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Optimising Pathology Logistics with Shared-Fleet Passenger and Freight Services: A Case Study on the Isle of Wight, UK

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Abstract

This study presents an optimisation algorithm to solve a collaborative vehicle routing problem with time windows. The algorithm was developed and tested on a real-world case study to investigate the potential for a shared-fleet operation involving public organisations, specifically, the Isle of Wight Council (IWC) and the National Health Service (NHS). The aim was to evaluate whether collaborative use of public-sector vehicles could reduce total fleet size, operational costs, and vehicle-kilometres travelled, while maintaining existing service levels. The study develops a two-stage optimisation algorithm that incorporates real-world constraints such as vehicle capacity, time windows, and pre-assigned mandatory stops. The first stage maximises the number of assignable collaborative tasks across fleets, while the second stage minimises the total travel cost conditional on this maximum assignment. Using historical data and a novel optimisation algorithm, vehicle movements were modelled to evaluate benefits in terms of cost savings, reduced CO_2 emissions and vehicle usage. The case study results generated by the algorithm suggested that considerable improvements could be made by integrating patient diagnostic collection rounds into the existing IWC minibus routes: (a 10.6% reduction in CO_2 emissions (644 kg/month) and vehicle kilometres (2300 km/month), a 20.2% reduction in working hours (219 h/month), and a 17.8% saving in cost (GBP (£) 3596/month) leading to IWC gaining a potential additional revenue of GBP (£) 54,829 annually while reducing costs by 22.4% for the NHS. The findings highlighted the potential benefits of shared fleet collaborations between public sector organisations, offering a model for similar collaborations in other public sector contexts.

Keywords: shared-fleet; horizontal collaboration; carrier collaboration; urban logistics; freight pooling; road congestion; healthcare logistics

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1. Introduction

'Last-mile' freight operations are the final stage of the supply chain, typically from a transportation hub to customers' locations, and involve numerous vehicles operated by different carriers performing similar tasks for different consignors, often at the same time and place [1,2]. In 2020, the World Economic Forum [3] forecast that, by 2030, the number of delivery vehicles and last-mile deliveries would increase globally by 36% and 78%, respectively, reflecting both business-to-consumer (B2C) and business-to-business (B2B) operations. Various sustainable solutions are being used or proposed to tackle the logistical challenges associated with successfully performing urban last-mile delivery to the consignee's satisfaction, including consolidation centres [4], mobile city hubs [5], collection points [6], and multi-party collaborations [7].

This paper introduces a collaborative vehicle routing problem with time windows for shared-fleet logistics collaborations. The problem addresses scenarios where one partner (i.e., vehicle provider) operates vehicles with pre-assigned, mandatory tasks subject to strict operational constraints, including fixed time windows, and the other partner or partners (i.e., task requesters) seek to integrate their own pickup and delivery tasks—also subject to time windows—into the provider's existing routes. The key challenge is to coordinate both sets of requirements without compromising the provider's core service requirements and quality. To address this problem, we develop a heuristic algorithm that generates optimised and feasible vehicle rounds. The algorithm ensures that the provider's original constraints are respected while accommodating as many additional tasks as possible from the requester.

The practical application and validation of this optimisation algorithm are demonstrated through a real-world case study on the Isle of Wight (an island of the south coast of the UK with a population of ~140,000, 'IoW'), involving a theoretical horizontal logistics collaboration between two public sector organisations: the National Health Service (NHS) and the Isle of Wight Council (IWC). Detailed operational data for the NHS pathology collection service, including timings, routes, task types, and load characteristics, were gathered through an observational ride-along study to help accurately model the 'business-as-usual' scenario and the requirements for integration. In this specific context, the challenge was to integrate these observed NHS pathology collection needs (the additional tasks) into the existing vehicle routes of selected IWC fleets (library service, car park cash collection, and school transport minibuses—the 'donor fleet' with mandatory tasks). The application aimed to determine the feasibility and potential benefits of such integration, specifically, quantifying potential vehicle reductions and cost savings for the NHS, while also exploring the revenue generation opportunities for the IWC.

The contributions of this paper are threefold: (i) We present and apply an optimisation algorithm developed for shared-fleet operations where the donor fleet has mandatory time-windowed tasks and requesters add tasks with time-windows. (ii) We demonstrate its application via a novel real-world case study focusing on a horizontal collaboration involving two public sector organisations (NHS and IWC) in a geographically constrained, semi-rural island setting, using historic operational data obtained from the ride-along and council records. (iii) We explore the practical feasibility, challenges, and quantifiable benefits of implementing such a shared-fleet approach across different types of existing local authority vehicle fleets, providing insights relevant to public sector logistics efficiency.

1.1. Previous Studies

Horizontal collaborative measures (i.e., asset sharing between logistics service providers at the same level of the supply chain) among public or private sector organisations can help retailers and parcel delivery service providers lower costs, emissions, congestion, and noise without compromising service quality [7]. Shared fleet logistics, where organisations work together to combine loads and optimise spare vehicle capacity, can be one approach to addressing inefficiencies in last-mile urban logistics [8–10]. At a time when reducing the carbon intensity of our transportation activity has never been more important, there is a strong interest from organisations in how they can achieve this without significant expenditure on new technologies, assets, and infrastructure.

Theoretical studies suggest significant economic savings can be realised from shared-fleet operations between private companies, with reported reductions in overall operating costs of between 9% and 52% [11–15], over business-as-usual operations. Real-world studies have largely focused on private sector shared-fleet operations rather than public institutions [16–20], with Aktas et al. [16] suggesting potential reductions of 17% and 22% in kilometres travelled and number of vehicle routes, respectively, when analysing vehicle capacity sharing in last-mile deliveries for London's online grocery sector. In Pamplona, Spain, Serrano-Hernandez et al. [17] studied a horizontal collaboration between four major supermarket chains in online grocery logistics. They dynamically solved Vehicle Routing Problems (VRP) and Multi Depot VRPs (MDVRP) using a biassed-randomisation algorithm. Their results indicated that the total distance driven reduced by 20.3% with limited cooperation and by 42.9% with full cooperation.

Vargas et al. [18] developed an algorithm based on a gain-sharing business model embedded within the FreightShare Lab Platform (FSLP) for quantifying the benefits of various shared-fleet solutions using data from a leading United Kingdom (UK) construction materials supplier. Operating full truckloads (FTL) and using anonymised data from 400 commercial heavy goods vehicle (HGV) fleets across the UK, the FSLP demonstrated significant reductions in CO_2 emissions (32%), mileage (12%) and cost savings (20%) through optimised shared-fleet usage.

Research on shared-fleet collaborations between public organisations, especially in healthcare logistics, is limited [9]. Grote et al. [8] used data from the NHS in the UK to study collaboration between their sample collection and patient transport services in Southampton. Combining patient transfer with pathology collection from GP (general practitioner, i.e., doctor) surgeries resulted in an estimated 16% cost reduction, 13% fewer vehicle kilometres, and a 12% reduction in CO_2 emissions (ibid). Aydemir et al. [9] examined a case where the local authority's electric courier fleet used for school meal logistics was shared with the NHS Trust to transport pathology samples from 78 doctors' surgeries to a laboratory, replacing a third-party logistics provider. The study indicated benefits could be gained for the NHS, including reductions of 17%, 3%, 69%, 40% and 27% in operating costs, vehicle kilometres travelled, CO_2 emissions, vehicle numbers, and total duty time, respectively.

