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A Genetic Algorithm Framework for Efficient Electric Patient Transportation

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Abstract. Transportation of people with limited mobility (elderly, persons with disabilities or pregnant women) to the different health care facilities for medical appointments is a big logistical problem. In the urban environment there are several factors that can make mobility difficult. To tackle this issue, we have designed a route planning system that incorporates time frame constraints for pick-up, drop-off, and journey time for each user, managed via a fleet of small-capacity electric vehicles. The system is based on a two-phase approach. In the first phase an insertion heuristic is used to build initial workable routes. These are enhanced by a genetic algorithm to obtain more efficient solutions. The major targets are to minimize the total operation time and CO2 emissions respecting the transportation needs of each patient. Several tests have been conducted to test the system with different parameter settings and circumstances. The results collected show significant gains in travel efficiency for all the developed routes, and the approach shows potential to be a reproducible sustainable solution for varied urban situations.

Keywords: Medical Transportation Optimization, Adaptive Routing Algorithm, Electric Mobility, Patient-Centric Logistic, Sustainable Urban Mobility, Genetic Algorithm.

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1 Introduction

The Dial-a-Ride Problem (DARP) (Cordeau & Laporte, 2007) has been extensively utilized to investigate assisted transportation routing considering real-world constraints like time windows and vehicle capacity. What sets this challenge apart from standard freight routing is the focus on passenger experience. Longer rides lead to disgruntled passengers and hence quality of service is a must have operational demand. Therefore, the adoption of electric vehicles is in line with the wider environmental obligations, since it helps to reduce pollutant emissions and operating expenses in the long run (Laporte & Pascoal, 2011). However, the introduction of EVs complicates the limited autonomy and the carefully planned recharging infrastructure (Pisinger & Ropke, 2007). The following work presents a hybrid two-phase approach that combines an insertion heuristic and genetic algorithm to develop, test and evaluate a low-capacity electric car routing system geared to ecological and inclusive mobility; to jointly cope with these difficulties. This technique enables the investigation of operationally realistic scenarios such as vehicle-specific technological restrictions, particular user needs and journey time considerations.

2 Related work

The DARP has been widely studied in operations research literature as an effective framework for assisted transportation problems. Early seminal efforts (e.g. Cordeau & Laporte, 2007) systematically catalogued solution techniques ranging from exact methods to heuristics and metaheuristics, setting a reference point for future study on the problem's computational complexity. Furthermore, the advent of electric vehicles and their incorporation in routing problems have led researchers to rethink classical routing models, pointing out the need to adapt these models to the constraints of electric range and recharging needs of electric fleets, as pointed out by Laporte & Pascoal (2011) and Van Hentenryck & Bent (2006). Socially, inclusive mobility has become a paradigm in urban transportation design as it directly affects the life quality of vulnerable groups and the long-term sustainability of city-wide transportation systems (Van Hentenryck & Bent, 2006). These works demonstrate that simulation-based methods are very interesting and useful for evaluating highly complex logistics systems operating under different conditions (Smith and Sturrock, 2024).

Genetic algorithms are one of the most productive research approaches to solve the DARP, because they can explore vast combinatorial search spaces under numerous simultaneous restrictions. This paradigm was initially used on the problem by Jørgensen et al. (2007). He developed an evolutionary method with insertion operators and penalty functions to direct the search towards practical and good quality solutions. Another work by Zelić et al. (2022) He proposes genetic operators to decrease service times and facilitate routing. Masmoudi et al. (2017) tackled the issue of heterogeneous fleets which is a common aspect of real-life aided transport operations. He proposed a hybrid technique combining a genetic search and local improvement procedures to dynamically balance vehicle assignments.

In Schenekemberg's work et al. (2022) He analyzed many private fleets and public transport provider cases and found that substantial coordination is needed for the efficient functioning of both. Schenekemberg et al. (2025) refined this work by integrating public transport alternatives in the model and suggested a BRKGA version to handle this multimodal complexity. Recently, Shimaoka et al. (2025) has modified the BRKGA framework, incorporating Q-learning. This approach permits the algorithm to adjust its behavior to changing problem conditions and increases its computational reliability.

3 Problem Description

For those with physical mobility constraints, travelling from their home to healthcare facilities to attend medical visits is a significant practical challenge. Conventional urban transit networks are often not built with this population group in mind, which results in uncomfortable journeys, physical effort, the inconvenience of several transfers and frequent delays. In contrast, the price burden of using private transport solutions such as taxis is sometimes unattainable for these people. To fill this gap, the following study proposes a dedicated transportation service for this group, implemented through a fleet of subcompact electric vehicles. Each vehicle is for the use of the mobility-impaired person and, if necessary, one accompanying person. Service requests are collected at least one day before the scheduled appointments and include the appointment time, the user's residential coordinates, and the user's mobility level evaluated on a specified scale. With this information, the system calculates daily routes and determines accurate pickup times for each user to ensure on-time arrival. The number of cars deployed is not fixed and varies according to the volume of requests received each day. All vehicles depart from a central depot, make their respective pickups and drop-offs, and return to the depot after the service day (see Fig. 1).

