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Adding trips to reduce travel times: optimising logistics with mobile depots

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Abstract: This study explores the benefits of integrating mobile depots into urban last-mile logistics. Although the deployment of zero-emission light vehicles, such as cargo bikes, has addressed key challenges, it has also created a need for more flexible warehousing. Mobile depots, i.e., vehicles functioning as dynamic storage hubs, offer this flexibility by supporting last-mile operations within designated urban districts.
We propose a partitioning approach that combines a Mixed-Integer Linear Program (MILP), which optimises the scheduling of depot routes, with a set of routing subproblems that address local demand at each depot stop. Using a case study in Oxford, England, we demonstrate that mobile depots, when paired with our optimisation method, can significantly reduce total travel times. This improvement is largely attributed to the depot's mobility that enables vehicles to make shorter (re-)loading trips. These findings contribute to the broader discussion on mobile warehousing models and their potential applications in various sectors, including manufacturing and supply chain management.

Keywords: Supply chains and networks; Smart transportation; Operations Research

1. BACKGROUND

Introduction. The ongoing efforts to minimise travel times in logistics have led to the study of routing problems through optimisation methods. Major challenges of last-mile logistics, such as operating costs, energy consumption, CO_2 emissions, and traffic congestion, have been addressed through the replacement of standard vehicles with cargo-bikes (Melo and Baptista 2017). The reduced loading capacity of the newly deployed vehicles has led to the development of novel location-routing and facility location strategies, such as mobile depots.

Mobile depots in routing. The integrated problem of deploying mobile depots in logistics has been introduced by (Halper and Raghavan 2011) as the Mobile Facility Location Problem (MFLP). Mobile depots support several emerging trends, e.g., the deployment of unmanned aerial vehicles (UAVs) (Li et al. 2020) and mobile lockers (Li et al. 2021) and their integration with crowd-shipping models (Mousavi et al. 2022). Hof and Schneider 2021 have named the problem of combining regular vehicles with mobile depots as Vehicle Routing Problem with Time Windows and Mobile Depots (VRPTWMD). The concept is not significantly different from a standard routing setting (Toth and Vigo 2014): all vehicles begin at a depot, from which packages for delivery are collected; then, each vehicle follows a route to deliver the loaded packages. Once all loaded packages have been delivered, the vehicles return to the depot to collect a new batch of packages and continue the process. It is clear that if the depot is mobile, rather than fixed at a designated location, it can be repositioned closer to clusters of demand, hence minimising travel times for load replenishment. However, the limited time window at each stop of a mobile depot imposes synchronisation constraints with the vehicles. These restrictions are difficult to handle using exact mathematical models, such as MILP, as shown in the experimental work of Hof and Schneider 2021 and Li et al. 2020. For datasets of realistic scale, Adaptive Large Neighbourhood Search (ALNS) approaches are opted.

Scope. Motivated by real-world logistics operations, we optimise the deployment of mobile depots through exact mathematical modeling, anticipating improved travel times compared to traditional fleet routing. To solve the incurring problem, we adopt a partitioning approach similar to that proposed by Wang et al. 2020. The problem is divided into two stages, each focusing on the routing of mobile depots and a fleet of vehicles, responsible for the delivery of requests to the recipients. The first stage determines a sequence of stops for each mobile depot. At each stop, an assigned set indicates the requests to be picked-up or delivered while the mobile depot is located at the same location. This approach generates multiple independent routing subproblems, which are addressed during the second stage: at each stop, the location is considered as the depot and the assigned requests are either picked-up or dropped-off by the fleet of vehicles. Solving these routing subproblems sequentially results in a complete routing schedule.

The first stage of the problem resembles '*districting*', a concept that aggregates customers to reduce the scale of routing problems, which is explored from an optimisa-

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tion perspective by Bender et al. 2020. To extend this idea and address additional constraints, such as capacity limits, we also explore recent literature on location-routing problems, concisely presented in by Windras Mara et al. 2021. A comprehensible and applicable MILP for a distance-constrained variant of the problem is presented by Almouhanna et al. 2020. For the second stage of the problem, it is clear that most of the numerous variants of routing problems on a single depot are applicable.