Interest in horizontal collaboration in logistics has led to related research in collaborative vehicle routing [21]. The specific optimisation needs vary based on the different factors considered, including vehicle type, fuel type, vehicle range, charging infrastructure availability, and carrying capacity [22]. Consequently, various optimisation techniques and vehicle routing problems have been explored to meet different collaboration needs. Defryn et al. [23] proposed a cooperative solution to the routing problem with profits, where multiple enterprises collaborate to serve their clients. Gansterer, Hartl, and Wieser [24] highlighted that businesses often fear losing clients and disclosing sensitive information to competitors, potentially negating synergy benefits. To address this, they modelled a multi-depot vehicle routing problem with pickups and deliveries, ensuring each company served a minimum number of customers and achieved a profit above a pre-agreed threshold.

Considering vehicle capacity constraints and collection/delivery requirements, including time windows, Wang et al. [25] developed a multi-objective optimisation model for a multi-depot, multi-period vehicle routing problem, and introduced a hybrid heuristic algorithm to solve a collaborative multi-depot vehicle routing problem with time window assignment. Mancini, Gansterer, and Hartl [26] introduced a collaborative vehicle routing problem considering time and service consistency along with workload balance, while Angelelli, Morandi, and Speranza [27] explored a demand-responsive optimisation approach for horizontally collaborating shared taxi service providers, addressing fairness by limiting the workload for each provider. Zhang et al. [28] examined a dynamic vehicle routing problem, where real-time decisions on accepting and adjusting service routes for dynamic pickup requests were made, showing that the method remained effective despite side constraints such as time windows and vehicle capacity.

While collaborative vehicle routing problems (CVRPs) have been widely addressed in the recent literature, the algorithm proposed in this study contributes a distinct approach in terms of its structure and practical applicability. Prior studies on collaborative logistics often adopt single-objective cost minimisation frameworks or weighted multi-objective models that balance route efficiency with service coverage using parameterised trade-offs (e.g., [21,25]). In contrast, the optimisation algorithm developed in this study applies to a more practical and well-defined lexicographic (hierarchical) structure that sequentially prioritises two objectives: (1) maximising the number of assigned collaborative tasks, and (2) minimising the total route cost, conditional on achieving the maximum assignment.

This approach eliminates the need to subjectively balance assignment versus cost through weight parameters or penalty terms. By explicitly decoupling these objectives into a two-stage optimisation process, the algorithm provides improved interpretability and control, which is particularly valuable in public-sector applications where service obligations often take precedence over marginal cost efficiencies. Future studies could further benchmark this algorithm against existing methods to clearly demonstrate differences in algorithmic structure, computational efficiency, and practical performance.

Furthermore, the algorithm's design directly reflects the operational constraints observed through an empirical case study. Unlike many existing CVRP models that assume flexible task allocation or relaxed time constraints, the proposed method accounts for fixed pre-assigned stops, strict time windows, and vehicle capacity and shift duration constraints—all derived from real-world operational data recorded during the ride-along with NHS pathology collection vehicles, and vehicle rounds data provided by the NHS and IWC. This empirical grounding enhances the model's relevance for public-sector logistics, addressing practical challenges that are often overlooked in more abstract optimisation frameworks.

1.2. Public Vehicle Fleets and Pathology Logistics

In the UK, city councils operate vehicle fleets for a variety of functions, including library services, housing maintenance, the delivery of school lunches, and the transport of goods and mail between different council locations. Covering the same geographical areas, the NHS employs a "hub-and-spoke" system to manage the transportation of pathology samples from GP surgeries through a network of pathology analysis laboratories situated at NHS hospitals [29]. The presence of multiple public sector vehicle fleets operating in the same space and time not only creates environmental challenges but also presents opportunities for shared fleet operations to improve operational efficiency and reduce carbon emissions.

Pathology logistics is crucial in healthcare as it involves the collection and transportation of medical samples from GP (general practitioner, i.e., doctor) surgeries to laboratories for testing. Efficient pathology logistics is essential for timely diagnosis of health issues, reducing delays, and minimising resource wastage. Specimens are stored at room temperature (not above 25 °C), kept out of direct heat or sunlight, and must be delivered to laboratories on the same day they are collected. Safety measures are also critical, especially for formalin, which releases formaldehyde vapours, necessitating careful handling to avoid harmful exposure. The transportation of patient diagnostic samples comes under the regulation UN3373 [30], and the NHS utilises specific sealed containers to transport samples from surgeries to the pathology laboratory. Given the centrality of pathology logistics to patient diagnostics, a reliable transportation system is essential from clinics to central laboratories.

In its pathology logistics framework, the NHS transports samples using both own-account vehicle fleets and contracted 3rd party courier services as part of its sample collection service. To further increase the efficiency of pathology services, the NHS has also worked to consolidate operations into 29 hub-and-spoke networks, a restructuring effort that began in 2017 to address variability in pathology delivery [29]. This network model not only aligns with the NHS long-term plan but also aims to optimise resources and enhance service quality and cost-efficiency.

The NHS on the Isle of Wight currently operates a sample collection service using three diesel vans (i.e., light goods vehicles with a gross vehicle weight of <3.5 tonnes). In addition to transporting samples from GP surgeries, these vehicles undertake ad hoc duties, including the distribution of internal posts and cleaning materials across NHS sites. Alongside this, the Isle of Wight Council manages multiple fleets to support public service delivery. The case study in which the proposed shared-fleet optimisation approach was used particularly considered the library service van, car park cash collection vehicle, and school minibuses.

2. Methods

This section details the development and application of a novel optimisation algorithm, performed on a real-world case study focused on pathology collection rounds on the IoW. The study compares two scenarios: the 'business-as-usual' (BAU), representing current operations, and the 'intervention scenario', which models proposed shared-fleet operations using the developed algorithm. A comprehensive description is provided, covering the algorithm itself, the analytical methods used for scenario comparison, the specific problem addressed, and the data used in the models, including key information gathered during the observational ride-along of the pathology sample collection process.

2.1. Problem Definition

The problem has an associated graph $G = (V, A)$, where V is the set of nodes representing all possible vehicle stopping locations, including depots. Let V_e denote the set of existing stops that are pre-assigned to specific vehicles and must be visited, and V_a represent additional tasks or stops introduced through shared-fleet collaboration, which can be assigned to any suitable vehicle. V is thus defined as $V = V_e \cup V_a \cup D$, where D is the set of depots housing the vehicles. Each depot $d \in D$ houses a limited number of vehicles, and there is a maximum driving time that can be assigned to each vehicle. A is the set of arcs connecting these locations. Associated with each arc $(i, j) \in A$ are a cost c_{ij} (e.g., driving distance) and a travel time t_{ij}.

V includes two primary types of task locations:

1. Existing Stops: A subset V_e of locations that are pre-assigned to specific initial vehicle routes and must be visited by those designated vehicles. These represent existing, required tasks for each route.
2. Collaborative Tasks: A subset V_a of locations associated with new service requests (pickups and/or deliveries) that arise from shared-fleet collaboration between different entities. These tasks are candidates for insertion into the existing routes.

Let O be the set of new collaborative tasks that need to be integrated into the vehicle schedules. Each task, $o \in O$, typically involves a pickup at a location p_o and a delivery at the location d_o. A quantity q_o (e.g., number of packages or volume) is associated with each task, which must be considered against the vehicle capacity, Q. Each task $o \in O$ has time window constraints: the pickup must occur within the interval $[e_{p_o}, l_{p_o}]$ where e_{p_o} and l_{p_o} represent the earliest and latest allowable times for pickup, respectively. Similarly, the delivery must occur within $[e_{d_o},\ l_{d_o}]$ where e_{d_o} and l_{d_o} denote the earliest and latest delivery times.

