Contents

1 Introduction **6**

1.1 Introduction 6

1.2 The home health care service 7

1.3 Motivations 8

1.4 Scope and objectives 9

1.5 Report structure 10

1.6 Conclusions 10

2 The Home Health Care Scheduling Problem: A Literature Review **11**

2.1 Introduction 11

2.2 Hierarchical optimization problems 11

2.3 The HCSP as a hierarchical COP 12

2.4 HCSP: the assignment component 14

2.4.1 Constraints 15

2.4.2 Objectives 16

2.4.3 Literature review 16

2.5 HCSP: the routing component 18

2.5.1 Constraints 19
2.5.2 Objectives 20
2.5.3 Literature review 20
2.6 The dynamic home care scheduling problem 21
2.6.1 Constraints 22
2.6.2 Objectives 25
2.6.3 Literature review 25
2.7 Conclusions 26

3 HCSP modeling and solving approach 28

3.1 Introduction 28
3.2 HCSP variant: the MTSP with time windows 29
3.2.1 Definition of the MTSP 30
3.2.2 Mathematical model 31
3.3 Solving approach: Tabu search 32
3.3.1 Description 33
3.3.2 Parameters 34
3.3.2.1 Initial solution 34
3.3.2.2 Neighborhood generation operators 34
3.3.2.3 Tabu list 35
3.3.2.4 Aspiration criteria 36
3.3.2.5 Intensification and diversification 36
3.3.3 Main TS algorithm 36
3.4 Conclusions 37

4 Simulation, Implementation and Computational results **38**

4.1 Introduction 38

4.2 Instances simulation 38

4.3 Implementation 39

4.3.1 Experimental context: ParadisEO 39

4.3.2 Parameters setting 42

4.3.3 Computational results 42

4.4 Conclusions 47

5 Conclusions and perspectives **48**

A Example of modified Solomon's instance **59**

B Detailed computational results **61**

List of Tables

4.1 Computational results for instances of the type R1 43

4.2 Computational results for instances of the type R2 44

4.3 Computational results for instances of the type C1 45

4.4 Computational results for instances of the type C2 45

4.5 Computational results for instances of the type RC1 46

4.6 Computational results for instances of the type RC2 46

A.1 The modified instance C101 60

B.1 Detailed result of instance: C101 62

B.2 Detailed result of instance: C201 63

B.3 Detailed result of instance: R101 64

B.4 Detailed result of instance: R201 65

B.5 Detailed result of instance: RC101 66

B.6 Detailed result of instance: RC201 67

List of Figures

4.1 Architecture of ParadisEO 40

4.2 Neighborhood search with ParadisEO 41

Chapter 1

Introduction

1.1 Introduction

The main purpose of our work is to present the home health care scheduling and to resolve it like a dynamic combinatorial optimization problem using the TS meta-heuristic. The objective of this chapter is to introduce the core problem studied in this master's thesis, the Home Care Scheduling Problem (HCSP). In order to do so, a general presentation of the concept of home health care is firstly introduced in section 2. In section 3, we will present our motivations for studying, modeling and solving the Home Care Scheduling Problem (HCSP) by stating the scope and the objectives of the project. The report structure will be presented in section 5 and the chapter will be concluded in the last section.

1.2 The home health care service

Home or domiciliary care is the provision of continuous and coordinated cares (medical and paramedical services) to patients in their own homes, according to a formal assessment of their needs with the aim of maintaining or improving their life conditions. This support is made by medical suppliers that are generally nurses, drug vendors, technicians, etc. The aim is to provide the care and support needed to assist people, particularly elderly people, people who need assistance due to illness and people with physical or learning disabilities to live as independently as possible in their own homes to maintain or improve their life conditions. The Home Health Care (HHC) services are a growing service industry which must face scheduling and routing problems. Its development is accelerated by several factors such as the introduction of innovative technologies, the population ageing, the increase in chronic pathologies, and the continuous pressure of governments to contain health care costs. Besides, HHC services provide complex and coordinated medical and paramedical cares to patients at their homes. Services include nursing, therapy activities, medical and social services, house cleaning, etc. Moreover, continual improvement in HHC is important for ensuring quality of patient cares which has become a vital objective. Technological advances in telecommunications allow the actors of the home health care system to exchange rapidly the required information to complete the asked for services. Patients can submit or ask for the service by phone call or internet queries. Hospitals or care agencies can schedule their medical staff and inform patients, in real time, about the team who visit them to complete the required treatment. From the stakeholder (hospitals, agencies) position, the objective of the HHC is to ensure effi-

ciently the service of patients. Service efficiency is defined by customers satisfaction and also the cost incurred by the completion of the service. To reach the announced objective of cost minimization, analytical models and solving algorithms can give a considerable support for decision makers and schedulers.

1.3 Motivations

Home health care services can be viewed as the problem of satisfying a set of patients queries to be served at their home. That is by employing a medical or a paramedical staff. Intuitively, many questions need to be answered such as:

1. Which staff member (or team) will be assigned to each patient?
2. Do nurses and caregivers will move alone or in groups to patients' homes? If some grouping is required, how to cluster them?
3. What are the routes to be followed by staff groups in order to move to patients' locations?

It is clear that the answer of each question is not trivial and each question represents a standalone optimization problem. The first question defines an assignment problem where the objective is to design an optimal affectation (assignment) of nurses to patients. The second question can define a clustering (grouping) problem and the aim is there to define the groups of caregivers who will move together using the same transportation tool. The third question is a routing problem where it asks for an optimal set of routes to be followed by medical groups to visit patients at their homes. All of these problems are highly constrained and a lot of constraints have to

be satisfied at each step. We can cite, staff workload constraints, routing constraints like time windows, etc. Moreover, these questions and problems are not independent, in the sense that the answer of the first question will be an input to the second question and then the answer of the second question will be the input of the third question. For instance, the proposed assignment (answer of question 1) will affect the design of the nurse groups that will move together. For example, nurses assigned to patients in the same city will move together. Following the defined groups, the routes will be designed in the third level. Thus, the Home Health Care Scheduling Problem named HCSP is explicitly to answer patients' demands for service at their homes. But, implicitly, it is a sequence of three dependent optimization problems. Such optimization problems are called Hierarchical problems or dynamic problems. Hierarchical problems are NP-Hard Combinatorial Optimization Problems.

1.4 Scope and objectives

The research project can be situated in the field of health care study from an analytical point of view. Particularly, it focuses on home health care services and how their operational schedules can be enhanced using Operations Research (OR) models and solving algorithms. The aim of this master project is then to handle a hierarchical problem which is the HCSP. We will attempt to present a comprehensive near-exhaustive review of the HCSP literature by presenting its main components (sub-problems). We will show that many versions of the HCSP can arise in real life and we will develop a Tabu Search (TS) based algorithm for solving a variant of the HCSP. An implementation and simulation step will be conducted to solve HCSP

instances obtained by modifying Solomon's benchmarks.

1.5 Report structure

This report will be organized as follows:

- Chapter 2 will present a review of the HCSP literature by describing a framework containing the major works for each HCSP component (Assignment, routing and the dynamic HCSP).
- Chapter 3 will be devoted to the description of the studied HCSP variant; we will present the basic assumptions and the solving approach which is the Tabu Search with intensification and diversification.
- Chapter 4 will provide the details of the problem simulation and solving algorithm implementation. It will report the computational results and their analysis.
- Chapter 5 will conclude the current work and presents some perspectives of future research.

1.6 Conclusions

In this chapter, we introduced and presented the problem object of the study. We mentioned the motivations behind handling the HCSP and the objectives we look for. In the next chapter, we present the literature review for the Home Care Scheduling Problem.