For the experimental part of this study, we employ the 'Lin–Kernighan–Helsgaun' (LKH-3) heuristic of Helsgaun 2017, which is widely used for benchmarking. LKH-3 has been successfully implemented in various routing problems, including the Traveling Salesman Problem (Helsgaun 2000) and the Capacitated VRP (Vidal 2022). More recently, it has inspired enhancements through Reinforcement Learning techniques (Zheng et al. 2023). For this study's experimental needs, we will utilize the CVRPTW module of the heuristic, either to compute local routing schedules at each stop of the mobile, or to acquire a baseline solution and evaluate the impact of mobile depots deployment.

2. PROBLEM DESCRIPTION

Let $\mathcal{N}$ be a set of daily requests. Each request $n \in \mathcal{N}$ must be picked up from a location p_n and delivered to a destination d_n. A fleet of identical vehicles $\mathcal{V}$ is supported by mobile depots $\mathcal{K}$ to carry out the delivery of the requests from their pickup points to the final recipient. Each request $n \in \mathcal{N}$ has an associated volume, w_n, each vehicle $v \in \mathcal{V}$ has a capacity Q, and each mobile depot $k \in \mathcal{K}$ has a capacity W. In practice, Q is significantly smaller than W; otherwise, deploying additional vehicles as depots would rarely lead to a reduction in total travel time.

The network is modeled as a graph of nodes, denoted by $\mathcal{I}$. Mobile depots travel across a subset of nodes, $\mathcal{J}$, which includes a central depot j^* and a set of geocenters, one per district. It is possible for the pickup or delivery location of a request to be the central depot j^*, while the remaining nodes in $\mathcal{I}$ represent all other pickup and delivery locations, p_n and d_n, where $p_n, d_n \neq j^*$. The routes of mobile depots consist of nodes in $\mathcal{J}$. The mobile depot can be stationed at selected candidate nodes of $\mathcal{J}$ for a specified time window. During this time interval, the vehicles will either collect requests n for delivery to their respective destinations, d_n, or pick up requests from p_n for transfer to the mobile depot. The districts and the central depot have time windows $[t_j^-, t_j^+]$ as operating hours. Beyond these, the pick-ups and deliveries should be completed during the interval in which the mobile depot is located at the stop. The mathematical annotations of the problem are consolidated to Table 1:

The two-stages problem (a) computes a schedule of the mobile depots, i.e., the sequence of stops, arrival and departure times, and the requests to be collected or dropped off at each stop, and (b) solves a local routing problem for each stop, with respect to the capacities of the vehicles and time windows. The objective of the problem is the minimisation of total travel time, for both mobile depots and vehicles. Figure 1 illustrates an indicative example of a mobile route which supports the operations of two vehicles.

Sets	
$\mathcal{N}$	Requests
$\mathcal{V}$	Vehicles
$\mathcal{K}$	Mobile depots
$\mathcal{I}$	Locations
$\mathcal{J} \subset \mathcal{I}$	Candidate stops
$\mathcal{J}^*$	Districts: $\mathcal{J} \setminus \{j^*\}$
Parameters	
$w_n,\ n \in \mathcal{N}$	Volume of request n
$p_n \in \mathcal{I},\ n \in \mathcal{N}$	Pickup location of request n
$d_n \in \mathcal{I},\ n \in \mathcal{N}$	Delivery location of request n
$t_j^-, t_j^+,\ j \in \mathcal{I}$	Time window of location j
$j^* \in \mathcal{J}$	Central depot
$c_{ij}^{\kappa},\ i, j \in \mathcal{I}$	Travel times from i to j by a mobile depot
$c_{ij}^{\nu},\ i, j \in \mathcal{I}$	Travel times from i to j by a vehicle
Q	Capacity of vehicles
W	Capacity of mobile depots
α	User-designated waiting time factor
Variables	
P_{njk}	1 if n is loaded into k at stop j, 0 otherwise
D_{njk}	1 if n is released from k at stop j, 0 otherwise
Γ_n^-	Time of release of n from a mobile depot
Γ_n^+	Time of load of n to a mobile depot
Δ_{jk}^-	Departure of k from stop j
Δ_{jk}^+	Arrival of k at stop j
y_{jk}	1 if k stops at j, 0 otherwise
x_{ijk}	1 if k travels from i to j, 0 otherwise
q_{jk}	Loaded volume of k at stop j