A route r is defined as a sequence of locations visited by a single vehicle, starting and terminating at its assigned depot, $r = (\sigma_r(0), \ldots, \sigma_r(n_r))$, where $\sigma_r(0) = \sigma_r(n_r) = d_k$ for the depot $d_k \in D$. Let R be the set of all feasible routes that could be considered in the solution. One distinctive feature of this problem is that each feasible route includes a pre-determined set of stops from V_e, which must be visited by their designated vehicles and cannot be reassigned. Additional tasks, including visiting nodes from V_a can be inserted into any route where feasible, provided that time-window, capacity, and maximum route duration constraints are met.

The total driving and waiting time of any feasible route $r \in R$ cannot exceed a driver's maximum shift duration, denoted as t_{max}.

A feasible solution to the problem is represented by a set of routes and the allocation of tasks in O to these routes, ensuring the following conditions:

- each collaborative task $o \in O$ (with pickup s_o and delivery d_o) is inserted into exactly one route or marked as unassigned.
- service at p_o and d_o must be completed within their respective time windows, meaning pickup at p_o occurs within $[e_{p_o},\ l_{p_o}]$ and delivery at d_o occurs within $[e_{d_o},\ l_{d_o}]$
- all pre-defined mandatory stops $v \in V_e$, associated with the initial routes are visited by their designated vehicles.
- the total load on a vehicle at any point during its route does not exceed its capacity Q, considering pickups and deliveries from both mandatory stops and inserted collaborative tasks.
- each route $r \in R$ is the time feasible, i.e., the arrival time at $\sigma_r(k)$, for $k = 1, \ldots, n_r$ is no earlier than the departure time at $\sigma_r(k-1)$ plus the travel time $t_{\sigma_r(k-1),\sigma_r(k)}$, plus the service time $t_{\sigma_r(k-1)}$ at $\sigma_r(k-1)$ either for collection or delivery, for $k \in \{1, \ldots, n_r\}$.
- it is allowable for routes to have waiting times anywhere in the route to meet time windows.
- the total duration of each route $r \in R$ does not exceed t_{max}.

The travel cost of a route r is defined by $\overline{c_r}$, which is the sum of the costs of the arcs, that is evaluated using Equation (1):

$$\overline{c_r} = \sum_{k=1}^{n_r} c_{\sigma_r(k-1),\sigma_r(k)} \tag{1}$$

We define a two-stage objective function with two sequential objectives. The primary objective (Equation (2)) is to maximise the number of collaborative tasks assigned:

$$\max Z_1 = \sum_{o \in O} \sum_{r \in R} a_{ro} x_r \tag{2}$$

Here, x_r is a binary decision variable, where $x_r = 1$ route r is used in the solution, and 0 otherwise. Additionally, a_{ro} is a parameter that can be calculated for each route r, where $a_{ro} = 1$ if a collaborative task o is included in the route r and 0 otherwise. Let Z_1^* be the maximum number of assigned tasks obtained from solving this primary objective. The secondary objective (Equation (3)), pursued after fixing the task assignment count at Z_1^*, is to minimise the total route cost:

$$\min Z_2 = \sum_{r \in R} \overline{c_r} x_r \tag{3}$$

subject to:

$$\sum_{o \in O} \sum_{r \in R} a_{ro} x_r = Z_1^*$$

Figure 1 illustrates the concept in general. An initial set of routes might show inefficiencies (left), while the optimised solution (right) integrates new tasks effectively, minimising travel distances/times and reducing overlaps.

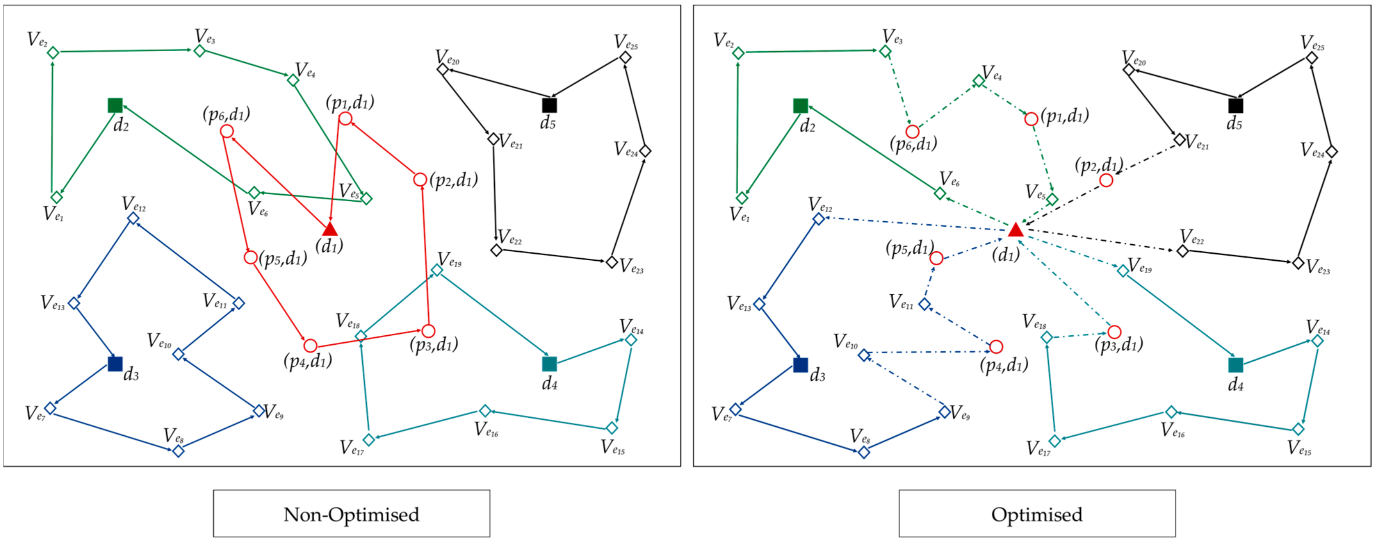


Figure 1. Toy example for demonstrating the optimisation problem. Small squares show the existing stops (i.e., the subset V_e) whilst big squares indicate individual depots for the vehicles (i.e., depots for the subset V_e). Red triangles show where the collaborative tasks are delivered. Pickup and delivery requests (red circles, i.e., the subset V_a) from the depot indicated by the red triangle are added to the 'shared' vehicle routes under the optimised scenario (shown in the figure on the right-hand side).

The optimisation algorithm aims to generate a feasible set of routes by inserting tasks from O into the initial routes containing mandatory stops. If not all tasks from O can be feasibly inserted into the available vehicle routes due to constraints (e.g., time windows, capacity, route duration), these unallocated tasks might require alternative fulfilment methods (e.g., an external service).

The primary objective is to allocate the collaborative tasks in O to the vehicle routes, respecting all constraints, while minimising the total transport cost (e.g., sum of $\overline{c_r}$ over all routes). Figure 2 outlines the algorithm's flowchart. It iteratively identifies feasible insertion points for tasks into routes, calculating the additional cost (primarily travel time/distance) for each potential insertion. Feasible insertions are ranked by cost, and insertions are selected (e.g., randomly from the best options) and applied to the routes. This process repeats over multiple iterations to find a high-quality solution that minimises the overall objective function in Equations (2) and (3).

2.2. Case Study

This study applies the developed optimisation algorithm to a real-world case study exploring a potential shared-fleet operation between the National Health Service (NHS) and the Isle of Wight Council on the Isle of Wight, UK. The NHS on the IoW currently operates a dedicated patient diagnostic sample collection service using three diesel vans handling pathology samples from GP surgeries alongside ad hoc tasks such as internal post and supply deliveries. Concurrently, the IWC manages distinct vehicle fleets for its library service, car park cash collection, and school transport minibuses.

