The Home Care Scheduling Problem: A modeling and solving issue

Jaber JEMAI
IS Department
CCIS - Imam University
Riyadh - Kingdom of Saudi Arabia
Email: jaber.jemai@ccis.imamu.edu.sa

Marouen CHAIEB
LARODEC Laboratory
ISG - University of Tunis
Tunis - Tunisia
Email: chaieb.marouene@live.fr

Khaled MELLOULI
LARODEC Laboratory
IHEC - University of Carthage
Tunis - Tunisia
Email: khaled.mellouli@ihec.rnu.tn

***Abstract*—The Home Care Scheduling Problem (HCSP) consists of designing a set of routes for medical service suppliers to visit a number of patients located at different places and asking for a set of medical tasks. The object of the HCSP is to define the required set of routes where the assigned workforce will travel in order to minimize the overall travelled distance. Therefore, the solution will define first the teams (crew) that will travel together for serving particular subset of patients. Then, the route of each team is defined. The problem shows a hierarchical nature where the solving algorithm should build first the service team that defines partially the set of potential customers to serve and then look for the routes to follow. In this paper, we studied and solved the HCSP after reviewing the literature on the HCSP. We modeled the HCSP as a multilevel (hierarchical) combinatorial optimization problem. Then, we focused on particular variant of the HCSP which is the Multiple Traveling Salesman Problem with Time windows (MTSPTW) where we implemented a Tabu Search based heuristic to solve a modified version of Solomons instances. The obtained results are reported, commented and validated.**

I. INTRODUCTION

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. The population taking benefit for home care scheduling contains, mainly of elderly peoples and people with physical or learning disabilities. 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. From the stakeholder (hospitals, agencies) position, the objective of the HHC is to ensure the efficiency of the service of patients. Service efficiency is defined by customers satisfaction and also the cost incurred by the completion of the service.

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) Will 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 an independent 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 that defines a set of routes to be followed by medical groups to visit patients at their homes. All of these problems are highly constrained. 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 asks explicitly for answering 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.

The next section provides a review of the HCSP literature by presenting its main components. Section 3 presents the proposed approach, describes the optimization model and presents the solving method. In the fourth section, we describe the implementation and the computational results. Finally, we discuss the conclusions and areas of future research of the HCSP in Section 5.

978-1-4673-5814-9/13/$31.00 ©2013 IEEE

II. Literature review

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.

A. HCSP: the assignment component

The first part of the home health care scheduling problem consists of defining the 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 nurses overall workload, breaks, etc. In this context, Ben Bachouch [4] described some of the considered constraints:

- The biggest workload of each nurse must be lesser than the upper bound of the workload of each nurse P_{max}.
- The smallest workload of each nurse must be greater than the lower bound of the workload of each nurse P_{min}.
- 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.
- etc.

In [28], Hertz and Lahrichi describe 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.

Generally, the objective of the assignment task is to balance the workload between workers [4], [28] 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 overstaffed 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 [28].

Assignment in health care problem is a consistent part of the assignment literature. Assigning in home health service is about the finding the best affectation of medical staff to patients. Mullinax and Lawley [34] cited some works focus on assignment in health care: Powers [37] suggests that excessive workloads are unsafe and promote poor quality of care. Moreover, fair workloads among nurses are essential for optimal quality of care as agreed by [19] [15] and [23]. Walts et al. [45] 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 [40] say 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. Punnakitikashem et al. [38] mention some researches studied nurse assignment to patients like the work of Overfelt [35] in which he proposed a modern patient classification systems partition the set of patients into groups, and each group is assigned to a nurse. Punnakitikashem et al. [38] developed a two stage stochastic integer programming model for a nurse patient assignment that considered uncertainty in patient care. Sundaramoorthi et al. [41] presented a simulation model from real data to evaluate nurse-patient assignments. Teoh [43] provided an overview of the workload measurement systems and its application to balance workload between workers. In [28], authors 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 [21] 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.

B. HCSP: the routing component

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. Routing costs consist generally of minimizing the number of used vehicles, the overall travelled distance, balancing tours in term of staff workload and the overall working time (accumulated durations of runs). The HCSP routing problem is subject to a large number of scheduling and routing constraints. According to [22] and [10] , 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 time.
- 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.