Table 1. Mathematical annotations

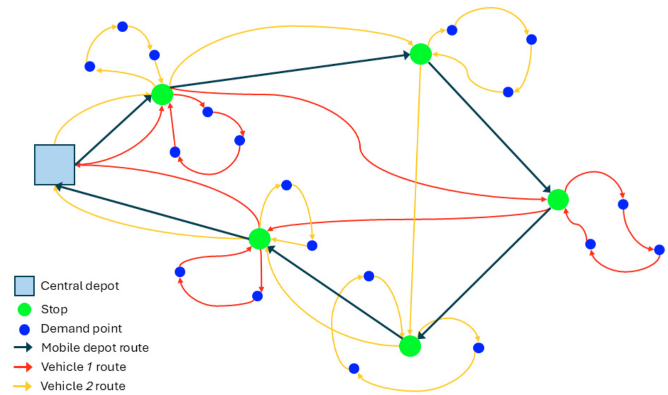

Fig. 1. A concise example for 1 mobile depot and 2 vehicles

3. SCHEDULING OF MOBILE DEPOTS

The following MILP model formulates the first stage of the problem, ensuring that all pickups and deliveries are assigned to stops, and that the selected stops are visited by the mobile depots within time intervals that allow for the completion of adjacent pickups and deliveries, respecting their time windows.

$$\min \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} \Big((1 + |\mathcal{V}|) \cdot c_{ij}^{\kappa} \cdot x_{ijk} + \sum_{n \in \mathcal{N}} (c_{jp_n}^{\nu} \cdot P_{njk} + c_{jd_n}^{\nu} \cdot D_{njk}) \Big) \tag{1}$$

subject to:

Assignment of requests to stops:

$$\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}} P_{njk} = 1 \qquad \forall n \in \mathcal{N} \tag{2}$$

$$\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}} D_{njk} = 1 \qquad \forall n \in \mathcal{N} \tag{3}$$

$$\sum_{j\in\mathcal{J}} P_{njk} = \sum_{j\in\mathcal{J}} D_{njk} \qquad \forall n \in \mathcal{N}, k \in \mathcal{K} \tag{4}$$

$$\Gamma_n^+ \leq \Gamma_n^- \qquad \forall n \in \mathcal{N} : d_n \neq j^* \tag{5}$$

Scheduling of mobile depots:

$$y_{jk} \geq P_{njk} \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K} \tag{6}$$

$$y_{jk} \geq D_{njk} \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K} \tag{7}$$

$$\Omega_{jk} \geq \alpha \cdot (c^{\nu}_{jp_n} + c^{\nu}_{p_n j}) \cdot P_{njk} \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K} \tag{8}$$

$$\Omega_{jk} \geq \alpha \cdot (c^{\nu}_{jd_n} + c^{\nu}_{d_n j}) \cdot D_{njk} \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K} \tag{9}$$

$$\Delta^-_{jk} - \Gamma^+_n \leq t^+_j \cdot (1 - P_{njk}) \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K} \tag{10}$$

$$\Gamma^+_n - \Delta^-_{jk} \leq t^+_j \cdot (1 - P_{njk}) \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K} \tag{11}$$

$$\Gamma^-_n - \Delta^+_{jk} \leq t^+_j \cdot (1 - D_{njk}) \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K} \tag{12}$$

$$\Delta^+_{jk} - \Gamma^-_n \leq t^+_j \cdot (1 - D_{njk}) \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K} \tag{13}$$

$$\sum_{i\in\mathcal{K}} x_{ijk} = y_{jk} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K} \tag{14}$$

