" function is used to calculate the distance traveled.

The goal of the objective function is to reduce the overall distance. The bike numbers are from (1 to 4) and the route order (S6 to S20) cells are the two instances of decision variables.

olver Parameters				Heln Table	×		Cor
Se <u>t</u> Objective: To: <u>M</u> ax	• Min	\$AA\$11	0	1	Outline	ne Da P⇒ Sc	
By Changing Variable \$\$\$6:\$T\$20	Cells:			<u>+</u>			Anal
				<u>A</u> dd <u>C</u> hange	Z	AA	AB
\$T\$6:\$T\$20 <= 4				<u>C</u> hange			
				Delete	Distance Trave	lled by Bikes	
				<u>R</u> eset All		1 8.36764 2 10.7793	
			~	Load/Save	Total Distance	3 9.17303 4 4.1843 e 32.5042	
Make Unconstrain	ed Variables Non-Ne	egative					
Select a Solving Method:	Evolutionary		\sim	Options			
Method:					Route biek1 Route bike2	0-15-13-11-	

Figure 16: The Model definition in the Solver Parameters.

Constraints guarantee that each bike may carry no more than 25 items, that the number of bikes utilized is between 1 and 4 (integer values), and each shop ID must be unique. NP-hard issues are best solved using the evolutionary solution approach since this approach finds the global optimum for decreased trip distances through iteration using the ideologies of genetic algorithms. This structured approach in Excel Solver ensures efficient routes planning and delivery optimization for e-cargo bikes.

5.8 The Logistic Daily Operational Cost Modeling Parameters

For the daily lease cost of electric-cargo bikes is formulated below.

No. of Days per month	30
Lease Price of one Urban Arrow e-cargo L bike per month including VAT (in pound)	154.8
No. of E-cargo bikes used	4
Total lease cost of 4 e-cargo bikes	619.2
Daily Lease cost of all 4 E-cargo bikes (in pound)	20.64

Figure 17: Daily E-cargo Bikes' Lease Expenses.

For electricity consumption cost per bike in kilometers traveled (in pound) calculation, we use the sample the kilometers traveled per bike to assemble the table.

Battery Capacity in kWh	0.5
Average km speed ride in central London (km/h)	15
Average kilometers travelled per full battery charge under 15 km/hour speed from Bosch calculation (km)	63
Distance Travelled by an e-cargo bike (km)	11.05044
Estimated Power consumption (kWh) by an e-cargo during distance travelled	0.087701905
Electricity cost per kWh (in pound)	0.245
Electricity consumption cost per bike in kilometers travelled (in pound)	0.021486967

Figure 18: Electricity consumption cost per bike in kilometers traveled.

For the total completion time and the labor wages, the following table functions are calculated step by step.

Total distance travelled (km)	65.17629
Average Speed (km/h)	15
Delivery time (Hours)	4.345086
loading and unloading parcel (minutes)	4
No. of Parcels to be delivered by e-cargo bike rider	80
Total Loading and unloading Time (in minutes)	320
Total Loading and unloading Time (in hour)	5.333333333
Total Completion Time (Hours)	9.678419333
Wages per hour for Rider (in pound)	12.42
Total Labor Wages (in pound)	120.2059681

Figure 19: Total completion time and Total labor wages.

The amount of carbon produced for each kWh of electricity generated (Kg CO2 per kWh)	0.23104
Estimated Power consumption (kWh) by all e-cargo bikes during distance travelled	0.517272143
Total CO2 Emission (kg)	0.119510556
In Gram	119.5105559

Figure 20: Total CO2 Emission By all E-cargo Bikes.

