Districting Decisions in Home Health Care Services: Modeling and Case Study

Sebastian Cortés[1(✉)], Elena Valentina Gutiérrez[1], Juan D. Palacio[2], and Juan G. Villegas[1]

[1] Departamento de Ingeniería Industrial, Facultad de Ingeniería, Universidad de Antioquia, Medellín, Colombia
{sebastian.cortes,elena.gutierrez,juan.villegas}@udea.edu.co
[2] Departamento de Ciencias Matemáticas, Escuela de Ciencias, Universidad EAFIT, Medellín, Colombia
jpalac26@eafit.edu.co

Abstract. Home health care (HHC) services are a growing segment in the global health care industry in which patients receive coordinated medical care at their homes. When designing the service, HHC providers face a set of logistics decisions that include the districting configuration of the coverage area. In HHC, the districting problem seeks to group small geographic basic units-BUs (i.e., city quarters) into districts with balanced workloads. In this work, we present a modeling approach for the problem that includes a mixed integer linear programming (MILP) formulation and a greedy randomized adaptive search procedure (GRASP). The MILP formulation solves instances up to 44 BUs, while the GRASP allows to solve instances up to 484 BUs in less than 2.52 min. Computational experiments performed with a set of real instances from a Colombian HHC provider, show that the GRASP can reduce workload imbalances in a 57%.

Keywords: Home health care · Districting
Mixed integer linear programming
Greedy randomized adaptive search procedure

1 Introduction

Social and economic factors, such as accessibility to food, primary health care, potable water, antibiotics and other medicines, have generated increases in population and life expectancy [23]. These phenomena have lead to a substantial increase in demand for home health care (HHC) services worldwide. In the U.S., 12,200 HHC providers were registered in 2011, and more than 4.7 million patients received HHC services [14]. In Europe, between 1% and 5% of the total public health budget is spent on HHC services [8,9]. In Colombia, registered HHC providers, which are mainly private companies, have increased from 482 as of December 2013, to 1,644 as of April 2018 [6].

J. C. Figueroa-García et al. (Eds.): WEA 2018, CCIS 916, pp. 73–84, 2018.
https://doi.org/10.1007/978-3-030-00353-1_7

One of the decisions that HHC providers face when designing the service is the districting configuration of the coverage urban area [10]. The districting problem (DP) consists of defining districts made up of several territorial basic units-BUs (i.e., city quarters), allocating to each district the available resources, so that the workload of the staff and the quality of services provided to patients are equitable [1]. The DP is critical in HHC and the impact of a districting configuration goes beyond network design and customer service considerations. The capacity of each medical staff is limited in each period, and their productivity is influenced by the size of the area in which the assigned patients are located [2]. If an urban area is divided into few large districts, medical staff will spend a significant proportion of their shifts travelling long distances among patients' homes, thus quality of care can be affected and possibly increased risk of complications and death could ensue. On the other hand, if districts are too many and too small, the coordination of patient's assignments and service delivery becomes more complex and less efficient [11]. Therefore, the districting configuration influences the quality of decisions at operative levels.

The DP arises from the political field since the 60's, and its applications include logistics transportation, school districting, commercial or design of sales territories, emergency services, police districting, disaster management, and electricity supply [17]. In this work we are interested in DP in HHC. To the best of our knowledge, four works have addressed the DP in HHC. In [4], the authors solved a DP in the management of public HHC services for a local community health clinic in Montreal, Canada. They modeled the situation as a multi-criteria optimization problem and solved it with a tabu search heuristic. Two criteria were considered in the objective function: the mobility of visiting staff and the workload equilibrium among districts. Authors were able to solve instances up to 32 BUs with six districts. The author in [2], studied a HHC districting problem through a set partitioning model, which was solved by a column generation heuristic that integrated ideas from optimization and local search. This approached allowed to solve instances up to 156 BUs with 32 districts. Authors in [3], modelled the DP in HHC through mixed-integer programming with two models: the first one aimed to equitably distribute medical staff workloads, while the second aimed to minimize a measure of compactness, i.e., the maximum distance between two BUs assigned to the same district. These models were able to solve instances from 10 to 100 BUs and districts from one to four. In [12], the authors studied the DP considering three factors: geographical distribution of the population, security conditions to access BUs, and trends in the demand for HHC services. They presented a bi-objective mathematical model. The first objective was to minimize the total travel workload, and the second one was to minimize the total workload deviations across all districts. Authors carried out a case study in the city of Cali, Colombia, and they solved instances up to 22 BUs and districts from one to 12, following a lexicographic approach.