$$\sum_{i\in\mathcal{K}} x_{jik} = y_{jk} \qquad \forall j \in \mathcal{J}, k \in \mathcal{K} \tag{15}$$

$$\Delta^-_{j^*k} \leq \Delta^+_{jk} \qquad \forall j \in \mathcal{J}^*, k \in \mathcal{K} \tag{16}$$

$$\Delta^+_{j^*k} \geq \Delta^-_{jk} \qquad \forall j \in \mathcal{J}^*, k \in \mathcal{K} \tag{17}$$

$$\Delta^-_{ik} + c^{\kappa}_{ijk} - \Delta^+_{jk} \leq M \cdot (1 - x_{ijk}) \qquad \forall i, j \in \mathcal{J}, k \in \mathcal{K} \tag{18}$$

$$\Delta^-_{jk} = \Delta^+_{jk} + \Omega_{jk} \qquad \forall j \in \mathcal{J}^*, k \in \mathcal{K} \tag{19}$$

$$\Delta^-_{j^*k} = t^-_{j^*} + \Omega_{j^*k} \qquad \forall k \in \mathcal{K} \tag{20}$$

Capacity constraints:

$$q_{j^*k} = \sum_{n\in\mathcal{N}:p_n=j^*} w_n \cdot P_{nj^*k} \qquad \forall k \in \mathcal{K} \tag{21}$$

$$q_{ik} + \sum_{n\in\mathcal{N}} w_n \cdot (P_{njk} - D_{nik}) - q_{jk} \leq W \cdot (1 - x_{ijk})$$
$$\forall j \in \mathcal{J}, i \in \mathcal{J} \setminus \{j\}, k \in \mathcal{K} \tag{22}$$

Variables:

$$P_{njk}, D_{njk} \in \{0, 1\} \qquad \forall n \in \mathcal{N}, j \in \mathcal{J}, k \in \mathcal{K}$$
$$\Gamma^-_n, \Gamma^+_n \geq 0 \qquad \forall n \in \mathcal{N}$$
$$t^+_j \geq \Delta^-_{jk}, \Delta^+_{jk} \geq t^-_j \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}$$
$$y_{jk}, x_{ijk} \in \{0, 1\} \qquad \forall i \neq j \in \mathcal{J}, k \in \mathcal{K}$$
$$\Omega_{jk} \geq 0 \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}$$
$$W \geq q_{jk} \geq 0 \qquad \forall j \in \mathcal{J}, k \in \mathcal{K}$$

Constraints (2) and (3) ensure that each request will be picked-up and dropped-off by a mobile depot. By constraints (4), the pick-up and drop-off of each request will be performed by the same mobile depot. (5) are precedence constraints between the time of pick-up and drop-off. If any request is expected to be picked-up or dropped-off at a stop j by mobile depot k, then k will visit stop j, as imposed by (6) and (7). To ensure adequate loading and unloading time at each stop, constraints (8) and (9) impose that the waiting time for each mobile depot at a stop must be at least as long as the direct connection time between the stop and the pickup or delivery location of any assigned request, scaled by a waiting time factor α. In our use-case, the value of α is set to 2. Constraints (10)-(13) define the release and loading times for each request assigned to a mobile depot. Each visited node must have an incoming and outcoming trip, as ensured by (14) and (15).

Constraints (16) and (17) ensure that the route of each mobile depot starts and ends at the central depot. The difference between the departure time and the arrival time of two consecutive stops must be set to the respective travel times, as imposed by the big-M set of constraints (18). The difference between the arrival and departure time at the same stop is the respective waiting time, as set by constraints (19) for all intermediate stops and (20) for the central depot.

The load of a mobile depot varies dynamically along its route. At the central depot, the load is initialized as the sum of the volumes of all requests to be picked-up (21). For each intermediate stop, the load is adjusted by reducing it by the volume unloaded at the previous stop and increasing it by the volume of parcels picked up at the current stop, as specified by constraints (22).

