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Home healthcare in Spanish rural areas: Applying vehicle routing algorithms to health transport management

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ABSTRACT

Depopulation of rural areas poses a range of new challenges for the provision of public services. Access to primary care centres is essential for promoting and protecting quality of life, especially for the older population. However, many rural municipalities face abandonment from public administrations by not even having a local clinic and forcing their dwellers to drive to the nearest facility. This research examines the adequacy of providing home healthcare (HHC) systems in such areas to avoid unnecessary trips. When designing routes to provide these services, decision-makers must take into account the following: *(i)* wide geographical spread of places to visit; *(ii)* difficulty in accessing some of these places with heavy medically equipped vehicles; and *(iii)* uncertainty regarding places to visit and availability of professionals. Our study identifies municipalities in which the travelling distance to the closest centre is above a desirable threshold, estimating the magnitude of the problem. Then, we provide an illustrative example in which an agile methodology is presented to design efficient routes that allow policymakers to offer HHC services of reasonable quality.

1. Introduction

The healthcare system has recently faced one of the worst episodes in recent history: the COVID-19 pandemic. One of the main outcomes of this experience is the evidence that response times in rural areas are slower than in urban ones [1,2]. This can be explained by a lack of healthcare resources in rural areas resulting from depopulation, an issue heightened by the fact that these areas are usually inhabited by older people [3]. One of the largest exodus from rural areas to urban centres in Europe occurred in the early decades of the 20th century. This was partly due to greater economic opportunities, such as new jobs, higher wages, and the availability of services [4]. This demographic phenomenon is known as rural depopulation and involves a decrease in the number of inhabitants in a given area compared to a previous period. This drop in population may be due to negative vegetative growth, a negative migratory balance, or both at the same time.

Rural areas in Spain represent 85% of the territory, although they are predominantly in four autonomous communities: Aragon, Castile and Leon, Castile-La Mancha and Navarre. According to the Instituto Nacional de Estadística (National Statistics Institute, INE, www.ine.es), the province of Segovia, in Castile and Leon, is one of the most badly affected by depopulation of its rural area, having lost more than 10% of its population from 2008 to 2023. Conversely, cities like Madrid have seen their population grow significantly, with an increase of around 4% in the same period. Such rural depopulation, both in Europe in general and Spain in particular, increases inequality between citizens: those in the most populated areas benefit from better infrastructure and economic, social, educational, cultural and health services [5], while residents in low-populated areas face a lack of opportunities. The latter also faces higher costs as citizens have to travel to more populated areas to access essential services. This scarcity of resources aggravates problems in providing health services to residents of low-population municipalities compared to large cities [5,6]. As an example of this disadvantage, rural citizens have to travel long distances to be treated by a specialist who will usually spend no more than 10 min with them [7].

In this context, our research aims to provide a novel approach to scheduling visits and designing routes in the context of providing a home healthcare (HHC) service in different municipalities in Spanish depopulated regions. Based on the premise that healthcare services

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should be less than 45 min away on foot for citizens in rural areas, we propose an agile methodology to optimise the routing of HHC vehicles for providing these essential services. Several scheduling and routing problems in non-health contexts were extensively studied in the literature, but the following factors make the version of the problem addressed in this study more challenging: *(i)* a wide geographic spread of locations to be visited (generally leading to higher economic and environmental costs); *(ii)* inaccessibility of some of these locations in heavy vehicles; and *(iii)* uncertainty regarding the prioritisation of visits (new urgent visits can appear at any time) and about the availability of healthcare staff. In order to put the proposed model into practice and explain its possible results, we focus on a specific case: a rural area in the province of Segovia.

Our study proposes thus an efficient model for scheduling visits and designing routes in HHC services in depopulated areas of Spain. The results highlight the need for policymakers to implement route management systems and support in-person visits alongside telemedicine services. These recommendations aim to improve healthcare logistics and address the challenges faced by the elderly population. Policymakers should consider our findings to enhance the delivery of healthcare in depopulated regions, ensuring better access and quality of care.

The rest of the article is organised as follows: Section 2 presents the background and literature review. Section 3 describes the data and methods used to carry out the research. Section 4 describes the Spanish healthcare system in rural areas. Section 5 introduces a case study that illustrates our methodology, also providing computational results. Section 6 offers a comprehensive discussion on the research results. The article ends with the main conclusions in Section 7, including recommendations for policymakers on how to organise healthcare logistics in depopulated areas.

2. Background and literature review

2.1. Revitalising rural health: The crucial role of primary care

This section delves into the challenges of primary healthcare in rural Spain, such as geographical dispersion and resource scarcity, affecting elderly care. It discusses healthcare disparities with urban areas and suggests solutions such as improving transportation and policy reforms.

Primary care plays a crucial role in delivering healthcare services in rural areas, where specific challenges affect the health and access to healthcare of the rural population. The literature has shown that older individuals constitute a significant portion of the rural population and heavily depend on their transportation system to access healthcare services [8,9]. However, the lack of public transportation and limitations in accessing transport services can hinder access to primary care, particularly for those who do not own a private vehicle [10]. The geographic distribution of healthcare centres in rural areas presents a significant challenge. The scattered nature of the rural population means that healthcare centres are often located at considerable distances from residential areas. This can result in long travel times and difficulties in accessing timely healthcare [8]. To address the issue of transportation in rural healthcare, [11] examines motorbikes as a solution for reducing the rural deficit in southeast Asia, where geographical distance and household finances are considered a major problem for accessing healthcare services. However, this is not the case in Spain, where the main population in rural areas is older and has difficulties with mobility. Furthermore, rural areas often face challenges in retaining healthcare staff, further limiting the availability of primary care services [12–14]. This lack of resources and trained personnel in rural areas contributes to healthcare disparities between urban and rural areas.

The rural population, especially older adults, may also experience socioeconomic challenges that affect their access to primary care. Studies have shown that rural areas often have higher poverty rates compared to urban areas [15]. Poverty and low socioeconomic status can hinder access to healthcare services and limit people's ability to cover the costs associated with healthcare, such as medications or specialised treatments. The lack of resources and healthcare services in rural areas can also impact the quality of care received. The limited availability of healthcare specialists in rural areas can make it difficult to access specialised care, resulting in more limited and less specialised healthcare for the rural population [15]. Additionally, healthcare needs in rural areas often relate to chronic diseases, requiring continuous and coordinated care. The lack of primary and specialised care services in these areas can lead to delays in the diagnosis and treatment of chronic diseases, negatively affecting the health and well-being of the rural population.

In Spain, the provision of healthcare services in depopulated areas presents specific challenges. According to the European Anti-Poverty Network (EAPN, www.eapn.es), 31.9% of the population living in rural areas considers their health to be fair, bad, or very bad, compared to 28.8% in more populated areas. This difference is more pronounced among the population over 65 years old in rural areas, where 57.5% perceive the health services to be fair, bad, or very bad, compared to 53.7% in urban areas. Additional measures are therefore needed to increase healthcare coverage in rural areas and reduce the gap in healthcare services between rural and urban areas. This includes improving transportation infrastructure, attracting and retaining healthcare professionals, implementing policies to reduce socioeconomic barriers, and ensuring the availability of specialised care services. By prioritising and investing in rural healthcare, we can enhance the health and well-being of the rural population and work towards reducing healthcare disparities between rural and urban areas.

2.2. Overcoming challenges in rural healthcare: Telemedicine and innovative solutions

This section explores the challenges faced by the ageing rural population in accessing healthcare, highlighting telemedicine as a key solution to overcome geographical barriers, and acknowledges the digital divide. It also examines complementary solutions like mobile health units and interdisciplinary collaboration to improve rural healthcare coverage.

Ageing rural population poses significant challenges in accessing necessary healthcare. In this regard, telemedicine emerges as a promising solution to enhance healthcare coverage in these areas. Telemedicine utilises telecommunications and electronic information technologies to deliver remote healthcare services, thus overcoming geographical barriers and enabling elderly individuals to access quality healthcare services without the need for extensive travel [16]. Numerous studies support the benefits of telemedicine in elderly care in rural areas. For instance, teleconsultation has demonstrated improved accessibility to specialised healthcare and reduced waiting times for patients [17]. Furthermore, telemedicine facilitates communication between primary and specialised care, enhancing care coordination for patients [18].

However, while it is true that these online health services are perceived as a beneficial tool for the rural population, and one that avoids the needs for trips to healthcare centres, the technological barrier is still a problem for the older population due to its limited use [19]. The digital divide stands as a primary obstacle, as many older adults may struggle to access and utilise the necessary technologies for online consultations [20]. To overcome this barrier, it is crucial to implement digital literacy programmes and provide adequate technical support to the elderly in these areas [21]. In addition to telemedicine, it is essential to explore alternative approaches that complement and strengthen healthcare coverage for elderly individuals in rural areas. Interdisciplinary collaboration among healthcare professionals plays a crucial role in this regard. Integrated care approaches can be developed to address the specific needs of elderly individuals in these areas [22].

A complementary solution to telemedicine is the implementation of mobile health units, which play a crucial role in extending health coverage in rural areas [23]. These mobile units allow health services to be brought directly to remote communities, providing in-person healthcare when needed [7]. Equipped with trained staff and specialised medical equipment, these units can perform physical examinations, diagnostic tests and provide treatment, complementing the virtual services offered by telemedicine [24]. However, the successful implementation of mobile health units requires careful and efficient planning of routes and visiting hours, especially in geographically dispersed areas. In this regard, the Vehicle Routing Problem (VRP) presents itself as an invaluable tool. The VRP is an optimisation problem that focuses on planning efficient routes for vehicles, taking into account various constraints and objectives [25,26].

2.3. Optimising HHC in rural areas through VRP

This section analyses the crucial role of the VRP in improving rural healthcare coverage and efficiency, focusing on temporal constraints and service synchronisation. It highlights the need for advanced algorithms and further research to develop effective healthcare solutions in under-researched rural areas.

In the context of rural healthcare, the VRP plays a crucial role in improving healthcare coverage and operational efficiency [27]. Several studies have addressed key aspects of the VRP in rural healthcare. For example, [26] emphasise the importance of considering temporal constraints in the VRP to ensure timely service delivery. These temporal constraints, known as time windows, specify the periods of time during which visits or deliveries can be made based on patient schedules and healthcare staff availability [28].