Our contribution in this work is three-fold. First, we present a modeling approach for the problem based on a mixed integer linear programming (MILP) formulation. Second, we implemented a greedy randomized adaptive search procedure (GRASP) to solve the problem. Third, we present a case study of a HHC provider which delivers services within the Aburrá Valley, in Antioquia, Colombia. The modeling approach allows to solve real large-scale instances for the DP in HHC, in suitable computational times. Furthermore, to the best of our knowledge, we are able to solve HHC instances with sizes up to three times the ones reported in the literature, while improving current districting configurations. The remainder of this paper is structured as follows. Section 2 presents the MILP model for the DP in HHC. Section 3 describes the proposed GRASP metaheuristic. Section 4 presents the comparison of the solution methods and the results of the case study. Finally, Sect. 5 summarizes the main findings and concludes the paper outlining future work opportunities.

2 Mathematical Model

In this section, we present a mixed integer linear programming model for the DP in the HHC context. This MILP is based on the *p-regions* formulation proposed by [7]. This kind of formulation, known as *flow p-regions model* (Flow^{PRM}) includes a group of decisions variables called flow variables which contribute to model contiguity conditions between BUs in the problem. This approach is initially inspired by [22], where contiguity is accomplished by assigning a flow unit from each BU of a region (district), to a previously selected sink for the district. The flows represent a graph which starting node is the sink defined and the flows are guided by arcs between the selected nodes (BUs). Each district has a BU as its sink and the network of flows is defined as arcs connecting adjacent BUs. If a BU is assigned to a district, then, that BU must provide a flow unit that goes to the sink of the district. Moreover, a flow can not be shared by more than one district.

We define the set of BU, $\mathcal{I}$ ($i \in \mathcal{I}$) and therefore, it is possible to consider the sets $\mathcal{N}_i$ which represent the set of BU adjacent to the basic unit i (i.e., the BUs that share at least one geographical point or line with i). Each BU i has a known workload denoted by c_i. Without loss of generality, c_i is measured in hours. Additionally, we define $\mathcal{K}$ as the set of districts. To make decisions with the Flow^{PRM}, we define the binary variable y_{ik} that takes the value of one if BU i is included in district k where $i \in \mathcal{I}$ and $k \in \mathcal{K}$. The variable t_{ij} is also binary and take the value of one if BU i and BU j are assigned to the same district. t_{ij} takes the value of zero, otherwise. To measure the flow that goes from BU i to BU j in a district k, we define the variable f_{ijk}. The binary variable w_{ik} takes the value of one if BU i is selected as sink; and w_{ik} is fixed to zero, otherwise. Finally, variable λ_k denotes the workload of the district k while variables λ_{max} and λ_{min} represent the maximum and minimum workload over the districts.

The proposed MILP inspired on the Flow^{PRM} follows:

$$\min z = \lambda_{max} - \lambda_{min} \tag{1}$$

subject to,

$$\sum_{k \in \mathcal{K}} y_{ik} = 1 \qquad \forall\, i \in \mathcal{I} \tag{2}$$

$$w_{ik} \leq y_{ik} \qquad \forall\ i \in \mathcal{I}, k \in \mathcal{K} \tag{3}$$

$$\sum_{i \in I} w_{ik} = 1 \qquad \forall\ k \in \mathcal{K} \tag{4}$$

$$f_{ijk} \leq y_{ik} \cdot (|\mathcal{I}| - |\mathcal{K}|) \qquad \forall\ i \in \mathcal{I}, j \in \mathcal{N}_i, k \in \mathcal{K} \tag{5}$$

$$f_{ijk} \leq y_{jk} \cdot (|\mathcal{I}| - |\mathcal{K}|) \qquad \forall\ i \in \mathcal{I}, j \in \mathcal{N}_i, k \in \mathcal{K} \tag{6}$$

$$\sum_{j \in \mathcal{N}_i} f_{ijk} - \sum_{j \in \mathcal{N}_i} f_{jik} \geq y_{ik} - (|\mathcal{I}| - |\mathcal{K}|) \cdot w_{ik} \qquad \forall\ i \in \mathcal{I}, j \in \mathcal{N}_i, k \in \mathcal{K} \tag{7}$$