4. INTERACTION BETWEEN THE TWO STAGES

The optimal solution of the MILP yields a set $\mathcal{S}$ of subproblems, each identified by the stop j and the mobile depot k. That is, a subproblem $\mathcal{S}_{j,k}$ includes a (disjoint) set of requests $N_{jk} = \{n \in \mathcal{N} | P_{njk} = 1 \vee D_{njk} = 1\}$. Each request has a pickup point and a delivery point. If $P_{njk} = 1$, then the pickup point of n is p_n, and if $D_{njk} = 1$, then the delivery point is d_n. If $P_{njk} = 1$ and $D_{njk} = 0$, then the delivery point is stop j. If $P_{njk} = 0$ and $D_{njk} = 1$, then the pickup point is j. All nodes involved have a time window, determined by the values of variables Δ^+_{jk} and Δ^-_{jk}. The fleet of vehicles to complete local operations is determined by the set $\mathcal{V}$.

Each subproblem $\mathcal{S}_{j,k}$ corresponds to a known routing problem, determined by the required operations. If a local district involves both pickup and delivery requests, the appropriate model is the Pickup and Delivery Problem with Time Windows (PDPTW). For uniform operations, the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) applies. In both cases, the stop duration, as set by constraints (8) and (9), may differ from the actual duration of local routes, potentially being either too short or unnecessarily extended. Any discrepancy between the scheduled end of the time window and the actual completion time of local routes is carried forward to subsequent stops of the mobile depot, dynamically updating its initial schedule. An algorithmic outline of this procedure is presented in Algorithm 1.

Algorithm 1 Routing using Mobile Depots

Let $R_k = [j^*]\ \forall k \in \mathcal{K}$ be the routes of mobile depots and $R_v = [j^*] \forall v \in \mathcal{V}$ be the routes of vehicles;
Solve the MILP;
Append stops $j \in \mathcal{J} : y_{jk} = 1$ to $R_k\ \forall k \in \mathcal{K}$;
for $j \in R_k$, $k \in \mathcal{K}$ **do**
    Set the completion time of vehicle k to station j equal to $M_{j,k} = 0$ and $\mathcal{S}_{j,k}$ as the local routing problem;
    Solve $\mathcal{S}_{j,k} \to M_{j,k}$;
    Append local routes to $R_v\ \forall v \in \mathcal{V}$;
    Set λ as $M_{j,k} - \Delta^-_{j,k}$;
    Add λ to $\Delta^+_{j',k}$, j' being the succeeding stop of k;
return $R_m\ \forall m \in \mathcal{V} \cup \mathcal{K}$;

5. EXPERIMENTAL SETTING

As discussed earlier, the motivation for exploring the deployment of mobile depots stems from insights gained from real use-case in last-mile logistics. In this section, we present the travel time reductions achieved through the deployment of mobile depots within the city network of Oxford, UK. Cargo bikes are well-suited to navigate the narrow streets of the city center and align with key objectives set by local authorities, such as promoting safer, zero-emission transportation options. However, their limited capacity necessitates multiple long trips for restocking, particularly due to the location of inventory facilities outside the city limits.

To address these challenges, we examined the use of larger cargo bikes as mobile depots to support parcel deliveries across city districts. In this approach, a mobile depot is preloaded at consolidation centers and then scheduled to station at designated stops within the city network for specified time intervals. During these intervals, smaller cargo bikes can collect parcels from the mobile depot and complete deliveries within nearby districts. This method aims to reduce the frequency of replenishment trips, as smaller cargo bikes have quicker and more convenient access to a reloading point, thereby improving overall delivery efficiency.

For this use-case, let $\mathcal{N}$ be a set of orders, $\mathcal{V}$ be the fleet of small cargo-bikes, and $\mathcal{K}$ be a singleton of a mobile depot. Set $\mathcal{J}$ contains the locations of candidate stops of the mobile depot, including a consolidation center, denoted by j^*. The pickup location of all orders is the consolidation center, i.e., $p_n = j^* \; \forall n \in \mathcal{N}$.