Chapter 2

The Home Health Care Scheduling Problem: A Literature Review

2.1 Introduction

The aim of this chapter is to present the main problem studied in this project which is the Home Health Care Scheduling Problem HCSP. We will present, first, the class of hierarchical optimization problems to which belongs the HCSP. Then, the HCSP literature is reviewed to illustrate the main contributions in modelling and solving the HCSP.

2.2 Hierarchical optimization problems

Many combinatorial optimization problems can be viewed as a particular combination and ordering of other optimization problems. There, the solution of the initial problem can be rebuilt by combining solutions of its subproblems. Generally, such

sub-decisions have to be token in a particular sequence (order) due to the fact that the solution of the upper level will define the level of optimality of the its following levels. Such kind of problems was defined as Hierarchical optimization problems and initially presented by Bracken and McGill [14] [15]. Other names may be found like Multi-level optimization problems [12] [28].

In the hierarchical optimization problems the decision making process is divided into different dependent levels. The decisions have to be token in a particular precedence order. That is, a decision or a solution of the first subproblem will affect the quality of the solution found in the subsequent level. Moreover, trying to optimize the overall problem solution needs a review of all token decision and not a solution of particular subproblem in a particular level. In the following section, we will study a hierarchical optimization problem which is the HCSP.

2.3 The HCSP as a hierarchical COP

The home health care is an emergent kind of health care service given at home. It consists of visiting patients at their homes and perform the required treatments without a need for moving patients. This type of service is generally given to elderly, handicapped and with special needs peoples. Patients suffering from long term maladies like Alzheimer. Moreover, some particular post-operational (after surgery) treatments can be completed at home without a need to carry them at the hospital. The hospital has a set of skilled caregivers able to perform the required task at patient homes. Basically, patients ask caregivers with particular skills to do the required treatments. Once assigned to patients, caregivers will move following specified routes to patients.

The home care service gains its importance from the considerable reduction in costs that may be incurred for patients and also for caregivers companies. The patient will have just to pay the service at home without extra charges related to hospitalization, transportation and overload of hospital facilities. The hospital or the company providing at home health care will gain benefit in term of patients satisfaction, low shortage rate of hospital facilities, etc.

The home health care problem asks, then, for finding the set of nurses assigned to each patients and also it needs to know the routes to be followed by each team of caregivers to reach its destination. Clearly, each decision comes as answer of a particular optimization problem. The first problem is an assignment problem where the question is on which caregiver will help which patient. The second problem, is on the routes to be followed by vehicles transporting nurses to reach their already assigned patients. Then, the solution of the assignment problem is an input to the routing problem. Consequently, the HCSP can be viewed and modeled as a hierarchical optimization problem. The literature on the HCSP, shows three types of studies of the problem: in first class the focus is on the assignment problem, in the second class of papers the main studied part is the routing problem and in some recent papers the problem is handled without omitting or hiding one of its two components. Subsequently, the next three subsections will present the relevant literature in each class.

2.4 HCSP: the assignment component

The home health care scheduling problem asks first for designing the set of assignments of nurses to patients. The proposed assignment has to respect the type of the service demanded by the patient. Generally, each treatment requires one or more caregiver skills. The visits have to be conducted within particular periods that can be specified by the patients or by the type of the treatment itself. Moreover, caregivers assignments will respect employment regulations and contracts in term of nurse's overall workload, breaks, etc. The HCSP assignment problem can be formally defined as follow: Given a set P of n patients located at different points in a transportation network and a set V of m caregivers hosted in a central point. Each patient p_i asks for particular treatments denoted s_i that can be covered by the company medical staff skills S; that's $s_i \in S$. Home cares have to be generally performed with respect to a particular time window $[e_i, l_i]$ where e_i is the earliest service time and l_i is the latest service time. The time window can be specified by the patient or by the medical treatment requirements itself. Furthermore, serving a patient p_i will generate a benefit c_i and employing a caregiver v_j will cost c_j. The assignment problems asks for designing a mapping from the set of caregivers V to the set of patients P. Many feasible assignments A may be found where:

$$A = \{(v_j, p_i), \text{ where } v_j \in V,\ p_i \in P \text{ and } s_i \subset s_j\}.$$

The HCSP problem looks for designing an optimal assignment $a \in A$ satisfying a set of constraints and optimizing a set of objectives. In the following subsections, we present the set of constraints and objectives of the HCSP's assignment component.

2.4.1 Constraints

The nurse task assignment process for home health care provider requires the respect of a large number of constraints. The proposed assignment should respect many constraints like caregivers availability, caregivers skills, qualifications required by tasks, employment contracts, patients preferences, etc. In this context, Ben Bachouch [5] described some of the considered constraints:

- The biggest workload of each nurse must be inferior or equal (limited) to P max (the upper bound of the workload of each nurse).
- The smallest workload of each nurse must be superior or equal (limited) to P max (the upper bound of the workload of each nurse).
- Each task is assigned to one and only one care worker according to a given rank.
- All the tasks must be realized into the working day of the care workers.
- The first task assigned to each care worker must begin after the beginning working hour of each care worker.
- The ending time of the last task assigned to each care worker must not exceed the ending working hour.
- Each task begins into his time window defined by the earliest and latest dates
- To realize a task, the care worker must have the required skills.

Another work that treats the same task is the work of Hertz and Lahrichi [45] in which they described the following constraints:

- The sum of work load of each nurse must be less than or equal to the average work load of all nurses.
- The sum of patients assigned to a nurse must be less than or equal to the average of the number of patients affected to all nurses.

2.4.2 Objectives

The purpose of the assignment task is to balance the workload between workers [45] [5] in order to enhance quality for patient caring and increase the quality of nursing works. Consistently balanced workloads help nursing managers to predict required staffing levels and identify over-staffed units more easily. Furthermore, distributing work fairly among nurses is essential for optimal quality of care. However, other objectives may be considered like maximizing benefits incurred by serving more patients with minimal number of caregivers. Given the number of potential objectives, the assignment problem can be modeled as single-objective or multi-objective problem [45].

2.4.3 Literature review

The assignment problem is a canonical optimization model and the problem has been widely studied from different positions. Assignment in helath care problem is a consistent part of the assignment literature. Assigning in home health service asks about the finding the best affectation of medical staff to patients. Mullinax and Lawley (2002) [55]cited some works focus on assignment in health care: Powers [59] suggests that excessive workloads are unsafe and promote poor quality of care. Drennan [32], Catterson [23] and Farnham et al. [36] agree that fair workloads among nurses are

essential for optimal quality of care. Walts et al. [69] develop a patient classification system and use an integer program to model and compute minimal staffing levels required to meet aggregate workload levels. Their approach provides significant reduction in staffing levels over current practice, while ensuring that nursing units are adequately staffed. Shaha and Bush [63] says that most patient assignments are based either on the intuitive judgment of the charge nurse or on the caseload method wherein each nurse is assigned the same number of patients. Drennan [32] says that it is not surprising that these methods lead to inconsistent workloads among nurses. Punnakitikashem et al. [60] mention some researchs studied nurse assignment to patients like the work of Overfelt [56] in which he proposed a modern patient classification systems partition the set of patients into groups, and each group is assigned to a nurse. Mullinax and Lawley [55] developed a neonatal acuity system to determine a nurse workload per patient and then used an integer linear programming model to propose patients-nurse assignment in a neonatal intensive care unit. Punnakitikashem et al. [61] developed a two stage stochastic integer programming model for a nurse patient assignment that considered uncertainty in patient care. Sundaramoorthi et al. [65] presented a simulation model from real data to evaluate nurse-patient assignments. Ben Bachouch et al. [5] mention some researchs studied nurse assignment to patients like Punnakitikashem [60] in which they developed an information technology prototype for assigning nurses to patients with the purpose of minimizing excess workload. Teoh [67] provided an overview of the workload measurement systems and its application to balance workload between workers. Lahrichi [45] aim to balance the workload of the nurses while avoiding long travels to visit patients. Abdennadher [1] discussed the nurse scheduling problem and a specific system named INTERDIP, is

presented using constraint logic programming. This system assists a human planner in scheduling the nurse working shifts for a hospital ward and provides a feasible planning in few minutes. Eiselt [34] in which they proposed a model for the assignment of tasks to individual employees, when several goals are considered and when there are constraints imposed by employees capabilities.