$$t_{ij} \geq y_{ik} + y_{jk} - 1 \qquad \forall i, j \in \mathcal{I} : i < j, k \in \mathcal{K} \tag{8}$$

$$\lambda_k = \sum_{i \in \mathcal{I}} c_i \cdot y_{ik} \qquad \forall k \in \mathcal{K} \tag{9}$$

$$\lambda_{max} \geq \lambda_k \qquad \forall\ k \in \mathcal{K} \tag{10}$$

$$\lambda_{min} \leq \lambda_k \qquad \forall\ k \in \mathcal{K} \tag{11}$$

$$\lambda_k \geq \lambda_{k-1} \qquad \forall k \in \mathcal{K} : k \geq 2 \tag{12}$$

$$y_{ik} \in \{0, 1\} \qquad \forall\ i \in \mathcal{I}, k \in \mathcal{K} \tag{13}$$

$$w_{ik} \in \{0, 1\} \qquad \forall\ i \in \mathcal{I}, k \in \mathcal{K} \tag{14}$$

$$t_{ij} \in \{0, 1\} \qquad \forall i, j \in \mathcal{I} : i < j \tag{15}$$

$$f_{ijk} \geq 0 \qquad \forall\ i \in \mathcal{I}, j \in \mathcal{N}_i, k \in \mathcal{K} \tag{16}$$

$$\lambda_k \geq 0 \qquad \forall k \in \mathcal{K} \tag{17}$$

$$\lambda_{max}, \lambda_{min} \geq 0 \tag{18}$$

The objective function (1) minimizes the workload imbalance measure as the difference between the maximum and minimum workload among all districts (i.e., the range of the workload). As pointed in [20], balance can be obtained in different activity measures (number of customers/patients, product/service demand, and workload), our formulation is flexible enough to handle any of these three measures. Constraints in (2) ensure that each BU is assigned to a single district k. Expressions in (3) assign one sink in a district k only to BUs that compose such district while equations in (4) force the model to fix only one sink to each district. The group of constraints (5) and (6) allow a flow between BUs i and j, only if both units are assigned to district k and also if i and j are contiguous. Inequalities in (7) force each BU i to supply at least one flow unit. If that BU is not a sink, then a net flow greater or equal to one is fixed for i. On the other hand, for BUs that represent sinks, these constraints allow a negative net flow of $|\mathcal{I}|-|\mathcal{K}|-1$ units since sinks do not have outflow. The expressions (8) set variables t_{ij} equal to one if BUs i and j are assigned to the same district k. Constraints (9) calculate in variables λ_k the total workload of each district. Inequalities in (10) and (11) define respectively the maximum (λ_{max}) and minimum workload (λ_{min}) included in the objective function (1). Constraints in (12) are valid inequalities that order the districts by non-decreasing workloads. These valid inequalities reduce the number of alternative symmetric solutions, and therefore decrease the computational effort required in the branch-and-bound procedure [21]. Finally, expressions (13) to (18) define the domain of the decisions variables.

As a graphical example of a solution of the $Flow^{PRM}$ model. Figure 1 shows the value of decision variables for a districting configuration. In this case BUs D, E G, and H form the district 1 so variables $y_{D,1}$, $y_{E,1}$, $y_{G,1}$ and $y_{H,1}$ take the value of one. Note also that E is assigned as the district sink, therefore three units of flow go to E (one unit per BU assigned to district 1).