6 Experiments Analysis and Results

6.1 First Model Experimentation (Population -200, MR-0.35)

The model is implemented using the excel function formulas and set the objective function, decision variable and constraints in the solver parameters box as mentioned in the above chapter. Before using the solver, the initial value of total distance traveled is 35.989 km which is randomly formulated with the simple excel functions without running the evolutionary solver. This initial value could be any kilometers. Then after setting solver parameters and the "evolutionary solver" method is used by setting a population size of 200 with mutation rate of 0.35 while default time setting of 30 for without improvement finding solution which is showed in Figure (6.1).

nu (Options	?	×
	All Methods GRG Nonlinear Evolutionary		
л г іz	Co <u>n</u> vergence:	0.0001	
z	<u>M</u> utation Rate:	0.35	
	Population Size:	200	
	<u>R</u> andom Seed:	0	
	Maximum Time without improvement:	30	
	Require <u>B</u> ounds on Variables		

Figure 21: Setting Evolutionary parameters.

As a result after satisfying all constraints, the total distance traveled by all 4 electric cargo bikes is 65.1629 km. When analyzing the route order, carry parcels and distance traveled of each e-cargo bike for instance the e-cargo bike 1 is carrying total 17 parcels for stores ID of 4, 14 and 2 meaning by the route order from the depot as "0" be (0-4-14-2-0) returning to the

depot again with kilometers traveled of 9.173 km. For the e-cargo bike 2 carries 22 parcels with route order of (0-8-1-15-3-0) by traveling 10.782 km. Moreover, for the rest two e-cargo bikes 3 and 4, the former traveled 17.86 km using the route order (0-10-5-13-9-0) transporting 21 parcels meanwhile the latter carries 20 parcels distance of 27.358 km using (0-7-11-6-12-0) route order.

S	Т	U	V	W	Х	γ	Z	AA	AB	AC	AD
E-cargo Bike	1										
Capacity	25										
Route Stores ID	E-Cargo Bike	Route trip Bike	Total distance	Parcels of Stores							
0		()				No. of E-cargo bike	Distance Travelled by Bikes		E-cargo Bike	Parcel Load
8	2	. () 0	0				9.17296			1
7	4	. () 0	0			1	9.17296		1	
4	1		4.184	5			2	10.78238		2	2 2
11	4		1 0	0			3	17.86274		3	
10	3	4	1 0	0			4			4	
6	4		0	0			Total Distancce	65.17629		Total Parcel	8
5	3	4	1 0	0							
14	1	. 14	2.73588	5							
2	1	2	2.25308	7							
1	2	2	2 0	0				· · · · · · · · · · · · · · · · · · ·			
13	3	2	2 0	0			Route biek1	0-4-14-2-0			
15	2	2	2 0	0			Route bike2	0-8-1-15-3-0			
3	2	2	2 0	0			Route bike3	0-10-5-13-9-0			
9	3	2	2 0	0			Route bike4	0-7-11-6-12-0			
12	4	. 2	2 0	0							
0		2	2 0								
		Total	9.17296	17.							Acti

Figure 22: Total distance traveled and route orders.

The total logistics operational cost is obtained based on the total distance traveled by all e-cargo bikes and calculates the rest expenses. When all e-cargo bikes travel to 65.176 km, the total labor wages are based on the total completion time that all bikes took to complete delivery which is 9.67 hours long thus, the wages costs are £120. 20. The total logistics operating expenses are including £0.126 of electricity consumption by all bikes in their kilometers traveled since 0.517 kWh are used by four bikes with daily lease bikes cost £20.64 then all together £141 of transportation costs has been accounted for.

Total Distance Travelled under Experimentation 1	65.17629
(population size 200, MR 0.35) (km)	
Estimated Power consumption (kWh) by all e-	0.517272143
cargo bikes during distance travelled	
Total Operational Completion Time (Hours)	9.678419333
Total Labour Wages (£)	120.2059681
Daily Lease cost of all 4 E-cargo bikes (£)	20.64
Electricity consumption cost of bikes in	
kilometers traveled (£)	0.126731675
Total Logistics Operational Cost (£)	141

Figure 23: Total logistics Operational Cost.