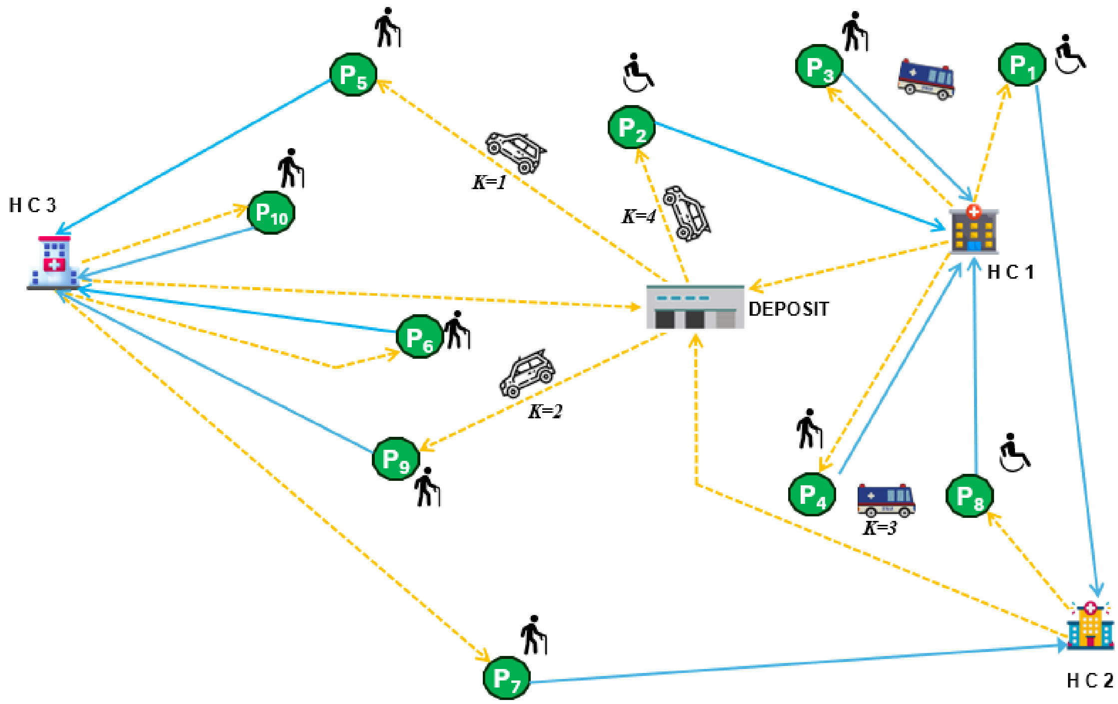


Figure. 1. Patient transportation to health centers.

4 Methodology

The suggested method is formally based on a DARP formulation that is specifically reconstructed to capture the particularities of individualized medical transportation. The three passenger-focused dimensions that distinguish this model from classical freight-based formulations: (i) each passenger is treated as an indivisible transportation unit that cannot be split across multiple vehicles; (ii) pick-up operations must strictly precede the corresponding delivery operations; and (iii) a high limit on ride duration is imposed to ensure passenger comfort and health during the service.

The system elements are grouped into four structured sets: the electric car fleet (*K*), the set of service requests (*R*), the set of pickup nodes (*P*) and the set of delivery nodes (*D*). The model is constrained by operational parameters, including pairwise travel time matrices (tij), time windows ([ai, bi]) that define the allowable time of service at each node, and a unit vehicle capacity (Q=1) that reflects the personalized, one passenger at a time nature of the service.

The goal function we propose is fleet vehicle operation time minimization. The above restrictions make the problem easy to solve in practice: each patient is assigned a pickup and a delivery event; vehicle movement is preserved over all nodes; and a precise temporal order between pickup and delivery events is maintained. The service is one-to-one which sets the capacity at Q=1 per vehicle, and the finite driving range of electric vehicles (E) is explicitly modelled to guarantee that sustainability issues stay embedded in the solution.

4.1. Sets and Indices

$K = \{1,\dots,m\}$ Set of electric vehicles.

$R = \{1,\dots,s\}$ Set of transportation requests.

$P = \{1,\dots,n\}$ Pickup nodes.

$D = \{n+1,n+2,\dots,2n\}$ Delivery nodes.

$V = \{0\} \cup P \cup D \cup \{2n+1\}$ Set of all nodes, where 0 is the initial depot and

2n+1 Final depot.

4.2. Parameters

t_{ij}: Travel time between nodes i and j.
$[a_i, b_i]$: Time window for node i.
s_i: Service time at node i.
$Q=1$: Vehicle capacity.
q_i: Load associated with node i.
$qi = +1$ si $i \in P$.
$qi = -1$ si $i \in D$.
Li: Maximum allowed travel time for patient i.
E: Maximum electric vehicle autonomy.
M: Large constant.

4.3. Decision Variables

x_{ijk}: Binary variable equal to 1 if vehicle k travels directly from node i to node j, and 0 otherwise.
T_{ik}: Vehicle arrival time k at node i
l_{ik}: Vehicle load k after visiting node i

4.4. Objective Function

The objective function minimizes total routing time for all vehicles:

$$min \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} t_{ij} x_{ijk}$$

4.5 Constraints

Each pickup and delivery node is visited exactly once:

$$\sum_{k=1}^{K} \sum_{j=1}^{n} x_{ijk} = 1, \quad \forall i = 1, \ldots, n$$

Flow conservation:

$$\sum_{j \in V} x_{ijk} - \sum_{j \in V} x_{jik} = 0 \quad \forall i \in P \cup D, \forall k \in K$$

Departure from and return to the depot:

$$\sum_{j \in V} x_{ijk} - \sum_{j \in V} x_{jik} = 0 \quad \forall i \in P \cup D, \forall k \in K$$

Time window constraints:

$$a_i \leq T_{ik} \leq b_i \qquad \forall i \in V, \forall k \in K$$

$$T_{jk} \geq T_{ik} + s_i + t_{ij} - M(1 - x_{ijk})$$

Pickup-delivery precedence:

$$T_{i+n,k} \geq T_{ik} + s_i \quad \forall i \in$$

Unit capacity constraints:

$$l_{jk} \geq l_{ik} + q_j - M(1 - x_{ijk})$$
$$0 \leq l_{ik} \leq 1$$

Electric range constraint: the total travel distance of each vehicle must not exceed its maximum autonomy E.

$$l_{jk} \geq l_{ik} + q_j - M(1 - x_{ijk})$$
$$0 \leq l_{ik} \leq 1$$

Variable domains: xijk ∈ {0,1} for all i,j ∈ V, k ∈ K; Tik ≥ 0 for all i ∈ V, k ∈ K.

$$l_{jk} \geq l_{ik} + q_j - M(1 - x_{ijk})$$
$$0 \leq l_{ik} \leq 1$$

5 Solution Method

Most combinatorial optimization problems, including the DARP, are NP-hard and lack an efficient exact solution strategy within acceptable timeframes. Therefore, a two-phase hybrid approach is employed.