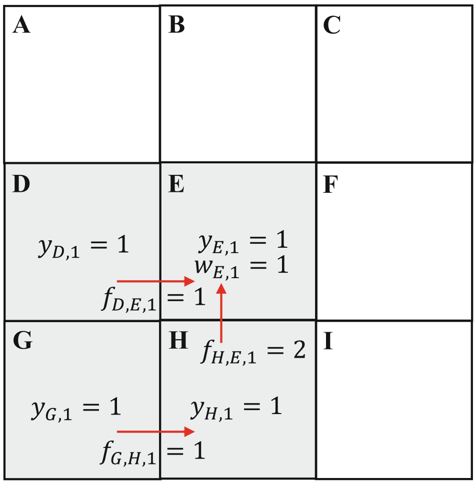

Fig. 1. Example of a solution of $Flow^{PRM}$ MILP

3 A GRASP to Solve the DP

To solve large instances of the DP, we rely on a GRASP metaheuristic. GRASP design provides a simple approach to solve efficiently a wide range of combinatorial optimization problems [16]. Particularly, in [18–20] the authors have shown that GRASP based heuristics are suitable for the solution of large-scale DPs. The proposed GRASP generates DP solutions in two phases, Algorithm 1 summarizes its main structure. In the first phase, we build an initial solution with $|\mathcal{K}|$ districts using procedure `BuildDistrictsRand` (line 4). The second improvement phase (lines 6–26) is a variable neighborhood descent (VND) procedure [13] that explores sequentially neighborhoods `DecreaseMaxLoad` and `IncreaseMinLoad` to improve the initial solution. The greedy randomized construction and VND cycle repeats for `MaxIterations` and the best solution found during the search is reported (line 28).

Greedy Randomized Construction. The greedy randomized construction phase (procedure `BuildDistrictsRand`) initializes the solution by selecting randomly $|\mathcal{K}|$ BUs as seeds of the districts to be created. Then, the procedure adds sequentially an adjacent BU to each one of the districts. To select the BU that

Algorithm 1. GRASP for the districting problem: general structure

```
1: function GRASP(DP,r,MaxIterations)
2:     z* ⟵ ∞, s* ⟵ ∅
3:     for r = 1 to MaxIterations do
4:         s_0 ⟵ BuildDistrictsRand(|K|,r)
5:         LocalOptimum ⟵ false, Neighborhood ⟵ 1
6:         while not LocalOptimum do
7:             if Neighborhood=1 then
8:                 s ⟵ DecreaseMaxLoad(s_0)
9:                 if f(s) ≤ f(s_0) then
10:                    s_0 ⟵ s
11:                else
12:                    Neighborhood ⟵ 2
13:                end if
14:            else
15:                s ⟵ IncreaseMinLoad(s_0)
16:                if f(s) ≤ f(s_0) then
17:                    s_0 ⟵ s
18:                    Neighborhood ⟵ 1
19:                else
20:                    LocalOptimum ⟵ True
21:                end if
22:            end if
23:            if f(s) ≤ z* then
24:                s* ⟵ s, z* ⟵ f(s)
25:            end if
26:        end while
27:    end for
28:    return s*
29: end function
```

will be added to a given district, we build a restricted candidate list ($\mathcal{RCL}$) with the adjacent BUs having the r smallest workloads. Then, the procedure picks randomly one BU from the $\mathcal{RCL}$ and adds it to the district. The randomized construction procedure iterates until all BUs belong to a district.

Variable Neighborhood Descent–VND. A VND is a deterministic variant of variable neighborhood search that explores sequentially several neighborhoods [13]. To solve the DP we embedded two neighborhoods within the VND. The first one, `DecreaseMaxLoad` (line 8 of Algorithm 1) selects the district of solution s_0 with the maximum load and evaluates if transferring one of its BUs to another adjacent district improves the objective function by reducing λ_{max}. By contrast, the second neighborhood, `IncreaseMinLoad` (line 15 of Algorithm 1) selects the district in s_0 with the minimum load and evaluates if adding a BU from its neighboring districts improves the objective function by increasing λ_{min}. If one of the neighborhoods improves the solution, VND restarts the search from the new improved solution using neighborhood `DecreaseMaxLoad`. On the other hand, if none of the neighborhoods improves the solution the search stops at a local optimum (line 20 of Algorithm 1). In our implementation, VND explores both neighborhoods using a best improvement strategy, i.e. it analyzes all the BUs of the district under consideration and selects the one that generates the maximum improvement of the objective function.

As pointed out in [20] some BUs cannot be removed from one district if their removal destroys the connectivity of the district. Formally, let $G(\mathcal{T})$ be the graph induced by the adjacency matrix of district $\mathcal{T}$. If $G(\mathcal{T} \setminus \{i\})$ $(i \in \mathcal{T})$ is not connected, then BU i cannot be removed from district $\mathcal{T}$. This definition coincides with the notion of *cut vertices* in graph theory [5]. Therefore, while exploring the neighborhoods in the VND we forbid the removal of any BU that is a cut vertex in the induced graph of its district.