6.2 Second Model Experimentation (Population -200, MR-0.15)

E-cargo Bike Route	Start Route	Stores' Delivery Points	End Route	Parcels Carry	Distance Travelled (km)	~	Options		?	×
The Route For E-cargo Bike 1	Depot	13-11-9-8	Depot	21	8.68364	All Methods GRG Nonlinear Evolutionary				
The Route For E-cargo Bike 2	Depot	1-15-5	Depot	17	5.79365	4	Co <u>n</u> vergence:	0.0001		
The Route For E-cargo Bike 3	Depot	12-10-14-7-6	Depot	24	15.28541	niz	Mutation Rate: Population Size:	0.15		
The Route For E-cargo Bike 4	Depot	2-3-4	Depot	18	4.345456	-	<u>R</u> andom Seed:	0		51
						Р	Maximum Time without improvement:	30		
						2.5745 2.2530 9312 2.7358				

Figure 24: (Left) Route orders and distance traveled by e-cargo bikes; (Right) Evolutionary Parameters of the Second Experiment.

The second trial is run by using the initial value of total distance traveled is 35.989 km setting population of 200 with MR of 0.15 and outcomes with improvement to 34.10 km is obtained for instance the route for e-cargo bike 1 from depot to 13, 11,9,8 to dept again traveled by 8.68 km with 21 parcels. The total logistics costs of £115 would be spent for one day delivery operations utilizing 0.27 kwh of battery power during traveled by bikes with 7.6 total completion time by bikers.

Total Distance Travelled under Experimentation 2	34.108156
(population size 200, MR 0.15) (km)	
Estimated Power consumption (kWh) by all e-cargo	0.270699651
bikes during distance travelled	
Total Operational Completion Time (Hours)	7.6072104
Total Labour Wages (£)	94.48155317
Daily Lease cost of all 4 E-cargo bikes (£)	20.64
Electricity consumption cost by bikes in kilometers	
traveled (£)	0.066321414
Total Logistics Operational Cost (£)	115

Figure 25: Daily logistics Expenses from the Second Trial.

6.3 Third Model Experimentation (Population -300, MR-0.15)

:-cargo Bike Route	Start Route	Stores' Delivery Points	End Route	Parcels Carry	Distance Travelled (km)	ıt		tions I Methods GRG Nonlinear Evolutionary		?	×
he Route For E-cargo Bike 1	Depot	15-13-11-10	Depot	23	8.367642	4		-			
he Route For E-cargo Bike 2	Depot	12-14-9-7	Depot	19	10.77925	-0-		Co <u>n</u> vergence:	0.0001		
['] he Route For E-cargo Bike 3	Depot	8-6-4	Depot	14	9.17303	niz	. 1	Mutation Rate:	0.15		
he Route For E-cargo Bike 4	Depot	1-2-3-5	Depot	24	4.184304	_	1	Population Size:	300		
							1	<u>R</u> andom Seed:	0		
						т		Maximum Time without improvement:	30		
							(Require <u>B</u> ounds on Variables			

Figure 26: (Left) Route orders and distance traveled by e-cargo bikes from Third Trial; (Right) Evolutionary Parameters of the Third Experiment.

Starting from the total distance traveled is 65.17629 km as initial, a population of 300 and the mutation of 0.15 are set. The result demonstrates that an improvement of cutting

traveled by 32.672 km to 32.504 km which is an impressive solution finding. Each route trip by e-cargo bike can be seen in figure 27. For a one-day delivery operation, the total logistics costs would be £114. The bikes would use 0.257 kwh of battery power and take 7.5 hours to complete.

Total Distance Travelled under Experimentation 3	32.50427
(population size 300, MR 0.15) (km)	
Estimated Power consumption (kWh) by all e-	0.257970397
cargo bikes during distance travelled	
Total Operational Completion Time (Hours)	7.500284667
Total Labour Wages (£)	93.15353556
Daily Lease cost of all 4 E-cargo bikes (£)	20.64
Electricity consumption cost by bikes in	
kilometers traveled (£)	0.063202747
Total Logistics Operational Cost (£)	114

Figure 27: Daily logistics Expenses from the Third Trial.