i. Insertion Heuristic

An insertion heuristic is used in the first phase to generate initial feasible solutions that satisfy all model constraints. Solutions are constructed by iteratively inserting request nodes (pickup and corresponding delivery) into vehicle routes until all demands are met.

ii. Genetic Algorithm

In the second phase, a genetic algorithm is used to refine the original solutions acquired from the heuristic. This metaheuristic evolves a population of candidate solutions (routes) by means of selection, crossover and mutation operators according to the objective function to identify better quality solutions. Figure 2 shows the individual construction technique used for the first pool of service requests. In the first step, the requests are randomly permutated and thus we increase the diversity of solutions in the population. Then, some of these re-ordered requests are picked to build the initial route assigned to that individual. This is repeated for the other unassigned requests, constructing more routes until all requests are assigned and a full individual is obtained. The genetic algorithm was configured with the following parameters: population size of 200 individuals, 2,000 generations as the stopping criterion, crossover rate of 0.6, initial mutation rate of 0.1 with adaptive adjustment (increasing by 0.02 per generation without improvement, up to a maximum of 0.8), tournament selection with size 4, and elitism retaining the top 10% of individuals per generation. A fixed seed was used for population initialization to ensure reproducibility, while the evolutionary process was left stochastic to promote solution diversity. Infeasible individuals generated during crossover or mutation are repaired by reinserting unassigned pickup-delivery pairs into the nearest feasible route position.

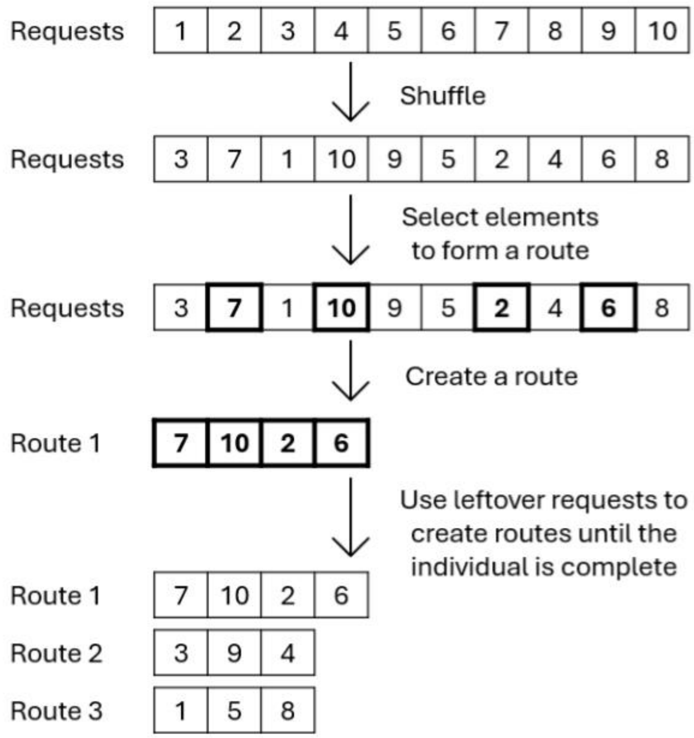


Figure 2. Insertion algorithm for DARP.

We use the crossover operator in the genetic algorithm at the route level, as seen in Figure 3. A continuous section of requests is removed from a designated route of the first parent. Next, this section is incorporated into the route structure of the second parent, and the remaining requests are reallocated while maintaining their relative ordering. The offspring thus obtained inherits features from both parents, thus allowing the constructive exchange of route sub-structures among individuals.

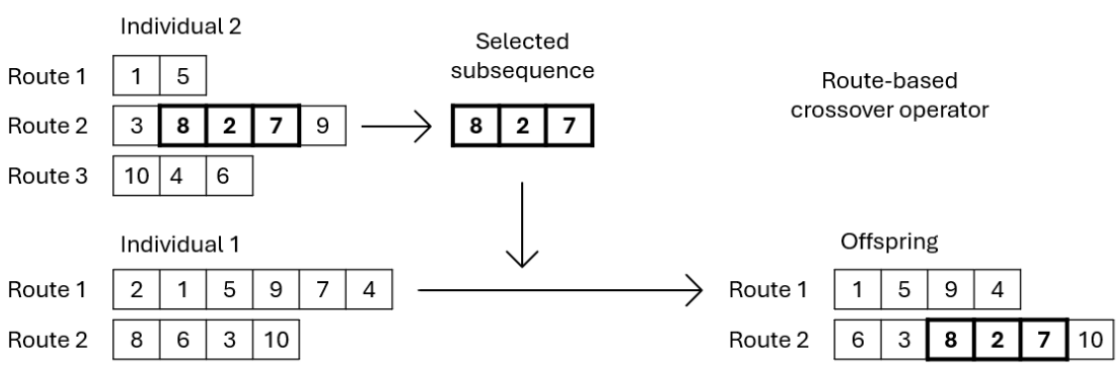


Figure 3. Crossover operator for DARP.

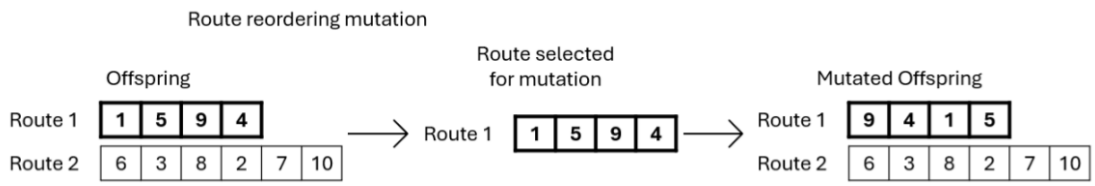


Figure 4. Mutation operator for DARP.

In figure 4 the route reordering mutation applied to an offspring individual is shown. A single route is selected for mutation, and the order of its requests is rearranged while preserving the remaining routes unchanged. This mutation operator introduces variability within a route without altering the assignment of requests to routes.