We evaluate the potential deployment of the mobile depot during peak hours, assuming that all candidate stop locations in $\mathcal{J}$ operate between 09:00 and 14:00. The network of Oxford is divided into five geographical districts. To assess the performance of Algorithm 1, we generate six groups of datasets: one for each district and one encompassing delivery requests across the entire network. Each group consists of five instances of 50 orders, with each order's delivery location confined to its respective district. While larger-scale instances could be considered, those exceeding 50 orders hold little practical relevance due to the capacity limitations of mobile depots and the duration of a shift. The consolidation center is positioned at the city boundary along the Oxford Ring Road, and 9 randomly selected locations within the city limits serve as candidate stops for the mobile depot. Order volumes range from 0.01 to 0.06 m^3, while the mobile depot has a capacity of 2.0 m^3 and each last-mile vehicle has a capacity of 0.2 m^3. Each dataset is solved using both 2 and 3 identical last-mile vehicles. For the sixth group, covering the entire city network, the city center demand represents 40-60% of total demand, simulating more realistic demand patterns - the exact percentage is determined randomly during the generation of a new instance.

Figure 2 shows the network of Oxford, the locations of the central depot and candidate stops, and the boundaries of the five geographical districts.

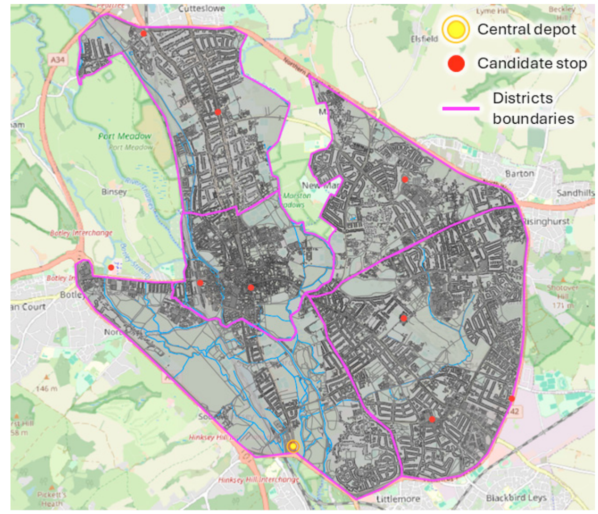

Fig. 2. The network of Oxford

All experiments were conducted on a server equipped with 32 AMD Ryzen Threadripper PRO 5955WX 16-core processors and 32 GB of RAM, running Ubuntu 22.04.5 LTS. To solve the MILP, we employed the *Gurobi 11.0.3* optimizer via the open-source optimization library *Pyomo 6.8.0* in *Python 3.10.12*. The geographical data used in Figures 2, 3 and 4 are obtained by Open Street Map[1].

To solve the routing subproblems, we employ the 'Lin – Kernighan – Helsgaun' (LKH-3) heuristic of Helsgaun 2017, which is widely used for benchmarking. LKH-3 has been successfully implemented in various routing problems, including the Traveling Salesman Problem (Helsgaun 2000) and the Capacitated VRP (Vidal 2022). More recently, it has inspired enhancements through Reinforcement Learning techniques (Zheng et al. 2023). For this study's experimental needs, we will utilize the CVRPTW module of the heuristic, either to compute local routing schedules at each stop of the mobile, or to acquire a baseline solution and evaluate the impact of mobile depots deployment.

To calculate travel times between nodes, we use an estimated distance (i.e., the euclidean distance multiplied by 1.3) and an average speed of $10\frac{\mathrm{km}}{\mathrm{h}} \approx 0.17\frac{\mathrm{km}}{\mathrm{min}}$. This allows us to set the `SCALE` parameter of LKH-3 to 8 (i.e., the euclidean distance in km multiplied by 8 is approximately equal with the travel time in minutes). Since the CVRPTW module in LKH-3 does not support multiple trips per vehicle, we replicated vehicles based on the total volume to be served, creating a sufficient fleet of last-mile vehicles. After generating solutions, the routes of the replicated vehicles were consolidated back into the routes of the original vehicles.