Conversely, [24,29] investigated the temporal dependencies of services in the context of the VRP in healthcare. In the case of [24], they proposed a mathematical model and a heuristic to address the synchronisation of visits and temporal precedences between services. In the case of [29], they solved the problem using a dynamic column generation approach within a branch-and-price framework, considering the temporal dependencies between visit start times.

Similarly, [25] proposed a branch-and-price algorithm to address the VRP in rural healthcare with lunch break requirements. [30,31] considered the VRP in rural healthcare with multimodal transportation. [32] studied the VRP in healthcare with multiple patient availability periods and proposed a mathematical model and a variable neighbourhood search-based heuristic to minimise service operation lead times, delays, and healthcare staff waiting times.

On the other hand, [33] expanded on this by examining the provision of healthcare services to patients in various facilities or those who are homebound. They developed a 3-step algorithm to construct weekly schedules for individual providers, balancing travel distance, workload, equity, and other factors, while considering patient time windows and nurse qualifications as soft constraints.

Further contributing to this area, [34] explored the increasing demand for home care services, focusing on the synchronisation of caregivers in social care. They highlighted the importance of decision support tools for efficient human resources management, especially when multiple visits are required in a single day. By modelling caregiver synchronisation and introducing dynamic time windows, their research offers a novel approach to improve service and travel time efficiencies, crucial for areas with limited healthcare resources like rural Spain.

Based on the aforementioned discussion, it is evident that the VRP plays an important role in healthcare. Despite the multitude of cases in the literature addressing this problem in HHC, further research focusing on the specific characteristics of each region is still needed to design effective solutions that enhance coverage and quality of healthcare [35]. This is the case with the present research, which addresses a case study of improving rural HHC in Spain, an area that has not been addressed in the existing literature.

2.4. The Spanish healthcare system: Challenges and strategies for rural areas

This section describes the three-tier structure of Spain's healthcare system and the Ministry of Health's strategies to improve rural care, such as continuous care points and resource enhancement. It also addresses challenges in rural service provision and proposes solutions for optimising HHC management.

The Spanish health system is guaranteed by the public sector as part of the welfare state. It provides free, universal healthcare: i.e. visits and access to emergency and specific treatments are free of charge. Other services, such as medicines, are subsidised.[1] The Spanish health system is organised in three levels: *(i)* a central administration, consisting of the Ministry of Health and Consumer Affairs, which is responsible for proposing, coordinating and implementing health policies; *(ii)* a regional organisation, being the health service of each autonomous community, comprising the centres, services and establishments that provide health services in the region; and *(iii)* health areas, which are the structures that group together sets of healthcare centres and primary care professionals within the autonomous community.

These health areas are divided into "basic zones" that serve as a framework for primary healthcare. In our study, we focus on the primary care centres, which are part of the basic level of care. Firstly, such care is provided at the patient's request, either through appointments or emergency services. Secondly, visits can be at the healthcare centres or the patient's home, depending on their healthcare condition. This healthcare level is also responsible for health promotion, health education and prevention and rehabilitation activities, among others.

In order to improve healthcare for the rural population, the Spanish Ministry of Health and Consumer Affairs [36] proposes the following strategies: *(i)* assigning each municipality in each region a point of continuous care (offering a health consultation service every day of the week); *(ii)* increasing human resources for healthcare; *(iii)* increasing material resources, such as equipping facilities with off-road vehicles for easier travel in rural areas (especially during the winter); *(iv)* establishing demographic criteria for social and geographical spread to match healthcare staff resources to these areas; and *(v)* managing the organisation of healthcare visits. Some urban planning initiatives in Spain, such as NESI,[2] also aim to ensure citizens have all their needs covered within a radius of: *(i)* less than 15 min if they live in a city; and *(ii)* less than 45 min if they live in a rural environment. Such initiatives match similar ones in cities such as Paris, Portland, Milan and Melbourne [37]. In some municipalities, the absence of primary healthcare centres is addressed by establishing smaller clinics, offering local examination facilities and reducing travel needs for patients. However, these clinics often face limitations in terms of continuous opening hours and the volume of patients they can visit. Consequently, the restriction affecting opening hours and the time the staff spends travelling to these clinics do not adequately mitigate the inequality in health service provision in rural areas. This gap in effective healthcare delivery motivates our study to propose an alternative solution, focusing on a well-planned and optimised HHC management system, designed to enhance accessibility and equity in healthcare services for rural communities.

3. Material and methods

The data used in this study is from 2021 and was extracted from several sources: *(i)* the National Statistics Institute (INE): population, population density (people per square kilometre of land area) and percentage of population over 65 years old; and *(ii)* the Spanish Ministry of Health and Consumer Affairs: postal addresses of primary care centres.

[1] https://www.sanidad.gob.es/estadEstudios/sanidadDatos/home.htm.

[2] https://nesi.es/.

The first step was to convert the postal addresses of the health centres into geographic coordinates. Next, the travel distance was calculated for each pair (health centre, municipality). For each municipality and health centre: *(i)* the travelling distance and time were calculated for the closest options; and *(ii)* the option with a shorter travelling time was saved. Both travelling distance and time were calculated for a car. Time travelling on foot was estimated assuming speeds of 4 km/h. Next, coverage was analysed on the basis of this information to obtain the percentage of population with access to a health centre providing essential services over a specific length of time. In particular, summary measures and plots were created to illustrate municipalities where visiting the nearest health centre took more than 45 min on foot.

3.1. Formal description of the problem

The study addressed a routing problem with regard to HHC services. The problem is known in the routing literature as the Team Orienteering Problem (TOP), and can be formally described as follows: given an undirected and complete graph $G = (V, E)$, where: *(i)* $V = \{0, 1, 2, \dots, n\}$ represents the depot, node 0, and a set of n patient nodes to be visited (if possible) at home; and *(ii)* $E = \{(i, j) : i, j \in V \text{ and } i \neq j\}$ is the set of edges connecting every pair of nodes. For each $(i, j) \in E$, we assume that traversing (i, j) has a distance – or time – based cost $c_{ij} = c_{ji} > 0$. There is a set K of vehicles available. We also assume that, in a given working day $d \in W = \{\text{Monday, Tuesday, \dots, Friday}\}$ visiting a patient node i has an associated reward $r_i^d > 0$. This reward measures the urgency level of visiting a patient $i \in V \setminus \{0\}$ during a given working day $d \in W$, so that patients requiring an urgent visit should offer an extremely high reward during day d, while patients with milder symptoms should offer a low (but still positive) reward during day d. Notice that these rewards might change each day. Thus, for instance, whenever a patient has not been visited at home during a day $d \in W$, then the reward on day $d + 1$ will increase. The way in which these variations in rewards occur will depend on the status of each patient, but it is assumed rewards can be modelled using a function $r_i^{d+1} = f(i, d+1, r_i^d, x_{ij}^{kd})$, where x_{ij}^{kd} is a binary decision variable that takes the value 1 if the edge $(i, j) \in E$ is used by a vehicle k to visit node j from node i in day d, and 0 otherwise.

We consider a multi-period scenario corresponding to each working week in which the list of patients to be visited at home, as well as the associated routing plans, must be defined at the beginning of each working day in W using a rolling horizon approach. The goal is to maximise the total reward collected at the end of the week while satisfying the following constraint: for each day $d \in W$, the total cost of any route does not exceed a threshold $C > 0$ (which may represent the maximum number of working hours per day or the maximum time per day that one driver can cover). Due to this constraint, it is likely that not all patients can be visited each day. However, our goal is to maximise the social welfare of our patients by the end of the week. In cases where the number of patients is exceptionally high, there is a possibility that the algorithm may struggle to find a solution where all the patients are visited. In such instances, it would be advisable for decision-makers to consider adding at least one additional vehicle to the fleet.

A solution to this problem is a set of routes for each day $d \in W$. In each day d, the routes will depart from the depot, will visit a subset of nodes in a specified order, and will arrive at the depot. The objective function is to maximise the total reward obtained by all patient nodes over all days, i.e.:

$$\max \sum_{d \in W} \sum_{k \in K} \sum_{(i,j) \in E} r_j^d \cdot x_{ij}^{kd} \tag{1}$$

Subject to the following constraints:

For each day $d \in W$ and for each node $j \in V \setminus \{0\}$, at most one vehicle can visit node j:

$$\sum_{k \in K} \sum_{i \in V} x_{ij}^{kd} \leq 1 \quad \forall j \in V \setminus \{0\},\ \forall d \in W \tag{2}$$

For each day $d \in W$ and each vehicle $k \in K$, there must be exactly one departure from the depot:

$$\sum_{j \in V \setminus \{0\}} x_{0j}^{kd} = 1 \quad \forall k \in K,\ \forall d \in W \tag{3}$$

For each day $d \in W$ and each vehicle $k \in K$, there must be exactly one arrival at the destination depot:

$$\sum_{j \in V \setminus \{0\}} x_{j0}^{kd} = 1 \quad \forall k \in K,\ \forall d \in W \tag{4}$$

For each day $d \in W$ and each vehicle $k \in K$, the total cost of the route cannot exceed a threshold $C > 0$:

$$\sum_{(i,j) \in E} c_{ij} \cdot x_{ij}^{kd} \leq C \quad \forall k \in K,\ \forall d \in W \tag{5}$$

Throughout the entire week, each node $j \in V \setminus \{0\}$ is visited at most once:

$$\sum_{d \in W} \sum_{k \in K} \sum_{i \in V} x_{ij}^{kd} \leq 1 \quad \forall j \in V \setminus \{0\} \tag{6}$$

For each non-visited node $j \in V \setminus \{0\}$ in day $d \in W \setminus \{Friday\}$, the reward in the next day $d + 1$ is increased by an absolute value of γ:

$$r_j^{d+1} = max\{r_j^d + \gamma, \Gamma\} \quad \text{if} \sum_{i \in V} \sum_{k \in K} x_{ij}^{kd} = 0 \qquad \forall j \in V \setminus \{0\}, \forall d \in W \setminus \{Friday\} \tag{7}$$

The binary decision variables x_{ij}^{kd} are bounded as follows:

$$x_{ij}^{kd} \in \{0, 1\} \quad \forall (i, j) \in E,\ \forall k \in K,\ \forall d \in W \tag{8}$$