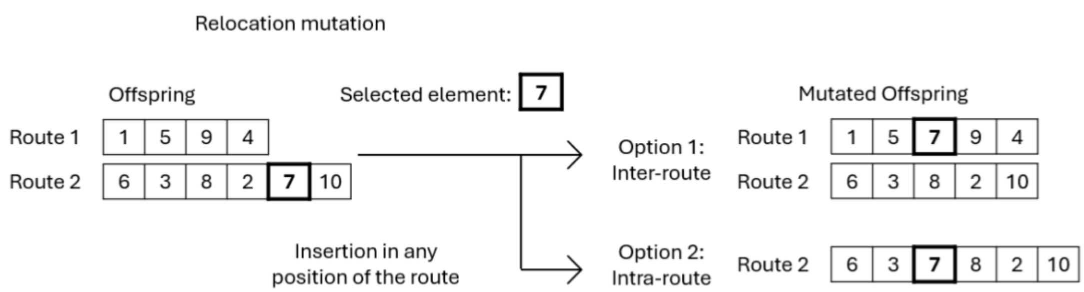


Figure 5. Relocation operation.

In figure 5 the relocation mutation applied to an offspring individual is shown. A single request is selected and removed from its original route. The selected request is then reinserted either into a different route (inter-route relocation) or into a different position within the same route (intra-route relocation). This mutation operator modifies the assignment or position of a request to enhance solution diversity.

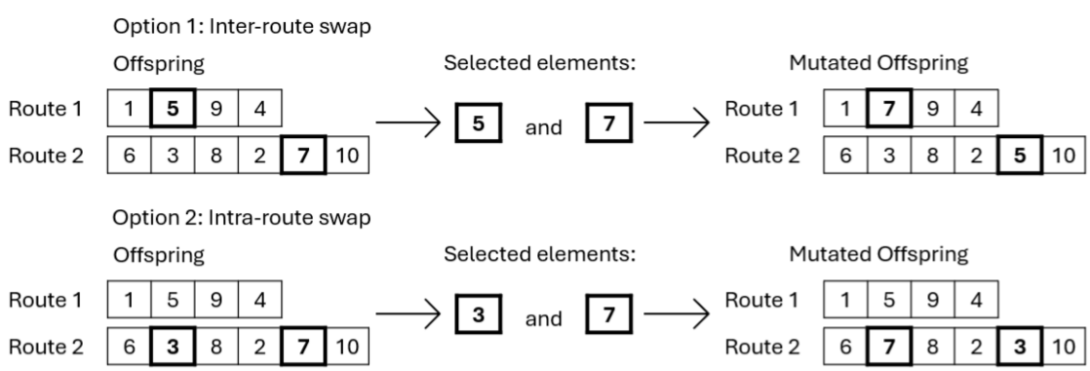


Figure 6. Swap mutation.

In figure 6, illustrates the swap mutation applied to an offspring individual. Two requests are selected and exchanged either between different routes (inter-route swap) or within the same route (intra-route swap). This mutation operator modifies the relative positions of requests while preserving the total number of routes and assigned requests, thereby increasing solution diversity.

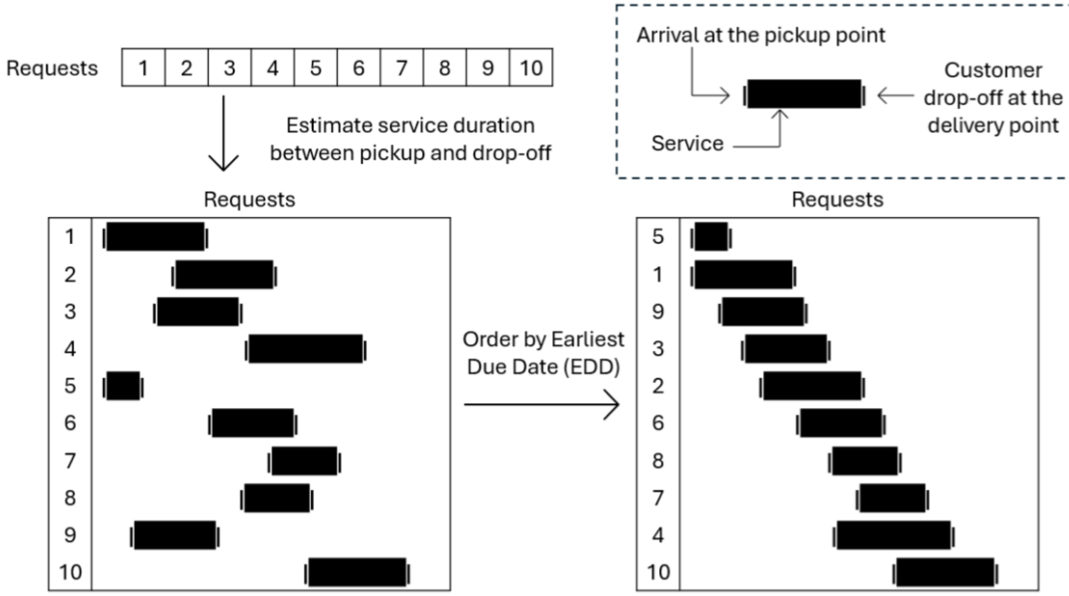


Figure 7. Temporal processing and ordering requests.