To evaluate the impact of deploying the mobile depot, we compare the results of Algorithm 1 with a baseline solution obtained using the LKH-3 algorithm, which considers only the last-mile cargo bikes. Deploying the mobile depot introduces a trade-off: while it may add to the overall travel times due to the mobile depot's own route, it is

[1] `https://download.geofabrik.de/europe/united-kingdom/england.html`

Table 2. Comparison between Algorithm 1 and LKH-3 CVRPTW - Travel times in minutes

Instance	Algorithm 1		LKH-3	
	$\lvert\mathcal{V}\rvert = 2$	$\lvert\mathcal{V}\rvert = 3$	$\lvert\mathcal{V}\rvert = 2$	$\lvert\mathcal{V}\rvert = 3$
ox_1	576	568	620	620
ox_2	636	633	700	699
ox_3	655	600	682	679
ox_4	606	544	611	611
ox_5	551	507	651	648
ox_avg	**604.8**	**570.4**	**652.8**	**651.4**
south_1	449	418	574	572
south_2	425	374	556	556
south_3	421	386	553	553
south_4	438	396	551	551
south_5	465	387	549	548
south_avg	**439.6**	**392.2**	**556.6**	**556.0**
north_1	515	515	883	883
north_2	674	547	890	890
north_3	538	503	893	893
north_4	482	504	849	846
north_5	659	478	846	845
north_avg	**573.6**	**509.4**	**872.2**	**871.4**
east_1	475	408	680	680
east_2	456	387	765	764
east_3	438	370	710	708
east_4	486	385	699	699
east_5	463	398	678	678
east_avg	**463.6**	**389.6**	**706.4**	**705.8**
center_1	322	282	537	535
center_2	308	294	496	494
center_3	321	274	511	509
center_4	329	301	532	532
center_5	319	271	460	455
center_avg	**319.8**	**284.4**	**507.2**	**505.0**
west_1	377	355	327	327
west_2	438	404	386	386
west_3	409	395	320	319
west_4	403	359	376	375
west_5	494	403	385	384
west_avg	**424.2**	**383.2**	**358.8**	**358.2**

expected to reduce travel times for the last-mile vehicles by minimizing the distances they need to travel for reloading. Both methods have similar runtimes of a few minutes. In Algorithm 1, the MILP is solved to optimality in under a minute, followed by the solution of multiple small-scale subproblems, as each stop is examined individually. In contrast, LKH-3 avoids solving an MILP but compensates with additional time spent on solving a larger routing problem, resulting in a balanced overall computational time compared to Algorithm 1.

Table 2 consolidates the results of Algorithm 1 alongside the direct routing of LKH-3 across all instances within the five groups. The columns labeled '$\lvert\mathcal{V}\rvert = 2$' and '$\lvert\mathcal{V}\rvert = 3$' indicate the number of last-mile vehicles used in each experiment. The numeric values represent total travel times in minutes. The prefix 'ox_' refers to datasets covering the entire Oxford network, while the remaining labels denote specific geographical districts involved.

We notice that deploying the mobile depot results in a substantial reduction in total travel times. This reduction is particularly observed in datasets focused on specific city districts compared to those covering the entire network. Additionally, while adding a third last-mile vehicle has minimal impact on direct routing, it significantly decreases