3.2. Proposed solving methodology

We introduce a Multi-Start Biased-Randomised algorithm to address this problem. These algorithms are effective and operate with a reduced set of parameters, minimising the fine-tuning process. Algorithm 1 outlines the main features of the proposed approach. In the first stage (lines 1–2), an initial solution (*initSolution*) is generated. This is achieved with the constructive heuristic introduced in [38] and summarised below. This constructive heuristic is inspired by the well-known savings concept [39] and extends it to an enriched concept for the characteristics of the TOP: some patients might not be covered in a specific day and both the reward and the savings in cost are considered when designing routes. In particular, these savings are defined as a linear combination of traditional savings and aggregated rewards. Therefore, initially, the constructive heuristic builds a dummy solution. This solution consists of one route for each patient: a vehicle departs from the depot, visits the patient, and then heads back towards the depot. Afterwards, the heuristic computes the savings associated with each edge connecting two patients. The savings represent the benefits obtained by visiting both patients in the same route instead of using two different routes. For an edge (i, j) and day d, the savings s_{ij}^{d*}, are defined as $s_{ij}^{d*} = \alpha s_{ij} + (1 - \alpha)(r_i^d + r_j^d)$ to account for the trade-off between cost-based savings $s_{ij} = c_{i0} + c_{0j} - c_{ij}$, and the rewards r_i^d and r_j^d. The α parameter is dependent on the heterogeneity of the customers in terms of rewards. Thus, in scenarios with high heterogeneity, α will be close to zero. On the contrary, α will be close to one for homogeneous scenarios. The specific value of α is automatically tuned for each problem instance, as it depends on the heterogeneity of the customers. Since the matrix of costs is symmetric, the savings do not depend on the direction in which the edge is traversed. Next, the list of edges is sorted from higher to lower savings. Routes are merged based on this sorted list: in each iteration of the merging process, the edge at the top of the list is selected and the two routes connected by this edge are merged into a new route if the constraint regarding the maximum cost per route is not violated. Finally, the heuristic selects the routes with the highest rewards, being the number of selected routes equal to the size of the vehicle fleet. At this point, a day of planning has been completed. Consequently, the reward (priority) of the remaining nodes (patients to be visited) is updated, and the heuristic is executed again with the remaining nodes. This process repeats until all planning days are completed or all patients are scheduled. To set up the α parameter, the constructive heuristic is run 10 times, varying the range of α from 0 to 1 and increasing its value by 0.1 in each execution. Subsequently, the α value associated with the best-found solution, in terms of reward, is utilised throughout the entire execution, and its solution is used as the *initSolution*. Notice that this process is not time-consuming since executing the deterministic heuristic is a fast process that takes just a few milliseconds. Once the *initSolution* is generated, it is copied as the best solution ($bestSolution$).

The second phase of our approach (lines 3–9) focuses on enhancing the *initSolution* by iteratively exploring the search space. This phase relies on a Multi-Start metaheuristic [40], incorporating biased-randomisation techniques and a local search to refine the solutions generated by the biased-randomised heuristic. In particular, this phase utilises a biased-randomised version of the constructive heuristic. Biased randomisation of heuristics [41] involves employing skewed probability distributions to induce a directed (biased) random behaviour of the heuristic. This transformation turns a deterministic method into a probabilistic one. These techniques are used when a discrete choice has to be made from a list of potential candidates. The list of candidates is sorted according to a problem-specific criterion, and probabilities are assigned to each element according to a skewed probability distribution. This returns different outputs each time the entire procedure is executed. In our case, a geometric probability distribution, controlled by a single parameter $\beta (0 < \beta < 1)$, is employed to induce this skewed behaviour for selecting edges from the list of savings. Based on various computational experiments conducted, we have determined that a good performance is achieved with $\beta = 0.3$. Similarly to the procedure for generating the *initSolution*, the biased-randomised heuristic is executed either for each planning period or until all patients have been planned, in order to obtain a new solution *newSolution*. After the *newSolution* is generated, a local search procedure is conducted around the *newSolution*. This procedure involves a well-known 2-opt local search [42], which is applied to each route of each period until further improvement is not possible. Specifically, only intra-route movements are evaluated in this case. Subsequently, a hashmap table [43] is utilised to store the best-found-so-far route for a given set of nodes. The process continues until no more improvements are achieved, returning the improved *newSolution*. If *newSolution* improves the objective function value of *bestSolution*, the latter is updated. The procedure is iteratively repeated to generate new solutions until the maximum computation time (*Tmax*) is reached.

Algorithm 1 Multi-Start Biased-Randomised Algorithm (nodes, planningPeriods, T_{max})

1: $initSolution \leftarrow constructiveHeuristic(nodes, planningPeriods)$
2: $bestSolution \leftarrow initSolution$
3: **while** T_{max} is not reached **do**
4: $newSolution \leftarrow bisedRandomisedHeuristic(nodes, planningPeriods, \beta)$
5: $newSolution \leftarrow 2optLSWithCache(newSolution)$
6: **if** $OF(newSolution) > OF(bestSolution)$ **then**
7: $bestSolution \leftarrow newSolution$
8: **end if**
9: **end while**
10: **return** $bestSolution$

3.3. Software employed

Python 3.10.7 was used to pre-process the raw data and call the OSRM software. In addition, the routing algorithm was also constructed and run in Python. The maximum computational time was set to 100 s per execution.

The OSRM software allowed the conversion of postal addresses to geographic coordinates and the calculation of travelling times. Finally, QGIS 3.28.3 was used to carry out the mapping for the study.

4. Descriptive analysis

Spain has a population of more than 47 million (10.6% of the total population in the European Union). Its population density is 95 people per square kilometre of land, below the European Union density of 112. The population aged 65 and over represents 20% of the total Spanish population (21% for the European Union), having steadily increased since 1960 when it was 8%. In Spain, there are 17 autonomous communities and two autonomous cities that are collectively known as autonomies. The autonomous communities are subdivided into 50 provinces, which are collections of municipalities, the latter being the basic local administrative division in Spain. There is a total of 8131 municipalities, including the autonomous cities. Spain's rural areas are home to 15.9% of the population, a total of 7,538,929 inhabitants. The demographic importance of small rural populations is corroborated by the fact that 60% of the population living in rural areas is registered in municipalities with fewer than 5000 inhabitants, half of whom are registered in municipalities with fewer than 2000 inhabitants. The autonomous communities with the highest percentage of population registered in rural municipalities (between 30% and 50%) are Aragon, Castile and Leon. Castile-La Mancha, and Navarre. Fig. 1 shows the distribution of population among municipalities. A number of major differences can be seen: Madrid and Barcelona have a municipal population of 3,305,408 and 1,636,732, respectively (in turn, representing 6.94% and 3.44% of the total population of Spain), while the capitals of rural provinces, Segovia and Soria, have a population of 51,258 and 39,695, respectively (representing 0.11% and 0.08% of the total Spanish population).

The distribution of primary care centres is represented in Fig. 2. The correlation between the number of primary care centres and population is statistically significant ($R^2 = 0.55, p\text{-}value = 0.000$). Of the 8131 municipalities in Spain, only 5846 (71.89%) have a local clinic, which in most cases does not provide continuous care, leaving the population without healthcare on certain days of the week. A total of 39 (0.48%) municipalities have no primary healthcare centre at all. The province with the highest number of municipalities (10) with no primary care centre or local clinic is Ourense (Galicia). By contrast, the province with the highest number of municipalities (311) with local clinics is Burgos (Castile and Leon). The municipality with the highest number is Madrid (129 primary care centres), followed by Murcia, Valencia and Barcelona (with 63, 56 and 55, respectively). At the provincial level, Soria is the province with the highest number of primary care centres per 10,000 habitants, 40.11, while Ceuta is the territory with the lowest: 0.36.

Fig. 3 employs multiple box-plots to show the travel time, in minutes, from the centre of each municipality to the nearest primary care centre. Notably, 99.93% of the municipalities have access to a centre within 45 min by car, 98.83% by bicycle, and 90.52% on foot. The diagrams display asymmetric distributions with a significant clustering of outliers in the upper range. Our study focuses on the 9.48% of municipalities, encompassing 771 municipalities across 50 provinces, these areas are situated over 45 min away on foot from a primary care centre. Specifically, the province of Segovia is analysed as a case study to demonstrate the benefits of implementing a transportation strategy for HHC in areas with limited public transport access and a predominantly ageing population. In Segovia, 11.8% of the municipalities are more than 45 min away on foot from primary care centres. The following section delves into the rationale for selecting Segovia as the province for the case study.

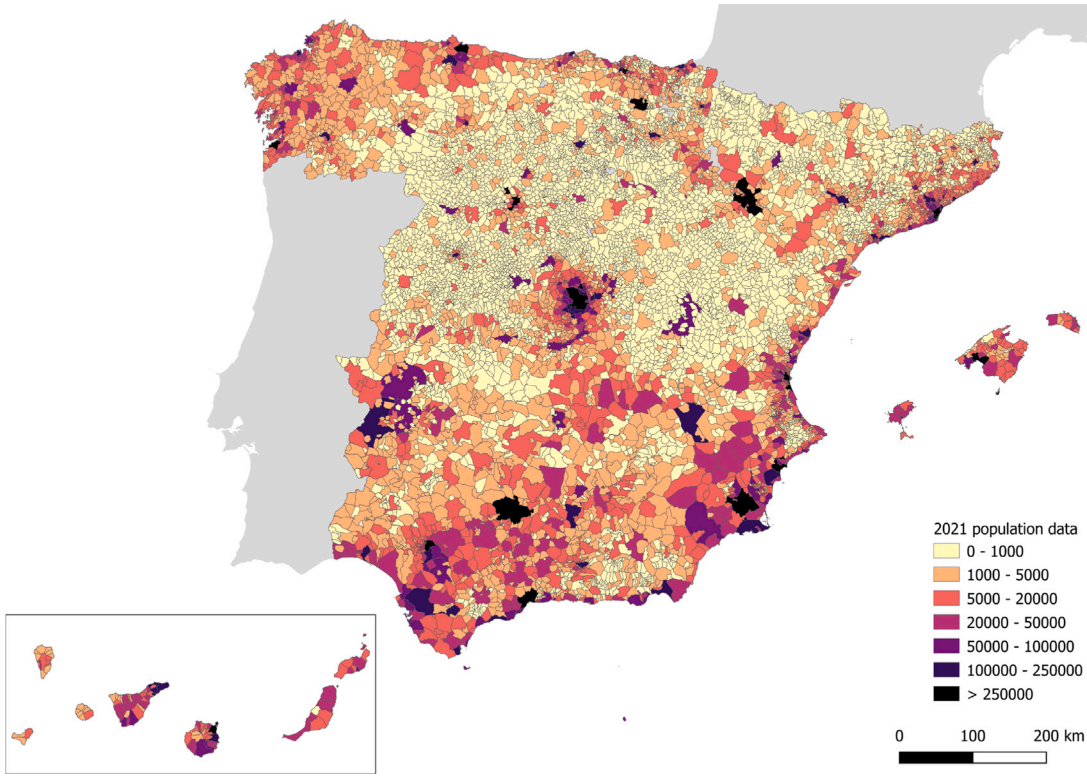

Fig. 1. Distribution of municipal population in Spain.

