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Operations management applied to home care services: Analysis of the districting problem

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ABSTRACT

In this paper, we focus on a specific operations management related issue faced by home health care (HHC) services, namely the districting problem. Our contribution consists of formulating the HHC districting problem as a mixed-integer programming model by considering criteria such as the indivisibility of the basic units (i.e. locations where patients live), compactness, workload balance between human resources and compatibility. The formulations developed are based either on balancing the personnel care workload or minimizing the travel distance to reach the patients. Computational results obtained from the models show that they enable to improve the service quality towards HHC patients as well as caregivers by optimizing the compactness and workload balance criteria.

1. Introduction

Recent developments in technological, social and economical environment have dramatically increased the need for improved service systems. Well designed service systems allow reducing costs and increasing customer satisfaction. This paper deals with a well-known type of service system, namely the home health care service. Home health care (HHC) which represents an alternative to the traditional hospitalization has been developed in France fifty years ago in order to solve the problem of hospitals' capacity saturation by providing to patients, at their home, complex and coordinated medical and paramedical care for a limited period which can be extended depending on patients' needs. This care is comparable, in terms of nature and intensity, to the one which would be delivered to the patient within a traditional hospitalization framework where the patient stays in the hospital to receive his/her treatment. HHC can be prescribed either by the family doctor or the doctor in charge of the patient in the hospital. Once admitted to a HHC structure, patients who suffer from pathologies such as cancer, nervous system diseases, circulatory system diseases, etc., receive medical and paramedical care based on one or several protocols/standards of care. The French HHC structures use twenty four protocols of care listed in the circular of May 30th, 2000 such as: the chemotherapy, radiotherapy, breathing assistance, palliative care, post-operation treatment, etc. [14]. Based on these protocols as well as on patients' social conditions, their age and their autonomy measured by the Karnofsky Performance Scale Index, a therapeutic project is then designed for each patient so that the number and average duration of visits required during the treatment of the patient within the HHC as well as the type and number of human and material resources required for the care delivered can be determined. The diversity of human resources that can be involved in the care (e.g. physicians, nurses, physiotherapists, social workers, home support workers, pharmacists, etc.) explains, as it will be described in detail later in the paper, the necessity of assigning to each patient a reference caregiver who is in charge of coordinating the execution of the therapeutic project. At this level, it is important to mention that most of HHC structures classify patients' therapeutic projects into categories named “profiles”. Indeed, patients whose therapeutic projects have similarities in terms of the expected duration of care, type, number and average duration of visits are grouped into the same profile.

During the last decade, HHC services have known an important growth. Indeed, the total number of HHC structures in France rose steadily from 68 structures in 1999 to 123 in 2005 and finally reached 271 structures in 2007. Despite the importance of the development of HHC services in practice, the amount of investigations dealing with operations management problems within the HHC context still remains modest, in comparison with earlier models developed for hospitals (e.g. [15,21,26], etc.). Most of the investigations considering HHC services mainly focus on either the problem of assigning caregivers to patients (or to visits) or the routing problem. Among the existing works developed so far, some models have been able to capture some of the specificities of HHC operations, i.e. what makes this care service different from the one delivered by hospitals, with respect to the way operations are managed. Hence, a first characteristic we can identify is the issue of the continuity of care in the HHC context defined by Shortell [29] as being the extent to which the medical

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and paramedical care are delivered by means of a sequence of coordinated and uninterrupted activities consistent with patients' needs, if possible by the same human resources. In practice, in order to guarantee the continuity of care in HHC, a patient is often assigned to only one caregiver, the reference caregiver, who follows the treatment of the patient during the time spent in the HHC structure. Most of time, the reference caregiver is the nurse who gives the paramedical care and coordinates the overall care with other caregivers such as the physician, social worker, etc. This is an important quality requirement of the HHC service due to the fact that it enables to preserve the service quality perceived by the patient since he/she receives the care from the same caregiver and thus does not have to continuously change his/her relationships with a new caregiver. A second characteristic of HHC operations is the necessity to integrate the patients' home within the care supply chain and hence to move the different flows of human and material resources needed for the care towards the patients' home. However, the diversity of human resources delivering the care and the variety of clinical and organizational decisions involved in the care delivery process need a tight coordination between different types of caregivers and material resources. Note that this coordination is especially difficult within this context since these resources are not grouped in the same health unit [12]. Another interesting problem which seems to us specific to HHC services concerns the consideration of human aspects while choosing the best organization for caregivers' teams. More specifically, if we consider one type of HHC caregivers, let's say the nurses, one may be interested in investigating the difference between two organizations: in the first organization, we assume that all nurses are grouped in a single team so that all the patients are treated by the same nurses' team independently of the basic unit where they live, while in the second organization, the area where the HHC structure operates is partitioned into several clusters (subareas), each of them being managed by a dedicated nurses' team. In our terminology, each cluster will be called a district. This second organization may enable not only to answer to a patient demand more quickly but also to increase the quality of service provided to him/her due to the diminution of the average time spent to reach him/her. Therefore, caregivers can spend more time in delivering care to patients. Furthermore, working in smaller areas, i.e. districts, within a smaller team may enhance caregivers' motivation since they can find a reinforced collaboration inside the team they belong to as well as a closer proximity with the HHC manager in charge of their team. Hence, the aim of a HHC structure in considering a districting approach may be to better manage its employees and, as a consequence, to satisfy patients more efficiently.

In this paper, we focus our attention on the districting problem due to the importance of such a decision in the achievement of HHC objectives in terms of improvement of the care delivery efficiency. Indeed, as explained above, the districting of a territory is a strategic HHC decision which aims at grouping basic units (a set of patients) into larger clusters, i.e. districts, so that these districts are "good" according to relevant criteria. These criteria can be related to the activity, demography or geographic characteristics of the basic units. Even if the districting approach can be viewed as time and resource consuming, it can have important impacts on caregivers' team structure and patients' satisfaction level.

This paper is organized as follows. In Section 2, we survey the literature related to our work: the first part of investigations reviewed concerns models that are developed in the operations management literature applied to HHC services while the second part is more related to the districting approach. In Section 3, we propose two mathematical formulations for the HHC districting problem. Results of computational experiments carried out on randomly generated instances to validate these two models are presented in Section 4. Finally, Section 5 presents some conclusions and perspectives that can be considered for future research.

2. Literature review

This part surveys two types of literature: operations management based models which have been proposed in the HHC literature and districting models developed in the operations research literature.

The three main issues treated in the existing HHC operations management literature are the problems of strategic resource dimensioning, districting and scheduling of human resources' activities. The first issue has been considered by Busby and Carter [9], who created a decision tool for the Simcoe County Community Care Access Center (SCCCAC) in Ontario. This tool enables to determine the trade-offs between three key factors: costs, service quality and patient waiting time. Based on these trade-offs, the SCCCAC could use this evaluation for determining the number of caregivers, with particular skills, and the quantity of different material resources necessary to satisfy the demand with the expected service quality level and minimum costs. De Angelis [16] has also addressed this problem for HHC structures providing services to AIDS patients. The author has developed a stochastic linear programming model which is linked to an epidemiological model and integrated the uncertainty in terms of patients' number and level of care required by each patient class.