The core optimisation challenge lies in integrating the NHS pathology collection tasks into the existing routes of the specified IWC fleets, ensuring that the IWC's primary service requirements remain the priority. Key objectives were to quantify potential benefits for the

NHS (e.g., vehicle reduction, cost savings) and assess the revenue generation potential for the IWC from undertaking this additional work.

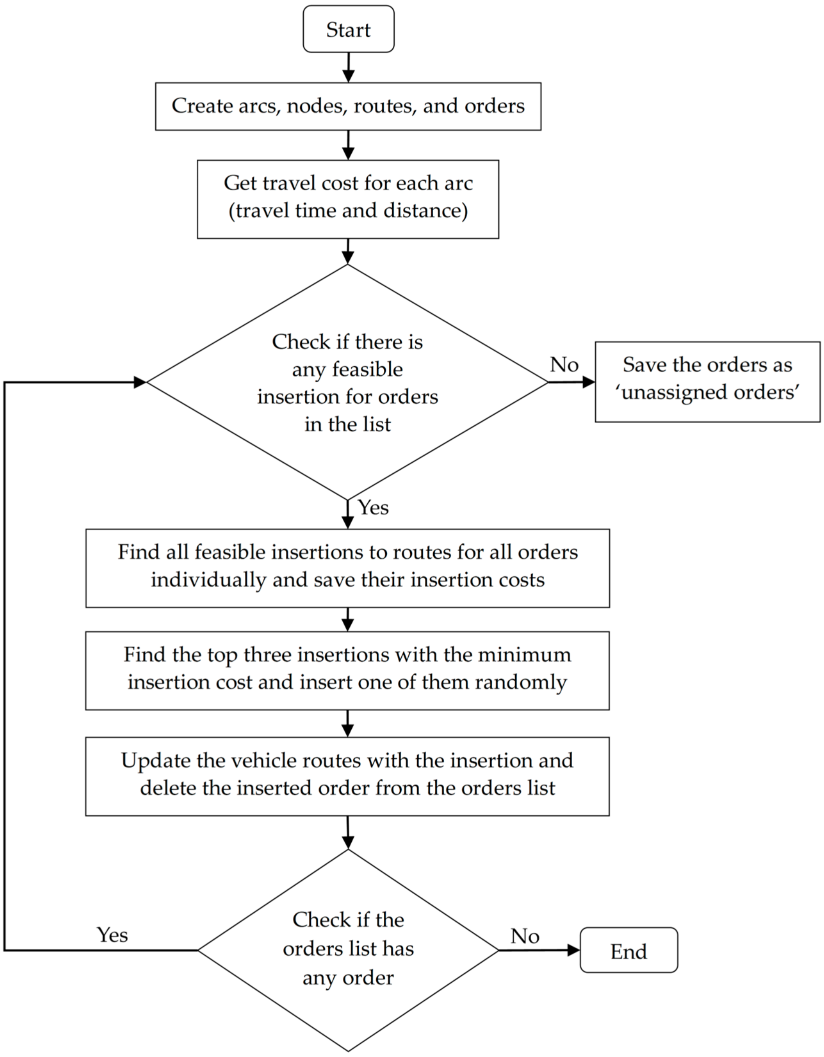


Figure 2. Flowchart of the optimisation algorithm.

This study is significant for several reasons: it addresses the novel collaboration between two public authorities, utilises real-world operational and load manifest data, and examines routing challenges within the unique context of a semi-rural island (having a population of ~140,000) with a restricted rural road network. The case study compares two scenarios: the 'business-as-usual' (BAU), reflecting current separate operations detailed through observational studies (see Section 2.2.2), and the 'intervention', which models the optimised shared-fleet operations resulting from the algorithm.

2.2.1. Data

To fully understand the potential for shared-fleet operations between municipal fleet operators, there are several key data that are needed to accurately determine the business-as-usual operations and quantify compatibility.

Of primary importance is obtaining recent historical records on vehicle activity, and this is best achieved through 'post-round' manifest data, provided by the logistics provider. For a given day, such a dataset would typically detail, as a minimum, the time a transaction took place (arrival and departure), the nature of the transaction (delivery or collection), the location (latitude/longitude or full address), and any special requirements associated with it (e.g., specific time-window constraints).

The study used two historical datasets providing information on vehicle round structures, daily vehicle movements (including locations visited and estimated typical arrival times), and pathology collection schedules for twelve months commencing 1 September 2023. One dataset covered eight IWC vehicles (comprising one library service diesel van, one cash collection vehicle—an electric Volkswagen e-Up—and six diesel school minibuses, Figure 3). The other dataset covered the daily pathology collection rounds of three NHS diesel vans. Additionally, a separate NHS dataset detailed the number of pathology samples produced daily by the 22 GP surgeries situated on the island and delivered to the pathology laboratory at St Mary's Hospital, Newport, Isle of Wight (Figure 3) during June 2020.

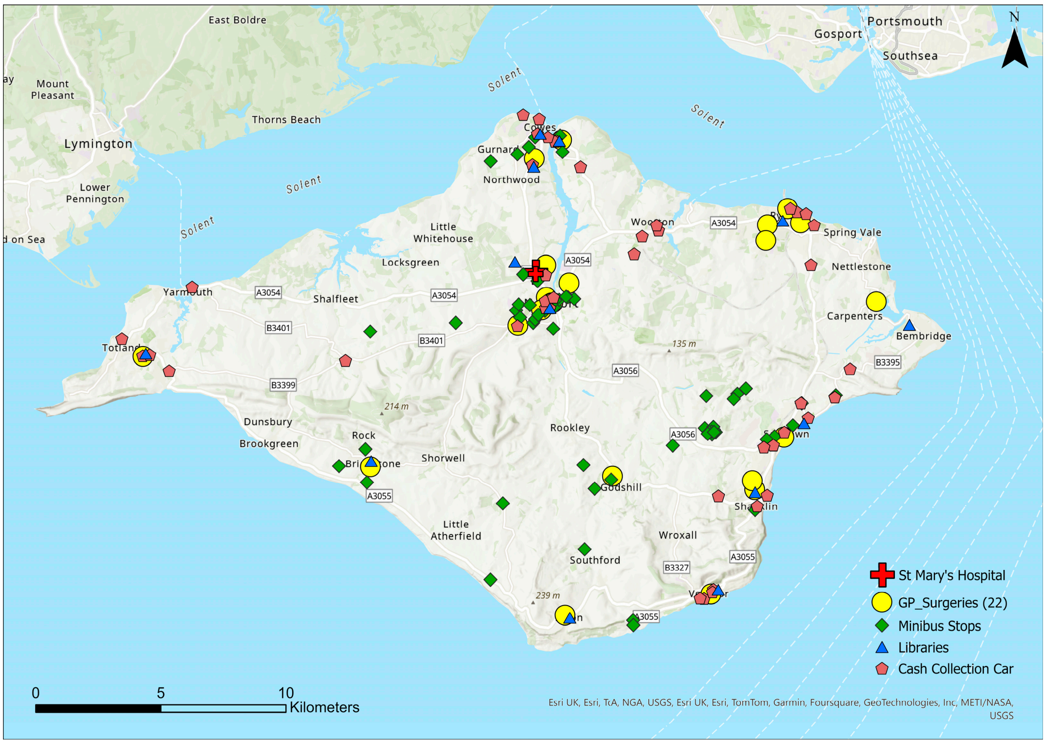


Figure 3. Spatial distribution of GP surgeries and Isle of Wight Council vehicle stops over one week in the business-as-usual operation. The red cross denotes St Mary's Hospital, the central hub for sample deliveries. Yellow circles represent GP surgeries contributing pathology samples, while triangles indicate the locations of libraries served. Diamond symbols mark the collection and drop-off points for school transport minibuses, and pentagons identify stops made by the cash collection vehicle.