4 Results

Initially, we analyze and compare Flow^{PRM} and GRASP in terms of the quality of the solutions obtained with both approaches and their efficiency to solve the DP in the HHC context. To compare the solution methods, we use four test instances based on the Home Health Care Program (Programa de Atención Domiciliaria–PAD, for its acronym in Spanish) offered by a Colombian health care provider in the Aburrá Valley (Antioquia). To analyze the impact of the size of the problem, we included instances with increasing number of BUs from 16 to 60. Moreover, we tested six different number of districts per instance, namely $|\mathcal{K}| = \{2, 3, 4, 0.25|\mathcal{I}|, 0.5|\mathcal{I}|, 0.75|\mathcal{I}|\}$.

The Flow^{PRM} formulation was solved with FICO's Xpress 8.1 optimizer. We report the best upper and lower bound found by the optimizer after a maximum solution time of one hour. The GRASP metaheuristic was implemented in Java using the Eclipse development environment. Moreover, to find the cut vertices of a given district we rely on the `jgrapht` package [15]. We set the parameters of GRASP to $r = 3$ and `MaxIterations`$= 5000$ after a detailed fine tuning process. Single runs of both methods were performed on a computer with an Intel core-i7 processor (6GB of RAM) running under Windows 7 64-bit.

Table 1 compares the results of Flow^{PRM} and GRASP. This table reports the objective function of the best interger solution (*Imb.*) and best lower bound (*Best LB*) obtained by the optimizer, the corresponding optimallity gap (*Gap*). For the GRASP this table include the objective found of the best solution found during the search (*Imb.*). We also report the running times (in seconds) of both methods. The table also reports the best-known solution (BKS) for each instance, values in bold indicate that a given method matched the BKS. Additionally, proven optima are underlined.

As it can be seen in the table, the MILP formulation reported optimal solutions in 10 out of 23 instances. All of them with less than 60 BUs. In the remaining instances, at least a feasible solution was found within the time limit. For the test instances with 60 BUs, no optimal solution was found for any of the values

Table 1. Comparison of Flow^{PRM} and GRASP for small DP instances

Instance				Flow PRM				GRASP	
Id	$\|\mathcal{I}\|$	$\|\mathcal{K}\|$	BKS	Imb.	Time (s)	Best LB	Gap (%)	Imb.	Time (s)
1	16	2	<u>2.05</u>	**2.05**	4.42	2.05	0.00	**2.05**	8.33
		3	<u>136.77</u>	**136.77**	68.83	136.77	0.00	**136.77**	2.92
		4	<u>442.69</u>	**442.69**	76.31	442.69	0.00	**442.69**	1.97
		8	1137.90	**1137.90**	3599.85	349.35	225.72	1137.96	0.86
		12	2772.58	**2772.58**	3600.15	2281.41	21.53	**2772.58**	0.73
2	29	2	<u>0.22</u>	**0.22**	3.84	0.22	0.00	0.33	14.99
		3	<u>4.82</u>	**4.82**	13.20	4.82	0.00	**4.82**	13.16
		4	<u>20.06</u>	**20.06**	307.14	20.06	0.00	28.60	6.58
		7	<u>123.00</u>	**123.00**	31.98	123.00	0.00	**123.00**	2.62
		15	255.98	**255.98**	3600.13	216.95	17.99	**255.98**	0.79
		22	255.98	**255.98**	3602.50	227.70	12.42	**255.98**	0.70
3	44	2	<u>2.20</u>	**2.20**	2.89	2.20	0.00	**2.20**	35.26
		3	104.14	**104.14**	3600.29	104.04	0.10	**104.14**	36.68
		4	<u>182.40</u>	**182.40**	7.28	182.40	0.00	190.86	16.11
		11	336.00	**336.00**	3600.32	304.83	10.23	**336.00**	1.38
		22	336.00	**336.00**	3600.92	327.28	2.66	**336.00**	0.98
		33	<u>336.00</u>	**336.00**	30.57	336.00	0.00	**336.00**	1.06
4	60	2	0.01	**0.01**	3600.26	0.00	100.00	0.04	145.17
		3	0.28	17.41	3599.97	0.00	100.00	**0.28**	111.90
		4	2.84	900.58	3600.41	0.00	100.00	**2.84**	44.94
		15	316.17	396.00	3605.50	260.01	52.30	**316.17**	3.27
		30	396.00	**396.00**	3602.26	318.99	24.14	**396.00**	1.90
		45	396.00	**396.00**	3601.23	374.06	5.87	**396.00**	1.49
Avg Time (s)					2059.14				19.73