The districting problem in the HHC context has been considered by mainly two authors. A multi-criteria approach have been first proposed in [6] for a local community health clinic in Montreal, Canada. This approach is based on criteria related to visiting personnel mobility and workload equilibrium which are combined into a single objective function but also on criteria related to the indivisibility of basic units, respect of borough boundaries and contiguity which are considered as hard constraints. The optimality of the method proposed in [6] has been reviewed in [24] by analyzing historical data which has underlined the fact that the approach proposed cannot forecast the fluctuation of the demand in each district. Furthermore, the model proposed in [6] has not been flexible enough in terms of assignment of caregivers to districts. In order to alleviate the overload of caregivers, [24] have proposed two solutions: the first one is a dynamic approach where the nurses are not assigned to a fixed district while the second consists of splitting the caregivers into two groups: the first one represents the caregivers assigned to a fixed district while the second one groups the caregivers that can work in all or a part of the territory.

Once the territory is divided into districts, the different resources must be assigned to the districts equitably. For this purpose, Boldy and Howell [7] have conducted a case study related to the allocation of home help resources to four geographical districts within the Devon Social Services Department.

A large amount of works in the HHC literature consider the scheduling of caregivers' activities which involves two hierarchical decisions. First, caregivers are assigned to patients or visits. Then, individual routes are constructed for each caregiver by determining at what time each visit must be done. To our knowledge, there is only one work that deals with the scheduling problem within the continuity of care context which has been conducted in [8]. The scheduling problem without considering the continuity of care has been treated by various authors. In this context, the patient is associated to a visit or a set of visits. The first decision support system has been proposed in [2] where the authors have presented a spatial decision support system that contains a special module for the daily scheduling of caregivers' activities. This module simultaneously assigns caregivers to patients' visits and generates the sequence in which the visits would be done. Cheng and Rich [13] have addressed the daily scheduling problem as a multi-depot vehicle routing problem with time windows and compatibility information. The objective of this daily scheduling is to minimize the total costs associated with the amount of overtime hours of the full-time nurses and the amount of hours of the part-time nurses. After that, another decision support system has been developed where the scheduling problem is formulated as a set partitioning model [18]. The objective consists of minimizing the total cost of assigning caregivers to the schedules related to the travel time, scheduled hours, preferences, etc. Bertels and Fahle [5] have also proposed a combination of linear programming, constraint programming and heuristics to assign the caregivers to visits and sort optimally the visits assigned to each caregiver such that the total transportation cost is minimized and the satisfaction of both patients and caregivers is maximized. Moreover, Hertz and Lahrichi [22] have proposed two mixed integer programming models for the allocation of caregivers to patients. Another decision tool has been proposed by Thomsen [30] who formulates the daily scheduling problem as a vehicle routing problem with time windows and shared visits (visits that have to be carried out by two caregivers). The objective consists of minimizing the total travel time, the number of unshared and unlocked visits (visits that are carried out by a non-reference caregiver) and the number of shared and unlocked visits. More recently, the daily scheduling problem have been addressed in [1] as a vehicle routing problem with time windows.

To conclude this literature review, we believe that, as we already pointed out in Section 1; one of the characteristics of innovative approaches that would help to improve the organization of the home care delivery service is the integration of specificities pertaining to HHC operations in the models being developed. Among examples of such models, we can refer to [8, 25] who have developed scheduling models within the continuity of care context, [30] who has considered the notion of coordinated shared visits, [16] who has proposed a stochastic linear programming model in which she has integrated the uncertainty of demand that is associated to HHC operations and [11] who have considered the coordination of human and material resources within the chemotherapy at home practice.

We now consider the second area of literature related to this paper, i.e., the districting problem, which consists of partitioning a territory into districts according to relevant criteria [3]. This problem has been formulated within the Operations Research literature in different manners and then solved either by managerial heuristics ([17,27]) or exact methods based on mathematical programming techniques ([4,10,19,20,23,28]). There are two major types of mathematical models related to the districting problems: the set-partitioning models and the location-allocation models.

Indeed, this problem has been widely treated since the late sixties in a broad range of applications including political districting; sales territory alignment and other services districting (e.g. school districting, salt spreading districting, police districting, electrical power districting, etc.). Hence, the political and the sales realms are the two most important applications in terms of number of publications. We present some of the districting models proposed in the literature for the sales and service territory realms due to the fact that they bear some similarities with the HHC districting problem. However, for more details in political districting literature review, the readers are referred to [3]. Indeed, the sales territory design is concerned with grouping sales coverage units into districts of salesmen's responsibility which must have approximately similar sizes in terms of number of customers or workloads. Hess and Samuels [23] have first applied a location-allocation model in order to maximize the total compactness of all districts while balancing the “activity” of the entire salesmen and minimizing the changes of the existing boundaries. After this, Fleischmann and Paraschis [20] have approached the sales territory alignment problem by a location-allocation model which respects the workload balance, compactness of the districts and indivisibility of the basic units. More recently, Rios-Mercado and Fernandez [28] have suggested a location-allocation model where the objective is the maximization of the total compactness while balancing activity among the contiguous districts.

Among other investigations, Ferland and Guenette [19] and Caro et al. [10] have developed mathematical models for the school districting problem which consists of specifying for each school the students who would attend it according to relevant criteria. Another type of services for which districting models have been developed is the electrical power districting which involves grouping electricity users units into districts of approximately equal revenue. The mathematical programming approach developed for this application is proposed by Bergey et al. [4] who have proposed a multi-criteria model that minimizes both the total compactness and the total deviation of revenue potential in each district from a target value.

3. Modeling the home health care districting problem

Remember that the districting of a territory aims at grouping basic units into larger clusters, i.e. districts, so that these districts are “good” according to relevant criteria. Note that the basic units represent an aggregation of patients living in the same location. Typically, basic units can be zip code areas, postal areas, streets, geo-code addresses, etc.

As explained before, adopting the districting approach in the HHC context would allow the improvement of the service quality towards the patients as well as the caregivers. Indeed, the fact that patients are grouped in a district would increase the reactivity of caregivers (in case of emergencies for instance) which in turn would conduct to better satisfy patients. Furthermore, this approach induces the reduction of the travel time and consequently the increase of the time dedicated to the direct care which would also help to improve the care delivery process efficiency. Another interesting effect of adopting the districting approach is the fact that it may improve working conditions. Indeed, the districting approach aims to balance the workload between the different districts which would conduct to a better equilibrium of the workload between the various teams whose members would be more satisfied and thus more motivated. Additionally, the fact that each district is under the responsibility of a single team may allow the development of long-term relationships between caregivers and patients which would result in a better quality of care and a higher efficiency of caregivers in terms of speed and quality of the care delivered. Finally, the districting approach may also facilitate human resources management practices due to the fact that dealing with smaller teams is easier than managing a larger team that groups all the human resources. In this section, we propose two mathematical formulations for the HHC districting problem for which we present assumptions adopted, criteria considered and notations used.