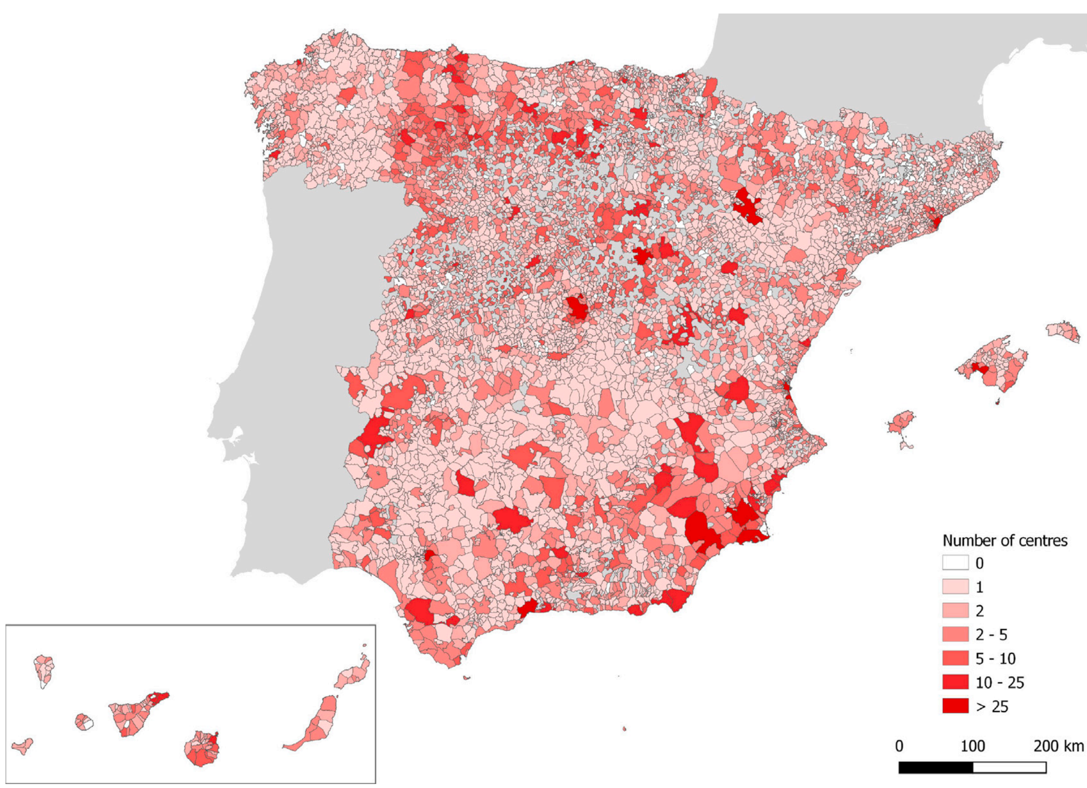

Fig. 2. Distribution of primary care centres in municipalities in Spain.

5. Case study: Segovia

The case of the province of Segovia serves as a clear example of the irregular distribution experienced in the Spanish territory, with a particular impact on rural areas. Segovia, a province with a small size and low population density, ranks as the third smallest in Spain in terms of the number of inhabitants. The disparity in population density figures between different areas of the province is evident (see Fig. 4).

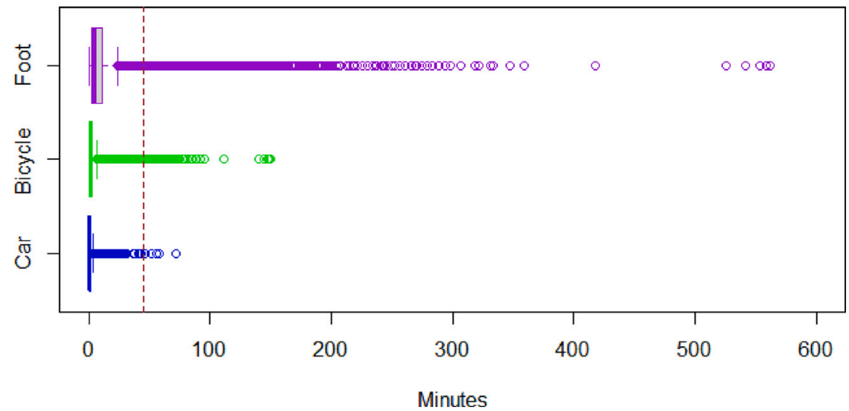

Fig. 3. Time to the nearest primary care centre. The dashed line indicates the 45-min threshold.

Segovia can be divided into two halves: the eastern part, generally less populated, and the western part, which houses a higher concentration of the total population. In the eastern half, a scarcity of population has been a constant when compared to its western counterpart. Currently, only a few municipalities in this area exceed a rate of 10 people per square kilometre. Riaza stands out as the most populous municipality, along with its neighbouring localities, which together account for a significant portion of the inhabitants in this area. In fact, of the most populated municipalities in Segovia, only three are located in this eastern part: Riaza, Ayllón, and Sepúlveda. On the other hand, the western half is characterised by a higher population density and is home to larger localities, including the provincial capital. Specifically, the capital of Segovia accounts for over a third of the total population, and when including its surrounding areas, the percentage increases to cover nearly half of the province's residents. While a significant part of Segovia has experienced population decline in recent years, the capital and its surrounding areas have managed to increase their numbers, standing out in the demographic panorama.

For these reasons, the province of Segovia presents itself as a compelling and representative choice for studying the improvement of healthcare coverage in rural areas. First, it is one of the least populated provinces in Spain. Second, it shows a declining population trend, which mirrors the demographic challenges faced by many rural regions across the country. Third, the uneven distribution of population and healthcare resources in Segovia exemplifies the disparities commonly observed in rural areas, where limited access to healthcare services can be a concerning issue. Lastly, the province's unique geographical layout, with densely populated western regions contrasting with sparsely populated eastern areas, offers valuable insights into how to effectively address healthcare needs in diverse rural settings. Overall, the case study of Segovia can shed light on best practices and innovative solutions to enhance healthcare provision, making it a relevant and informative case for improving healthcare coverage in rural regions.

5.1. Description of the scenario

We adopted a realistic scenario to illustrate the approach taken in our proposed model. We chose to implement our routing algorithm, aimed at providing healthcare coverage for households located more than 45 min away on foot from the nearest primary care centre, in the province of Segovia. Specifically, we selected 210 randomly chosen patients to be included in the proposed case study. To begin, we identified the central location from which all home-based routes would originate. This central location needed to be equipped with the necessary infrastructure for managing the route operations effectively. To select this central location, we utilised network centrality techniques to determine the primary care centre closest to the homes of all 210 patients who were currently outside the coverage area and needed to be visited.

Ultimately, the municipality chosen as the central depot for our case study was Aguilafuente. We opted for a single central location, rather than multiple ones corresponding to each case, in order to minimise the investment required for converting these facilities into operational centres for daily route dispatches in the management of home-visit routes. Our objective was to plan daily routes while taking into account the following modelling conditions, which were considered as parameters in our model:

- Working time for each healthcare vehicle (C parameter): 8 h. Our model allows for the adjustment of this parameter to select different working shifts. For this case study, we considered only one shift.
- Average visit time per patient (service time): 10 min. Our model also permits the modification of the service time. For our case study, we used the minimum service time stipulated by the Spanish healthcare system for each primary care patient.
- Number of healthcare vehicles used in the simulation: 4, 5, and 6. We employed different numbers of healthcare vehicles to conduct a sensitivity analysis.
- Planning horizon: 5 days (Monday to Friday). Due to the limited number of healthcare vehicles available, not all patients could be visited on the same day. This approach aligns with practical constraints.
- Patients are assigned priority levels (ranging from 1 to 5), with higher-priority patients scheduled for earlier visits during the week.
- Each patient visit carries a reward, with higher-priority patients offering greater rewards. These rewards are equal to the priority levels multiplied by 10. The parameters governing the update of rewards from one day to the next for patients who were not visited, denoted as γ and Γ, were configured with values of 10 and 50, respectively. Notably, 50 represents the maximum reward initially assigned and 10 signifies the increment when transitioning from a specific priority level to the nearest higher one.

5.2. Results of the case study

Table A.1 in Appendix provides detailed results for scenarios involving 4, 5 and 6 healthcare vehicles. These results encompass the total daily rewards per vehicle, visit durations in minutes, distances covered in kilometres, and associated costs in euros per kilometre. The subsequent discussion will delve into these results, accompanied by relevant figures.