These data can also be corroborated against vehicle tracking data (where vehicles are equipped with GPS systems). An area that is harder to quantify from such sources is the ad hoc work that can often take place as part of such rounds, particularly in health logistics operations, where one-off movements of equipment, paper records, and supplies may occur informally between sites. It is vital to try and gain an accurate picture of this additional activity, and whether the donor fleet could accommodate this more 'dynamic' work when needs arise. In discussions with the individual fleet transport managers as part of this research, this element was of most concern, and how such random activities could be effectively scheduled into a donor fleet whose primary work was of a different nature. Another related issue raised was that of contingency in terms of service reliability during times of vehicle maintenance or breakdown, and how this would be provided.

From the two NHS datasets (vehicle rounds and pathology samples), the following observations were made:

1. The number of samples generated per GP surgery ranged from 1 to 50 per day, reflecting the varying number of patients, with an average of 15 samples per GP surgery per day.
2. Each surgery was visited twice daily (one surgery was visited three times daily, and two were visited only once). Collections typically took place in the morning and afternoon, with a single pack of samples collected at each visit with a small or a large red sample container (see Section 2.2.2).
3. Each NHS vehicle collected specimens from up to ten GP surgeries during either morning or afternoon rounds before transporting them to St Mary's Hospital.
4. Each NHS vehicle also dropped off an empty sample container at each GP surgery when making a collection.
5. All collections and deliveries took place on weekdays.

2.2.2. Business-as-Usual (BAU) Scenario

The distances travelled by vehicles and the duration of each round were derived from the IWC and NHS datasets provided. The methodology used builds on previous work quantifying BAU logistics practices in the NHS Solent region [9]. Using Google Maps, the distances and travel times (i.e., average travel times for the route between two postcodes) between the postcodes of each stop along the vehicle's route were quantified and confirmed using GraphHopper, a web-based application similar to Google Maps. Additionally, the route characteristics were confirmed during the ride-along through GPS tracking of the vehicles.The working hours (route durations) were determined by calculating the difference between the recorded times of the vehicles leaving and arriving back at the depot (excluding breaks), as indicated in the datasets.

CO_2 emission factors were taken from the WebTAG tables provided by the Department for Transport (DfT) [31] and the "Manager's Guide to Distribution Costs" published by the Freight Transport Association (FTA) in the UK [32]. These values were 0.28 kg/km for diesel vehicles and 0.07 kg/km for electric/hybrid vehicles. While these assumptions provide a simplified representation, more advanced emissions modelling could not be applied due to the absence of detailed data on speed profiles, congestion levels, gradients, and driver behaviour.

Vehicle operating costs were obtained from the Freight Transport Association Ireland (FTAI)'s Manager's Guide to Distribution Cost Report 2023 [33]. A profit margin of 3% (i.e., costs multiplied by 1.03) was applied to the estimated costs, aligning with logistics industry standards [34], except for the IWC's internal service costs. Courier driver wages were assumed to reflect the standard rate for drivers of light rigid vehicles ($\leq$7.5 tonnes gross vehicle weight), at GBP (£) 13.02 per hour, inclusive of overtime and productivity payments. All vehicles were assumed to have a single operator. A cost per km value, obtained from the report, was £0.25/km, which includes depreciation, fuel, and maintenance. Insurance was calculated at £9.03 per day (based on 251 working days in 2023) [33], as it is more practical not to include the insurance cost in the per-kilometre calculation. The same operational costs were assumed for electric/hybrid vehicles, based on evidence that the total cost of ownership is similar for both vehicle types in Europe [35].

Ride-Along Observational Study on the NHS Vehicle Rounds

To establish a detailed baseline representing the 'business-as-usual' (BAU) scenario, an observational ride-along study was conducted. This involved accompanying two of the three NHS pathology collection vehicles (Figure 4) during representative daily rounds (Round 2 and Round 3) on 19 February 2025. The primary objective was to gain a comprehensive understanding of the current operational workflow, timings, constraints, and tasks handled, thereby providing empirical data for subsequent analysis and modelling.

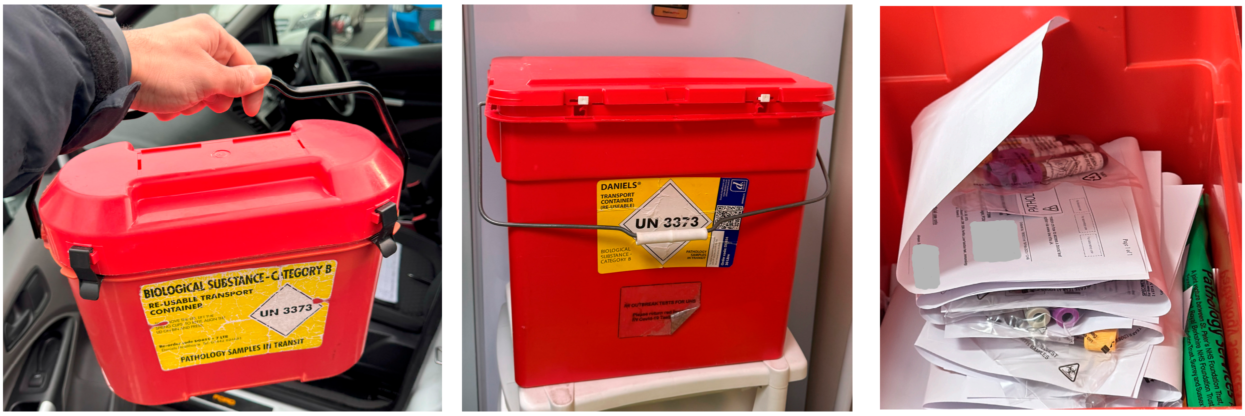
Figure 4. One of the NHS's three diesel vans, currently being operated on the pathology sample collection rounds. Image by authors.

Data collected during the ride-along included:

- GPS Tracking: Precise vehicle routes, travel times between stops, and dwell times at each location were recorded using GPS tracking devices. These data allowed for accurate mapping and time analysis of the rounds.
- Weight Measurement: Portable hand-held scales were used to measure the weight of items collected or delivered at various stops, providing data on vehicle load characteristics.
- Observational Notes and Photography: Detailed notes documented standard operating procedures, driver decision-making (particularly regarding routing based on experience), parking challenges, unexpected delays, and the nature of tasks. Photographs captured vehicle types, various cargo items (sample containers, equipment boxes, pharmacy bags, internal post), and typical road conditions.

The observed NHS vehicle rounds (Rounds 2 and 3) involved a diverse range of tasks beyond their primary function. The core activity was the scheduled collection of pathology samples from GP surgeries using standardised red containers (Figure 5) and their subsequent delivery to St Mary's Hospital. Samples must be contained in 3-layer packaging (Figure 5c) as dictated by the P650 packaging regulations [30]. Additionally, the rounds included several other regular duties: the transportation of podiatry equipment in blue boxes (delivering sterilised items from the hospital and collecting used ones from the surgeries), handling pharmacy logistics (collecting pharmacy bags and delivering them to specific locations), delivering daily blood samples from St Mary's Hospital to the ferry terminal, and managing the collection and delivery of internal post between NHS sites and GP surgeries. Furthermore, the drivers performed various ad hoc tasks as needed, which on the day of observation included delivering photocopier paper, transporting a broken wheelchair for repair, and covering a missed sample collection for another round due to traffic delays.