2.5 HCSP: the routing component

The main goal of the HCSP is to ensure a care for patients at their homes. That aim can be basically achieved by assigning care providers to patients and then moving the medical staff to serve the assigned patients. Then, once an assignment $a \in A$ is defined another question emerges which is on the routes to follow in order to visit patients. The efficiency of the overall home care service can be improved by examining the routing and scheduling decisions involved. Better routing and scheduling allows this business to achieve savings in their costs and, often times, an expansion in their service capabilities. Nowadays, performing routing tasks on a daily basis is not a choice but an obligation in the home health care industry.

The HCSP routing component can be defined by as set of care providers $v_i \in V$ hosted in a central point that can be a hospital or another staff grouping location. Each nurse v_i have to visit in a particular order as set of its already assigned patients $p_j \in P$ following the already defined also assignment a. Each patient j is identified by a location in the transportation network and distant to another patient k by a distance d_{jk}. Moreover, the service at patient j have to be conducted within a time interval $[e_j, l_j]$ and it will take the amount of time t_j. The goal of the HCSP routing

problem is to find the optimal set of routes to be followed by care providers vehicles to reach patients home and to complete the required treatments. To achieve a good scheduling, the routing component must consider the already proposed assignment and minimize transportation costs. The staff routes have many restrictions and the solution must balance many, often conflicting, objectives. In the following subsections, we detail the HCSP routing constraints and objectives.

2.5.1 Constraints

The HCSP routing problem is subject to a large number of scheduling and routing constraints. According to Eveborn et al (2005) and Bouazza Elbenani (2008), the optimal solution requires the respect of the following constraints:

- Each nurse have to respect the proposed assignment and he must visit the affected patients in a particular order.
- Each patient have to be visited exactly the number of required visits generally set to one visit.
- Care providers visits must be carried within the predefined time window.
- Each staff member has given planned breaks such as meals; sufficient travel time between visits must be allocated.
- Staff members visits will complete their circuits starting from the central point and then going back home at a defined moment (10h00 in [13]).

Additional operational constraints may be found like the precedence constraints between visits. For instance, a blood sampling visit has to precede any treatment

(second visit) determined by the results of the blood analysis.

2.5.2 Objectives

The purpose of the routing task is to make a schedule of allocation of patients to caregivers while taking into account a set of constraints and ensuring a set of goals. The premium objective of the routing task is to satisfy all customers. Additionally, many other routing objectives may be considered like:

- Minimizing the number of used vehicles.
- Minimizing the overall travelled distance.
- Balancing tours in term of staff workload.
- Minimizing the overall working time (accumulated durations of runs).

2.5.3 Literature review

The literature on routing problem is huge. Health care routing problem was also extensively studied to model and solve the routing component of the HCSP. Eveborn et al. [35] said that repeated matching was first used by Forbes [39], in bus crew scheduling is the basis for solving vehicle routing problems. There are many articles devoted to staff scheduling. One area is the airline industry, many works in this domain like the work of Hoffman and Padberg [46] and Gamache et al. [40] that showed that improved schedules has a considerable positive impact. In some applications, the schedules must be cyclic and examples of such applications are found in Mason et al. [52] and Beaumont [9]. Problems also differ whether the definition of a shift or task.

If the schedule is determined in advance [8, 52]. One area in the service industry that has attracted lot of attention is hospital and/or nurse scheduling we have the example of Dowsland [33] and Valouxis and Houses [68]. Also in the area of call centers like the work of Lin et al. [50]. Many heuristic methods have been used in the literature that we can mention the use of genetic algorithms by Cai [19], simulated annealing by M.J. Brusco and Jacobs [17] and tabu search [47, 33]. A variety of optimization based methods can be found like [53, 6]. Constraint programming is also used by itself or in combination with standard optimization models [20, 16]. Many applications use column generation techniques together with set-partitioning models [62, 40, 52]. In [13, 11], authors developed a computerised system which solves the nurse scheduling and the routing home care nurses problems. Cheng [27] formulated the routing home care nurses problem as a vehicle routing problem with time windows and multiple depots. Eveborn [35] introduced a scheduling problem for a variety of home care providers which is modeled as a set partitioning problem and solved with a repeated matching algorithm. Cheng [27] cited some of works about routing where the goal was to minimize the amount of work by minimizing the amount of travel needed. They considered that the home health care problem is, more generally, a vehicle routing problem with and without time windows (VRPTW).

2.6 The dynamic home care scheduling problem

The dynamic home care scheduling problem is a difficult task that aims to optimize both assignment and routing tasks. The problem is to find a feasible working plan for all nurses that have to respect a variety of hard and soft constraints, and prefer-

ences. It aims to find an operational working plan for the nurses without separating the assignment component and the routing component. Thus, there will be no initial assignment present as input to the routing problem and then have to be respected. The objective for the dynamic HCSP is to find the final health care manpower schedule without explicitly dividing the problem into different levels. As defined in the first section the HCSP can be viewed as multi-level optimization problem called also hierarchical optimization problem where decisions are token at different levels and each decision will affect the optimality of its following problem. For instance, the assignment obtained at the first level (the assignment component) will define the level of optimality of the routing problem. Then and in order to achieve a global optimal working plan, it is obvious to consider the different parts (level) of the HCSP as a unit without partitioning it into sub-problems.

The dynamic HCSP is defined as the problem of finding the set of routes to be followed by a set of caregivers to serve a set of treatments requested by a set of patients. It aims to optimize routes for each care worker in order to minimize the distance traveled providing that the capacity and service time window constraints are not violated.

2.6.1 Constraints

In dynamic HCSP, both assignment and routing constraints are defined and have to be respected in an a final feasible solution. Chananes et al. [24] presented some constraints to guarantee both good assignment and routing tasks that we can cite:

- Care workers are scheduled according to the requirements of the clients, who

may require more than one activity/visit per day.

- The demand has substantial peaks during the morning and early evening.
- Each activity must be delivered within a specified time window and location.
- Each activity can involve only one visit by one care worker so the maximum number of routes is equal to the number of care workers.
- The care workers start from their homes and return after finishing all their assigned activities. The total traveling distance is the sum of the distance from the care worker's home to the first client, the distances between the successive clients and the distance from the last client back to the workers home.
- For critical, medical activities the time window is a target time of 5 min. For non-critical activities the window is 15 min.
- If a care worker arrives before a time window, the service cannot begin and a waiting- time is incurred. If a care worker arrives after time window (late), the solution is infeasible.
- The maximum capacity of each worker is 7.5 h per day, including travel time.
- Each worker is assumed to be available 24 h per day, but can be used for only 7.5 h in that period.
- The travel speed of a care worker is assumed to be 30 miles per hour and traffic conditions are ignored.
- Locations are represented by easting and northing coordinates for each postcode.

- Some issues have been neglected, such as client-carer familiarity, skill-matching requirements, shift patterns and male/female preference for care workers.

Bertels [11] presented some constraints to guarantee both good assignment and routing tasks like all jobs must be cover by different schedules.