Figs. 5 and 6 showcase various route combinations for the 4, 5, and 6 healthcare vehicles operating in the province of Segovia, as they visit the 210 patients residing in municipalities without coverage from the nearest primary care centre. Both figures specify the day of the week on

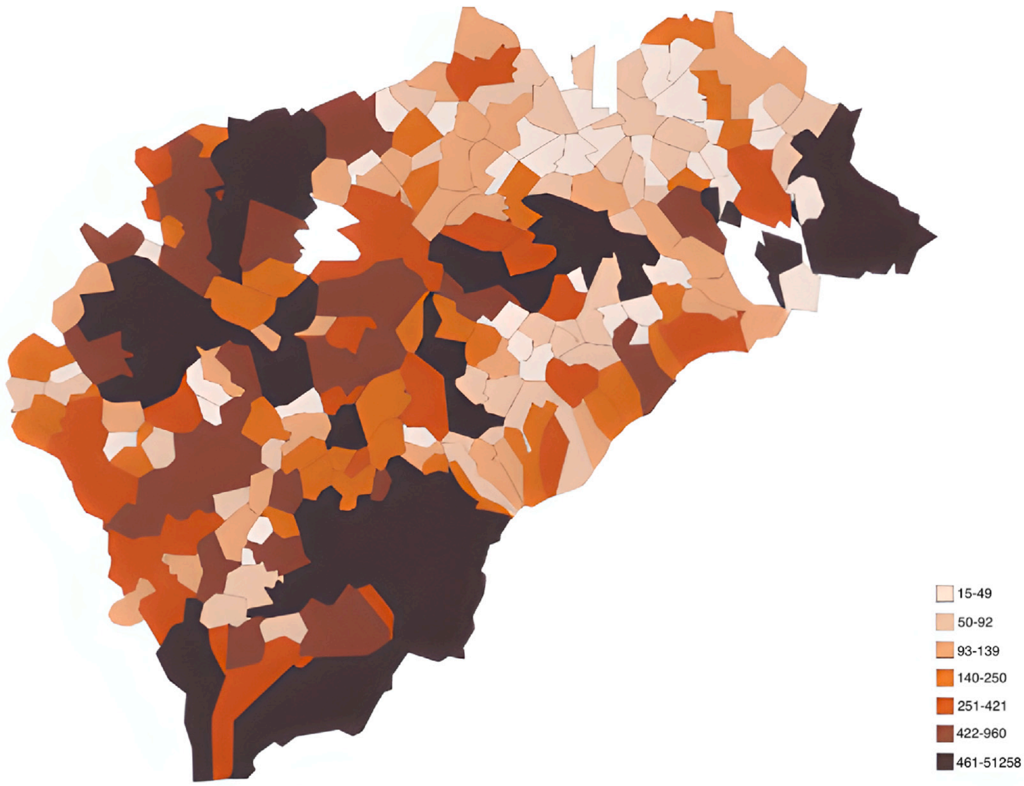

Fig. 4. Population density by municipality in the province of Segovia (Spain).

which each home visit occurs. Fig. 5 shows the total time in minutes to carry out the entire home care process. Meanwhile, Fig. 6 shows the estimated total cost in relation to the kilometres travelled on each route. It is worth noting that electric healthcare vehicles were used to reduce the environmental impact of managing the routes and that the estimated cost per kilometre was 0.43 Euros [44]. The cost comparison takes into account only the cost of routes (Euros/km). In no case does it consider the cost of personnel associated with driving the vehicle.

Therefore, both figures provide a detailed illustration of the total time and estimated cost associated with the routes of healthcare vehicles serving patients in the province of Segovia. However, it is imperative to emphasise that, although these indicators are crucial for the efficiency of route management, the underlying priority of our operation is the timely care of all patients. By implementing a dynamic prioritisation strategy, we ensure that patients with the most urgent healthcare needs are attended to first. This methodology allows us to comply with the scheduling of home visits throughout the week, maintaining the principle that each patient receives the necessary care at the right time. Consequently, the operational efficacy, reflected in terms of time and cost, complements and reinforces our central commitment to the punctual and effective delivery of healthcare services, always ensuring that all patients are attended to by the end of the week.

To demonstrate the utility of our proposal, we compared the results of our solution, with 6 vehicles travelling to attend the 210 patients, with the current scenario (see Fig. 7) of health staff travelling to each patient's home from their primary care centre (i.e. without coordinating routes, each patient visited by the primary care centre corresponding to their postcode). As an example for the comparison, we focused on the municipalities that were to be visited on Thursday, which were: *(i)* Aldehuela del Condonal; *(ii)* Bercimuel; *(iii)* Castrojimeno; *(iv)* Cerezo de Arriba; *(v)* Collado Hermoso; *(vi)* Corral del Ayllon; *(vii)* Frumales; *(viii)* Fuente de Santa Cruz; *(ix)* Juarros de Riomoros; *(x)* Mara-zoleja; *(xi)* Munopedro; *(xii)* Orejana; *(xiii)* Pajarejos; *(xiv)* Roda de Eresma; *(xv)* San Martin *y* Mudrian; *(xvi)* Sotillo; *(xvii)* Uruenas; *(xviii)* Valle de Tabladillo; and *(xix)* Valseca. For each municipality,

Table 1
Total summary of average time spent per fleet per week and total cost per fleet used in route management (considering both outward and return journeys).

	Total thursday time (min)	Total thursday cost (euros)
Scenario 1 (current): Each primary care centre that corresponds to each patient sends a home healthcare vehicle.	2701.60	899.99
Scenario 2 (model): Application of our model. Depot at Aguilafuente with 6 vehicles to manage home routes.	1340.44	412.24

the corresponding primary care centre was consulted through publicly available information from the Government of Castile and Leon. In the event that the municipality had a clinic with limited opening hours (for example, Wednesdays only), the health centre in Segovia (capital) was considered the origin. It should be remembered that with the application of our model for a fleet of 6 vehicles, only 4 vehicles were operational on Thursdays, as they were sufficient to cover the full demand for home visits. Table 1 compares Thursday in the current healthcare scenario, in which a vehicle is dispatched from each primary care centre, with the results of applying our route management model.

It is crucial to highlight that we have chosen a specific day of the week, in this case, Thursday, to conduct the comparison for strategic reasons. It is important to underline that the particular day selected does not have a significant impact on the overall results; any other day of the week could have been equally suitable for the analysis. Thus, our objective was to focus on any day of the week that would allow us to illustrate the case study clearly and coherently, without the day itself being a determining factor. By opting for a specific day, in this case, Thursday, as a reference point for the comparison, we have effectively highlighted the disparities between the current healthcare scenario and the results obtained when implementing our route management

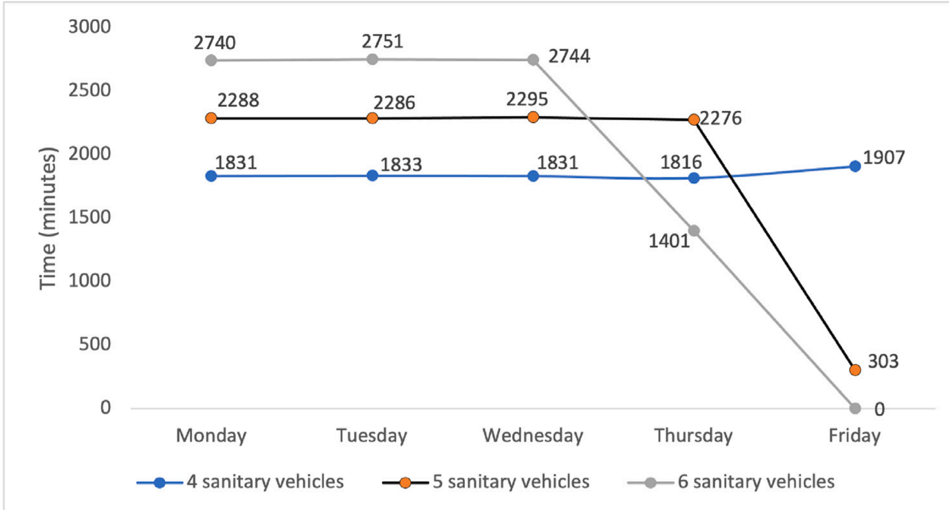

Fig. 5. Comparison of the time per day in the management of routes with 4, 5 and 6 vehicles to provide health coverage to 210 patients in the province of Segovia.

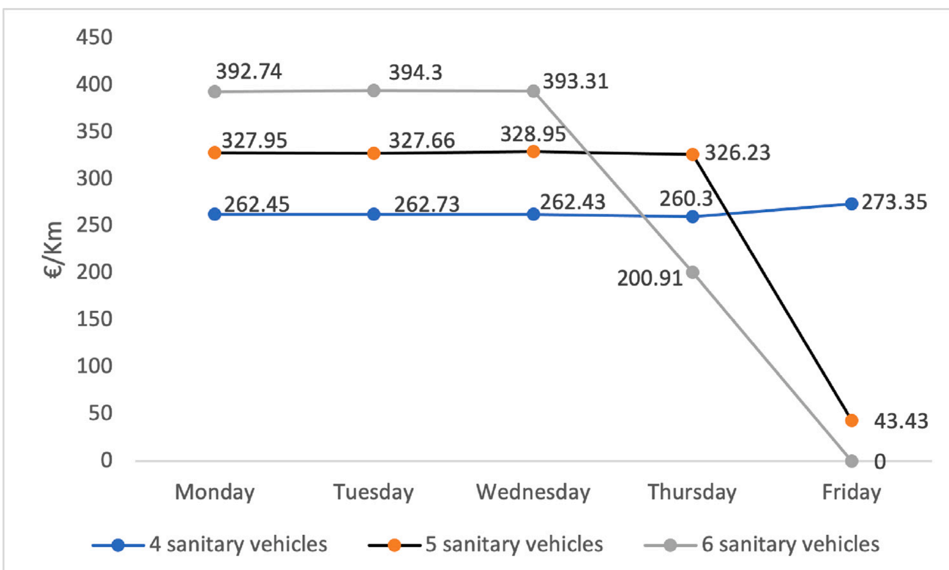

Fig. 6. Comparison of the ratio euros/kilometre per day in the management of routes with 4, 5 and 6 vehicles to provide health coverage to 210 patients in the province of Segovia.

model. This choice provides a robust foundation for presenting the findings accurately and with focus. The consistency in the chosen day of comparison has enabled a coherent and significant evaluation of the results, enhancing the reliability and relevance of our analysis.

When analysing the total costs presented in Table 1, it is essential to consider how they were calculated. The costs were obtained by multiplying the total kilometres covered in each healthcare route itinerary by the rate of 0.43 Euros per kilometre, which is based on data from the literature and reflects the cost for an electric vehicle. In our proposed model, the optimisation algorithm has played a key role in efficiently determining the most optimal routes. As a result, we have effectively reduced the total kilometres travelled, making the system more resource-efficient and cost-effective. Conversely, in the current scenario, the route simply represents the itinerary taken by a vehicle travelling from the primary care centre of reference to the patient's home and then returning to the starting point.