3.1. Assumptions

In the models that we have developed, we would assume, without loss of generality, that:

- A.1 Patients admitted to the HHC structure suffer from the same pathology.
- A.2 Patients who live in a given basic unit can have different profiles.
- A.3 A patient profile is assumed to be known when he/she is admitted to the HHC structure and does not change during his/her stay within the HHC system.
- A.4 The number and average duration of visits that characterize a patient's profile are known and are the same among the patients who have the same profile.
- A.5 The number of patients admitted to the HHC structure is known in advance and does not change while considering the districting problem.
- A.6 Human resources delivering care to patients are of the same type, namely the nurses, who are multi-skills, i.e. able to treat the different profiles associated with the pathology considered, among all the basic units.
- A.7 All the basic units are covered which means that all the patients admitted to the HHC have to be assigned to a district.
- A.8 There is an enough number of nurses available. Each nurse has a predetermined capacity (i.e. he/she can handle a certain volume of workload). This capacity is identical between the different nurses.

A.9 The number of districts to design is predetermined by the HHC managers.
A.10 The distance metric used is the network distance since it reflects the real time spent by a nurse between the basic units.
A.11 The districting is done once for a relatively long period of time.

3.2. Criteria considered

We consider the following criteria for the HHC districting problem:

- The compactness can be integrated into the models in two ways. First, the compactness can be formulated as a hard constraint by limiting the maximum distance between two basic units that would be assigned to the same district (i.e. Model 1). The second formulation consists of minimizing a compactness measure which is the maximum distance between two basic units assigned to the same district (i.e. Model 2).
- The accessibility is also crucial in the HHC context since it is related to the easiness by which the caregivers can travel within a district, for example by means of public transportation, private cars, etc. The accessibility can also be assessed by the respect of geographical obstacles such as mountains, bodies of water, etc.
- The conformity of the districts designed to the administrative boundaries facilitates the organization of health care delivery procedures and the work with community agencies.
- The indivisibility of basic units where each basic unit must be assigned to one and only one district. This criterion is considered in order to avoid interference between caregivers' responsibilities and to establish long-term relationships with patients.
- The workload balance is essential for the design of "good" districts. It consists of having almost the same workload in the different districts. The analysis of the workload shows that it is essentially composed of the care workload and the travel time. Since the travel time is related to the distances between the different patients' home whose reduction is guaranteed by the compactness criterion, we consider only the care workload which depends on the number of patients visited by the caregiver as well as the profile of these patients.

Note that in comparison with our model, Blais et al. [6] have not considered the different patients' profiles separately. Moreover, we propose two models where the accessibility criterion can be considered as a hard constraint to respect whereas they have considered it as an objective function to optimize. Additionally, they have formulated the workload as the sum of the total travel time and the total visit time (care workload) that has been optimized. On the contrary, we balance the districts according to the care workload, the travel time being related to the compactness criterion. Hence, based on the preferences that HHC managers would have, we propose two mathematical formulations for the HHC districting problem which consider the compactness and care workload balance criteria either as a hard constraint to respect or an objective function to optimize.

3.3. Decision variables

We define the following decision variables:

- x_{ij}: Assignment decision variables. $x_{ij}=1$ if the basic unit i ($i=1\ldots N$) is assigned to district j ($j=1\ldots M$) and 0 otherwise.
- wd_j: Total care workload of district j ($j=1\ldots M$).
- *gap_max*: The maximum deviation (expressed as a percentage) between the care workload associated to each district and the average care workload among all districts.
- *distance*: The maximum distance that separates two basic units that are in the same district, among all the districts.

3.4. Parameters

We use the following notations for the parameters of the models:

- N: number of basic units.
- M: number of districts to design.
- H: number of patients' profiles considered.
- b_h: Number of visits required by a patient of profile h ($h=1\ldots H$) during his/her stay within the HHC system.
- T_h: Average duration of a visit relative to the profile h ($h=1\ldots H$).
- P_{ih}: Number of patients living in the basic unit i ($i=1\ldots N$) and having the profile h ($h=1\ldots H$).
- d_{ik}: Distance between the basic units i ($i=1\ldots N$) and k ($k=1\ldots N$).
- d_{max}: Maximum distance allowed between two basic units that can be assigned to the same district.
- D: Set of basic units' pairs (i, k) where $(i,k)\in D$ if and only if $d_{ik}>d_{max}$ (used in Model 1).
- $\overline{wd}$: Average care workload among all districts.
- τ: Admissible percentage deviation of the workload associated to a given district in comparison with the average workload among all districts (used in Model 2).
- e_{ik}: Compatibility index. $e_{ik}=1$ if the basic units i and k are compatible, and 0 otherwise. The basic units i and k can be incompatible for several reasons: a) existence of geographical obstacles between them, b) difficulty or impossibility to travel from one basic unit to another by the means of transportation used by the caregivers (public transportation, private cars, etc.) or c) they do not belong to the same administrative district.
- E: Set of basic units' pairs (i, k) where $(i,k)\in E$ if and only if $e_{ik}=0$.

3.5. Formulations of the problem

Depending on the HHC managers' preferences, two formulations can be developed for modeling the HHC districting problem.

3.5.1. Model 1

This model corresponds to the case where a HHC manager prefers to define a maximum average waiting time for the patients (or a minimum average reactivity) which can be guaranteed by fixing an upper bound for the distance allowed between two basic units that are assigned to the same district (d_{max}). Alternatively, Model 1 can be used in cases where the HHC manager wants to achieve an objective of care workload distributed equitably, so that the total care workload of each of the teams working in the different M districts is as close as possible to the average care workload. This workload equilibrium can be achieved by considering the following objective function:

$$\text{Minimize} \max_{j=1,\ldots,M} \left| wd_j - \overline{wd} \right| \tag{1}$$

Since this expression is not linear, the resolution of the corresponding mathematical model is difficult. However, it is possible to linearize it by introducing another decision variable *gap_max* and adding two hard constraints that relate *gap _max* to wd_j and $\overline{wd}$. To summarize, the formulation of Model 1 is the following:

$$\text{Minimize } gap\_max \tag{2}$$

s.to

$$wd_j = \sum_{i=1}^{N}\sum_{h=1}^{H} P_{ih} b_h T_h x_{ij} \quad \forall \quad j=1,\ldots,M \tag{3}$$

$$\overline{wd} = \frac{\sum_{i=1}^{N}\sum_{h=1}^{H} P_{ih} b_h T_h}{M} \tag{4}$$

$$gap\_\max \geq \frac{wd_j - \overline{wd}}{\overline{wd}} \quad \forall \quad j = 1, \ldots, M \tag{5}$$

$$gap\_\max \geq \frac{\overline{wd} - wd_j}{\overline{wd}} \quad \forall \quad j = 1, \ldots, M \tag{6}$$

$$\sum_{j=1}^{M} x_{ij} = 1 \quad \forall \quad i = 1, \ldots, N \tag{7}$$

$$x_{ij} + x_{kj} \leq 1 \quad \forall \quad (i,k) \in E, \quad j = 1, \ldots, M \tag{8}$$

$$x_{ij} + x_{kj} \leq 1 \quad \forall \quad (i,k) \in D, \quad j = 1, \ldots, M \tag{9}$$

$$x_{ij} \in \{0,1\} \quad \forall \quad i = 1, \ldots, N \quad j = 1, \ldots, M \tag{10}$$

The objective function (2) coupled with constraints (5) and (6) guarantee the minimization of the maximum deviation of the care workload from the average care workload among all districts. Constraints (3) and (4) define respectively the care workload of each district and the average care workload among all districts. Constraint (7), together with constraint (10), assumes that each basic unit is assigned to one and only one district. The compatibility is guaranteed by constraint (8). Finally, constraint (9) is related to the compactness criterion where the distance between two basic units assigned to the same district is bounded by the distance d_{max}. This upper bound guarantees the containment of the travel time within each district.