We show in Figure 7, the temporal preprocessing step applied to the whole set of transportation requests. For each pending request, the total service duration is computed by measuring the time duration between the pickup location and the related delivery location. The projected completion timeframes are used to arrange all the requests by the Earliest Due Date (EDD) rule, which gives priority to the requests with the tightest constraints. The obtained sorted sequence is then used directly as input for the greedy insertion technique

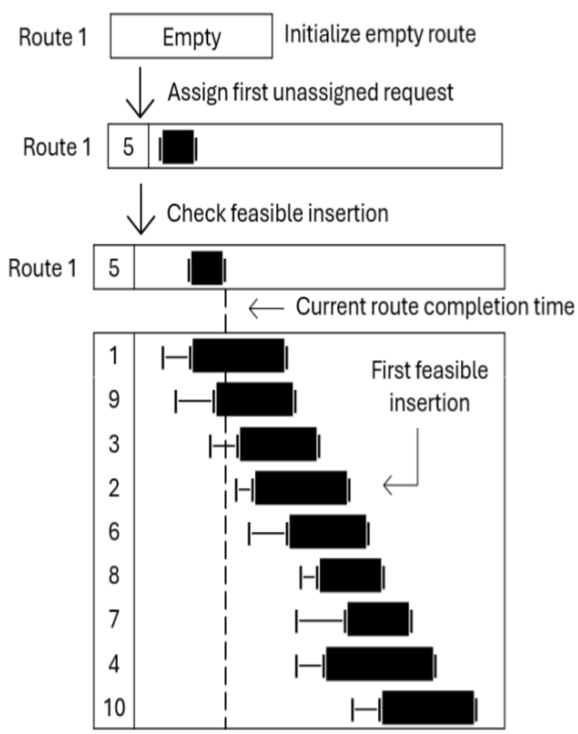


Figure 8. Greedy insertion procedure for feasible route construction.

In Figure 8 the greedy insertion process used to construct routes is shown. An empty route is initialized, and the first unassigned request is inserted as the initial service. Subsequently, the feasibility of inserting each remaining request is evaluated by comparing its service interval with the current route completion time. Requests are analyzed following the EDD ordering, and the first request that satisfies the temporal feasibility condition is inserted into the route.

Figure 9, illustrates the final stage of the greedy insertion procedure. Requests are sequentially inserted into the current route while feasible insertions exist. When no additional requests can be feasibly inserted, the current route is closed, and a new empty route is initialized. The process is repeated by assigning the next unassigned request as the initial service of the new route until all requests have been assigned.

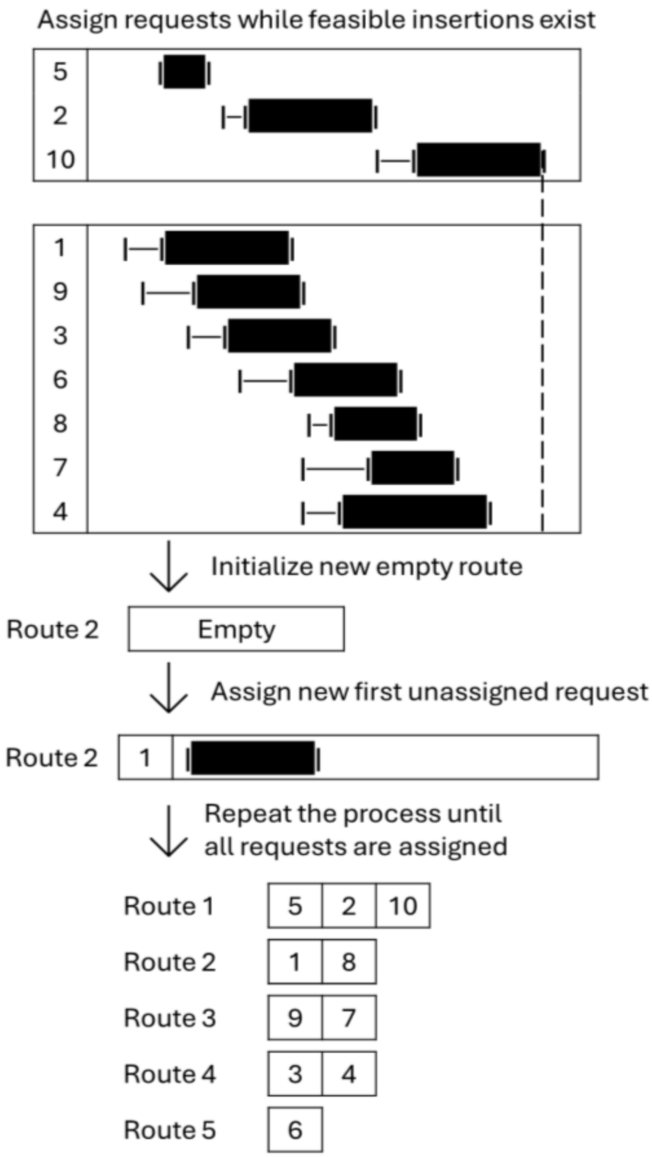


Figure 9. Final stage of genetic algorithm for DARP.

6 Computational Experimentation and Results

The experiments presented in this section were carried out using instances based on the genuine geographic coordinates of the city of Apizaco, Tlaxcala, using the parametric setting described in Table 1. The evaluation consists of observing the model's behavior under different average traffic speeds and different request assignment methods.

All the experiments were conducted in Python 3.11.7 and executed on a MacBook Pro M2 with macOS Tahoe 26.2 with 16 GB RAM. Each scenario was assessed for a unique combination of geographical locations, vehicle capacities, typical travel speeds and fleet numbers.

Table 1 Parameters for generating DARP model scenarios

Parameter	Range	
Number of patients	30	
Vehicle capacity	1	
Number of vehicles	3	
Average vehicle speed (km/h)	[30,40,50,60]	
Location	**Geographic Coordinates (Latitude, Longitude)**	
Depot	19.405616	-98.116672
Health Center 1	19.408711	-98.117801
Health Center 2	19.407471	-98.143169
Health Center 3	19.410048	-98.153091
C1	19.40119286	-98.11210224
C2	19.4133677	-98.12297694
C3	19.40412905	-98.12336313
C4	19.41339381	-98.11523578
C5	19.39747239	-98.12604577
C6	19.39577711	-98.11038953
C7	19.40274716	-98.11747152
C8	19.41168296	-98.10680437
C9	19.40216339	-98.12008775
C10	19.40830179	-98.11962145
C11	19.41195728	-98.11872301
C12	19.41118261	-98.11139306
C13	19.39698836	-98.10816916
C14	19.39911613	-98.11707224
C15	19.40548454	-98.11889748
C16	19.39647185	-98.11399789
C17	19.40548526	-98.11705483
C18	19.41030474	-98.12171912
C19	19.40698346	-98.11164191
C20	19.40318144	-98.11189702
C21	19.40845134	-98.11746982
C22	19.4045082	-98.12215326
C23	19.40603094	-98.11643912
C24	19.40192311	-98.11962005
C25	19.41488584	-98.1242535
C26	19.39651862	-98.11086262
C27	19.40993903	-98.1072317
C28	19.41384118	-98.11572362
C29	19.40384219	-98.11988693
C30	19.40457333	-98.11970422

In Figure 10 we show the location of the different patients and the location of the facilities to which they must be transferred and the position of the depot. These are checked to ensure that it is right. The different parameters to be utilized for the experiment are generated to get good results. Otherwise, new values are established to ensure that they are viable.