6.4 Fourth Model Experimentation (Population -100, MR-0.45)

E-cargo Bike Route	Start	Stores' Delivery	End	Parcels	Distance		Options	2	×
The Route For E-cargo Bike 1	Depot	9-14-12	Depot	13	8.89523	ut	1		~
The Route For E-cargo Bike 2	Depot	2-3-5-4	Depot	24	4.82826				
The Route For E-cargo Bike 3	Depot	13-8-7-6	Depot	21	7.87897	4	Convergence:	0.0001	
The Route For E-cargo Bike 4	Depot	1-15-11-10	Depot	22	8.20766	niz	Mutation Rate:	0.45	
							Population Size:	100	
							<u>R</u> andom Seed:	0	
						т	Maximum Time without improvement:	30	
							✓ Require Bounds on Variables		

Figure 28: (Left) Route orders and distance travelled by e-cargo bikes from the Fourth Trial; (Right) Evolutionary Parameters of the Fourth Experiment.

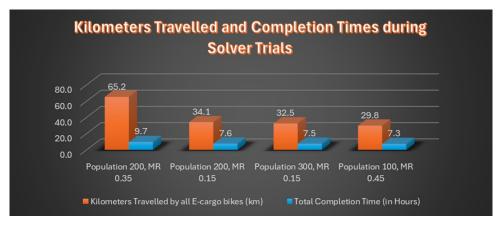
Setting up a population of 100 and a mutation rate of 0.15, the total distance traveled is initially at 65.17629 km.

Total Distance Travelled under Experimentation 4	29.810128
(population size 100, MR 0.45) (km)	
Estimated Power consumption (kWh) by all e-	0.236588317
cargo bikes during distance travelled	
Total Operational Completion Time (Hours)	7.3206752
Total Labour Wages (£)	90.92278598
Daily Lease cost of all 4 E-cargo bikes (£)	20.64
Electricity consumption cost by bikes in	0.057964137
kilometers traveled (£)	
Total Logistics Operational Cost (£)	112

Figure 29: Daily logistics Expenses from Fourth Trial.

This is another excellent solution finding, as the result shows that was improved by 35.366 km to 29.810 km. Figure 28 shows every route ride by each e-cargo bike with parcel numbers

for each store. Logistics expenses for a delivery operation lasting one day would total £112. With 7.3 hours to finish the operations, however, the bikes would require merely 0.236 kwh of battery power capacity.



6.5 Distance Traveled Kilometers under Trials' Parameters

Figure 30: Kilometers Traveled and Completion Times during Solver Trials.

The above chart on "Kilometers Traveled and Completion Times during Solver Trials" offers a comprehensive view of the efficiency improvements achieved with the evolutionary excel solver engine. Initially, the travel distances of 65.2 km and 34.1 km were derived from the random starting point of 35.989 km using the Excel solver engine. The first trial, with a population of 200 and an MR of 0.35, resulted in the longest distance of 65.2 km and the highest completion time of 9.7 hours. This indicates an inefficient scenario with high operational demands. In contrast, with the same population but a lower MR of 0.15, the distance was nearly halved to 34.1 km, reducing the completion time to 7.6 hours, thus demonstrating the solver's effectiveness in enhancing efficiency by optimizing parameters. Further optimization was achieved in subsequent trials. Starting from the 65.2 km distance, the solver reduced the travel distances to 32.5 km and 29.8 km by adjusting population sizes and mutation rates. For instance, with a population of 300 and an MR of 0.15, the distance was cut down to 32.5 km with a completion time of 7.5 hours. The most efficient scenario was observed with a population of 100 and an MR of 0.45, achieving the shortest distance of 29.8 km and the lowest completion time of 7.3 hours. The comparison across different trials reveals key insights that reducing the mutation rate in a stable population size initially improves efficiency significantly. However, the solver engine's iterative adjustments, especially with higher mutation rates and smaller populations, yield the most substantial efficiency gains. The travel distance decreased notably from the initial 35.989 km to 29.8 km, and the completion time was minimized from 9.7 hours to 7.3 hours.