Health care routing problem was extensively studied to model and solve the routing component of the HCSP. In [22], authors said that repeated matching was first used by Forbes [25], 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 [29] and [26] 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 [32] and [7]. Problems also differ whether the definition of a shift or task. If the schedule is determined in advance [32] and [6]. One area in the service industry that has attracted lot of attention is hospital and/or nurse scheduling we have the example of [20][44]. Also in the area of call centers like the work of Lin et al. [30]. Many heuristic methods have been used in the literature that we can mention the use of genetic algorithms [13], simulated annealing [12] and tabu search [20]. A variety of optimization based methods constraint programming, column generation, set partitioning models was also used [14][11][39]. In [8] and [10], authors developed a computerised system which solves the nurse scheduling and the routing home care nurses problems. Cheng [18] formulated the routing home care nurses problem as a vehicle routing problem with time windows and multiple depots. Eveborn [22] 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 [18] 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).

C. The hierarchical home care scheduling problem

The hierarchical 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 preferences. It looks for an operational working plan for the nurses without separating the assignment component and the routing component.

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.

In dynamic HCSP, both assignment and routing constraints are defined and have to be respected in an a final feasible solution. Chananes et al. [16] and Bertels [8] presented some constraints to guarantee both good assignment and routing tasks that we can cite:

- 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.
- 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.
- All jobs must be covered at one and only time, any starting point for a job has to respect the hard time window.

Many different and often conflicting objectives may be considered in the HCSP. 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 satisfy employee preferences.
- To distribute work equally.

The HCSP was, basically, viewed as an assignment problem with a less important routing component or routing problem with some assignments. 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 [16]. The authors in [16] cited some works in this field like [46] in the domain of airline crew scheduling, the work of Bialas et al. [9] in the domain of bus and truck driver scheduling and [17] for optimizing a routing problem in call centers. A decision support system called LAPS CARE has been developed to aid the staff-planning task [22]. Chananes [16] 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 [8] cited some works about dynamic HCSP like in [18] that described a combined mixed-integer programming (MIP) and heuristics approach. In [7] a decision support system that is based on simple scheduling heuristics was proposed. Most of these use constraint programming techniques in order to model and solve the nurse rostering problem. Classical vehicle routing with time windows [24][27] reflects the mobility aspect of the problem, but ignores any further restriction.

III. HCSP MODELING AND SOLVING APPROACH

Health home are services can be analytically represented by the HCSP as shown in the previous section. 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.

1) 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.
2) 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.
3) 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 patients home.
4) Suppose that nurses can provide many treatments and the patients may ask for many nurses 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.

A. The Multiple Traveling Salesman Problem with Time Windows

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][33]. In the following, we report the Big-M formulation from [3]. 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 where V is the set of vertices and e_i and l_i are respectively the earliest and the latest service time of customer i:

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

Subject to:

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

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

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

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

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

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.

B. 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 [42]. 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 [27].

IV. Simulation, Implementation and Computational results

A. Instances simulation

In order to simulate MTSPTW instances, we choose to modify the 6 sets of Solomon's benchmarks of the Vehicle Routing Problem with Time Windows (VRPTW). The modifications applied to standard Solomons benchmarks are:

1) Vehicles 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 s_j.
3) Time windows, locations ar maintained.

B. Experimental context and parameter settings

The HCSP solving approach has all been implemented using the tabu search metaheuristic from the ParadisEO-MO library [36]. ParadisEO is a C++ LGPL open source object-oriented framework for evolutionary computation that has been developed through an European joint work. The rich set of ParadisEO-MO modular classes are combined to develop single solution based metaheuristics. 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. 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.

C. Computational results

To demonstrate the efficiency of the implemented TS heuristic for solving the modified solomons benchmarks, we report the following results in the next Table for the the geographical data.

TABLE I. Detailed result of instance: C101

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 II. Detailed result of instance: R101

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 III. Detailed result of instance: RC101

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

V. Conclusions

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. The HCSP is is by definition a hierarchical optimization problem where the assignment and routing components should be solved mutually and dependently. However, the large part of HCSP contributions address on of the components and neglect another. In this paper, we review present HCSP literature and we propose a modeling and solving issue. We announced the assumptions under which the HCSP can be reduced to a TSP with Time windows. Consequently, we proposed and implement a tabu search based heuristic for solving modified version of the Solomon's benchmarks of the VRPTW.

References

[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] 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.

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

[5] 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.

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

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

[8] 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.

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

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

[11] 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.

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

[13] 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.

[14] 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.

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

[16] 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.

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

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

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

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

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

[22] 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.

[23] 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.

[24] 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.

[25] 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.

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

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

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

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

[30] 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.

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

[32] 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.

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

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

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

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

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

[38] 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.

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

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

[41] 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.

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

[43] 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.

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

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

[46] 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.