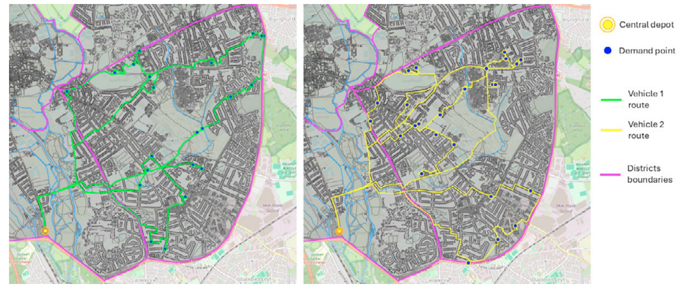

Fig. 3. 'south_': Direct routing by LKH-3

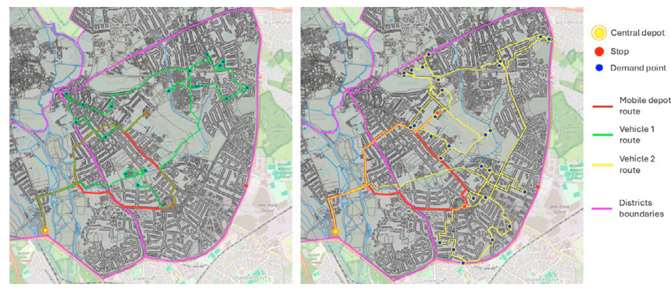

Fig. 4. 'south_': Mobile depot deployment by Algorithm 1

total travel times when combined with a deployed mobile depot.

Figure 3 illustrates the routes of the two last-mile vehicles for the dataset 'south_1' before the mobile depot is deployed, while Figure 4 shows their routes after deployment. In the direct routing approach, the vehicles must return to the central depot multiple times due to their limited capacities. In contrast, with the support of a mobile depot, the vehicles return to the central depot only at the end of their daily shift, once all deliveries are completed.

Beyond travel time considerations, the LSP should evaluate additional costs before deploying a mobile depot. Each additional trip incurs monetary expenses, including labor and operational costs. On the other side, inventory costs decrease as the central depot plays a reduced role in logistics operations. Moreover, the presence of mobile depots in local districts enhances flexibility in case of disruptions, allowing unserved parcels or same-day requests to be addressed more efficiently.

6. FUTURE WORK

Our computational evidence suggests that mobile warehousing can have substantial benefits also in manufacturing. Indicatively, the use of mobile depots in industrial environments could facilitate the transportation and storage of tools and parts. The expected reduction in transportation times may lead to decreased idle times and a significant increase in overall productivity. More promisingly, integrating mobile depots with innovative inventory management strategies could encourage the adoption of Just-In-Time (JIT) manufacturing and help achieve zero-inventory goals (Lyu et al. 2020).

Transportation within and beyond industrial facilities plays a critical role in the efficiency of production lines, as the synchronization between distinct units strongly depends on it. Such transportation may involve the movement of tools, equipment, or stock from internal or remote warehouses to production lines. Improper scheduling of dynamically adjusted transportation in industrial settings can lead to increased idle times, thereby reducing production efficiency. Several benefits of incorporating mobility in manufacturing have already been documented in the literature. For example, dynamic relocation of modules has been identified as a pertinent application for the Mobile Facility Location Problem (MFLP) by Allman and Zhang 2020. This highlights the potential utility of the proposed methodology in facilitating the deployment of mobile depots. Autonomous vehicles and robots play a key role in transportation within manufacturing. For instance, Horan et al. 2011 focuses on deploying Automated Guided Vehicles (AGVs) on predesignated routes within a manufacturing environment. More recently, Xuan et al. 2024 examined the use of autonomous mobile robots to connect warehouses with production operations. The work of Baquero et al. 2020, regarding forecasts of inventory requirements in mobile warehouses, is also of interest.

We note that the presented use-case is a specialised variant of a broader class of routing problems known as the Pickup and Delivery Problem with Transfers (PDP-T). This problem extends the conventional Pickup and Delivery Problem by allowing requests to be transferred from one vehicle to another at intermediate locations, referred to as *transfer points*, between the pickup and delivery locations. Although this problem has been formulated as a MILP (Cortés et al. 2010), practical applications often require (meta)heuristic methods, such as Adaptive Large Neighborhood Search (ALNS) Masson et al. 2013. Recent advancements in exact methods have been reported by Lyu and Junfang Yu (2023), who demonstrated the performance of MILP formulations on datasets with a maximum of 30 requests, a number that decreases to 5 when considering time windows for completing pickups and deliveries. By examining the broader class of this problem, we may identify ways to relax certain assumptions that limit the computation of more effective schedules (e.g., estimated waiting times at each stop), thereby facilitating the optimal integration of mobile depots.

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