6.6 Analyzing Electricity Costs and Battery Power Consumptions On Travels

The chart illustrates the power consumption and electricity costs for kilometers traveled and highlights the relationship between distance traveled and energy use in one day logistics delivery operations. As travel distance increases, both power consumption and electricity costs rise significantly for instance the shortest distance of 29.8 km, the power consumption is 0.24 kWh, resulting in an electricity cost of £0.058. As the distance increases to 32.5 km, power consumption slightly increases to 0.26 kWh with a cost of £0.063. For 34.1 km, the power consumption further increases to 0.27 kWh, and the cost rises to £0.066. The most substantial increase is observed at 65.2 km, where power consumption jumps to 0.62 kWh, and the electricity cost escalates to £0.126.

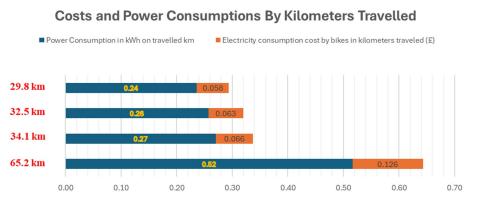
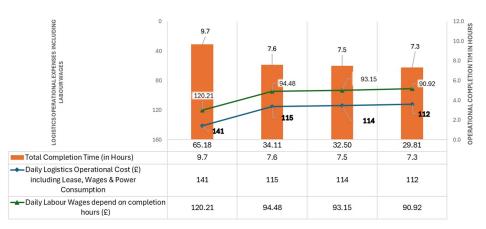


Figure 31: Costs and Power Consumptions by Kilometers Traveled.

The comparison of these data points reveals a notable trend since the rate of increase in power consumption and cost is more pronounced over longer distances. For instance, the power consumption almost doubles when the distance increases from 34.1 km to 65.2 km (from 0.27 kWh to 0.62 kWh), and the cost similarly doubles (from £0.066 to £0.126). This sharp increase underscores the exponential growth in energy requirements and expenses associated with longer travel distances. The data implies that optimizing travel distances can significantly reduce power consumption and associated costs. The relatively low increases in power consumption and cost between shorter distances (29.8 km to 34.1 km) suggest that slight optimizations can yield marginal savings. However, the substantial difference observed at 65.2 km indicates that minimizing longer travel distances is critical for achieving considerable energy and cost efficiency.

6.7 Analyzing Total Daily Logistics Operational Costs by Travels

The provided above chart shows that the logistics operational costs and travel distances offer crucial insights into the relationship between travel distance, time, and expenses. The trends reveal the shorter travel distances result in significantly lower operational costs and labor wages. For instance, the longest distance traveled, 65.18 km, incurs the highest operational cost of £141 and labor wages amounting to £120.21, with a total completion time of 9.7 hours. In contrast, the shortest distance, 29.81 km, results in the lowest operational cost of £112 and labor wages of £90.92, with a completion time of 7.3 hours. This indicates that reducing travel distance by approximately 35.37 km leads to substantial savings of £29 in operational costs and £29.29 in labor wages for a day delivery operation for the courier service provider.



TOTAL ONE DAY LOGISTICS OPERATIONAL COSTS DURING TRAVELS

Figure 32: Total One Day Logistics Operational Cost by Travel Distances.

The data highlights the direct dependency of operational costs and labor wages on travel

distance. As travel distance decreases, there is a corresponding reduction in both time and expenses. For example, reducing the travel distance from 65.18 km to 34.11 km not only decreases the operational cost from £141 to £115 but also lowers the labor wages from £120.21 to £94.48. This significant drop underscores the impact of efficient route planning on overall cost savings. Further reductions, such as from 34.11 km to 29.81 km, although smaller, continue to demonstrate cost efficiency, with operational costs decreasing to £112 and labor wages to £90.92. These findings emphasize the importance of optimizing travel routes in logistics management. Shorter distances not only enhance operational efficiency by reducing completion times but also lead to significant financial savings. The clear correlation between travel distance and costs suggests that logistics operations can achieve better efficiency and cost-effectiveness through meticulous route planning and distance optimization. Thus, focusing on minimizing travel distances emerges as a key strategy for reducing operational costs and improving overall logistics performance.

