Chemotherapy outpatient scheduling: case study from Tunisia

Asma BOURAS[1], Malek MASMOUDI[2], Nour El Houda SAADANI[3], Zied BAHROUN[4]

[1]Mediatron Lab, Higher School of Communications of Tunis, University of Carthage,
Faculty of Sciences of Tunis, University of Tunis El Manar, Tunis, Tunisia
asma.bouras@fst.utm.tn

[2]LASPI, F-42334, IUT, University of Saint Etienne, Jean Monnet, F- 42000,
University of Lyon, F-42023, Roanne, France
malek.masmoudi@univ-st-etienne.fr

[3]Université de Tunis El Manar, F.S.T., LIP2-LR99ES18, 2092 Tunis, Tunisie.
houda.saadani@ensi.rnu.tn

[4]Industrial Engineering, ESM Graduate Program, College of Engineering, American University of Sharjah,
PO Box 26666, Sharjah, UAE
zbahroun@aus.edu

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1. Introduction:

In this paper, our aim is to develop operations planning and scheduling methods for chemotherapy patients with the objective of minimizing the patient waiting time of the daily activity. This problem is considered as a multi-stage hybrid flow-shop problem with additional resources constraints. We provided a mathematical model to generate balanced appointment schedules for oncologist visit, pharmacist drugs' preparation and chemotherapy treatment. Numerous studies used optimization methods to schedule appointments by offering optimal solutions which support developments in patient flow and resource exploitation of healthcare systems [8, 14]. Simulation, on the other hand, can handle well large and complex systems with the flexibility to adapt to difficult constraints [3, 13]. Sadki et al. [9] developed an integer programming model to control oncologist and chemotherapy appointments with the objective of minimizing a weighted combination of patient waiting time and makespan (clinic total working time). They assumed that nurses have enough capacity and they considered only the treatment stage. Condotta et al. [4] has developed a multilevel template for patient appointment scheduling with the main objectives of minimizing patients' waiting times and nurses' workload. Liang et al [7] presented a multi-objective optimization model to solve the patient scheduling problem in a primary care delivery model (each patient is assigned to a primary nurse every time he/she comes to the clinic). The two objectives are minimizing total overtime and total excess workload. Constraints method is used to solve the model which used different nursing care delivery models. Hahn-Goldberg et al. [6] developed a dynamic schedule template which was associated to a proactive template. They considered only drug's preparation stage and treatment stage and proved that the dynamic template works better under uncertainty conditions. Turckan et al. [13] developed an integer programming model to solve the deterministic chemotherapy outpatient scheduling problem. Because of the huge number of patients per day, 50 patients, they judged the integer programming solving time as too long. So, they developed a heuristic based on the longest treatment time first to decrease the computational time. The objective was to balance the acuity of patients serviced by a particular nurse as opposed to maximizing resources' utilization. Pharmacy constraints were not considered. Santibanez et al. [10] created a scheduling system for a large chemotherapy clinic in British Columbia, ElMekkawy and Bates [1] and Yokouchi et al. [16] used simulation to define the best appointment scheduling rules by varying arrival rates, and nurse schedules by varying the number of nurses at each time interval. The main objective was to minimize patients' waiting time. Tanaka [12] used simulation to test different scheduling rules based on bin-packing algorithms and describe the time allocated for pre-treatment process, preparation and nursing. Woodall et al. [13] used simulation based optimization to define the optimal nurse schedules with the objective of minimizing expected waiting times. Dobish [5] studied the daily patient schedule and the duration of the treatments to better organize the flow patients and to permit enough time for each department to complete their part of treatment. Shashaani [11] developed an integer programming model to determine the optimal appointment schedule and use it as an input to the simulation model to estimate the impact of variability in service times on patient waiting times.

2. Problem Statement

The treatment process begins as follow: a patient goes to the laboratory to take a blood specimen collection. Then, he/she has a medical examination taken by his/her own primary doctor in the department. The primary doctor checks the appropriateness of a prior prescription based on the examination results. If the doctor approves the prescription, then the final order is given. There are two pharmacists who prepare the mixing of the drugs. After having the medical examination, the patient waits for her/his treatment. When drugs are ready, the nurse start setting up the patient and then control him/her along the injection. Patients receive their treatments while sitting on treatment seats (or chairs). One nurse can take care of four patients at the same time. After the treatment, she examines the patient and provides instructions for home care. The proposed problem can be considered as a multi stage flow shop problem with additional resources and parallel machine. It consists on assigning patients to different starting times of each stage of treatment process, which necessitates a specific resource with different requirements. To the best of our knowledge, there are no notable works, in the literature, that offer an efficient solution to this problem in reasonable time considering all treatment stages and all resources.