Table 2. Speed Variation between 30 and 60 km/h Using 5 Vehicles.

		Insertion Heuristic					Genetic Algorithm			
		Boarding and Alighting Time (min)	Travel Time (min)	Idle Time Between Services (min)	Total Operating Time (min)		Boarding and Alighting Time (min)	Travel Time (min)	Idle Time Between Services (min)	Total Operating Time (min)
	Vehicle 1	6.57	116.19	80.57	203.33		6.57	118.17	78.6	203.33
	Vehicle 2	11.52	67.95	114.24	193.7		9.2	47.19	72.24	128.63
30 km/h	Vehicle 3	10.85	74.87	108.95	194.67		9.42	74.65	55.67	139.74
	Vehicle 4	6.99	73.86	56.78	137.64		8.83	81	100.51	190.33
	Vehicle 5	5.61	66.38	62.11	134.11		7.52	85.12	101.47	194.1
	Total	41.54	399.25	422.65	863.45		41.54	406.13	408.49	856.13
	Vehicle 1	6.57	87.14	104.36	198.08		8.27	88.87	100.94	198.08
	Vehicle 2	11.52	50.96	128.84	191.32		12.57	53.23	121.72	187.51
40 km/h	Vehicle 3	10.85	56.15	124.47	191.48		7.56	58.67	129.05	195.28
	Vehicle 4	6.99	55.4	71.13	133.52		9.39	52.45	66.2	128.04
	Vehicle 5	5.61	49.78	75.29	130.68		3.76	48.35	78.57	130.68
	Total	41.54	299.43	504.09	845.08		41.55	301.57	496.48	839.59
	Vehicle 1	6.57	69.71	118.64	194.92		10.51	65.59	118.82	194.92
	Vehicle 2	11.52	40.77	137.61	189.89		11.26	40.21	138.42	189.89
50 km/h	Vehicle 3	10.85	44.92	133.78	189.56		6.34	47.41	78.86	132.6
	Vehicle 4	6.99	44.32	79.74	131.05		5.84	42.65	81.21	129.71
	Vehicle 5	5.61	39.83	83.19	128.63		7.58	42.64	135.36	185.58
	Total	41.54	239.55	552.96	834.05		41.53	238.5	552.67	832.7
	Vehicle 1	6.57	58.1	128.16	192.82		8.08	44.25	137.73	190.06
	Vehicle 2	11.52	33.97	143.45	188.94		7.81	37.19	140.75	185.75
60 km/h	Vehicle 3	10.85	37.44	139.99	188.28		10.03	35.6	85.19	130.82
	Vehicle 4	6.99	36.93	85.48	129.4		8.12	45.93	133.2	187.26
	Vehicle 5	5.61	33.19	88.46	127.26		7.5	35.74	88.46	131.7
	Total	41.54	199.63	585.54	826.7		41.54	198.71	585.33	825.59

Table 3. Vehicle Type Comparison

Tipo de vehículo	ICEV	BEV
Energy Autonomy	0.08 l/km	0.17 kWh/km
Storage Capacity	40 l	60 kwh
Driving Range	500 km	352.94 km
CO_2 Emissions	120 g/km	50 g/km

b. Experimental Results

In Table 2, we show the comparative performance of the Insertion Heuristic and the Genetic Algorithm. Four operational metrics are reported for all speed levels examined, for a fleet of five vehicles: boarding and alighting time, trip time, idle time and total operating time.

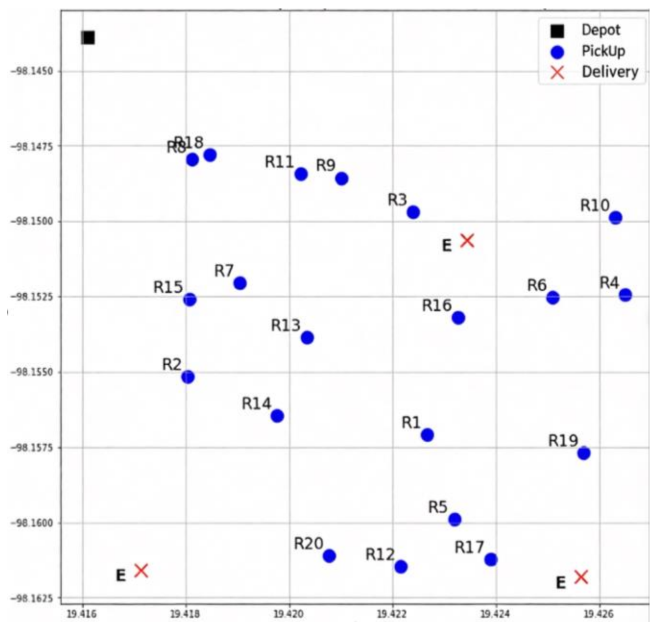


Figure 10. Location of Patients, Health Centers, and Vehicle Storage. X axis (Latitude), Y axis (Longitude).