6.8 Analyzing Total Daily Logistics Operational Costs by Travels



Figure 33: Total CO2 Emission by All E-cargo Bikes Depend on Travel Distances.

The chart on "Total CO2 Emission by All E-Cargo Bikes During Travel" presents an analysis of kilometers traveled and corresponding CO2 emissions. The data reveals a direct relationship between travel distance and CO2 emissions, with significant variances observed across different travel distances. The longest distance traveled, 65.18 km, results in the highest CO2 emissions of 119.51 grams. As the distance decreases CO2 emissions also decline. For instance, at 34.11 km, emissions are reduced to 62.54 grams, demonstrating a substantial decrease of 56.97 grams. Further reductions in distance to 32.50 km and 29.81 km result in CO2 emissions of 59.6 grams and 54.66 grams, respectively. These findings highlight the importance of minimizing travel distances to reduce environmental impact. Comparing the data points, it is evident that even modest reductions in travel distance led to notable decreases in CO2 emissions. The decrease from 65.18 km to 34.11 km was nearly half the emissions, indicating a strong correlation between distance and emissions. Smaller reductions, such as from 32.50 km to 29.81 km also show a meaningful impact though less pronounced. In conclusion, the chart underscores the significant environmental benefits of optimizing travel distances in logistics operations. By reducing the kilometers traveled, substantial reductions in CO2 emissions can be achieved contributing to more sustainable practices. This analysis highlights the critical role of efficient route planning in minimizing the carbon footprint of logistics activities.

6.9 Maps Routes Scheduling Demonstrations Results from The Evolutionary Excel Solver Engine's Trials Experiments

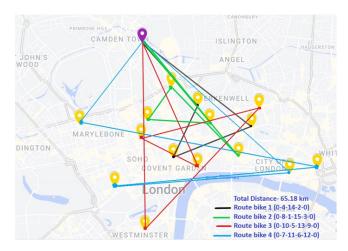


Figure 34: Scheduling Routes of First Trial Distance 65.18 km (the worst routing result).

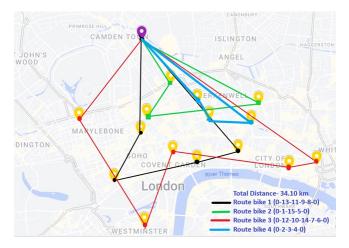


Figure 35: Scheduling Routes of Second Trial Distance 34.1 km.

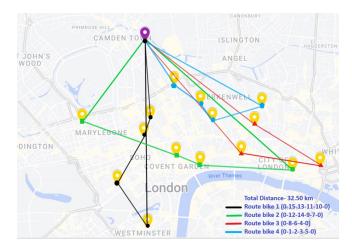


Figure 36: Scheduling Routes of Third Trial Distance 32.50 km.

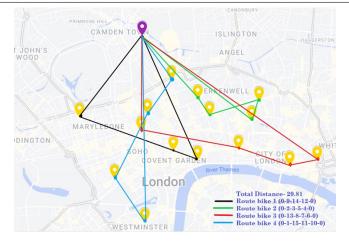


Figure 37: Scheduling Routes of Last Trial Distance 29.81 km (The optimal routing result).

7 Future Scope and Recommendations

The density of large populations in urban areas has led to a rise in carbon dioxide emissions in modern societies. Metropolitan centers like central London's main goal are to reduce these pollutants while considering decreasing the urgent climate crisis and traffic congestion. Consequently, one effective method for accomplishing this objective in freight transportation would be the usage of e-cargo bikes. In addition to reducing traffic and greenhouse gas emissions, the use of electric-cargo bikes for freight transportation in urban areas has a more positive impact on society. It does this by actively improving the last-mile delivery logistics and lowering the operational costs that current transportation businesses encounter, while simultaneously reducing air and noise pollution.