3.5.2. Model 2

In Model 1, we consider the case where the main objective is to balance the care workload. However, a HHC manager could prefer defining a tolerance interval that ensures that each district's care workload does not deviate from the average care workload by more than a pre-specified percentage τ. The main objective would then consist of minimizing the compactness measure i.e. the maximum distance between two basic units assigned to the same district as follows:

$$\underset{j=1,\ldots,M}{Minimize} \left(\max_{\substack{i=1,\ldots,N \\ k=1,\ldots,N}} \left(d_{ik} * x_{ij} * x_{kj} \right) \right) \tag{11}$$

This objective function would help to improve the reactivity of caregivers and to reduce the waiting time of patients as much as possible. Similar to Model 1, this objective function is not linear. It is possible to transform it into a linear one by introducing a decision variable *distance* to minimize which must respect an additional constraint. To summarize, the formulation of Model 2 is as follows:

$$\text{Minimize } distance \tag{12}$$

s.to

$$distance \geq d_{ik} * \left(x_{ij} + x_{kj} - 1 \right) \quad \forall \quad i = 1, \ldots, N \quad k = 1, \ldots, N \quad j = 1, \ldots, M \tag{13}$$

$$wd_j = \sum_{i=1}^{N} \sum_{h=1}^{H} P_{ih} b_h T_h x_{ij} \quad \forall \quad j = 1, \ldots, M \tag{14}$$

$$\overline{wd} = \frac{\sum_{i=1}^{N} \sum_{h=1}^{H} P_{ih} b_h T_h}{M} \tag{15}$$

$$\sum_{j=1}^{M} x_{ij} = 1 \quad \forall \quad i = 1, \ldots, N \tag{16}$$

$$x_{ij} + x_{kj} \leq 1 \quad \forall \quad (i,k) \in E, \quad j = 1, \ldots, M \tag{17}$$

$$(1-\tau)\overline{wd} \leq wd_j \quad \forall \quad j = 1, \ldots, M \tag{18}$$

$$wd_j \leq (1+\tau)\overline{wd} \quad \forall \quad j = 1, \ldots, M \tag{19}$$

$$x_{ij} \in \{0,1\} \quad \forall \quad i = 1, \ldots, N \quad j = 1, \ldots, M \tag{20}$$

The analysis of constraints (14), (15), (16), (17) and (20) of Model 2 is the same as for Model 1. The objective function (12) and constraint (13) guarantee the minimization of the maximum distance traveled among all districts, the care workload equilibrium being considered in constraints (18) and (19) which define the minimum and maximum allowable care workload within each district as a percentage of $\overline{wd}$.

Note that the quality of results associated with Model 1 and Model 2 depends respectively on the maximum distance allowed between two basic units that can be assigned to the same district d_{max} and the admissible percentage deviation τ chosen by the HHC manager.

4. Computational results

The purpose of this section is to analyze the behavior of the models proposed for the HHC districting problem by testing each model on 4 scenarios. Table 1 presents the objective function and hard constraints that have to be respected for each of the eight scenarios considered.

For each scenario, we begin by setting the values of the number of basic units N, number of districts to design M, number of profiles H, maximum distance between two basic units that can be assigned to the same district d_{max} (in Model 1) or percentage deviation τ (in Model 2). After that, for one instance, we generate randomly the distance matrix $d_{(N,N)}$, number of visits b_h, average duration of the visits T_h relative to the profile h, number of patients P_{ih} having the profile h and living in the basic unit i and compatibility matrix $e_{(N,N)}$. Notice that the latter parameter is generated only for testing scenarios 2 and 3 where we consider the compatibility constraint. We solve the problem for one instance where we calculate the value of *gap _max* (Model 1) or *distance* (Model 2). If a solution (optimal or simply feasible) could be obtained within 60 min of computation, the problem is considered feasible for this instance. We repeat the random generation of $d_{(N,N)}$, b_h, T_h, P_{ih} and $e_{(N,N)}$ 20 times and then evaluate the mean *gap _max* (Model 1) or the mean *distance* (Model 2) over these 20 instances that have equal N, M, H, d_{max} (or τ) values and different $d_{(N,N)}$, b_h, T_h, P_{ih} and $e_{(N,N)}$ values as well as the feasibility percentage over these 20 instances.

These parameters are generated as follows:

- The problem dimension: it refers to the number of basic units N and the number of districts to design M. By considering 4 different values of N (N ∈ {10, 20, 40, 100}) and M (M ∈ {1, 2, 3, 4}), we

Table 1
Criteria considered in each scenario.

	Model 1	Model 2
Scenario 0	Objective function (2) Constraints (3), (4), (5), (6), (7), (10)	Objective function (12) Constraints (13), (14), (15), (16), (20)
Scenario 1	Objective function (2) Constraints (3), (4), (5), (6), (7), (9), (10)	Objective function (12) Constraints (13), (14), (15), (16), (18), (19), (20)
Scenario 2	Objective function (2) Constraints (3), (4), (5), (6), (7), (8), (10)	Objective function (12) Constraints (13), (14), (15), (16), (17), (20)
Scenario 3	Objective function (2) Constraints (3), (4), (5), (6), (7), (8), (9), (10)	Objective function (12) Constraints (13), (14), (15), (16), (17), (18), (19), (20)

generate 4 types of instances: very small, small, medium and large size instances. Note that the case $M=1$ corresponds to the organization of the care delivery without adopting the districting approach and will serve as a basis for our numerical analysis.