- All jobs must be covered at one and only time, any starting point for a job has to respect the hard time window.
- To require enough time to provide the service and to travel to the next job before the next job starts.
- To respect lower bound on the working time.
- To respect upper bound on the working time.
- To ensure that no job is carried outside the work time interval of the nurse.
- To guarantee to have all hard qualifications of a job covered by the assigned nurse.
- In order to model the cost function, the authors have to define their measure for violating soft constraints. Any violation of a soft time window will be penalized by a factor proportional to the earliness or lateness. More constraints are added to sum up all penalties, and normalize these numbers.
- Another constraint is added to guarantee that the double sum accumulates the travel time needed to travel between any two consecutive jobs for all schedules.
- Another constraint models the total working time of a nurse.

2.6.2 Objectives

The purpose of the home health care problem is to answer patients requirements by defining schedules to be followed by medical manpower in order to visit patients at their homes and complete the demanded treatments. Many different and often conflicting objectives may be considered. Such objectives can be derived first from the assignment problem objectives and also those of the routing problem. We can find then the following dynamic HCSP potential objectives:

- To reduce the traveling distance and hence traveling costs of the care workers;
- To improve worker utilization by reducing the waste of travel and consequently reducing the number of workers required;
- To increase customer service by satisfying all service requirements within their specified time windows;
- To free-up care managers time, they can undertake a more regulatory and strategic role.
- To minimize costs
- To satisfy employee preferences
- To distribute work equally.

2.6.3 Literature review

The HCSP was, basically, viewed as an assignment problem with a less important outing component or routing problem with some assignment. That is the focus was set

on the routing part or the assignment part. However, some interesting works consider the problem as unit and gave the same importance to the routing and the assignment and they conclude that an efficient scheduling has to optimize while assigning and also while routing [24]. The authors in [24]cited some works in this field like [71] in the domain of airline crew scheduling, the work of Bianco [12] in the domain of bus and truck driver scheduling and [25, 50] for optimizing a routing problem in call centers. A decision support system called LAPS CARE has been developed to aid the staff-planning task [35]. Chananes [24] presents the novel application of a collaborative population-based meta-heuristic technique called Particle Swarm Optimization (PSO) to the scheduling of home care workers. Bertels [11] cited some works about dynamic HCSP like the work of Cheng [27] that described a combined mixed-integer programming (MIP) and heuristics approach. In Begur [9] a decision support system that is based on simple scheduling heuristics was proposed. They mention in the context also the works of Abdennadher [1], Burke et al. [18], Cheng [26](1997) and Mason [52] as examples. Most of these use constraint programming techniques in order to model and solve the nurse rostering problem. Classical vehicle routing with time windows [37] [41] reflects the mobility aspect of the problem, but ignores any further restriction.

2.7 Conclusions

In this chapter, we proposed a framework for studying the hierarchial HCSP by presenting its main subproblems. We reviewed the HCSP literature by distinguishing the works focusing on the assignment component, the routing component and those

dealing with the hole problem and considering it as a unit. The next chapter will be devoted to present the HCSP variants and the assumptions token to obtain such particular variants. We will focus on an HCSP variant named the Multiple Traveling Salesman Problem with Time Windows. We will report its mathematical model and describe the proposed solving approach.

Chapter 3

HCSP modeling and solving approach

3.1 Introduction

The HCSP is by definition a hierarchical or multilevel optimization problem as shown in the previous chapter. The final solution of the HCSP is made by sequencing the solutions of its main subproblems mainly the assignment component and the routing component. In this chapter, we will present different variants of the HCSP; we will focus on the variant Multiple Traveling Salesman Problem with Time Windows (MTSPTW). We will present a mathematical model for the MTSPTW and the chosen solved approach the Tabu Search (TS).

3.2 HCSP variant: the MTSP with time windows

Health home are services can be analytically represented by the HCSP as shown in the previous chapter. However, the HCSP can be viewed as general problem where all kinds of home health care services can be converted to. Besides that, some real life HHC problems may be less restrictive than the basic HCSP depending on the hospital or agency business rules. We can find many variants of the HCSP following the considered assumptions and hypothesis. In the following we will describe some particular variants of the HCSP based on the number of different skills of a nurse and the number of treatments required by a patient.

- If the HCSP suppose that each nurse has one skill and each patient will ask for one treatment, then the assignment component is implicitly removed and the problem will consist on routing the set of caregivers to their already defined patients. However, more HCSP constraints are maintained. This kind of problems can be modeled as a Multiple Traveling Salesman Problem with Time Windows where a TSP with time window is defined for each nurse.

- If each staff member is described with one skill and patients may ask or more than one treatment (skill), then the routing problem is less important than the assignment subproblem. The major focus here is on which nurse will be assigned to serve each patient. Therefore, the objectives are generally those of the assignment component mainly workload balance. Such problems are generally assignment problems with a post-assignment part to define the routes to follow.

- Similarly to the previous case, if each nurse come with one skill and patients demand many treatments, the primary aim of the problem is to find the assignment and then design the paths for reaching patient's home.

- Suppose that nurses can provide many treatments and the patients may ask for many nurse's skills, then the problem will return to its initial definition and both parts (assignment and routing) will have the same importance for optimizing and then finding the best operational decisions. For this particular type health care variants, the problem have to be tackled without dividing it into two subproblems.

For some variants like the MTSPTW the objective is clear and the problem is well defined. But, for other instances the major or primary objective is generally defined by decision makers. They have to mention which problem or component (assignment or routing) is more important than the other. Another more natural and interesting alternative is to model the HCSP as a multiobjective optimization problems. In the remaining of this project, we will focus on modelling and solving the MTSPTW.

3.2.1 Definition of the MTSP

Basically, the multiple traveling salesman problem with time windows is an extension of the canonical Traveling Salesman Problem (TSP). The TSP asks for defining the optimal route for a salesman to visit a set of customers dispersed on a transportation network. In the basic TSP, a feasible solution must ensure that each customer will be visited exactly one. The MTSPTW consists of defining a TSP with Time Windows TSPTW for each medical staff and then design the route to follow for that caregiver.

Additional constraints related to time windows and workload have to be considered. The TSPTW has intended recently some interest to model and represent particular optimization problems arising in real life and also to find lower bounds to evaluate approximate optimization [2, 54, 7, 4, 58, 38].

The TSPTW in the context of HCSP can be defined as follow. Let $G = (V; A)$, be a graph where V is the set of customers and A is the set of arcs in G. To each customer is associated a time window noted $[e_i, l_i]$. Each arc $(i; j) \in A$ has a distance d_{ij} representing the cost of moving from i to j. A solution is feasible if the start time at each node is contained in its time window. Moreover, each customer have to be visited exactly once. An optimal solution to the problem is a feasible tour with minimum cost (distance).

3.2.2 Mathematical model

In this section, we report the Big-M formulation from [4]. The Big-M formulation defines the decision variable x_{ij} to be 1 if i is followed by j in the final solution or not. The variable s_i represents the time where the service starts at customer i. Following is the Big-M formulation:

$$Min \sum_{i,j \in V} x_{ij} d_{ij} \quad (1)$$

Subject to:

$$\sum_{j \in V} x_{ij} = 1 \qquad \forall j \in V \qquad (2)$$

$$\sum_{i \in V} x_{ji} = 1 \qquad \forall i \in V \qquad (3)$$

$$s_i + t_{ij} - (1 - x_{ij})M_{ij} \leq s_j \qquad \forall (i,j) \in A \qquad (4)$$

$$e_i \leq s_i \leq l_i \qquad \forall i \in V \qquad (5)$$

$$x_{ij} = 0 \qquad \forall i,j \in V \qquad (6)$$

where $Mij = e_i - l_j + t_{ij}$. The constraints (2) and (3) ensure that the x_{ij} variables with value 1 in a feasible solution. The constraints (4) ensure that start times at the nodes are increasing along any path (as $t_{ij} > 0$) and therefore directed cycles cannot exist in the solution. Finally, the constraints (4) and (5) together ensure that the solution respects time windows.