Table 4 Comparative Results between BEV and ICEV Vehicles

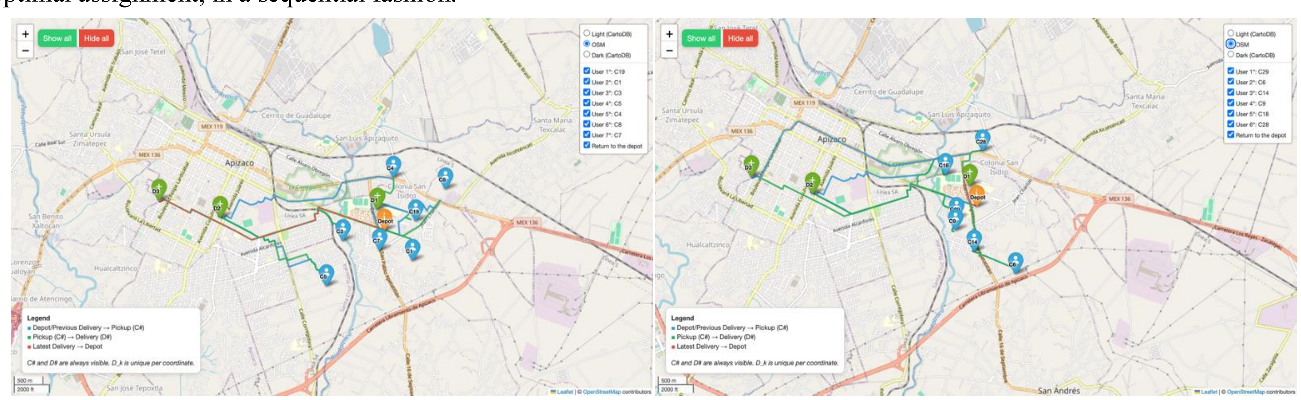
Scenario				Calculated Times						Total Energy Consumption		Total CO2 Emissions g/km	
Algorithm Used	Users	Destinations	Speed	Total Time (min)	Number of Vehicles	Idle Time (min)	Driving Time (min)	Distance (km)	Dwell Time (min)	ICEV (l)	BEV (kwh)	ICEV	BEV
Insertion	30	3	30	863.44	5	422.65	399.25	220.395	41.54	17.63	37.47	26447.40	11019.75
Optimization	30	3	30	856.13	5	408.49	406.13	223.82	41.54	17.91	38.05	26858.40	11191.00
Insertion	30	3	40	845.07	5	504.09	299.43	227.32	41.54	18.19	38.64	27278.40	11366.00
Optimization	30	3	40	839.59	5	496.48	301.57	228.74	41.54	18.30	38.89	27448.80	11437.00
Insertion	30	3	50	834.05	5	552.96	239.55	234.242	41.54	18.74	39.82	28109.00	11712.08
Optimization	30	3	50	832.71	5	552.67	238.5	233.367	41.54	18.67	39.67	28004.00	11668.33
Insertion	30	3	60	826.7	5	586.54	199.63	240.16	41.54	19.21	40.83	28819.20	12008.00
Optimization	30	3	60	825.58	5	585.33	198.71	240.25	41.54	19.22	40.84	28830.00	12012.50

i. Performance Analysis and Environmental impact Analysis

We note that the genetic algorithm offers better performance than the insertion heuristic, in all evaluated configurations, with reduced total operating times and higher global efficiency. To set the offered improvements into a broader context, we performed an energy and environmental analysis by comparing Battery Electric Vehicles (BEVs) with Internal Combustion Engine Vehicles (ICEVs) using reference consumption figures for compact-class vehicles as shown in Table 3.

In Table 4, we present the total energy consumption and CO_2 emission values for the two types of vehicles and all studied scenarios, computed using the route distances obtained by the optimization technique. These calculations show that time optimization and environmental consciousness are not mutually exclusive: BEVs always had significantly lower CO_2 emissions than the combustion engine vehicles, which validates the environmental justification of the proposed fleet mix.

The genetic algorithm with an average speed of 60 km/h was the fastest among all tested setups, performing all the 30 patient journeys in 825.58 min. This setup was the best in terms of minimizing circulation time, but had the longest trip distances, and thus longer idle time, higher energy consumption and higher emissions than the lower-speed scenarios. However, this structure is best suited for the main purpose of this study. Figure 11 lists the particular routes taken by each vehicle under this optimal assignment, in a sequential fashion.



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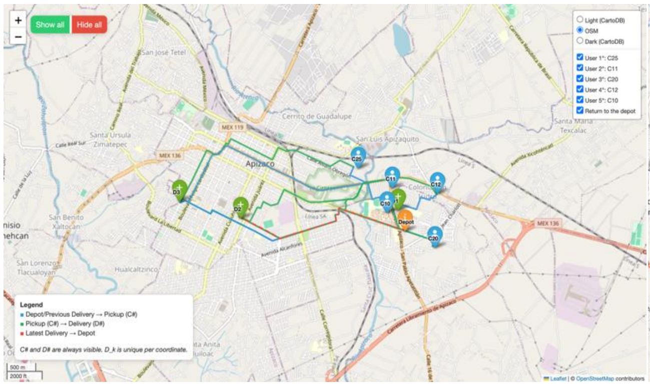

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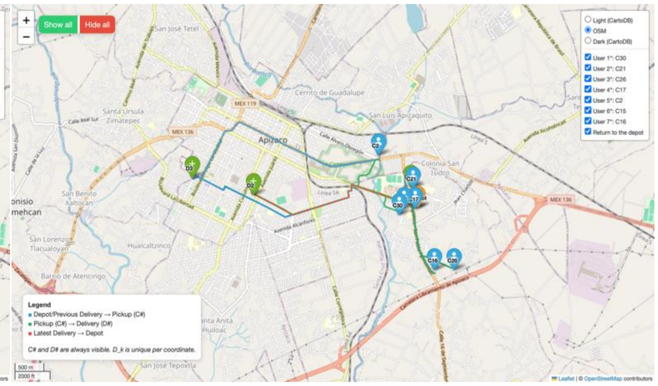

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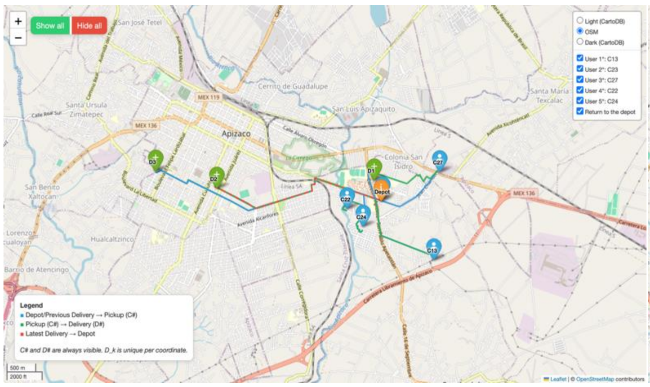