- The distance matrix $d_{(N,N)}$ is generated as follows:
  - For each basic unit i, we randomly generate an abscissa X_i and an ordinate Y_i from a uniform distribution DU (0, 200).
  - For each pair of basic units i and k, the distance d_{ik} is then calculated according to the formula:

$$d_{ik} = \sqrt{(X_i - X_k)^2 + (Y_i - Y_k)^2} \tag{21}$$

- The number of profiles H is equal to 2.
- The number of visits b_h and the average duration of the visits T_h relative to the profile h, are generated randomly from uniform distributions respectively DU (0, 2) and DU (0, 5).
- The number of patients P_{ih} having the profile h and living in the basic unit i is generated randomly from a discrete uniform distribution DU (0, 20).
- The percentage deviation τ of each district care workload from the average care workload can be equal to 100%, 10% or 1%.
- The maximum distance between two basic units assigned to the same district, d_{max} can take different values that vary from 50 to 300: $d_{max} \in \{50, 60, 70, \ldots, 290, 300\}$.
- The compatibility matrix $e_{(N,\,N)}$ is generated as follows:
  - We fix a weight p_{max} that represents, for each basic unit i, the maximum ratio of incompatibilities with the other basic units k ($k=i+1 \ldots N$): $p_{max} \in \{0, 0.05, 0.1, \ldots, 0.3, 0.35\}$
  - For each line i of e:
    a We fix $e_{ii}=1$.
    b We randomly generate $e_{ik\ (k=i+1\ldots N)}$ such that the ratio of the number of zeros in the right part of the line i is less or equal to p_{max}.
  - For each column i of e:
    a $e_{ik\ (k=i+1\ldots N)} = e_{ki}$

The models proposed in this paper are coded in C++. All tests were run under Windows XP with an Intel Core Duo CPU (3 GHz) and 2 Go of RAM. We used a standard MIP software (CPLEX11.1) with the solver default settings.

4.1. Model 1

4.1.1. Scenario 0

This scenario is conducted in order to analyze the effect of varying the number of basic units N and the number of districts to design M on the mean *gap_max*. Therefore, we consider different values of N ($N \in \{10, 20, 40, 100\}$) and M ($M \in \{1, 2, 3, 4\}$) and we randomly generate for each couple (N, M) 20 instances as explained before. Since this scenario does involve neither the compatibility nor the compactness constraints i.e. constraints (8) and (9), feasible solutions could be found for all the instances considered. Results from Table 2 that display the values of mean *gap_max* of each 20 instances' set characterized by a couple (N, M) show that:

- For a given N, the higher is M, the worse is the mean gap_max (i.e. the worse is the workload balance) since it is more difficult to have equal workloads among the districts.
- For a given M, the higher is N, the better is the mean *gap_max* due to the fact that a high number of basic units increases the chance of getting equitably loaded districts.

For the remaining scenarios, all our numerical examples have been run for $M=2$, 3 and 4. Since the results of different values of M yield the same qualitative behavior, we therefore present the numerical results associated with the case $M=2$ in the following sub-sections. Additional results for $M=3$ are provided in the Appendix A.

4.1.2. Scenario 1

Within the framework of this scenario, we intend to study the impact of the compactness constraint on the mean *gap_max* for different values of N ($N \in \{10, 20, 40, 100\}$). Since the key parameter related to the compactness constraint is d_{max}, we experiment different values of d_{max} which vary between 90 and 290 in steps of 20. For each combination (N, d_{max}), we generate randomly 20 instances as explained before. Notice that the value of d_{max} is defined by the HHC managers on the basis of the satisfaction level of patients admitted to the HHC structure. Indeed, a small value of d_{max} reduces the average waiting time of the patients (especially in case of emergencies) which would improve the service quality level. In Table 3, we display the feasibility percentage of each 20 instances' set relative to a combination (N, d_{max}) and the mean *gap_max* values of the 20 instances' sets which correspond to 100% of feasibility.

From Table 3, we can make the following observations:

- For a given N, the percentage of feasible instances increases when the value of d_{max} increases.
- On the contrary, for a given d_{max}, the feasibility percentage decreases as long as the value of N increases.
- The value of d_{max} from which the problem becomes feasible for all the instances increases when N increases.
- For a given d_{max}, the higher is N, the better is the mean *gap_max*.
- For a given N, by increasing the maximum distance d_{max}, we decrease the mean *gap_max*. Indeed, by increasing d_{max}, we enlarge the number of possible basic units' grouping which leads to an improvement of the mean *gap_max*.

4.1.3. Scenario 2

The objective of this scenario is to study the impact of the compatibility constraint on the mean *gap_max* for different values of N ($N \in \{10, 20, 40, 100\}$). We then vary the key parameter p_{max} between 0 and 0.35 in steps of 0.05. We remember that the value of p_{max} reflects the nature of the territory where the HHC delivers the care to patients. Indeed, important values of p_{max} characterize rural areas or urban areas where the traveling between the different basic units is difficult. Table 4 shows the feasibility percentage of each 20 randomly generated instances' set relative to a pair (N, p_{max}) and the mean *gap_max* values of the 20 instances' sets which correspond to 100% of feasibility.

According to Table 4:

- For a fixed value of N, as long as the ratio of incompatibilities increases, the feasibility percentage decreases.
- Similarly, for a given value of p_{max}, the higher is N, the worse is the feasibility percentage.
- The threshold value of p_{max} from which the feasibility percentage becomes equal to 0 decreases when N increases. Indeed, the last two points can be explained by the fact that, for a fixed value of p_{max}, the number of incompatibilities increases when N increases which leads to the reduction of the basic units' grouping possibilities.
- For a fixed value of N, by increasing the ratio p_{max}, the mean *gap_max* increases. Actually, when p_{max} increases, the number of grouping possibilities decreases and thus the mean *gap_max* increases.

Table 2
Mean *gap_max* of Scenario 0.

N		10	20	40	100
M	1	0.0000%	0.0000%	0.0000%	0.0000%
	2	0.4031%	0.1448%	0.0192%	0.0008%
	3	1.5112%	0.3955%	0.0472%	0.0033%
	4	6.3625%	0.7809%	0.0834%	0.0132%

Table 3
Feasibility percentage and mean *gap_max* of Scenario 1.

N	10		20		40		100	
d_{max}	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*
90	0%		0%		0%		0%	
110	10%		0%		0%		0%	
130	25%		5%		0%		0%	
150	45%		25%		5%		0%	
170	100%	1.8699%	70%		10%		0%	
190	100%	0.6504%	85%		75%		5%	
210	100%	0.4248%	100%	0.1574%	100%	0.0471%	100%	0.0026%
230	100%	0.4212%	100%	0.1465%	100%	0.0423%	100%	0.0019%
250	100%	0.4031%	100%	0.1448%	100%	0.0403%	100%	0.0012%
270	100%	0.4031%	100%	0.1448%	100%	0.0398%	100%	0.0010%
290	100%	0.4031%	100%	0.1448%	100%	0.0192	100%	0.0008%

Table 4
Feasibility percentage and mean *gap_max* of Scenario 2.

N	10		20		40		100	
p_{max}	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*
0	100%	0.4031%	100%	0.1448%	100%	0.0019%	100%	0.0008%
00.05	100%	0.4031%	100%	0.1448%	100%	0.0665%	0%	
00.1	100%	0.4031%	100%	0.2216%	0%		0%	
00.15	100%	0.9815%	30%		0%		0%	
00.2	100%	2.4092%	0%		0%		0%	
00.25	75%		0%		0%		0%	
00.3	45%		0%		0%		0%	
00.35	0%		0%		0%		0%	

4.1.4. Scenario 3

This scenario represents a generalization of the last two scenarios. Three key parameters are then varied N ($N \in \{10, 20, 40, 100\}$), d_{max} ($d_{max} \in \{100, 150, 200, 250, 300\}$) and p_{max} ($p_{max} \in \{0, 0.05,\ldots, 0.3, 0.35\}$). We present in Table 5 the results for N = 10. Further results (for N = 20, 40 and 100) can be found in Appendix B. Notice that Scenario 1 is a special case of Scenario 3 for which p_{max} is equal to 0 as well as Scenario 2 for which $d_{max} = 290$. Consequently, as Table 5 and Appendix B show it, the results obtained in both Scenarios 1 and 2 can be generalized for the different values of respectively p_{max} and d_{max}. Furthermore, Table 5 and Appendix B display that for a given N, the higher is p_{max}, the higher is the threshold value of d_{max} from which the problem becomes feasible.