3.3 Solving approach: Tabu search

The Operations Research (OR) field offer a huge toolbox of methods, techniques, algorithms and software for solving combinatorial optimization problem. We can find exact algorithms that find the optimal solution of the studied problems, but they fail where the problem increase in dimensionality. Particularly, exact algorithm like branch and bound, dynamic programming, etc are suitable for solving small problem. For NP-hard class of optimization problems, obtaining the optimal in a reasonable time is not trivial. That is, a class of solving approaches were proposed to give a good compromise between the cost of the obtained solution and the time needed to find it. They are called heuristics or generally metaheuristics [66].

Metaheuristics represent a class of problem solving generic algorithms generally inspired from nature. We can cite Genetic Algorithms (GA), Simulated Annealing

(SA), Ant Systems (AS), Tabu Search (TS), etc. All these algorithms have proved their efficiency, with variable performance, in solving and handling a wide variety of optimization problems. Choosing a particular metaheuristic for solving an optimization problem depend generally on the number of parameters to set and if the heuristic is convergent asymptotically to an optimal solution. For solving the TSPTW, we select to implement a Tabu Search based heuristic. Our choice is explained by the reduced number of the TS algorithm parameters and also the experimental performance of the TS on routing problems [42].

3.3.1 Description

Tabu Search metaheuristic have been initially presented by Glover [43, 44] to be an evolved optimization problem solving metaheuristic. Tabu search is a metaheuristic that have the ability to guide the search process in order to ameliorate the neighborhood generation and evaluation mechanism. TS employ deterministic acceptance criteria by using a memory that constitutes an essential feature of TS. The basic features of tabu search are listed in the following:

- Initial solution generation algorithm,
- Neighborhood generation mechanisms,
- The memory (Tabu list),
- Tabu list size,
- Aspiration criteria
- Intensification and diversification schemas.

3.3.2 Parameters

In the following subsections, we will detail the parameters of the Tabu search metaheuristic.

3.3.2.1 Initial solution

Tabu search based heuristics start exploring the solutions space from an initial solution. The initial solution can be feasible or unfeasible and it will be used to apply a set of neighborhood generation operators to move to another solution in the search space. Generally, the initial solution is generated using a basic algorithm like the Sweeping algorithm or the Clarke and Write algorithm. However, it is possible to generate a random initial solution by randomly combining the set of patients (customers or cities). The performance of the heuristic depends on the quality of the initial solution. That is, some heuristic algorithms performs a multiple starting strategy where the initial solution is changed from a run to another in order to find the best one.

3.3.2.2 Neighborhood generation operators

In order to explore the search space, the TS metaheuristic and other local search heuristic implement the concept of neighborhood operators. These operators consists of doing some transformation on an input solution to create a set of other solutions named neighborhood. Many operators were proposed and implemented. We can cite and describe the followings [42]:

- The swap operator: It consists of taking two patients and swap their position in the current solution. By iteratively applying the swap operator over all possible

customers a neighborhood will be created.

- The k-opt operators: It is a set of operators by changing the value of k that is have to be greater than 2. We can find the 2-opt, 3-opt, etc. For example the 2-opt takes as input two routes (or 2 paths) and two different nodes each per route. Then, it will break the first route in its corresponding first point and complete it with the second part of the second route starting from point 2. The same action is done to complete second route where is it will be completed by the second part of the first route. Consequently and iteratively over all possible routes (paths) and all customers a very large neighborhood is created.

- Ejection chains: Proposed by Vigo and Roucairol, they consists of taking two sequences (paths) defined by a starting point and an end point from the current solution. The considered chain will be copied from the current route to the next route iteratively until reaching the last route. This operator was widely implemented particularly for hard optimization problems with time windows.

Once an operator is applied and the neighborhood is generated, the algorithm will select the best found new solution and it will consider it will be the new initial solution to continue exploring the search space.

3.3.2.3 Tabu list

The tabu list is the main feature of the TS metaheuristic; it is a particular storage space designed to save temporarily the set of already visited solution (those selected from the generated neighborhood). The process of selecting the next initial solution from the neighborhood has to verify that the selected solution is not in the Tabu list.

Consequently, the next chosen solution can be worst than already visited solutions and the algorithm will break its basic gradient descent. The tabu list is the memory that allows the search process to escape local minima. Its size is a major parameter for the success of the TS implementation and its value depends generally from the size of the problem. The tabu list size is generally static. But, in some implementations it is tuned dynamically to allow a better exploration of the search space.

3.3.2.4 Aspiration criteria

As mentioned before, selecting the next solution in the iterative search process should verify that it is not in tabu list. Sometimes, it is possible to find better solutions but they belongs to the tabu list. To overcome this limit, the TS metaheuristic use an aspiration criteria allowing the acceptance of better solutions even if they are tabu.

3.3.2.5 Intensification and diversification

The concepts of intensification and diversification were added to the basic TS algorithm by Taillard [66]. But, they can added to any local search based algorithm. The intensification consists of extensively searching around good solutions by using suitable operators and increasing the size of the tabu list. The diversification aims to explore new regions in the search space. The objective is simply to cover all possible zones where good solutions can be found. The diversification can be implemented using dynamic tabu list and some neighborhood operators.

3.3.3 Main TS algorithm

The main Tabu search metaheuristic operates as follows [44]: Some stopping condition

Algorithm 1 Tabu Search

Step 1: Choose an initial solution $i \in S$. $i^* = i$ and $k = 0$

Step 2: Set $k = k+1$ and generate a subset V^* of solution in $N(i, k)$ such that either one of the Tabu conditions is violated or at least one of the aspiration conditions holds.

Step 3: Choose a best $j \in V^*$ and set $i = j$.

Step 4: If $f(i) < f(i^*)$ then set $i^* = i$.

Step 5: Update Tabu and aspiration conditions.

Step 6: If a stopping condition is met then stop. Else go to Step 2.

can be used:

- No feasible solution in the neighborhood of solution i.
- A maximum number of iterations is reached.
- The number of iterations since the last improvement of i^* is larger than a specified number.

3.4 Conclusions

In this chapter, we presented the real variants of the HCSP that may appear in real life following the business rules. We announce the assumption used to consider the MTSPTW variant of the the HCSP to solve it. The solving approach was to implement a tabu search based metaheuristic for solving the MTSPTW. In the next chapter, we will detail instances simulations, TS implementation and computational results.

Chapter 4

Simulation, Implementation and Computational results

4.1 Introduction

In this chapter, we will focus on the technical details of the implementation of the TS based heuristic for solving modified instances of Solomon's benchmarks. We will report also the obtained computational results.

4.2 Instances simulation

In order to simulate MTSPTW instances, we choose to modify the benchmarks of Solomon of the Vehicle Routing Problem with Time Windows (VRPTW). Solomon's instances are divided into six classes. The geographical data are randomly generated in problem sets R1 and R2, clustered in problem sets C1 and C2, and a mix of random and clustered structures in problem sets by RC1 and RC2. Problem sets

R1, C1 and RC1 have a short scheduling horizon and allow only a few customers per route (approximately 5 to 10). In contrast, the sets R2, C2 and RC2 have a long scheduling horizon permitting many customers (more than 30) to be serviced by the same vehicle. The modifications applied to standard solomon's benchmarks are:

1. The vehicle are considered as nurses and to each nurse is associated a skill s_i.
2. Customers are transformed to be patients and each patient asks for a particular treatment represented by the required skill.
3. Time windows, locations ar maintained.

The modified instances represents now 56 instances of the MTSPTW. The appendix 1. presents the modified instance C101.

4.3 Implementation

4.3.1 Experimental context: ParadisEO

The HCSP solving approach has all been implemented using the tabu search metaheuristic from the ParadisEO-MO library [57]. ParadisEO is a C++ LGPL open source object-oriented framework for evolutionary computation that has been developed through an European joint work. ParadisEO integrates many services including visualization facilities, on-line definition of parameters, application checkpointing, etc.