The ride-along provided significant insights into the complexity and variability of the existing service (Table 1). Analysis of the observed rounds (specifically Rounds 2 and 3) yielded key quantitative data, including total daily distances travelled (approximately, 140–156 km per vehicle), total travel times (approximately, 4 h 18 min per vehicle, excluding breaks), number of stops per round (30–33), and average dwell times (approx. 5 min, often incorporating waiting time for scheduled collections).



(**a**) (**b**) (**c**)

Figure 5. Standard diagnostic specimen containers being used for pathology sample collections: (**a**) Small container (7 L, dimensions 245 × 362 × 158 mm) [36]; (**b**) Large container (30 L, dimensions 716 × 408 × 453 mm) [36]; (**c**) Patient diagnostic samples with 3-layer packaging (barcodes and signature have been blurred for confidentiality reasons). All images were taken by the authors.

Table 1. Summary of operational metrics for observed NHS rounds.

	Round 2	**Round 3**
Start Time (hh:mm)	09:30	09:30
End Time (hh:mm)	18:00	18:00
Number of Stops	30	33
Total Distance (km)	155.83	139.91
Total Travel Time (hh:mm:ss)	04:19:00	04:18:00
Average Dwell Time (min)	5.03	4.61
Max Dwell Time (min)	17	24
Min Dwell Time (min)	2	1
Mode Dwell Time (min)	2	2
Average Sample Container Weight * (kg)	2.3	1.57
Average Collection Weight (kg)	5.0	3.55
Max Collection Weight (kg)	23.2	10.9

*—The average weight of samples collected with red containers only, excluding other types of collections, e.g., podiatry equipment, ad hoc collections.

The core task observed during the ride-along involved the scheduled collection of pathology samples from GP surgeries. These collections generally occur at designated times, typically starting around 10:30 in the morning and 14:30 in the afternoon, with most GP surgeries visited twice daily. A notable exception is only one surgery, which receives three collections per day. Operational flexibility allows vehicles to wait at a surgery if they arrive before the scheduled collection time. While the actual service time for sample collection is typically brief (2–3 min), the average observed dwell time at locations visited in two vehicle rounds, including potential waiting periods and delivery of the samples, was 4.82 min. The dwell times for delivering samples to the pathology laboratory ranged from 7 to 14 min, with an average of ~10 min. Furthermore, the mode dwell time at visited locations was just 2 min, showing that the sample collection process was generally efficient—75% of all dwell times were under 5 min.

Drivers commence their rounds equipped with a standard set of empty containers, typically four large and one small (Figure 5). At each collection point, usually the surgery's reception area, a container with collected samples is picked up, and a corresponding empty container is left in its place. A critical part of the driver's procedure involves verbally confirming with reception staff that all available samples, including any recently taken ones not yet placed in the container, have been accounted for. Each sample has an identifying record receipt attached (Figure 5c).

At the end of each round (both morning and afternoon), all collected samples are consolidated, typically into the large red containers, and delivered to the central pathology service laboratory located at St Mary's Hospital. Containers are used both for swapping at GP surgeries and for the consolidation of samples at the delivery location. When drivers deliver samples collected from the surgeries, they first consolidate all specimens into red containers before the delivery. Upon completing the delivery, they collect a corresponding number of empty containers from the laboratory. Drivers have authorised access for these deliveries, particularly within the hospital premises, and usually use foldable trolleys to transport the containers efficiently, especially for the final delivery to the laboratory. During the observed day, Round 2 involved sample collections from 19 GP surgeries, while Round 3 visited 13 GP surgeries.

Operational factors influencing the rounds were also documented. Route selection relied heavily on driver experience and preference rather than standardised routing software, allowing flexibility but potentially introducing inefficiencies. The road network, comprising rural roads and potentially congested town centres, impacted travel times, with acknowledged limitations due to the observation occurring in winter (lower traffic) compared to potentially busier summer months. The study confirmed that while the service has scheduled elements, significant variability exists due to the integration of diverse tasks and ad hoc requirements. This rich, real-world data gathered through the ride-along formed the essential empirical basis for defining the parameters and performance metrics of the BAU scenario used in this paper's comparative analysis.

2.2.3. Intervention Scenario (Shared-Fleet Collaboration)

Within the proposed shared-fleet collaboration model, all pathology samples were assumed to be transported by IWC vehicles rather than NHS vans. The intervention scenario integrates IWC vehicles (totalling eight) to undertake both existing council tasks and pathology sample collection from 22 GP surgeries, differing from the BAU scenario in which NHS vans are responsible for doing pathology collection rounds. NHS pathology staff were assumed to continue with ad hoc responsibilities, including internal post distribution.

Daily task schedules covering a five-day working week (Monday to Friday), which combined IWC assignments with sample collection and delivery tasks, were generated using historical datasets from both the NHS and IWC. The intervention scenario simulated operations for one week (with tasks repeated weekly), and the outcomes were extrapolated by four to represent a monthly period. Task specifications, including time window constraints, were defined, and the daily task lists were used as input for the optimisation algorithm and for PTV Route Optimiser (a commercial software package) [37], enabling comparison between the BAU case, the commercial optimiser, and the proposed algorithm.

Through close consultation with IWC staff, adhering to given working hours and designated time windows for completing time-sensitive tasks was deemed critical to the success of the operation. For example, IWC minibuses were used for school runs in the morning (7:00 a.m. to 9:00 a.m.) and afternoon (2:30 p.m. to 4:30 p.m.). The library service vehicle operated from 8:30 a.m. to 4:30 p.m. on weekdays, except Mondays and Friday afternoons. At the request of the IWC library service fleet manager, libraries must be visited at set times. The cash collection service car operated from 6:30 a.m. to 2:00 p.m., with scheduled visiting times for car parks, when the vehicle would be unavailable for pathology sample collections. Therefore, the time windows for IWC vehicles are strict as the vehicles must arrive at the existing locations on their rounds at certain times.

All routes were optimised to comply with regulations requiring drivers to take a minimum 45 min break after driving for no more than 4.5 h. The optimisation also considered vehicle charging needs and allowed for miscellaneous tasks. More flexible tasks, such as sample collection and delivery, were re-optimised alongside other tasks to create an efficient overall schedule. Sample collection time windows were set from 9:00 a.m. to 12:00 p.m. and 2:00 p.m. to 5:30 p.m. to align with GP surgery opening times (generally 8:30 a.m. to 6:00 p.m. on weekdays). Delivery time windows for collected samples to be delivered to St. Mary's Hospital were established from 10:00 a.m. to 2:00 p.m. (morning rounds) and 4:00 p.m. to 6:00 p.m. (afternoon rounds). Furthermore, time windows for collection and delivery were confirmed through close consultation with NHS staff. It was also confirmed that IWC drivers do not require additional training to carry out pathology sample collections; however, site access permissions for NHS facilities must still be arranged.

IWC vehicle capacities were factored into the optimisation to ensure a maximum of 15 sample containers could be carried simultaneously by each vehicle. This included the cash collection car (maximum 923 L with a range of 205 km) and the library service van (3.6 cubic metres of load space). Minibuses were also confirmed to carry up to 15 sample containers simultaneously. Service times per stop were taken from ride-along study results and used as input for the modelled scenario, with five minutes allocated for collections and eight minutes for deliveries of pathology samples.

Break requirements for IWC drivers were incorporated, including a minimum 60 min lunch break and 10–15 min afternoon breaks, with weekly working hours capped at 37.5. For the single electric vehicle included in the intervention scenario, at least 50 min were allocated for charging.