considered for $|\mathcal{K}|$. This shows that the DP becomes harder to solve as the number of BUs grows. Likewise, instances with few districts seem easier to solve for the optimizer, since most of the optimal solution come from instances with 2 to 4 districs. On the other hand, the GRASP matched the optimal solution in 7 out of 10 instances and matched the upper bound found by Flow^{PRM} in another 8 instances. Remarkably, in the instances with 60 BUs (where the optimizer always stopped due to the time limit), GRASP results improve the solution of Flow^{PRM} in 3 out of 6 instances and matched the upper bound in another 2. Furthermore, the average running time of GRASP (19.73 s) is far below the one of Flow^{PRM} (2059.14 s). In summary, these results evidence the need to resort to approximate approaches such as GRASP in larger DP instances.

4.1 Case Study

The data of the case study is based on the information of the PAD operation for 2015. During this year, the HHC provider served 1349 acute patients located in the urban area of the Aburrá Valley (Antioquia). The coverage area of the service includes 484 BUs (city quarters). Figure 2(a) shows a heat map according

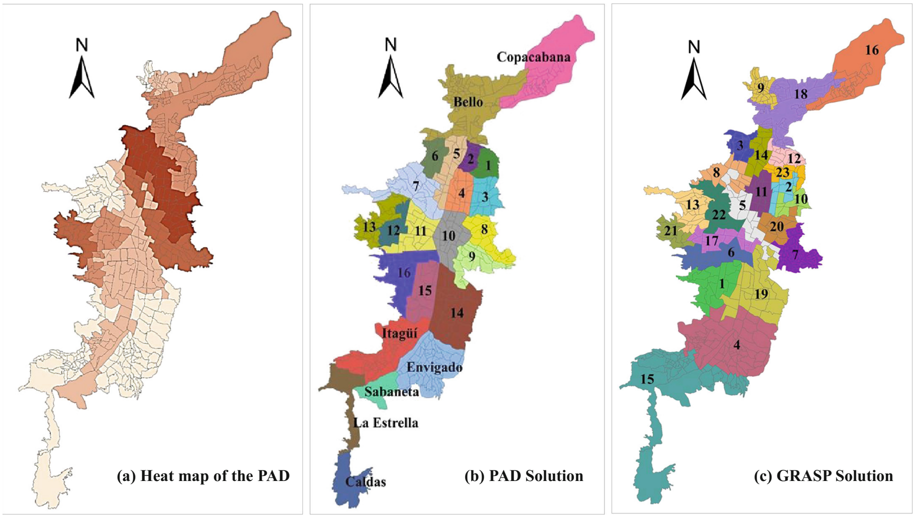

Fig. 2. Heat map of workload in the Aburrá Valley (a), current districting decisions (b), and GRASP solution for the case study (c)

to the workload in these quarters. The PAD used as districting solution the political division of the territory: the 16 communes of Medellín (capital city of Antioquia) and the other 7 municipalities of the Aburrá Valley (depicted in Fig. 2(b)). Therefore, the coverage area was divided into 23 districts. However, as it can be seen in Fig. 3, using this type of districting solution in practice does not guarantee a workload balance between the medical staff.

Service demands for HHC services of the PAD, and therefore workloads, were estimated in hours. Other works in the literature estimate HHC demands and workloads in hours [3,4,12], and only one considers demand as number of home visits [2]. Measuring such estimations in hours allows to include the variability in demand for HHC services derived from the diversity of medical procedures and types of patients. Consequently, we calculated demand estimations considering the type of medical procedure, the epidemiological profile of the covered population, and the frequencies of home visits.