ParadisEO-MO is an extended version of the EO framework that includes some features related to single solution-based metaheuristics. ParadisEO-MO is a general-purpose software framework dedicated to the design and the implementation of single

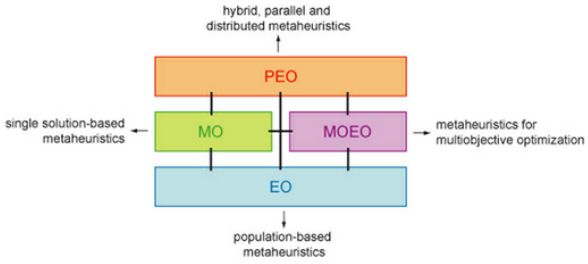

Figure 4.1: Architecture of ParadisEO

solution based metaheuristics and tools for fitness landscape analysis. It is based on a conceptual model that tends to unify a substantial number of state-of-the-art methodologies proposed so far. All those methods are here considered as simple variants of the same structure: a fine-grained decomposition of the general schema of local searches.

ParadisEO-MO is a white-box, object-oriented, C++, easy-to-use framework, portable across both Unix-like (Linux, MacOS) and Windows systems. The frame-

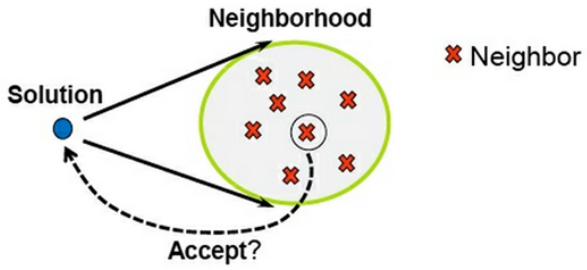

Figure 4.2: Neighborhood search with ParadisEO

work embeds some features and techniques for "fitness landscape analysis" and aims to provide a set of classes allowing to ease and speed up the development of computationally efficient programs. The rich set of ParadisEO-MO modular classes are combined to develop single solution based metaheuristics.

The related source code is maintained and regularly updated by the developers. Moreover, the framework perpetually evolves according to the needs and facilitates the development of new algorithms, either sequential or parallel, with a minimum

effort. The ParadisEO-MO module is based on a clear conceptual separation of the solution methods from the problems they are intended to solve. This separation confers a maximum code and design reuse to the user. For instance, to solve your own real-coded problem by means of local searches, you have just to define your evaluation function and your neighborhood structure. This makes from ParadisEO-MO a valuable tool for the scientific research community, the educational world and industrial organizations. The module tends to be used by both researchers and practitioners, non-specialists and experts, and has proven its validity and high flexibility by enabling the resolution of many academic and real-world problems.

4.3.2 Parameters setting

The results presented below are base on the following Tabu search parameters:

- Initial solution is randomly generated.
- Tabu list size=100.
- Neighborhood generation operators are the 2-opt and Swap operators.
- Stopping condition: maximum number of iterations is 1000.

4.3.3 Computational results

To demonstrate the efficiency of the implemented TS heuristic for solving the modified solomon's benchmarks, we report the following results in the next Tables. We will organize the computational results by type of the problem (R1, C1, R2, etc).

Instance Type	Name	Distance	Time (ms)
R1	R101	2049	4940
	R102	1980	4864
	R103	2009	5035
	R104	1982	4902
	R105	1982	4907
	R106	1999	4865
	R107	2000	4922
	R108	1931	4859
	R109	1905	4802
	R110	1939	4805
	R111	1957	4833
	R112	1932	4937

Table 4.1: Computational results for instances of the type R1

Instance Type	Name	Distance	Time (ms)
R2	R201	2030	5005
	R202	1838	4962
	R203	1997	5300
	R204	1940	5007
	R205	1924	5376
	R206	1970	5005
	R207	1956	5098
	R208	1901	5364
	R209	2031	4715
	R210	1903	4911
	R211	2006	4750

Table 4.2: Computational results for instances of the type R2

Instance Type	Name	Distance	Time (ms)
C1	C101	2509	5449
	C102	1413	5249
	C103	1982	5309
	C104	1547	5338
	C105	2081	5181
	C106	3029	5296
	C107	2602	5432
	C108	2623	5903
	C109	2547	5768

Table 4.3: Computational results for instances of the type C1

Instance Type	Name	Distance	Time (ms)
C2	C201	2579	5543
	C202	2609	5826
	C203	2393	5875
	C204	2509	5852
	C205	2467	5852
	C206	2535	5721
	C207	2559	5844
	C208	2558	5659

Table 4.4: Computational results for instances of the type C2

Instance Type	Name	Distance	Time (ms)
RC1	RC101	2703	4640
	RC102	2574	4742
	RC103	2855	5537
	RC104	2731	4721
	RC105	2732	4694
	RC106	2750	4677
	RC107	2867	4651
	RC108	2647	4613

Table 4.5: Computational results for instances of the type RC1

Instance Type	Name	Distance	Time (ms)
RC2	RC201	2808	5686
	RC202	2785	5693
	RC203	2793	5667
	RC204	2755	5350
	RC205	2790	5228
	RC206	2694	5642
	RC207	2744	5318
	RC208	2631	5552

Table 4.6: Computational results for instances of the type RC2

4.4 Conclusions

The object of this chapter is to validate the MTSPTW model proposed for representing the HCSP problem under the assumption defined in chapter 3. We implemented the TS metaheuristic using ParadisEO and we reported the obtained results. The performance of the solving approach validate the model and appear competitive if compared to similar approaches.

Chapter 5

Conclusions and perspectives

The interest in the problems of health is growing in the current life. Many areas are involved such as home care services and emergency services. In addition, requirements of patients and environmental issues provide a significant importance to health costs. Last years, many researches are done in health domain which cooperates in its improvement. The needs of automatic helps are primordial. As the information retrieval which helps in sorting and having pertinent document by a simple query. In addition, to facilitate the detection of concept many annotation systems are developed in order to extract information by moving from an instructed document to a structured one, and their resolution technologies have been critical for production companies (hospitals, cliniques,..).

In this master's thesis we deal with the problem of the HCSP. This problem consist to conduct a set of routes for a set of care givers that allows them to serve patients in their home while minimizing the distance of the tour, respecting window time (Ready time and due date) of patients.

Before getting into the resolution of this problem, we presented the problem as a combinatorial optimization problem. Then, we have detailed the metaheuristic which resolved our problem. Furthermore, we have formalized and modeled our HCSP. Therefore, a synthesis of literature concerning HCSP was presented. Since the HCSP is an NP-hard problem, solution for large instances cannot be obtained using exact methods in rational computational time. Thus, we adopted a TS metaheuristic based heuristic with intensification and diversification to solve some HCSP benchmarks. The related experiments were tested on modified versions of the Solomon's instances.

The perspectives of this work was multiple and it opens a wide area for exploring hard combinatorial optimization problems which are the hierarchical problem. It is clear that in this work we reduced the hardness of the HCSP to the MTSPTW using a realistic assumption. But we explored a new area of research with many perspectives, we can cite the following future investigations of hierarchical problems mainly the HCSP:

1. Consider the HCSP variant with an assignment, staffing and a routing components for modelling and solving.

2. Model the hierarchical HCSP as multiobjective optimization problem by considering routing objectives and assignment objectives.

3. Explore the potential of more evolved solving techniques for handling the hierarchical HCSP such the Approximate Dynamic Programming (ADP) algorithm.

Bibliography

[1] Abdennadher S. (1999), Schlenker H. Nurse scheduling using constraint logic programming. In: Proceedings of the 11th conference on innovative applications of artificial intelligence. Menlo Park, CA: AAAI Press; p: 83843.