4.2. Model 2

4.2.1. Scenario 0

This scenario is conducted in order to analyze the impact of varying the number of basic units N and the number of districts to design M on the mean *distance*. We then consider different values of N ($N \in \{10, 20, 40, 100\}$) and M ($M \in \{1, 2, 3, 4\}$). Since this scenario does involve neither the compatibility nor the workload balance constraints i.e. constraints (17), (18) and (19); the problem is feasible for all the instances. The mean *distance* obtained for different values of N and M are presented in Fig. 1 which shows that:

- For a given N, the mean *distance* decreases when the number of districts to design M increases. Indeed, the design of more districts may conduct to grouping basic units that are closer to each other.
- For a given M, the higher is N, the higher is the mean *distance*. In fact, by increasing the number of basic units, we increase the probability of grouping basic units that are far from each other.

As for Model 1, we have conducted numerical tests for M = 2, 3 and 4 whose results have the same qualitative behavior. We therefore present in the following sub-sections the numerical results associated with the case M = 2 while those associated with M = 3 are provided in Appendix C.

Table 5
Feasibility percentage and mean *gap_max* of Scenario 3 for N = 10.

d_{max}			100	150	200	250	300
p_{max}	0	Feasibility percentage	10%	45%	100%	100%	100%
		mean *gap_max*	18.7662%	5.0126%	0.4356%	0.4031%	0.4031%
	0.05	Feasibility percentage	10%	45%	100%	100%	100%
		mean *gap_max*	18.7662%	5.0126%	0.4356%	0.4031%	0.4031%
	0.1	Feasibility percentage	10%	45%	100%	100%	100%
		mean *gap_max*	18.7662%	5.0126%	0.4356%	0.4031%	0.4031%
	0.15	Feasibility percentage	5%	30%	100%	100%	100%
		mean *gap_max*	34.7353%	5.9463%	1.9070%	0.9815%	0.9815%
	0.2	Feasibility percentage	5%	20%	85%	100%	100%
		mean *gap_max*	34.7353%	15.7677%	3.5948%	2.4092%	2.4092%
	0.25	Feasibility percentage	0%	5%	65%	75%	75%
		mean *gap_max*		21.2576%	13.2271%	12.3814%	12.3814%
	0.3	Feasibility percentage	0%	5%	35%	45%	45%
		mean *gap_max*		21.2576%	13.9517%	13.3025%	13.3025%
	0.35	Feasibility percentage	0%	0%	0%	0%	0%
		mean *gap_max*					

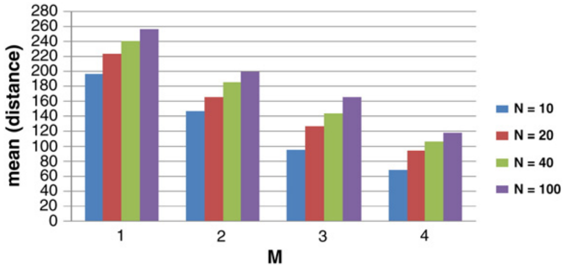

Fig. 1. Mean *distance* of Scenario 0.

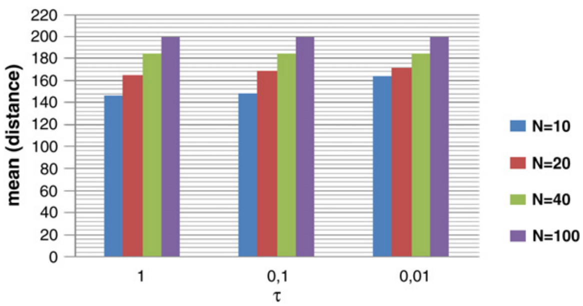

Fig. 2. Mean *distance* for Scenario 1.

4.2.2. Scenario 1

The objective of this scenario is to analyze the effect of the workload balance constraint on the mean *distance* for different values of N (N ∈ {10, 20, 40, 100}). Since this criterion depends on the admissible percentage deviation of the district workload from the average workload τ, we vary the values of τ ($\tau \in$ {100%, 10%, 1%}). Within the framework of this scenario, feasible solutions could be found for all the instances considered. As can be seen from Fig. 2:

- For a given τ, the higher is N, the higher is the mean *distance*.
- For a given N, by decreasing the admissible percentage deviation τ, we increase the mean *distance*. Indeed, when we decrease τ, we reduce the tolerance interval of the care workload and thus the number of possible combinations between the basic units which leads to a worse value of the mean *distance*.

4.2.3. Scenario 2

In this scenario, we vary the key parameter p_{max} ($p_{max} \in \{0, 0.05, \ldots, 0.3, 0.35\}$) in order to analyze the mean *distance* behavior when we integrate the compatibility constraint for different values of N (N ∈ {10, 20, 40, 100}). Table 6 which displays the feasibility percentage and the mean *distance* of each 20 instances' set relative to a couple (N, p_{max}) shows that the impact of p_{max} and N on the feasibility percentage as well as the impact of N on the threshold value of p_{max} from which all the instances become infeasible are in keeping with the first three results pointed out in the sub-Section 4.1.3. Moreover, the computational results presented in Table 6 prove that:

- For a given value of p_{max}, the higher is N, the higher is the mean *distance*.
- For a given value of N, the mean *distance* increases when the ratio of incompatibilities increases. Actually, when p_{max} increases, the number of grouping possibilities decreases and thus the mean *distance* increases.

4.2.4. Scenario 3

As explained before in sub-Section 4.1.4, this scenario represents a generalization of the last two scenarios within which we vary the values of three key parameters i.e. N (N ∈ {10, 20, 40, 100}), τ ($\tau \in \{1, 0.1, 0.01\}$) and p_{max} ($p_{max} \in \{0, 0.05, \ldots, 0.3, 0.35\}$). The analysis of Table 7 and Appendix D which display the feasibility percentage and the mean *distance* for respectively N = 10, 20 and N = 40, 100 indicate that the results of Scenarios 1 and 2 are valid for respectively different values of p_{max} and τ. Furthermore, Table 7 and Appendix D point out that:

- For a given N and a given p_{max}, the feasibility percentage decreases as long as the value of τ decreases.
- For a given τ and a given p_{max}, the higher is N, the worse is the feasibility percentage.
- The threshold value of p_{max} from which all the instances become infeasible increases when τ increases.

Since now, we have analyzed the results of applying the two models proposed for the HHC districting problem. However, even if the mathematical formulations of these two models differ, they represent the same criteria among which the workload balance and the compactness criteria are formulated differently. Consequently, it is possible to obtain, for given values of N and M the same performance in terms of workload balance and compactness by applying either Model 1 or Model 2. In the next section, we use an illustrative example to compare the different results obtained by both models.