First, they provide substantial cost savings by lowering the fuel and maintenance costs compared to traditional delivery vans. Answering the research questions and objectives, the research experiment shows that e-cargo bikes can improve a day operational efficiency from £141 to £112 through effective optimized routing plan, proving their economic feasibility. From an environmental point of view, e-cargo bikes lessen noise pollution and enhance the quality of the air in cities. Based on the research, there was a significant decrease in CO2 emissions due to a reduction in travel distance from 65.176 km to 29.810 km. E-cargo bikes lessen the carbon footprint of delivery operations by reducing the dependency on fossil fuels, which aids in the combating climate change. Moreover, the fact that they operate more silently than conventional delivery trucks add value to a more pleasant urban environment, reducing complex congestion scenario and vehicle occupancy rate on city roads.

The research paper on "Optimized Vehicle Routing Problem for The Last Mile E-Commerce Parcels Delivery Using E-Cargo Bikes" successfully demonstrates the potential of e-cargo bikes in enhancing the efficiency and sustainability of last-mile delivery operations. By utilizing an evolutionary excel solver, various parameters such as population size and mutation rates were optimized, resulting in significant reductions in travel distance and completion times. The optimal scenario achieved a reduction in travel distance from 65.17629 km to 29.810 km, with a corresponding decrease in operational time from 9.67 hours to 7.3 hours. This translates to substantial savings in logistics costs and energy consumption, showcasing the potential benefits of e-cargo bikes as green logistics solutions for urban settings.

Although e-cargo bikes have advantages such as drivers are exempt from the need for a driver's license, there are some limitations that e-cargo bikes are limited to supporting kinds of businesses because they are designed to handle only packages, not pallets. Therefore, parcels have relatively small sizes and weights, and their travel distances must be short therefore suitable for narrow areas operations. Apart from these restrictions, there are also problems of not enough recharging establishments for them in the targeted area London while the investment costs could be vary depending on bike product models and power

advancements which around $\pounds 6,000+$ thus, initiated by government doing expanding the number of leasing programs would allow businesses to test the bikes and gain a better understanding of their potential use which help businesses to shift to greener vehicles. However, the adoption of e-cargo bikes in congested dense zone has received attention, the urban infrastructure and road space allocations must to be modified by policy makers since most bicycle lanes are designated for regular bicycles whereas e-cargo bikes may occupy more space which depending on sizes meanwhile extended bicycle racks for parking e-cargo bikes are ideals.

Furthermore, the research focused solely on deliveries in this case study and excluded pickups of goods from the analysis. Practical terms, it is possible to pick up packages during delivery tours. Consequently, it is possible to expand the pick-up service facility through further research into pickup and delivery vehicle routing problems (PDVRP). If the model is reconstructed in varying weather, terrain and different load-dependent then the model's respective route sequences and outcome measures can perhaps fluctuate in the vehicle routing. Thus, in future, more in-depth research may address the vehicle routing problem under different climatic conditions with different landscape and pay-load utilizing the e-cargo bike for the transportation operation. While sharing e-cargo bikes with public transports could be new area for future research which is also interesting project to be practiced by the logistics providers using trains, and buses for integration of inland freights transport modes with e-cargo bikes and e-vans possible under support by governments to providers for the omni transport flows within the regions saving costs, and rapid transport time slots available options to response quick order demands for effective last mile delivery.

Nevertheless, e-cargo bikes have the potential to improve the sustainability and efficiency of last-mile delivery operations, as demonstrated by the above study and findings. Significant reductions in travel distance and completion times were achieved under capacitated vehicle routing problem (CVRP) by optimizing parameters such as population sizes and mutation rates using the evolutionary excel solver method achieved objectives of minimizing travel distances and daily operational cost while less carbon footprint during tours. In the best-case scenario, the travel distance was lowered from 65.17629 km to 29.810 km, and the operating time was reduced from 9.67 hours to 7.3 hours. This indicates the feasibility of e-cargo bikes as green logistics solutions in urban environments and results in significant savings in energy consumption and logistics costs which consequently improved air as reducing emission that indirectly minimize vehicle occupied rate on urban city roads.

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