As can be seen from the results for the case study of Segovia province in which we implemented our modelling proposal, we managed to reduce HHC times and halve management costs through optimal route planning. Our model therefore allows us to explore different scenarios for this planning, such as varying the number of available healthcare vehicles, the total number of patients to be visited in municipalities at risk of exclusion, and even the availability of the vehicle drivers who sometimes work for 24 h and rest for 72. Whatever the case, our model allows us to plan routes to coordinate HHC and provide coverage to municipalities that do not have a continuous primary care service every day of the week or where the care centre is more than 45 min away on foot. The model is thus a highly useful tool for route management when establishing the optimal scenario.

5.3. Scalability and robustness of the algorithm

Due to the fact that the proposed algorithm utilises biased randomisation components (a geometric probability function), inducing a controlled random behaviour while preserving the logic behind the heuristic, we have carried out a study to validate its scalability and robustness in terms of solution quality. To carry out this study, we have generated a synthetic large instance, given that the instance of Segovia, the largest one available, comprises only 210 patients. Therefore, we

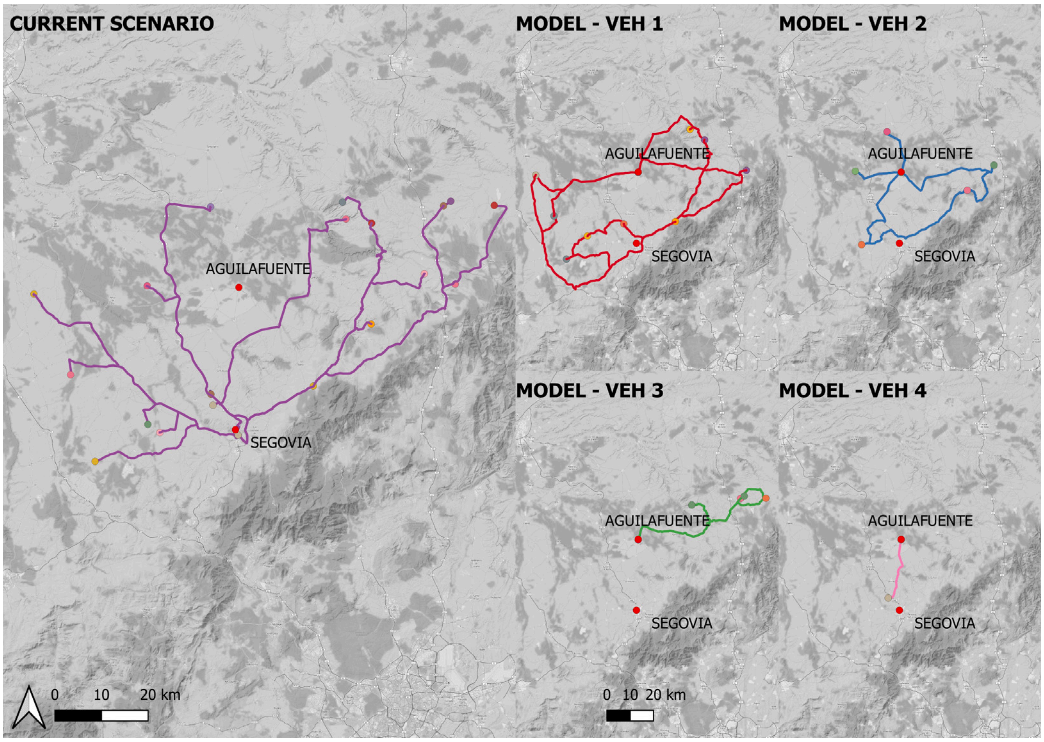

Fig. 7. Comparison of the current route management scenario for healthcare to municipalities without healthcare coverage with the application of our optimal route planning model.

have extended the Segovia instance by introducing fictitious patients in the province of Segovia at random until reaching a total of 500 patients. This algorithm was executed 10 times, with 10 randomly generated seeds, for a maximum computational time of 100 s per execution. The use of different random seeds ensures that each execution of the algorithm or simulation starts with a different set of random numbers. This is important for testing the robustness and consistency of algorithms, especially in scenarios such as optimisation, where we wish to see how the algorithm performs under various initial conditions. Table 2 shows the results obtained from each execution, and the computational time invested in obtaining the best solution found. As can be seen, the average reward obtained is 12,432, with a standard deviation of 60.46. The maximum reward achieved was 12,520, while the minimum reward was 12,330, representing a gap about 1.54% between the worst and best solutions. Regarding the computational times, on average, the algorithm requires 67.11 s to obtain the best solution found. Note that, although the different executions were carried out sequentially, the algorithm's design is embarrassingly parallel [45]. Its design allows for the execution of different independent instances with different seeds in parallel, either through the use of shared memory techniques, employing threads on both CPUs and GPUs, or through a distributed memory paradigm using message passing [46]. In both cases, only a final synchronisation would be necessary to select the best solution obtained from the different executions, keeping the wall-clock time nearly equivalent to the serial execution.

5.4. Analysis of rewards distributions and number of visits

This subsection conducts a comprehensive analysis of rewards distribution and patient visits based on day and route. The problem instance involves 500 patients, and various scenarios with different numbers of vehicles are explored. Table 3 presents the results for 8 vehicles, with the first two columns denoting the day and route/vehicle number. The third and fourth columns provide information on the number of patients and the total reward, while the final five columns outline the reward distribution as a percentage for patients visited with rewards of 50, 40, 30, 20, and 10, respectively. Each day is detailed in 9 rows, corresponding to each route/vehicle, plus an additional row presenting the total number of patients, total reward, and the mean percentage of patients visited with each reward category. Observations reveal a decreasing trend in the number of patients visited over the five days, while the total reward does not exhibit a significant pattern. On the first day, the reward distribution appears varied across days, with the average percentage indicating a higher value for high rewards. However, some patients are visited with the minimum reward of 10. As not all users are visited on the first day, the rewards for non-visited patients increase on the second day. This accounts for the rise in the average percentage of patients visited with the highest reward and 0% of patients visited with the lowest reward. On the third day, there is a 0% occurrence of patients with rewards of 10 and 20. By the fourth day, there is a 0% occurrence of patients with rewards of 10, 20, and 30. On the last day, all rewards are from patients with a reward of 50. However, the total number of patients visited is 294, significantly below the total of 500 patients. In this scenario, decision-makers may contemplate increasing the fleet size.

Table 4 delineates the solutions for the 500-patient scenario with fleet sizes of 8, 10, and 12, facilitating a comparison among them. The table structure mirrors the previous one but consolidates information by fleet size and day. As anticipated, augmenting the fleet size correlates with an increase in both the total number of patients visited and the total reward. Specifically, expanding the fleet size from 8 to 10 results in a 20.41% surge in the total number of patients visited and a 21.17% rise in the total reward. Similarly, elevating the fleet size from 10 to 12 yields a 15.82% upswing in the total number of patients visited and a 15.23% increase in the total reward. Notably, the reward distributions do not exhibit substantial variations.

6. Discussion

Our research focused on improving HHC coverage in rural areas through a routing approach in the province of Segovia (Spain). The

Table 2
Obtained results for a large synthetic instance using 10 different random seeds.

# Run[a]	Monday		Tuesday		Wednesday		Thursday		Friday		Tot.Rew.[d]	Comp.
	Rew.[b]	Km.[c]	Rew.	Km.	Rew.	Km.	Rew.	Km.	Rew.	Km.		Time (s)[e]
1	2380	413.39	2500	422.11	2620	460.16	2620	472.58	2400	609.16	12 520	44.97
2	2160	406.93	2490	441.71	2640	463.00	2640	456.60	2400	614.28	12 330	69.22
3	2340	411.59	2540	413.02	2550	433.82	2640	509.81	2400	609.98	12 470	86.33
4	2310	408.12	2390	417.86	2660	431.46	2640	510.80	2400	598.87	12 400	47.08
5	2210	381.95	2430	465.68	2610	456.43	2640	469.88	2450	593.66	12 340	86.53
6	2380	394.95	2370	456.91	2600	432.06	2690	493.58	2450	612.84	12 490	97.08
7	2310	384.24	2400	428.00	2630	463.61	2670	499.13	2450	589.81	12 460	53.89
8	2300	382.69	2550	399.06	2560	471.92	2620	514.58	2400	613.98	12 430	87.32
9	2390	394.72	2450	398.01	2560	477.40	2630	513.56	2450	598.47	12 480	58.47
10	2270	344.90	2400	448.55	2620	482.70	2710	492.10	2400	614.51	12 400	40.25
Avg.[f]	2305	392.35	2452	429.09	2605	457.25	2650	493.26	2420	605.56	12 432	67.11

[a] *Run*. Number of executions with different seeds to assess the scalability and robustness of the algorithm.
[b] *Rew*. Indicates the total reward achieved on that day in the management of HHC for each execution of the algorithm. A high reward signifies attending to more patients with urgent visits. A low value indicates attending to patients of lesser urgency.
[c] *Km*. Indicates the total kilometres travelled on that day in HHC management for each execution of the algorithm.
[d] *Tot.Rew*. Indicates the total sum of rewards at the end of the working week in HHC management for each execution of the algorithm.
[e] *Comp.Timesec*. Execution time, expressed in seconds, taken by the algorithm to find the best solution for HHC management. The algorithm runs for 100 s, generating multiple solutions, and records the best solution found, as well as the time taken to do so.
[f] *Avg*. Indicates the average outcome of rewards, minutes spent, kilometres travelled, the total reward obtained at the end of the working week, and the total time difference (in seconds) between the worst and best execution solutions of the algorithm during HHC management.

results obtained present relevant findings that can significantly contribute to addressing demographic challenges and disparities in access to healthcare services in rural regions. In the following section we carry out a discussion of the results obtained, focusing especially on the implications of our proposed routing and planning of an HHC service for rural areas.

6.1. Improving availability and reliability of HHC service in rural areas

The case study conducted in the province of Segovia presents valuable findings that directly relate to the availability and reliability of public services, as observed in other publications in the literature [47,48]. The fact that Segovia is one of the least populated provinces in Spain and experiences a declining population trend highlights the demographic challenges faced by many rural regions. These demographic characteristics can impact the availability of healthcare services, as it is crucial to ensure that services are accessible to all citizens in dispersed areas. The implementation of an optimal routing model allows reaching patients in municipalities with limited coverage, significantly improving service availability by ensuring that more people have access to home healthcare, especially the elderly who predominantly reside in these areas and cannot drive.