4.3. Duality between Model 1 and Model 2

For testing the duality of the two models, we consider Scenario 1. We begin by fixing the key parameter of Model 2, $\tau = 1$ and varying N (N ∈ {10, 20, 40, 100}). For each instance k (k = 1…20) corresponding to a pair (N, 1), we apply Model 2 in the context of Scenario 1. This gives us the value of the maximum *distance* between two basic units that can be assigned to the same district for each instance. We consider that this value "$distance_k$" corresponds to the maximum distance that must be respected for this instance k according to the constraint (9) of Model 1. We can thus determine, by solving Model 1, the *gap_max* of each instance k (k = 1…20) corresponding to the pair (N, $distance_k$). Table 8 presents the performance measures of the two models for five instances among the twenty instances tested by applying the procedure described above.

Table 6
Feasibility percentage and mean *distance* of Scenario 2.

N		10		20		40		100	
		Feasibility percentage	Mean *distance*	Feasibility percentage	Mean *distance*	Feasibility percentage	Mean *distance*	Feasibility percentage	Mean *distance*
p_{max}	0	100%	145,908	100%	165,000	100%	184,927	100%	199,577
	00.05	100%	145,908	100%	165,000	100%	211,915	0%	
	00.1	100%	145,908	100%	196,828	0%		0%	
	00.15	100%	155,798	30%	219,819	0%		0%	
	00.2	100%	167,167	0%		0%		0%	
	00.25	75%	179,339	0%		0%		0%	
	00.3	45%	183,285	0%		0%		0%	
	00.35	0%		0%		0%		0%	

Table 7
Feasibility percentage and mean *distance* Scenario 3 for N = 10 and 20.

N			10			20		
τ			1	00.1	00.01	1	00.1	00.01
p_{max}	0	Feasibility percentage	100%	100%	100%	100%	100%	100%
		mean *distance*	145,908	147,802	164,426	165,000	168,691	171,135
	00.05	Feasibility percentage	100%	100%	100%	100%	100%	100%
		mean *distance*	145,908	147,802	164,426	165,000	168,691	171,135
	00.1	Feasibility percentage	100%	100%	100%	100%	100%	100%
		mean *distance*	145,908	147,802	164,426	196,828	196,846	201,879
	00.15	Feasibility percentage	100%	100%	75%	30%	25%	10%
		mean *distance*	155,798	156,043	168,076	219,819	217,079	221,015
	00.2	Feasibility percentage	100%	100%	55%	0%	0%	0%
		mean *distance*	167,167	174,625	179,508			
	00.25	Feasibility percentage	75%	35%	5%	0%	0%	0%
		mean *distance*	179,339	171,142	151,842			
	00.3	Feasibility percentage	45%	10%	0%	0%	0%	0%
		mean *distance*	183,285	171,207				
	00.35	Feasibility percentage	0%	0%	0%	0%	0%	0%
		mean *distance*						

After that, we calculate for Model 1, the percentage deviation of the care workload from the average care workload, of each instance k. This percentage deviation is formulated as $(\tau_1)_k = 1 - gap_{\max_k}$. The mean values of τ_1 that correspond to the different values of N are presented in Table 9. Notice that the values of τ_1 are close to τ and that the bigger is N, the closer is τ_1 to the value of τ that we consider for Model 2.

These results show that for improving the workload balance (Model 1), we should reduce the number of districts to design. On the contrary, for reducing the distances traveled within each district (Model 2), it is better to partition the territory as much as possible. It is also clear that the respect of the hard constraints related to the compatibility and workload/compactness explains the existence of infeasible instances as well as the worsening of the workload balance or the compactness measure.

Table 8
Results of Scenario 1 considered for Model 1and Model 2 for instances 1, 5, 10, 15 and 20.

		Instance	1	5	10	15	20
N	10	Model 2 *distance*	132,012	155,285	157,971	131,781	164,535
		Model 1 *gap_max*	No solution	78.654	No solution	No solution	15.745
	20	Model 2 *distance*	198,263	168,708	155,940	141,963	165,321
		Model 1 *gap_max*	2.680	No solution	0.477	4.390	7.865
	40	Model 2 *distance*	186,993	177,787	199,215	187,052	187,522
		Model 1 *gap_max*	2.111	3.604	1.073	No solution	1.638
	100	Model 2 *distance*	190,589	203,882	197,695	205,872	198,222
		Model 1 *gap_max*	No solution	No solution	0	No solution	0.015717

Table 9
Mean values of τ_1.

N	10	20	40	100
τ_1	0.918	0.988	0.999	1.000

5. Conclusion and perspectives

In this paper, we developed two models for the districting problem applied to HHC structures. We also presented a numerical analysis based on different instances generated randomly. This enabled us to evaluate the impact of the key parameters on the workload balance and compactness criteria. Indeed, their analysis indicates that for a given M, p_{max} and d_{max} (Model 1) or τ (Model 2), by increasing N, the feasibility percentage and the mean *distance* are weakened while the mean *gap_max* is improved. Similarly, for a given N, p_{max} and d_{max} (Model 1) or τ (Model 2), the feasibility percentage decreases and the mean *gap_max* or *distance* increases as long as p_{max} increases or the value of d_{max} (Model 1) or τ (Model 2) decreases. Furthermore, for a fixed value of N, the higher is the number of districts to design M, the higher is the mean *gap_max* and the less is the mean *distance*.

Since this work was based on instances generated randomly, we consider, in our ongoing research, to apply the proposed models to a real case of a HHC structure. In this context, developing a heuristic approach for solving the real instances represents also an interesting research priority.

Furthermore, we intend to consider several extensions of the models we propose. The first extension concerns the periodic revision of the districting problem on a rolling horizon so that new information on demand related to the number of patients who need the care, level of care required by each patient, changes in the number of caregivers, etc. can be integrated to the districting decision. This process of revision of the districting (i.e. the redistricting problem) can also respect additional constraints such as a maximum number of changes in basic unit–district assignments over a period of time in order to preserve the development of relationships between patients and caregivers, the organization of the work of caregivers with local community agencies, etc.

A potential second extension would concern the possibility to optimize simultaneously the care workload and the travel distance criteria while forming the districts. This can be done by using a multi-criteria approach which consists on formulating the problem as a weighted sum of the maximum deviation of the district care workload from the average care workload and the maximum distance between two basic units that can be assigned to the same district. Such approaches have been applied for solving the districting problem in other realms such as the electrical power districting problem or the political districting.

Overall, we must keep in mind that the objective of this work is not to develop a total automatic procedure but to propose a decision support system for the HHC managers who would modify solutions obtained by the mathematical models based on their experience. This interaction would probably conduct to more suitable solutions according to the criteria that are difficult to quantify. Furthermore, the HHC managers should verify the efficiency of adopting the districting approach for improving the human resources management in terms of its impact on increasing human resources motivation and work satisfaction.