To improve the districting decisions of the PAD, we ran several times the GRASP method for the DP instance with 484 BUs using a rook contiguity measure (i.e., two BUs are considered as adjacent if they share a segment in the map). The best solution found by GRASP (depicted in Fig. 2(c)) has an objective function of 2298.17 hours of workload imbalance. This result represents a 57% reduction of the workload imbalance obtained with the districting operated in 2015 (with an imbalance of 5317.85 hours). Figure 3 compares the workload of the new 23 districts of the solution proposed by GRASP against those of the previous PAD solution. As it can be seen in this figure, GRASP generates solutions with a more even workload distribution. This can be accomplished because the GRASP districts adapt to the patient's distribution in the coverage area. Small districts in the north are consistent with the high patient's density in this part of the Valley. Whereas, districts in the south have a small patient density. Then, they have to be larger in order to obtain similar workloads for the medical staff assigned to this part of the territory.

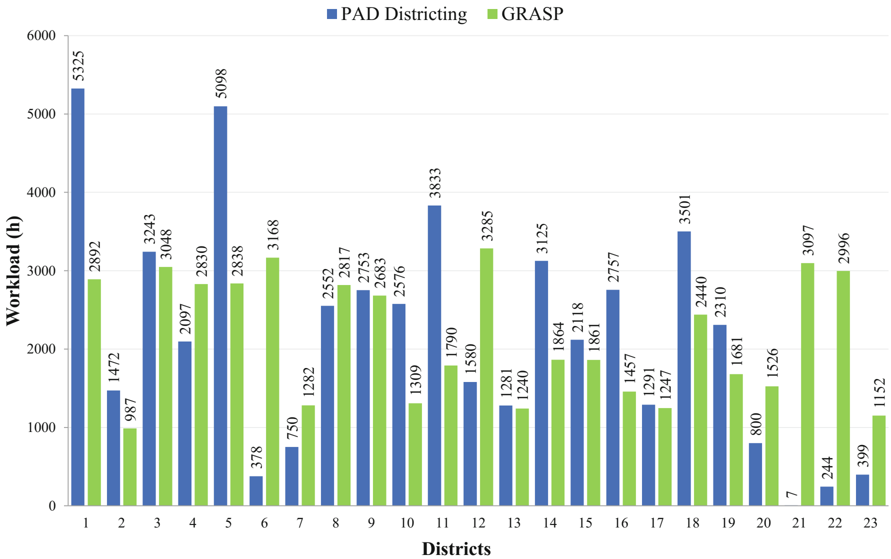

Fig. 3. Comparison of the workload of the 23 districts for the PAD and GRASP solutions

5 Conclusions

In this work, we proposed a modeling approach for the districting problem in HHC, based on two strategies. First, we adapted a MILP model based on a *p-regions* formulation, called Flow^{PRM}. The model ensures contiguity through a set of flow variables that represent a graph, and minimizes workload imbalance. For the second strategy, we implemented a GRASP metaheuristic which consists of a greedy randomized phase that designs feasible initial solutions in parallel, from a set of random seeds, and a local search that improves initial solutions by exploring two neighborhoods. We evaluated and compared the Flow^{PRM} and the GRASP in terms of the quality of the solutions, and their efficiency to solve the DP in HHC. Furthermore, we carried out a case study with a HHC provider from Antioquia, Colombia. The case study allowed to evaluate the modeling approach with real large-scale instances, and to evidence improvement opportunities in the districting configuration for HHC services.

According to the results, the Flow^{PRM} reported optimal solutions for 44% of the test evaluated, all of them of less than 60 BUs. For the remaining 56%, the model found at least one feasible solution within one hour. For instances with

60 BUs, no optimal solution was found, which evidenced the need for more efficient approximate solution methods. The GRASP matched the proven optimal solutions in 74% of the cases, and it improved 13% of the solutions found by the Flow^{PRM}, in instances with more than 60 BUs. These improvements were achieved within an average computational time far below from the ones of the Flow^{PRM}. The modeling approach was also evaluated through a case study with a real HHC provider, which delivers these service in a coverage area with 484 BUs. The approach found solutions in reasonable computation times (2.52 min on average), and results evidenced that the current districting configuration can be improved by 57%. Moreover, and to the best of our knowledge, the approach proposed is the first to solve large-scale instances up to 484 BUs for the districting problem in the HHC context.

As a future research opportunity, the inclusion of travel times within the modeling approach can provide better districting configurations. The time that medical staff spends on travelling between patients' homes is a large proportion of their working time, and therefore modeling the problem considering such factor will give a better representation of districting decisions. This inclusion generates challenges in terms of mathematical modeling and solution methods.