We developed a mathematical formulation of the problem and provided two solving techniquesto generate balanced appointment schedules for oncologist visit, pharmacist drugs' preparation and chemotherapy treatment. Numerical experiments based on real world data collected from a Tunisian clinic show the capability of the proposed method to reduce patients' waiting times.

3. Deterministic approach

In this paper we consider the same problem presented in Bouras et al. [2], it consists in assigning patients to different starting times of each stage of treatment process, which necessitates a specific resource with different requirements. The developed mathematical model generates balanced appointment schedules for chemotherapy unit taking into consideration the oncologist visit, pharmacist drugs' preparation and chemotherapy treatment.

4. Approximate approach

Since the mathematical model is not efficient to solve large instances i.e. optimal solutions cannot be found in a polynomial time especially with big instances, we decided to develop approximated techniques that can reach a satisfying solution in a reasonable time. To evaluate the performance of such methods and examine the quality of their solutions, we compare them to the best solution found by the MIP.

First, a construction heuristic (*H1*) is provided to solve the problem in a low computation time. The heuristic is composed of two steps: The first step is to arrange patients according to a priority degree that is calculated based on the processing time. The second step is dedicated to the patients' assignation to the machine. These two steps are applied to the first stage (consultation). The processing time here is the duration of the consultation. The two steps are repeated for the second stage and then for the third stage. The processing time for the second stage is the duration of the preparation and the processing time for the third stage is the duration of the injection. At each of the three stages, jobs (patients) are sorted in the decreasing order of their priority degrees (see algorithm) then assigned one by one to the less loaded machine. This approach allows avoiding machines' idle time.

Then, a tabu list local search (*H2*) is adapted to solve the problem under study. In the following, the detailed implementations of the TS are described. We, first, distinct two neighborhoods:

- Neighborhood *N1* is obtained by exchanging two non-successive patients in the first stage.
- Neighborhood *N2* is obtained by exchanging two successive patients in the first stage.

A tabu list is defined to avoid cyclic moves: inverse exchanges are forbidden during a certain number of iterations. The algorithm stops its searching process if *Nmax* successive iterations are performed without improving the current solution,

5. *Results*

Since the intention is for the model to be used in real time with real instances, it is important to note that for the majority of the runs, a feasible solution is found very quickly. We have varied the number of patients as follows: [5, 10, 15, 20, 25]. For each problem size, 5 tests were generated and solved. We tested the proposed model with 10 chairs, 2 pharmacists, 3 oncologists and 5 nurses. For the mathematical model, we obtained the optimum solution for all tested cases. The execution with Cplex is limited to a number of patients equal to 25 due to memory size problems. For each test, we calculate the relative gap between the solutions provided by Cplex and the metaheuristic. To improve the solution, we calibrated our metaheuristic to fix their parameters. This is done by running a series of tests. Every test is executed many times until we obtain close solutions from one execution to another. We fixed the stopping parameter Nmax of the tabu search to 500 for P > 5 patients. For each instance, we took the solution returned by the heuristic H1 as initial solution and run our metaheuristic. The results showed that our metaheuristic can reach a satisfying solution in a reasonable timewith about 6% of average relative gap to the MIP solution. We resumed with studying the contribution of both the intensification procedures by running some tests with and without it, we noticed that it had a slight impact, as only 2% of the returned solution were better with the intensification procedures. The result is that the tabu search method is still very efficient and in the studied issue the big impact on scheduling is the starting patient order (in stage 1).

6. *Conclusion*

In this paper, we proposed an exact resolution for scheduling patients for multiple stages in an outpatient chemotherapy department. We developed a MILP model where the objective is to minimize the waiting time of all patientduring daily activity in a Tunisian clinic. The model is formulated then tested with Cplex. It gave an optimal solution while P is less than 20 patients. We presented a heuristic that can reach satisfying solutions in a reasonable time and a metaheuristic method, a tabu search, in order to improve the solutions returned by the heuristic. We led then an experimental study and show that our heuristic had a good performance for small and medium instances. The experiments also show that our metaheuristic is good performing, with about 6% of average relative gap to the MIP solution.

The next step of this work is to introduce new neighborhood structures as well as an efficient intensification procedure to the tabu search method. We have then to study chemotherapy scheduling problem under uncertainty in the processing times of the operations.

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