Appendix A. Computational results associated to Model 1 for M = 3

In this appendix, we present the computational results associated with Model 1 when we consider Scenarios 1 and 2 for M = 3. As Scenario 3 represents a combination of Scenarios 1 and 2, the computational results associated to it are not presented here. However, they can be provided on demand.

Table A1
Feasibility percentage and mean *gap_max* of Scenario1.

N	10		20		40		100	
d_{max}	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*	Feasibility percentage	Mean *gap_max*
90	35%	38.9030%	0%		0%		0%	
110	70%	29.3799%	15%	12.4262%	0%		0%	
130	95%	22.3711%	60%	13.1502%	20%	12.0852%	0%	
150	100%	9.2841%	95%	5.0357%	55%	1.2508%	5%	0.0001%
170	100%	2.0086%	100%	0.0851%	100%	0.1528%	65%	0.0343%
190	100%	1.7642%	100%	0.0147%	100%	0.1173%	100%	0.0176%
210	100%	1.6051%	100%	0.0048%	100%	0.1115%	100%	0.0107%
230	100%	1.5861%	100%	0.0026%	100%	0.1043%	100%	0.0073%
250	100%	1.5861%	100%	0.0022%	100%	0.1043%	100%	0.0071%
270	100%	1.5861%	100%	0.0022%	100%	0.1043%	100%	0.0080%
290	100%	1.5861%	100%	0.0022%	100%	0.1043%	100%	0.0068%

Table A2
Feasibility percentage and mean *gap_max* of Scenario 2.

N	10		20		40		100	
p_{max}	Feasibilitypercentage	*Mean gap_max*	Feasibility percentage	*Mean gap_max*	Feasibility percentage	*Mean gap_max*	Feasibility percentage	*Mean gap_max*
0	100%	1.5112%	100%	0.4212%	100%	0.1043%	100%	0.0068%
0.05	100%	1.5112%	100%	0.4212%	100%	0.1188%	100%	0.0606%
0.1	100%	1.5112%	100%	0.4212%	100%	0.1576%	0%	
0.15	100%	1.9519%	100%	0.4629%	15%	15.0127%	0%	
0.2	100%	2.3756%	100%	1.2655%	0%		0%	
0.25	100%	4.2716%	80%	11.3519%	0%		0%	
0.3	100%	4.7516%	5%	9.6227%	0%		0%	
0.35	100%	9.1318%	0%		0%		0%	
0.4	95%	10.4941%	0%		0%		0%	
0.45	65%	14.5959%	0%		0%		0%	
0.5	65%	14.5959%	0%		0%		0%	
0.55	10%	35.8739%	0%		0%		0%	
0.6	0%		0%		0%		0%	

Appendix B. Computational results associated to Model 1 applied to Scenario 3 for N = 20, 40, 100 and M = 2

Table B1
Feasibility percentage and mean *gap_max* of Scenario 3 for N = 20.

d_{max}			100	150	200	250	300
p_{max}	0	Feasibility percentage	0%	25%	100%	100%	100%
		mean *gap_max*		3.3296%	0.1632%	0.1448%	0.1448%
	0.05	Feasibility percentage	0%	25%	100%	100%	100%
		mean *gap_max*		3.3296%	0.1632%	0.1448%	0.1448%
	0.1	Feasibility percentage	0%	0%	65%	100%	100%
		mean *gap_max*			0.9148%	0.2216%	0.2216%
	0.15	Feasibility percentage	0%	0%	5%	30%	30%
		mean *gap_max*			27.1218%	6.9352%	6.9352%
	0.20–0.35	Feasibility percentage	0%	0%	0%	0%	0%
		mean *gap_max*					

Table B2
Feasibility percentage and mean *gap_max* of Scenario 3 for N = 40.

d_{max}			100	150	200	250	300
p_{max}	0	Feasibility percentage	0%	0%	95%	100%	100%
		mean *gap_max*			0.0625%	0.0404%	0.0192%
	0.05	Feasibility percentage	0%	0%	20%	95%	100%
		mean *gap_max*			0.1380%	0.0718%	0.0665%
	0.1–0.35	Feasibility percentage	0%	0%	0%	0%	0%
		mean *gap_max*					

Table B3
Feasibility percentage and mean *gap_max* of Scenario 3 for N = 100.

d_{max}			100	150	200	250	300
p_{max}	0	Feasibility percentage	0%	0%	60%	100%	100%
		mean *gap_max*			0.0002%	0.0019%	0.0008%
	0.05	Feasibility percentage	0%	0%	0%	0%	0%
		mean *gap_max*					
	0.1–0.35	Feasibility percentage	0%	0%	0%	0%	0%
		mean *gap_max*					

Appendix C. Computational results associated to Model 2 for M = 3

As in Appendix A, we present in this appendix the computational results associated to Model 2 when we consider Scenarios 1 and 2 for M = 3. The computational results associated to Scenario 3 can be provided on demand.

Table C1
Feasibility percentage and mean *distance* of Scenario 2.

τ	N	10	20	40	100
1	Feasibility percentage	100%	100%	100%	100%
	mean *distance*	96,340	127,209	143,549	165,442
0.1	Feasibility percentage	100%	100%	100%	100%
	mean *distance*	129,832	135,568	144,310	165,442
0.01	Feasibility percentage	25%	100%	100%	100%
	mean *distance*	160,963	145,714	145,780	165,442

Table C2
Feasibility percentage and mean *distance* of Scenario 3.

N		10		20		40		100	
		Feasibility percentage	Mean *distance*	Feasibility percentage	Mean *distance*	Feasibility percentage	Mean *distance*	Feasibility percentage	Mean *distance*
p_{max}	0	100%	96,340	100%	126,476	100%	143,549	100%	165,442
	0.05	100%	96,340	100%	126.476	100%	171,488	100%	219,764
	0.1	100%	96,340	100%	143,768	100%	191,334	0%	
	0.15	100%	106,580	100%	155,526	10%	223,479	0%	
	0.2	100%	112,410	80%	179,163	0%		0%	
	0.25	100%	131,486	5%	194,088	0%		0%	
	0.3	100%	136,230	0%	186,471	0%		0%	
	0.35	90%	143,975	0%		0%		0%	
	0.4	65%	147,252	0%		0%		0%	
	0.45	10%	158,231	0%		0%		0%	
	0.5	10%	144,068	0%		0%		0%	
	0.55	0%	144,068	0%		0%		0%	
	0.6	0%		0%		0%		0%	

Appendix D. Computational results associated to Model 2 applied to scenario 3 for N = 40, 100 and M = 2

Table D1
Feasibility percentage and mean *distance* Scenario 3 for N = 40 and 100.

N			40			100		
T			1	0.1	0.01	1	0.1	0.01
p_{max}	0	Feasibility percentage	100%	100%	100%	100%	100%	100%
		mean *distance*	184,927	184,927	184,927	199,577	199,577	199,577
	0.05	Feasibility percentage	100%	100%	100%	0%	0%	0%
		mean *distance*	211,915	211,915	212,561			
	0.1–0.4	Feasibility percentage	0%	0%	0%	0%	0%	0%
		mean *distance*						

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