The uneven distribution of population and healthcare resources in Segovia also raises concerns about the reliability of healthcare services in rural areas. Route optimisation ensures a more equitable distribution of healthcare services and enhances service reliability by ensuring that all patients have the opportunity to be treated in a timely and efficient manner. This improvement in service reliability is essential to address disparities in access to healthcare and ensure more effective delivery of healthcare services. Thus, the proposed routing solution becomes an additional alternative to complement other solutions such as teleconsultations, with the aim of maximising healthcare coverage and service reliability [49].

The approach in the Segovia case study mirrors the principles outlined by [33], particularly in the efficient construction of weekly schedules for healthcare providers, similar to our method of route optimisation for HHC. Similarly, the focus of [34] on efficient human resource management in homecare services complements our strategies in addressing the challenges of healthcare service delivery in rural settings.

Furthermore, the implementation of the proposed routing model allows greater flexibility in scheduling and visits, further enhancing the reliability of home healthcare services in rural areas, as well as patient comfort and attention. These elements also align with other contributions in the literature on the role that public service should play regarding patient comfort and attention [50]. By prioritising patient care and scheduling visits according to their relevance, it is possible to ensure that those with greater healthcare needs receive timely attention. This consideration aligns with the approach of [51], who advocated for a multi-objective routing approach to provide solutions that meet individual preferences and improve service reliability. The proposed routing model not only enhances the availability and reliability of healthcare services in rural areas but also provides a patient-centric approach that can lead to more efficient and effective healthcare delivery.

Proposition 1. *An integrated home healthcare (HHC) routing model that prioritises coordination, accessibility, and reliability is essential for rural populations. This will enhance service availability and patient-centred care, addressing HHC access disparities in rural areas while maximising overall service reliability.*

6.2. Ensuring quality, safety and accessibility: An integrated model for rural HHC routing

In terms of quality, our model is built upon precise and reliable data for optimal healthcare routing. The strategic selection of a central depot, in this case, located in the municipality of Aguilafuente, ensures equitable coverage distribution and efficient route management. This key consideration is crucial for implementing our model and aligns with suggestions from previous studies to ensure an optimal VRP solution [52]. By accounting for factors like patient service time and priority of care, we emphasise the importance of addressing individual patient needs, guaranteeing personalised and high-quality healthcare [53].

Regarding safety, our coordinated route planning model mitigates risks associated with vehicle travel to patients' homes by ensuring the shortest and most efficient routes. As demonstrated in the literature, increased travel distance correlates with a higher accident risk [54]. Moreover, our model reduces travel for vulnerable patients residing in rural areas, who often face mobility challenges, thus minimising accident risks. This aligns with existing literature stressing the need for public services, including transportation, to prioritise patient safety [55].

Lastly, it is essential to consider the importance of patient awareness regarding HHC coverage to ensure proper utilisation and understanding

Table 3
Reward distributions and number of visits for a solution to the 500-patient instance with a fleet size of 8 vehicles.

		Patients	Total reward	Percentage distribution of total rewards for each level by vehicle				
				Rew. 50	Rew. 40	Rew. 30	Rew. 20	Rew. 10
Day 1	Vehicle 1	7	340	85.7%	14.3%	0.0%	0.0%	0.0%
	Vehicle 2	10	330	20.0%	40.0%	0.0%	30.0%	10.0%
	Vehicle 3	8	300	37.5%	25.0%	12.5%	25.0%	0.0%
	Vehicle 4	9	290	22.2%	22.2%	22.2%	22.2%	11.1%
	Vehicle 5	8	290	37.5%	12.5%	25.0%	25.0%	0.0%
	Vehicle 6	7	290	57.1%	28.6%	0.0%	0.0%	14.3%
	Vehicle 7	8	280	25.0%	25.0%	25.0%	25.0%	0.0%
	Vehicle 8	8	260	0.0%	37.5%	50.0%	12.5%	0.0%
		65	2380	35.6%	25.6%	16.8%	17.5%	4.4%
Day 2	Vehicle 1	7	320	57.1%	42.9%	0.0%	0.0%	0.0%
	Vehicle 2	9	320	33.3%	22.2%	11.1%	33.3%	0.0%
	Vehicle 3	9	320	33.3%	22.2%	11.1%	33.3%	0.0%
	Vehicle 4	9	320	22.2%	44.4%	0.0%	33.3%	0.0%
	Vehicle 5	7	310	57.1%	28.6%	14.3%	0.0%	0.0%
	Vehicle 6	8	310	50.0%	12.5%	12.5%	25.0%	0.0%
	Vehicle 7	7	300	57.1%	28.6%	0.0%	14.3%	0.0%
	Vehicle 8	8	300	50.0%	0.0%	25.0%	25.0%	0.0%
		64	2500	45.0%	25.2%	9.3%	20.5%	0.0%
Day 3	Vehicle 1	9	360	33.3%	33.3%	33.3%	0.0%	0.0%
	Vehicle 2	8	340	62.5%	0.0%	37.5%	0.0%	0.0%
	Vehicle 3	8	340	37.5%	50.0%	12.5%	0.0%	0.0%
	Vehicle 4	8	330	50.0%	12.5%	37.5%	0.0%	0.0%
	Vehicle 5	7	320	71.4%	14.3%	14.3%	0.0%	0.0%
	Vehicle 6	7	310	71.4%	0.0%	28.6%	0.0%	0.0%
	Vehicle 7	7	310	57.1%	28.6%	14.3%	0.0%	0.0%
	Vehicle 8	7	310	57.1%	28.6%	14.3%	0.0%	0.0%
		61	2620	55.1%	20.9%	24.0%	0.0%	0.0%
Day 4	Vehicle 1	7	340	85.7%	14.3%	0.0%	0.0%	0.0%
	Vehicle 2	7	340	85.7%	14.3%	0.0%	0.0%	0.0%
	Vehicle 3	7	330	71.4%	28.6%	0.0%	0.0%	0.0%
	Vehicle 4	7	330	71.4%	28.6%	0.0%	0.0%	0.0%
	Vehicle 5	7	330	71.4%	28.6%	0.0%	0.0%	0.0%
	Vehicle 6	7	320	57.1%	42.9%	0.0%	0.0%	0.0%
	Vehicle 7	7	320	57.1%	42.9%	0.0%	0.0%	0.0%
	Vehicle 8	7	310	42.9%	57.1%	0.0%	0.0%	0.0%
		56	2620	67.9%	32.1%	0.0%	0.0%	0.0%
Day 5	Vehicle 1	6	300	100.0%	0.0%	0.0%	0.0%	0.0%
	Vehicle 2	6	300	100.0%	0.0%	0.0%	0.0%	0.0%
	Vehicle 3	6	300	100.0%	0.0%	0.0%	0.0%	0.0%
	Vehicle 4	6	300	100.0%	0.0%	0.0%	0.0%	0.0%
	Vehicle 5	6	300	100.0%	0.0%	0.0%	0.0%	0.0%
	Vehicle 6	6	300	100.0%	0.0%	0.0%	0.0%	0.0%
	Vehicle 7	6	300	100.0%	0.0%	0.0%	0.0%	0.0%
	Vehicle 8	6	300	100.0%	0.0%	0.0%	0.0%	0.0%
		48	2400	100.0%	0.0%	0.0%	0.0%	0.0%

of the necessary procedures to access the service [56]. Even with a well-coordinated and planned healthcare model in rural areas, all efforts could be in vain if potential patients are unaware of the service's availability. Therefore, proactive measures by public administrators to disseminate this information to all stakeholders will be paramount [57]. A comprehensive approach that addresses quality, safety, and accessibility will result in an integrated healthcare solution that enhances services in rural areas.

Proposition 2. *The optimisation and planning of routes for HHC require accurate and reliable data, as well as personalised care that addresses the individual needs of patients. To maximise the quality of healthcare services in rural areas, it is essential to implement effective communication strategies with patients.*

6.3. Sustainable HHC: Electric vehicles and efficient routing

An important aspect of our study is the focus on using electric vehicles for home visits. This strategic decision demonstrates a clear commitment to sustainability and reducing the carbon footprint of our proposed model for public healthcare. Opting for electric vehicles, which produce lower carbon emissions compared to internal combustion engine vehicles, significantly contributes to mitigating the effects of climate change and improving air quality in rural areas [58].

The adoption of electric vehicles not only brings environmental benefits but also has a positive impact on the quality of life for both patients and healthcare staff conducting home visits [59]. Electric vehicles produce less noise and vibrations than internal combustion engine vehicles [60], which helps avoid increasing noise pollution in rural communities. Additionally, by reducing air pollution, the risks of respiratory and cardiovascular problems in the local population are reduced, resulting in a significant improvement in public health [61].

Another relevant aspect of the proposed routing model is the optimisation of home healthcare routes. Efficient route planning and strategic coordination of visits lead to a reduction in the total mileage covered by healthcare vehicles. This reduction not only results in cost savings but also translates to a decrease in the ecological footprint associated with transportation. This focus on energy efficiency and sustainability in providing home healthcare services aligns with the work of [62], who emphasise the importance of optimising public transportation considering environmental impacts as a significant aspect of service

Table 4
Reward distributions and number of visits for a solution to the 500-patient instance with a fleet size of 8, 10, and 12 vehicles.

		Patients	Total reward	Percentage distribution of total rewards for each level by vehicle				
				Rew. 50	Rew. 40	Rew. 30	Rew. 20	Rew. 10
8 veh.	Day 1	65	2380	35.6%	25.6%	16.8%	17.5%	4.4%
	Day 2	64	2500	45.0%	25.2%	9.3%	20.5%	0.0%
	Day 3	61	2620	55.1%	20.9%	24.0%	0.0%	0.0%
	Day 4	56	2620	67.9%	32.1%	0.0%	0.0%	0.0%
	Day 5	48	2400	100.0%	0.0%	0.0%	0.0%	0.0%
		294	12 520	60.7%	20.8%	10.0%	7.6%	0.9%
10 veh.	Day 1	78	2900	37.8%	25.3%	18.0%	14.0%	5.0%
	Day 2	81	3070	43.3%	21.1%	10.7%	24.9%	0.0%
	Day 3	70	3090	58.3%	26.7%	15.0%	0.0%	0.0%
	Day 4	65	3110	80.0%	20.0%	0.0%	0.0%	0.0%
	Day 5	60	3000	100.0%	0.0%	0.0%	0.0%	0.0%
		354	15 170	63.9%	18.6%	8.7%	7.8%	1.0%
12 veh.	Day 1	92	3410	33.9%	28.2%	20.9%	12.8%	4.1%
	Day 2	95	3550	43.5%	16.4%	13.8%	26.3%	0.0%
	Day 3	81	3560	58.1%	25.2%	16.7%	0.0%	0.0%
	Day 4	74	3560	81.9%	18.1%	0.0%	0.0%	0.0%
	Day 5	68	3400	100.0%	0.0%	0.0%	0.0%	0.0%
		410	17 480	63.5%	17.6%	10.3%	7.8%	0.8%

quality. Furthermore, our findings are consistent with the research of [63], who highlight the relevance of considering energy efficiency in healthcare route planning to reduce environmental impact.