[2] Albiach J., Sanchis J. M. and Soler D. (2008), An asymmetric TSP with timewindows and with time-dependent travel times and costs: An exact solution through a graph transformation, European Journal of Operational Research, Volume 189, Issue 3, p: 789802.

[3] Altinkemer K., Gavish B.(1991), Parallel savings based heuristics for the delivery problem, Operations Research 39, p: 456469.

[4] Ascheuer N., Fischetti M., Graotschel M.(2001), Solving the asymmetric travelling salesman problem with time windows by branch-and-cut, Mathematical Programming, Ser. A 90, p:475 - 506.

[5] Ben Bachouch R. (2010) An optimization model for task assignment in home health care. IEEE Workshop on Helath Care Management (WHCM10), Venise: Italie.

[6] C. Barnhart, E.L. Johnson, G.L. Nemhauser, M.W.P. Savelsbergh, P.H. Vance (1998), Branch-and-Price: Column generation for solving huge integer programs, Operations Research 46 , p: 316332.

[7] Bar-Yehuda R., Even G., and Shimon S. (2005), On Approximating A Geometric Prize-Collecting Traveling Salesman Problem With Time Windows, Journal of Algorithms,Vol 55/1, p: 76-92.

[8] Beasley J.E., Cao B. (1996), A tree search algorithm for the crew scheduling problem, European Journal of Operational Research 94, p:517526.

[9] Beaumont N.(1997), Scheduling staff using mixed integer programming, European Journal of Operational Research 98, p: 473484.

[10] Begur S.V., Miller D.M. ,Weaver J.R. (1997), An integrated spatial dss for scheduling and routing home-health-care nurses. Interfaces; 27(4), p:3548.

[11] Bertels S. (2006), Fahle T. A Hybrid Setup for a Hybrid Scenario: Combining Heuristics for the Home Health Care Problem.Computers and Operations Research; vol 33; p:2866-2890.

[12] Bialas W.F., Karwan M.H.(1982), On two-level optimization. IEEE Trans. Automat. Control, AC-27, p: 211214

[13] Bouazza E., Jacques A. F and Viviane G (2008). Mathematical Programming Approach for Routing Home Care Nurses, Proceedings of the IEEE IEEM.

[14] Bracken J., Falk J.E., McGill J.M. (1973), Mathematical programs with optimization problems in the constraints. Oper. Res., 21, p:3744

[15] Bracken J., Falk J.E., McGill J.M. (1974), Equivalence of two mathematical programs with optimization problem in the constraints. Oper. Res., 22 , p: 11021104

[16] Brailsford S.C., Potts C.N., Smith B.M.(1999), Constraint satisfaction problems: Algorithms and applications, European Journal of Operational Research 119, p:557-581.

[17] Brusco M.J., Jacobs L.W.(1993), A simulated annealing approach to the cyclic staff-scheduling problem, Naval Research Logistics 40 6984.

[18] Burke E., De Causmaecker P., Vanden Berghe G. (1999), A hybrid tabu search algorithm for the nurse rostering problem. In: McKay B,Yao X, Newton CS, Kim JH, Furuhashi T, editors. Simulated evolution and learning. Lecture notes in artificial intelligence, vol. 1585. Berlin: Springer; p:18794.

[19] Cai X., Li K.N.(2000), A genetic algorithm for scheduling staff of mixed skills under multi-criteria, European Journal of Operational Research 125 359369.

[20] Caprara A., Focacci F., Lamma E., Mello P., Milano M., Toth P., Vigo D. (1998), Integrating constraint logic programming and operations research techniques for the crew rostering problem, SoftwarePractice and Experiences 28, p:4976.

[21] Carpaneto, G., DellAmico, M., Fischetti, M., and Toth P. (1989), A branch and bound algorithm for the multiple depoot vehicle scheduling problem, Networks, 19, p:531-548.

[22] Caseau, Y., and Koppstein, P. (1992), A A Cooperative-Architecture Expert System for Solving Large Time/Travel Assignment Problems. In Database and Ex-

pert Systems Applications, proceedings of the International Conference in Valencia, Spain, eds A. Min Tjoa and I.Ramos, Springers-Verlag, Wien, p:197-202.

[23] Catterson J. (1988). How busy are you? Nursing Times 11, p: 2831.

[24] Chananes A., Pisal Y., Paul R. D.(2007), PSO-based algorithm for home care worker scheduling in the UK. Computers and Industrial Engineering 53, p: 559583.

[25] Cheang, B., Li, H., Lim, A., and Rodrigues, B. (2003). Nurse scheduling problems A bibliographic survey. European Journal of Operational Research, 151, p:447460.

[26] Cheng B.M.W., Lee J.H.M., Wu J.C.K. (1997), A nurse rostering system using constraint programming and redundant modeling. IEEE Transactions in Information Technology in Biomedicine (1): p:4454.

[27] Cheng E., Rich J.L. (1998), A Home Health Care Routing and Scheduling Problem. Technical report CAAM TR-04. Rice University.

[28] Colson B., Marcotte P., and Savard G. (2007), An overview of bilevel programming. Annals of Operations Research, 153, p:235-256.

[29] Desrochers M., Verhoog T.W. (1991), A new heuristic for the fleet size and mix vehicle routing problem, Computers and Operations Research 18, p:263-274.

[30] Desrochers, M., Lenstra, J.K, Savelsbergh, M.W.P. and Soumis F. (1988), Vehicle routing with time windows: optimization and approximation. In Vehicle Routing: Methods and Studies, eds B. Golden and A.A. Assad, North-Holland, Amsterdam, p:65-88.

[31] Desrosiers, J., Dumas., Y, Solomon, M, and Soumis, F. (1995), Time Constrained Routing and Scheduling. In Handbooks in Operations Research and Management Science, Vol. 8, eds M.O. Ball, T.L. Magnanti, C.L. Monma and G.L. Nemhauser, Elsevier Science, Amesterdam, p:35-129.

[32] Drennan V. (1990). Striving for fairer workloads. Nursing Times 10, p:12-14.

[33] Dowsland K.A. (1998), Nurse scheduling with tabu search and strategic oscillation, European Journal of Operational Research 106, p:393-407.

[34] Eiselt H. A. and Mirianov V. (2008), Employee positioning and workload allocation, computers and operations research, vol 35, p: 513-524.

[35] Everborn, P., Flisberg, P., and Ronnqvist, M. (2006). LAPS CARE An operational system for staff planning of home care. European Journal of Operational Research, 171, p:962-976.

[36] Farnham J.A., Maez-Rauzi V. and Conway K. (1992). Balancing assignments: a patient classification system for a step-down unit. Nursing Mngt 23, p: 49-54.

[37] Fisher ML.Vehicle routing. In: Ball MO, Magnanti TL, Monma CL, Nemhauser GL, editors. Network routing. Handbooks on operations research and management science, vol. 8, Amsterdam: North-Holland; 1995. p: 1-33.

[38] Focacci F., Lodi A., Milano M. (2002), A hybrid exact algorithm for the TSPTW. INFORMS Journal on Computing 14, p:403-417.

[39] Forbes M.A., Holt J.N., Kilby P.J., Watts A.M. (1991), A matching algorithm with application to bus operations, Australasian Journal of Combinatorics 4, p: 7185.

[40] Gamache M., Soumis F., Marquis G., Desrosiers J.(1999), A column generation approach for large-scale aircrew rostering problems, Operations Research 47,p: 247263.

[41] Gendreau M., Laporte G., Potvin J-Y. (1997), Vehicle routing: modern heuristics. In: Aarts EHL, Lenstra JK, editors. Local search in combinatorial optimization. NewYork: Wiley; p: 31136.

[42] Gendreau M. Metaheuristics in Vehicle Routing. ICORES 2012.