Vehicle distances and travel times were computed using the Google Routes API (29 June 2023 release) within the custom optimisation algorithm. For PTV Route Optimiser outputs, distances and travel times were directly extracted from the software. Costs and emissions were then derived using the same procedures applied in the BAU scenario. To account for vehicle limitations, a constraint was imposed to ensure that the total distance travelled in each route did not exceed the 205 km operating range of the electric cash collection vehicle.

During the feasibility assessment of the IWC/NHS shared-fleet operations, PTV Route Optimiser was effective in generating efficient daily vehicle routes for the intervention scenario. However, the internal optimisation algorithm used by the software is commercially sensitive and therefore not disclosed, although it is based on conventional methods such as the travelling salesman problem [38]. By contrast, the bespoke optimisation algorithm developed for this study produced feasible routes by minimising both total distance and travel time over the test week. Multiple feasible solutions (30 runs) were compared to identify the lowest-cost outcome, whereas PTV Route Optimiser produced a single solution that did not necessarily reflect the optimum. Finally, the proposed vehicle rounds were reviewed with IWC fleet service managers and drivers to confirm their practicality.

3. Results and Discussions

The shared-fleet vehicle route optimisation algorithm generates feasible solutions to the problem and the case study presented in this paper, addressing the time-windows and the other specific practical constraints for the IoW case study. The algorithm ended up with a solution for the case study, selected with the minimum travel time cost among the other feasible solutions after performing 100 iterations.

Although the optimisation algorithm produced feasible solutions for the case study, it is important to consider the scalability of the algorithm. The complexity of the algorithm was polynomial, and it was anticipated that it could handle larger problems, providing solutions with similar quality. For instance, a shared fleet operation, previously modelled for the city of Southampton (a population of approximately 260,000), which examined the collection of pathology samples from 78 GP surgeries using Southampton City Council's fleet of 9 electric vans [9], could be effectively modelled with the algorithm presented in this study.

The solutions from the shared fleet optimisation algorithm presented in this study were also compared with those from the PTV Route Optimiser software. While the PTV Route Optimiser produced a single solution that was not necessarily feasible for practical application, our algorithm was capable of generating multiple feasible solutions with minimum cost values, optimising for travel time and distance. When compared with the single solution generated by the PTV algorithm, our algorithm achieved better outcomes, with an average daily reduction in total distance travelled of 73.7 km.

With respect to the feasibility and potential advantages of shared-fleet operations, the analysis of vehicle movements under the BAU scenario revealed substantial overlap between NHS and IWC service areas (Figure 3). This overlap highlights opportunities for implementing a collaborative shared-fleet system and for optimising vehicle rounds through the proposed algorithm.

In the intervention scenario, a limited number of vehicles were used by the algorithm. Eight vehicles (seven on Mondays, excludes the library service vehicle), which were based at different depots (1 library service vehicle, 6 school minibuses, and 1 cash collection car), were assigned, resulting in eight daily routes except Mondays. Consultations with IWC staff confirmed the feasibility of the algorithm-generated routes, taking into account operational constraints such as driver breaks, maximum working hours, and the need to maintain school transport services. In some cases, minibus routes incorporated sample collections alongside scheduled afternoon school runs, which were reviewed with IWC staff and deemed feasible.

To assess the effectiveness of shared-fleet collaboration, a comparative analysis was undertaken between the BAU and intervention scenarios (Table 2). The intervention produced a notable reduction in CO_2 emissions of 10.6% (644 kg/month), largely attributed to the use of three fewer vehicles (four fewer on Mondays due to the library vehicle not being available). Vehicle kilometres travelled also decreased by 10.6% (equivalent to 2300 km/month). Moreover, significant reductions were achieved in fleet size, working time, and costs, with declines of 27.3% (three vehicles per day), 20.2% (~218 h/month), and 17.8% (GBP £3596/month), respectively.

Annual estimates extrapolated from monthly averages indicated potential annual savings of 720 vehicle routes (three per day), amounting to 27,600 km travelled, ~2617 h of working time, 7.728 t of CO_2 emissions, and GBP (£) 43,146 in costs (Table 2). The longest route for the electric cash collection service vehicle was 103.52 km, well within the vehicle's range limit of 205 km, suggesting that all routes are feasible for electric vehicles in terms of distance travelled, and the shared fleet operation can be more sustainable by transitioning to electric vehicles.

The maximum number of packages (red sample containers) carried in a vehicle together was eight, which is under the vehicle capacity, confirming that the vehicle capacity is not a problem in this case. The modelled collaboration between IWC and the NHS met all transportation requirements for pathology samples and IWC's daily services (i.e., library book distribution, cash collection, and school drop-off and pickup). While cumulative savings are detailed in Table 2, distinct cost reductions associated with each service were noteworthy, suggesting a 51% reduction in working hours and a 55% decrease in costs for the NHS, and reducing working time from 450 h/month (BAU) to 218 h/month (intervention).

Table 2. Results generated by the algorithm and monthly statistics for IWC and NHS vehicles, with a comparison of the BAU and the intervention scenarios.

Scenario	Fleet	Distance (km/Month)	Working Time (h/Month)	Costs (GBP (£)/Month)	CO_2 Emissions (kg)
Business-as-Usual	NHS (3)	7971	450	8032	2232
	Minibuses (6)	11,035	475	9124	3090
	Cash Col. Car (1)	1063	92	1644	74
	Library Van (1)	1583	64	1405	443
	Total	***21,652***	***1081***	***20,206***	***6063***
Modelled Shared fleet	Minibuses (6)	15,799	670	12,857	4424
	Cash Col. Car (1)	1857	116	2159	130
	Library Van (1)	1696	76	1594	475
	Total	***19,352***	***863***	***16,610***	***5419***
Net Effect (*Modelled − BAU*)	Minibuses (6)	4764	195	3733	1334
	Cash Col. Car (1)	794	24	515	56
	Library Van (1)	113	12	189	32
	Total	***−2300 (10.6%)***	***−218 (20.2%)***	***−3596 (17.8%)***	***−644 (10.6%)***

It is also worth mentioning that although there was not a considerable change in collection/delivery time for the pathology samples in the intervention scenario, the service quality of sample collection had increased by making two collections (morning and afternoon) from each surgery in the intervention scenario compared to the BAU scenario in which 6 surgeries out of 22 were visited only once (in the morning). This enabled the samples taken from the patients in the afternoon to be collected and analysed on the same day.

The results demonstrated considerable cost-saving potential for the NHS, alongside opportunities for the IWC to generate additional income. Such financial benefits are particularly relevant in the context of austerity-related budget pressures faced by local government authorities (LGAs). Public sector organisations, including the NHS and IWC, could therefore adopt policies to take advantage of these gains. The annual potential additional revenue for the IWC was estimated at GBP (£) 54,829 (including a 3% profit margin) from the provision of the sample collection service to the NHS. If these savings were evenly distributed between IWC and NHS, each organisation would achieve an annual profit of GBP (£) 21,576, corresponding to a 22.4% reduction in the NHS's sample collection service costs.

Furthermore, policies aimed at improving the efficiency of public service vehicle fleets could also mitigate negative externalities linked to road-based logistics, such as air pollution and congestion, particularly where electric vehicles are deployed. While this study focused on a specific UK public sector context, the implications have broader international significance. Public authorities—including national and local governments, healthcare providers, educational institutions, and infrastructure organisations—may also benefit from adopting collaborative approaches and enhancing fleet capacity utilisation.

3.1. Practical Issues

Implementing a shared fleet operation, while beneficial, comes with practical challenges and constraints that need addressing for wider implementation [9,18,39]. Dialogue with the fleet management staff at the NHS and IWC identified the following issues:

1. Ensuring the appropriate use of medical carrier bags to avoid contamination and that security seals are not compromised once leaving the originating surgery.