Proposition 3. *It is necessary to implement a sustainable approach through the use of electric vehicles in the planning and optimisation of routes for HHC, which will generate a clear commitment to service quality, public health and the environment.*

7. Conclusions

The model proposed here fulfils the objective of designing a more efficient system for scheduling visits and designing routes in the context of HHC services in depopulated regions of Spain. Our study should be considered by policymakers and managers in the healthcare field to implement route management systems to complement other services, such as video calls with specialist physicians [19], especially if we consider that people residing in rural areas are generally elderly with significant disadvantages in using technology [64]. Through the HHC solution we propose, people with difficulties in using technology can be accompanied to follow up specialist video consultations. With this system, a healthcare professional, such as a nurse or paramedic, can carry out in-person visits to ensure that the specialist's instructions are appropriately followed.

Our study has important theoretical implications for the health and public service management literature. The successful application of the optimal routing model highlights the relevance of considering the coverage, reliability and accessibility of healthcare services in rural areas, especially those with ageing populations and technological limitations. These findings enrich the understanding of how to optimise health service delivery in geographically dispersed contexts and provide a solid basis for future research in the field of logistics and route planning in healthcare. Furthermore, the inclusion of electric vehicles in route planning highlights the need to incorporate sustainable practices in healthcare, contributing to the growing literature on sustainability in healthcare services.

The practical implications of the results of this study are of great relevance for policy makers and decision makers in the field of healthcare in rural areas. Successful implementation of the optimal routing model offers a practical solution to improve the efficiency and quality of HHC services in depopulated regions. Policy makers can use these findings to design effective strategies to ensure better coverage and timely care for rural communities. Consideration of a heterogeneous fleet of vehicles, including electric vehicles, provides a concrete opportunity to reduce operational costs and improve the environmental sustainability of health services. Also, the reactive approach and scheduling of visits for more than one week allows for greater flexibility and adaptability in healthcare delivery, enabling efficient allocation of resources and prioritisation of attention to those patients who require more urgent care. These practical implications can be instrumental in improving patient satisfaction and optimising the use of available resources in resource-constrained rural settings.

Lastly, our study also opens up several lines of future research. One critical area, acknowledging a limitation in our current model, is the need to balance more effectively the maximisation of overall reward with the number of patients served. Our initial focus on maximising rewards, primarily due to constraints in the early stage of our research, may not have adequately addressed the equilibrium between service reach and reward magnitude. Future studies should aim to refine this aspect by incorporating a more comprehensive objective function, considering both the total reward and the number of visits. This enhancement will better align our model with the practical demands of healthcare delivery, particularly in rural settings.

Furthermore, the coverage study could be extended by considering not only the primary care centre closest to all points (centrality) as the depot, but also the second closest one. This would cater to scenarios where the first may be closed or has no available capacity/resources. Additionally, exploring the effect of introducing more vehicle types, such as helicopters, may yield further useful insights considering that their use may be advisable for mountainous areas or those with limited road infrastructure. Another promising avenue is to develop an algorithm that schedules visits for more than one week, allowing for the consideration of each patient's level of urgency and adopting a reactive approach where visits can be redesigned (adding or removing visits). Lastly, considering a heterogeneous fleet comprising both combustion engine and electric vehicles, each with different capacities, adaptations, and limitations, would be a fruitful line of research, enhancing the practical applicability and environmental sustainability of the model.

In essence, these future research pathways, while addressing the limitations of our initial model, also open up broader possibilities for enhancing healthcare delivery in rural areas. They present an opportunity to align our model more closely with the realities of rural healthcare, where the challenges are unique and demand innovative, flexible solutions.

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Table A.1
Results for home visits with 4, 5 and 6 healthcare vehicles.

	Results for home visits with 4 healthcare vehicles																								
	Monday				Tuesday				Wednesday				Thursday				Friday					Total for the week			
	Rew.[a]	Min.[b]	Km.[c]	€/Km.[d]	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.		Rew.	Min.	Km.	$\bar{xp}$ €/Km.[e]
	710	458	152.67	65.65	490	457	152.33	65.5	380	460	153.33	65.93	210	454	151.33	65.07	110	545	181.67	78.12		1900	2374	791.33	68.43
	610	459	153	65.79	480	460	153.33	65.93	290	451	150.33	64.64	210	455	151.67	65.22	90	455	151.67	65.22		1680	2280	760.00	65.36
	490	455	151.67	65.22	440	458	152.67	65.65	270	460	153.33	65.93	170	452	150.67	64.79	50	452	150.67	64.79		1420	2277	759.01	65.27
	490	459	153	65.79	400	458	152.67	65.65	260	460	153.33	65.93	150	455	151.67	65.22	10	455	151.67	2287		1310	459	762.34	65.56
Avg.	575	457.75	152.58	65.61	452.5	458.25	152.75	65.68	300	457.75	152.58	65.61	185	454	151.33	65.07	65	476.75	158.92	68.33	**Total**	6310	9218	3072.68	264.63
	Results for home visits with 5 healthcare vehicles																								
	Monday				Tuesday				Wednesday				Thursday				Friday					Total for the week			
	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.		Rew.	Min.	Km.	$\bar{xp}$ €/Km.
	580	459	153	65.79	490	456	152	65,36	260	459	153	65.79	150	458	152.67	65.65	30	225	75	32.25		1510	2057	685.67	61.99
	550	459	153	65.79	430	455	151.67	65.22	250	459	153	65.79	140	454	151.33	65.07	30	78	26	11.18		1400	1905	635,00	63.25
	500	459	153	65.79	420	460	153.33	65.93	240	459	153	65.79	70	452	150.67	64.79	–	–	–	–		1230	1830	610.00	65.58
	490	459	153	65.79	340	460	153.33	65.93	220	460	153.33	65.93	70	452	150.67	64.79	–	–	–	–		1120	1831	610.33	65.61
	460	452	150.67	64.79	330	455	151.67	65.22	200	458	152.67	65.65	70	460	153.33	65.93	–	–	–	–		1060	1825	608.34	65.40
Avg.	516	457.6	152.53	65.59	402	457.2	152.4	65.53	234	459	153	65.79	100	455.2	151.73	65.25	30	151.5	50.5	21.72	**Total**	6320	9448	3149.34	321.83
	Results for home visits with 6 healthcare vehicles																								
	Monday				Tuesday				Wednesday				Thursday				Friday					Total for the week			
	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.	Rew.	Min.	Km.	€/Km.		Rew.	Min.	Km.	$\bar{xp}$ €/Km.
	580	459	153	65.79	370	460	153.33	65.93	230	457	152.33	65.5	90	441	147	63.21	–	–	–	–		1270	1817	605.66	65.13
	550	459	153	65.79	360	458	152.67	65.65	230	456	152	65.36	80	425	141.67	60.92	–	–	–	–		1220	1798	599.34	64.49
	500	459	153	65.79	310	460	153.33	65.93	200	459	153	65.79	60	457	152.33	65.6	–	–	–	–		1070	1835	611.66	65.78
	490	459	153	65.79	300	460	153.33	65.93	190	456	152	65.36	20	78	26	11.18	–	–	–	–		1000	1453	484.33	62.77
	460	452	150.67	64.79	300	460	153.33	65.93	180	458	152.67	65.65	–	–	–	–	–	–	–	–		940	1370	456.67	65.46
	450	452	150.67	64.79	250	453	151	64.93	110	458	152.67	65.65	–	–	–	–	–	–	–	–		810	1363	454.34	65.12
Avg.[f]	505	456.67	152.22	65.46	315	458.5	152.83	65.72	190	457.33	152.44	65.55	52.5	350.25	116.75	50.2	–	–	–	-	**Total**[g]	6310	9636	3212.00	388.75

[a] *Rew.* Indicates the total reward achieved that day for each vehicle used in HHC. A high reward indicates having attended to more patients with urgent visits. A low value indicates having attended to patients of lesser urgency.

[b] *Min.* Indicates the total minutes spent by each vehicle in carrying out HHC on that day.

[c] *Km.* Indicates the total kilometres travelled by each vehicle for conducting HHC on that day.

[d] Euro/Km. Calculated by multiplying the total daily kilometres travelled by each vehicle for HHC by the cost of €0.43 per kilometre, based on [44].

[e] $\bar{xp}$ €/Km. Indicates the weighted average for the euro-per-kilometre ratio of each vehicle used for HHC over the entire working week, calculated using the following formula: $\bar{xp}$ €/Km $= \frac{\sum_{i=1}^{n} Km_i \cdot euro/Km_i}{\sum_{i=1}^{n} Km_i}$.

[f] *Avg.* Indicates the average outcome of rewards, minutes spent, kilometres travelled, and the euro-per-kilometre ratio for the vehicles used in HHC.

[g] *Total.* Indicates the total sum of rewards, minutes spent, kilometres travelled, and the euro-per-kilometre ratio for the vehicles used in HHC over the entire working week.

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CRediT authorship contribution statement

Cristian Castillo: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Eduard J. Alvarez-Palau:** Funding acquisition, Supervision, Validation, Visualization, Writing – original draft. **Laura Calvet:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Javier Panadero:** Formal analysis, Methodology, Writing – review & editing. **Marta Viu-Roig:** Visualization, Writing – original draft. **Anna Serena-Latre:** Data curation, Methodology. **Angel A. Juan:** Conceptualization, Validation.

Declaration of competing interest

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Data availability

Data will be made available on request.

Appendix

See Table A.1.

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