Acknowledgments. The authors are grateful to Universidad of Antioquia, specifically to the *Vicerrectoría de Investigación*, for their partial funding in the research project PRV16-1-03. We also thank the *IPS Universitaria* and their HHC program (PAD) for providing the information used in this work.

References

1. Bashir, B., Chabrol, M., Caux, C.: Literature review in home care. In: 9th International Conference on Modeling, Optimization & Simulation (2012)
2. Bennett, A.R.: Home Health Care Logistics Planning. Doctoral dissertation, Georgia Institute of Technology (2010)
3. Benzarti, E., Sahin, E., Dallery, Y.: Operations management applied to home care services : analysis of the districting problem. Decis. Support. Syst. **55**(2), 587–598 (2013). https://doi.org/10.1016/j.dss.2012.10.015
4. Blais, M., Lapierre, S.D., Laporte, G.: Solving a home-care districting problem in an urban setting. J. Oper. Res. Soc. **54**(11), 1141–1147 (2003). http://www.palgrave-journals.com/doifinder/10.1057/palgrave.jors.2601625
5. Bondy, J.A., Murty, U.S.R.: Graph Theory with Applications. Macmillan, London (1976)
6. Colombia, Ministerio de Salud y Protección Social: Registro Especial de Prestadores de Servicios de Salud (2018). https://prestadores.minsalud.gov.co/habilitacion/
7. Duque, J.C., Church, R.L., Middleton, R.S.: The p-regions problem. Geogr. Anal. **43**(1), 104–126 (2011)
8. Fikar, C., Hirsch, P.: Home health care routing and scheduling: a review. Comput. Oper. Res. **77**, 86–95 (2017)
9. Genet, N., Boerma, W., Kroneman, M., Hutchinson, A., Saltman, R.: Home care across Europe: case studies (2013)

10. Gutiérrez, E.V., Vidal, C.J.: Home health care logistics management: framework and research perspectives. Int. J. Ind. Eng. Manag. (IJIEM) **4**(3), 173–182 (2013)
11. Gutierrez, E.V.: Home Health Care Logistics Management Problems: An Integrated Approach to support Decisions with Hierarchical Interdependencies. Doctoral dissertation, Universidad del Valle (2014)
12. Gutiérrez, E.V., Vidal, C.J.: A home health care districting problem in a rapid-growing city. Revista Ingenieria y Universidad **19**(1), 87–113 (2015)
13. Hansen, P., Mladenović, N., Todosijević, R., Hanafi, S.: Variable neighborhood search: basics and variants. EURO J. Comput. Optim. **5**(3), 423–454 (2017)
14. Harris-Kojetin, L., Sengupta, M., Park-Lee, E., Valverde, R.: Long-term care services in the United States: 2013 overview. Vital Health Stat. Ser. 3, Anal. Epidemiol. Stud. **37**, 1–107 (2013)
15. Naveh, B.: JGraphT - a free Java graph library (2018). https://github.com/jgrapht/jgrapht
16. Resende, M.G., Ribeiro, C.C.: Optimization by GRASP: Greedy Randomized Adaptive Search Procedures. Springer, New York (2016). https://doi.org/10.1007/978-1-4939-6530-4
17. Ricca, F., Scozzari, A., Simeone, B.: Political districting: from classical models to recent approaches. Ann. Oper. Res. **204**(1), 271–299 (2013)
18. Ríos-Mercado, R.Z.: Assessing a metaheuristic for large-scale commercial districting. Cybern. Syst. **47**(4), 321–338 (2016)
19. Rios-Mercado, R.Z., Escalante, H.J.: GRASP with path relinking for commercial districting. Expert Syst. Appl. **44**, 102–113 (2016)
20. Ríos-Mercado, R.Z., Fernández, E.: A reactive GRASP for a commercial territory design problem with multiple balancing requirements. Comput. Oper. Res. **36**(3), 755–776 (2009)
21. Sherali, H.D., Smith, J.C.: Improving discrete model representations via symmetry considerations. Manag. Sci. **47**(10), 1396–1407 (2001)
22. Shirabe, T.: A model of contiguity for spatial unit allocation. Geogr. Anal. **37**(1), 2–16 (2005)
23. World Bank: Life expectancy learning module (2011). http://www.worldbank.org/depweb/english/modules/social/life/