2. Guaranteeing the safety of children when collections are made between stops (e.g., providing school passenger assistants) and ensuring that protocols are set up such that the driver does not have to leave the vehicle when collections are made.
3. Managing variable collection times within a week, which may cause difficulties for healthcare professionals in preparing samples on time.
4. Dealing with overly restrictive collection or delivery time windows.
5. Handling unforeseen delays in vehicle operations (e.g., traffic jams, breakdowns, driver health issues) and allowing for some contingency (the NHS frequently uses taxi services in such eventualities).
6. Addressing fluctuations in travel or loading/unloading times, which may result in unreliable journey schedules.
7. Navigating existing contracts and service level agreements, which may inhibit or delay operational changes.
8. Overcoming potential legal issues for public sector fleet operators associated with undertaking contract work 'for-hire-and-reward' for third parties.
9. Ensuring the drivers' access requirements for restricted areas in various NHS sites.
10. Applying quality control mechanisms to monitor and mitigate risks linked to in-vehicle conditions such as temperature or vibration.
11. Mitigating risks associated with loss or damage to items being carried.
12. Convincing stakeholders of the benefits of participation.
13. Ensuring that sufficient spare vehicle capacity is maintained.
14. Maintaining efficient vehicle rounds that are regularly monitored and revised to meet changing demands.

Active engagement among stakeholders is essential for shared fleet operations between public sector organisations to identify opportunities and establish mutual benefits. A mutually beneficial agreement should detail work requirements, management processes, and financial and legal issues. Reaching such agreements may be challenging due to managers' conflicting priorities, silo thinking, lack of awareness or consideration for such opportunities, and general resistance to change.

At present, the authors are collaborating with two local government authorities in the Solent region and two NHS Trusts, using case study analysis to encourage adoption of shared-fleet operations and to initiate dialogue aimed at launching pilot trials.

3.2. Research Limitations

It is important to acknowledge the temporal differences in the data used. The IWC and NHS vehicle fleet data were provided in September 2023, while the sample generation data were obtained in June 2020. Variations in seasonal patterns, traffic conditions, demand fluctuations, and operational practices across different periods may introduce biases. However, the historical pathology sample generation dataset revealed a stable monthly volume, with no discernible seasonal variation or evidence of inconsistent demand. Consequently, under real-world implementation, it is improbable that the IWC vehicle fleet would face unexpected fluctuations in sample collection beyond those already considered in the analysis.

The current optimisation model assumes ideal operational conditions without explicitly accounting for real-time disruptions such as traffic congestion, vehicle breakdowns, adverse weather, or unforeseen delays. While historical averages and typical scenarios were considered, the absence of real-time adjustment mechanisms limits the model's capability to handle dynamic operational disruptions. The algorithm can be rerun in the event of a vehicle breakdown to find a feasible solution. However, further research is needed to address key disruptions, such as the immediate unavailability of vehicles due to breakdowns or servicing, or the lack of a driver due to illness or insufficient replacements.

Moreover, the IoW is particularly susceptible to potential issues with the routes, as it has some of the worst cases of coastal erosion in Britain, in addition to occasional road closures due to bad weather, flooding, and roadworks. Therefore, future work is also needed on dynamic rerouting to improve the real-world applicability of the model.

The feasibility of implementing shared-fleet operations extends beyond technical optimisation and encompasses significant legal and institutional considerations. Issues such as liability, data protection, contractual agreements, regulatory compliance, and insurance arrangements have not been explicitly addressed in this study. These institutional and legal factors could pose barriers to the practical implementation of the shared-fleet model. Future research should thoroughly examine these dimensions, including stakeholder perspectives and policy requirements, to provide a comprehensive evaluation of the viability and sustainability of such collaborative logistics practices.

Furthermore, the benefits identified in this study are specific to the examined case study. Savings estimated in this study are subject to the discretion of the parties involved in the collaboration (i.e., the NHS and the IWC) in terms of sufficiency. The NHS would need to decide whether the expected savings are sufficient, bearing in mind the highlighted potential disadvantages above. To comprehensively evaluate the feasibility and effectiveness of shared-fleet operations across the public sector, it is essential to conduct real-world trials and extend collaborations to include a wider range of stakeholders. Undertaking new case studies and pilot trials would provide a more comprehensive understanding of the associated benefits and limitations, inform future decision-making, and support the adoption of efficient and sustainable transport practices in the public sector.

4. Conclusions

This study presented a novel algorithm to solve the collaborative vehicle routing problem with time windows and tested it on a real-world case study, which investigated the potential for shared-fleet operations between public organisations, specifically the National Health Service (NHS) and Isle of Wight Council (IWC) in the UK, to optimise the collection of patient diagnostic (pathology) samples from surgeries. The case study compared a business-as-usual (BAU) scenario where only NHS vans were used with an intervention scenario integrating the IWC school minibus, cash collection, and library service vehicle routes with NHS pathology collections. Using historical data and the optimisation algorithm presented, vehicle movements were modelled to evaluate benefits in terms of cost savings, reduced CO_2 emissions, and vehicle usage.

The findings confirmed both the feasibility and advantages of shared-fleet operations in the public sector, demonstrating positive environmental and operational outcomes. Implementation of the intervention scenario resulted in reductions of 10.6% in CO_2 emissions, 10.6% in vehicle kilometres travelled, and 27.3% in the number of vehicle routes. These outcomes indicate that broader adoption of shared-fleet strategies could play a valuable role in mitigating transport-related and environmental challenges.

From an economic perspective, the intervention delivered notable efficiency gains, with cost reductions of 17.8% and working time savings of 20.2%. In addition, the collaboration created an opportunity for IWC to generate supplementary annual revenue of GBP (£) 54,829, with potential profits of GBP (£) 21,576 for both the IWC and NHS if savings were distributed equally. Such financial benefits are particularly important for local authorities facing austerity-induced budget constraints. Overall, the results highlight the capacity of shared-fleet collaboration to address both environmental and financial sustainability challenges, while promoting more efficient use of public sector vehicle fleets.

Future research could expand on the methodological aspects of the optimisation approach introduced in this study. In particular, formal benchmarking against other collaborative routing algorithms, sensitivity analysis of the hierarchical structure, and exploration of adaptive or real-time variants of the model would contribute to advancing methodological understanding in shared public-sector logistics. Additionally, investigating the algorithm's performance under varying institutional rules, uncertainty in task durations, or dynamic task arrivals could help generalise its application and further reinforce its scientific contribution.

These findings have significant implications for public-sector vehicle fleet management and decision-making. Adopting policies that actively investigate shared-fleet operations to optimise vehicle routes can result in major advantages and possible savings for the public sector. To validate and support these results, it is essential to conduct real-world trials of shared-fleet collaborations. Such trials would provide insight into practical considerations, including the negotiation of new contracts for the use of IWC vehicles in pathology transport, the replacement of NHS internal courier services, and the development of cost allocation frameworks and business models among participating organisations.

In summary, this study makes three principal contributions. First, it introduces a novel optimisation algorithm for shared-fleet operations, tested with real-world data, and demonstrates the feasibility and prospective benefits of such collaborations. The study also addresses healthcare logistics requirements for specialised payloads in a semi-rural context—an area that has received limited attention in prior research. Second, it quantifies the practical benefits of shared-fleet collaboration, highlighting its operational and financial value. Third, it underscores the potential for broader application of shared-fleet strategies by other public-sector organisations worldwide facing comparable logistical and sustainability challenges.

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