[43] Glover F. (1989), Tabu Search -Part I, ORSA Journal of Computing 1, p:190-206.

[44] Glover F. (1990), Tabu Search -Part II, ORSA Journal of Computing 2, p:4-32.

[45] Hertz A. and Lahrichi N. (2006), A patient assignment algorithm for home care service, les cahiers du GERAD.

[46] Hoffman K.L., Padberg M.(1993), Solving airline crew scheduling problems by branch-and-cut, Management Science 39, p: 657-682.

[47] Jarrah A.I.Z., Bard J.F., de Silva A.H.(1994), Solving large-scale tour scheduling problems, Management Science 40, p: 1124-1150.

[48] Laporte, G., Nobert, Y., and Aprin, D. (1984), Optimal Solutions to Capacitated Multidepot Vehicle Routing Problems, Congressus Nemeruntium, 44, p:283-292.

[49] Laporte, G., Nobert., Y, and Taillefer, S. (1988), Solving a Family of Multi-Depot Vehicle Routing and Location-Routing Problems, Transportation Science, 22, p:161-172.

[50] Lin, C. K. Y., Lai, K. F., and Hung, S. L. (2000). Development of a workforce management system for a customer hotline service. Computers and Operations Research, 27, p:9871004.

[51] Mason A.J., Ryan D.M., Panton D.M.(1998), Integrated simulation, heuristic and optimisation approaches to staff scheduling, Operations Research 46, p: 161175.

[52] Mason A.J., Smith M.C. (1998) A nested column generator for solving rostering problems with integer programming. In: Caccetta L, Teo KL, Siew PF, Leung YH, Jennings LS, Rehbock V, editors. International conference on optimisation: techniques and applications. p: 827834.

[53] Mingozzi A., Boschetti M.A., Ricciardelli S., Bianco L.(1999), A set partitioning approach to the crew scheduling problem,Operations Research 47, p: 873898.

[54] Mitrovi-Mini S., Krishnamurti R. (2006), The multiple TSP with timewindows: vehicle bounds based on precedence graphs, Operations Research Letters, Volume 34, Issue 1, Pages 111120

[55] Mullinax C. and Lawley M. (2002). Assigning patients to nurses in neonatal intensive Care Journal of the Operational Research Society 53, p:25-35.

[56] Overfelt, F. (2004) Nursing ratiosare they good or bad? Proceedings of the 16th Annual Society for Health Systems Management Engineering Forum, Orlando, Florida.

[57] Paradiseo home page: http://paradiseo.gforge.inria.fr/, Last visit: 05/06/2012

[58] Pesant G., Gendreau M., Potvin J.Y., Rousseau J.M. (1998), An exact constraint logic programming algorithm for the travelling salesman problem with time windows. Transportation Science 32, p:12-29.

[59] Powers J. (1993), Accepting and refusing assignments. Nursing Mngt 24, p:64-73.

[60] Prattana P. and Rosenberger J. M. (2006) An Optimization-Based Prototype for Nurse Assignment. Proceedings of the 7th Asia Pacific Industrial Engineering and Management Systems Conference 2006 17-20 December, Bangkok, Thailand.

[61] Punnakitikashem P., Rosenberger J.M., and Behan, D.B. (2005) Stochastic programming for nurse assignment. Technical Report COSMOS 05-01, The University of Texas at Arlington.

[62] Ribeiro C.C., Soumis F.(1994), A column generation approach to the multiple-depot vehicle scheduling problem, Operations Research 42,p: 41-52.

[63] Shaha S. and Bush C. (1996). Fixing acuity: a professional approach to patient classification and staffing. Nursing Econ 14: p:346-356.

[64] Stefan B., and Torsten F. (2006), A hybrid setup for a hybrid scenario: combining heuristics for the home health care problem. Computers and Operations Research 33, p: 2866-2890.

[65] Sundaramoorthi, D., Chen, V.C.P., Rosenberger, J.M., Kim, S.B., and Behan, D.B. (2006) A data-integrated simulation model to evaluate nurse-patient assignments. Technical Report IMSE 06 - 05, The University of Texas at Arlington.

[66] Talbi E-G., Metaheuristics: from design to implementation, Wiley, 2009.

[67] Teoh Sheu Siew C. and Abdul Ghani N. (2006), An overview of nurses workload measurement system and workload balance, proceedings of the 2nd IMT-GT Regional Conference on Mathematics, Statistics and applications, Universiti Sains Malaysia, Penang, June 13-15, 2006.

[68] Valouxis C., Houses E. (2000), Hybrid optimization techniques for the workshift and rest assignment of nursing personnel, Artificial Intelligence in Medicine 20, p:155-175.

[69] Walts L. and Kapadia A. (1996). Patient classification system: an optimization approach. Healthcare Manager Rev 21: 75-82.

[70] Wark P., Holt J.(1994), A repeated matching heuristic for the vehicle routeing problem, Journal of Operational Research Society 45 1156-1167.

[71] Yan, S., and Tu, Y. (2002). A network model for airline cabin crew scheduling: Case study. European Journal of Operational Research, 140, p:531-540.

Appendix A

Example of modified Solomon's instance

We report in this appendix, the instance C101 of Solomon after modification. It contains 10 nurses and 100 patients.

P-NO.	X	Y	DEMAND	READY	DUE	SERVICE	REQ. SKILL
0	40	50	0	0	1236	0	—
1	45	68	10	912	967	90	s01
2	45	70	30	825	870	90	s04
3	42	66	10	65	146	90	s05
4	42	68	10	727	782	90	s06
5	42	65	10	15	67	90	s08
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
96	60	80	10	95	156	90	s07
97	60	85	30	561	622	90	s08
98	58	75	20	30	84	90	s09
99	55	80	10	743	820	90	s10
100	55	85	20	647	726	90	s04

Table A.1: The modified instance C101

Appendix B

Detailed computational results

In this appendix, we report the detailed results per nurse for some selected instances from each type of solomon's benchmarks.

Nurse No	Initial distance	final distance	Time (ms)
1	461	258	537
2	500	231	535
3	512	297	589
4	520	254	643
5	554	257	624
6	335	203	437
7	543	284	742
8	410	251	526
9	484	235	531
10	346	239	285

Table B.1: Detailed result of instance: C101

Nurse No	Initial distance	final distance	Time (ms)
1	352	210	361
2	566	308	744
3	404	239	439
4	437	267	443
5	498	273	639
6	576	358	997
7	403	217	437
8	539	256	629
9	407	237	441
10	329	214	413

Table B.2: Detailed result of instance: C201

Nurse No	Initial distance	final distance	Time (ms)
1	277	186	486
2	402	213	766
3	308	205	397
4	352	222	320
5	296	178	333
6	463	227	400
7	393	205	769
8	305	190	490
9	416	209	399
10	367	214	580

Table B.3: Detailed result of instance: R101

Nurse No	Initial distance	final distance	Time (ms)
1	346	172	483
2	244	143	406
3	415	241	671
4	355	207	390
5	445	178	592
6	342	199	483
7	276	181	390
8	414	238	624
9	395	232	483
10	383	209	483

Table B.4: Detailed result of instance: R201

Nurse No	Initial distance	final distance	Time (ms)
1	563	301	550
2	468	267	463
3	424	279	382
4	404	236	458
5	543	304	552
6	457	295	468
7	365	277	461
8	426	293	383
9	416	214	460
10	433	237	463

Table B.5: Detailed result of instance: RC101

Nurse No	Initial distance	final distance	Time (ms)
1	713	308	743
2	474	272	529
3	392	287	530
4	405	246	546
5	507	275	624
6	365	242	437
7	550	316	437
8	516	312	515
9	381	248	437
10	572	302	530

Table B.6: Detailed result of instance: RC201