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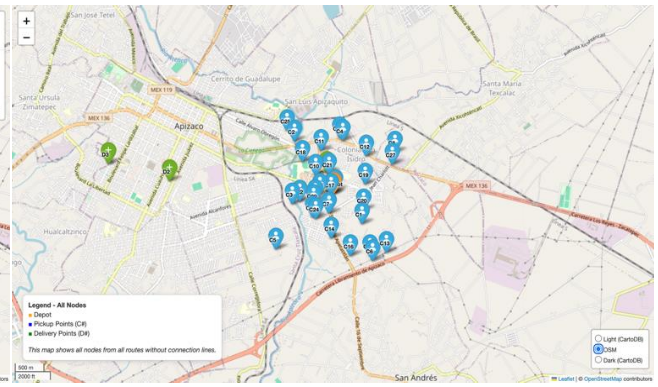

f)

***Figure 11**. Optimal routes at 60 km/h for all 30 patients across five vehicles. a) Routes assigned to Vehicle 1, showing pickup and delivery sequences from the depot. b) Routes assigned to Vehicle 2. c) Routes assigned to Vehicle 3. d) Routes assigned to Vehicle 4. e) Routes assigned to Vehicle 5. f) Complete network displaying all vehicle routes simultaneously, illustrating the spatial coverage of the proposed solution.*

6 Conclusions

This work addressed the challenge of transferring people with reduced mobility from their origin to different healthcare locations for medical appointments. The problem was formulated as a Dial-a-Ride Problem (DARP) with a homogeneous fleet of subcompact electric vehicles. The service requests fluctuate from day to day in pick-up/drop-off locations and user mobility levels. A two-phase solution methodology was applied, where an insertion heuristic was used to construct initial workable solutions, and a genetic algorithm was used to improve the results. We observe that the results were satisfactory and showed the feasibility of efficient and effective route planning for real world scenarios in urban contexts. The experiments based on real locations show that the required number of vehicles is not constant but depends on daily demand. Therefore, the proposed solution can be adopted by transportation systems as a fleet management tool to improve routing and reduce vehicle operating costs.

7 References

Cordeau, J.-F., & Laporte, G. (2007). The dial-a-ride problem: Models and algorithms. *Annals of Operations Research, 153*(1), 29–46. https://doi.org/10.1007/s10479-007-0170-8

Jørgensen, R. M., Larsen, J., & Bergvinsdottir, K. B. (2007). Solving the dial-a-ride problem using genetic algorithms. *Journal of the Operational Research Society, 58*(10), 1321–1331. https://doi.org/10.1057/palgrave.jors.2602287

Laporte, G., & Pascoal, M. M. B. (2011). Minimum cost path problems with relays. *Computers & Operations Research, 38*(1), 165–173. https://doi.org/10.1016/j.cor.2010.04.010

Masmoudi, M. A., Braekers, K., Masmoudi, M., & Dammak, A. (2017). A hybrid genetic algorithm for the heterogeneous dial-a-ride problem. *Computers & Operations Research, 81*, 1–13. https://doi.org/10.1016/j.cor.2016.12.008

Mourad, A., Puchinger, J., & Chu, C. (2019). A survey of models and algorithms for optimizing shared mobility. *Transportation Research Part B: Methodological, 123*, 323–346. https://doi.org/10.1016/j.trb.2019.02.003

Parragh, S. N., Dörner, K. F., & Hartl, R. F. (2008). A survey on pickup and delivery problems: Part II: Transportation between pickup and delivery locations. *Journal für Betriebswirtschaft, 58*(2), 81–117. https://doi.org/10.1007/s11301-008-0036-4

Pisinger, D., & Ropke, S. (2007). A general heuristic for vehicle routing problems. *Computers & Operations Research, 34*(8), 2403–2435. https://doi.org/10.1016/j.cor.2005.09.012

Schenekemberg, C. M., Chaves, A. A., Coelho, L. C., Guimarães, T. A., & Avelino, G. G. (2022). The dial-a-ride problem with private fleet and common carrier. *Computers & Operations Research, 147*, Article 105933. https://doi.org/10.1016/j.cor.2022.105933

Schenekemberg, C. M., Chaves, A. A., Guimarães, T. A., & Coelho, L. C. (2025). Hybrid metaheuristic for the dial-a-ride problem with private fleet and common carrier integrated with public transportation. *Annals of Operations Research, 351*(1), 809–847. https://doi.org/10.1007/s10479-024-06136-9

Schneider, M., Stenger, A., & Goeke, D. (2014). The electric vehicle-routing problem with time windows and recharging stations. *Transportation Science, 48*(4), 500–520. https://doi.org/10.1287/trsc.2013.0490

Shimaoka, T., Kameda, J., Tokunaga, J., & Ebara, H. (2025). Extension of biased random-key genetic algorithm with Q-learning for dial-a-ride problem. *IEEE Access, 13*, 184999–185010. https://doi.org/10.1109/ACCESS.2025.3624131

Smith, J. S., & Sturrock, D. T. (2024). *Simio and simulation: Modeling, analysis, applications* (7th ed.). Simio LLC. https://textbook.simio.com/SASMAA7/

Van Hentenryck, P., & Bent, R. (2006). *Online stochastic combinatorial optimization*. MIT Press.

Zelić, S., Đurasević, M., Jakobović, D., & Planinić, L. (2022). Solving the dial-a-ride problem using an adapted genetic algorithm. In S. Bandini, F. Gasparini, V. Mascardi, M. Palmonari, & G. Vizzari (Eds.), *AIxIA 2021 – Advances in artificial intelligence* (Lecture Notes in Computer Science, Vol. 13196, pp. 689–699). Springer. https://doi.org/10.1007/978-3-031-08421-8_47