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Agents Endowed with Uncertainty Management Behaviors to Solve a Multiskill Healthcare Task Scheduling

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Abstract Health organizations are complex to manage due to their dynamic processes and distributed hospital organization. It is therefore necessary for healthcare institutions to focus on this issue to deal with patients' requirements. We aim in this paper to develop and implement a management decision support system (DSS) that can help physicians to better manage their organization and anticipate the feature of overcrowding. Our objective is to optimize the pediatric emergency department (PED) functioning characterized by stochastic arrivals of patients leading to its services overload. Human resources allocation presents additional complexity related to their different levels of skills and uncertain availability dates. So, we propose a new approach for multi-healthcare task scheduling based on a dynamic multi-agent system. Decisions about assignment and scheduling are the result of a cooperation and negotiation between agents with different behaviors. We therefore define the actors involved in the agents' coalition to manage uncertainties related to the scheduling problem and we detail their behaviors. Agents have the same goal, which is to enhance care quality and minimize long waiting times while respecting degrees of emergency. Different visits to the PED services and regular meetings with the medical staff allowed us to model the PED architecture and identify the characteristics and different roles of the healthcare providers and the diverse aspects of the PED activities. Our approach is integrated in a DSS for the management of the Regional University Hospital Center (RUHC) of Lille (France). Our survey is included in the French National Research Agency (ANR) project HOST¹.

Keywords decision support system; pediatric emergency department; multiskill task scheduling; multi-agent system; cooperation; negotiation.

¹Hôpital: Optimisation, Simulation et évitement des Tensions (ANR-11-TecSan-010 : <http://host.ec-lille.fr/wp-content/themes/twentyeleven/docsANR/R0/HOST-WP0.pdf>)

1. Introduction

In emergency departments, many patients have to wait for a long time (sometimes more than 10 hours) before seeing a doctor. These long delays are unacceptable and can endanger patients' lives or cause serious sequela. This long waiting time phenomenon highlights the need to review the process of managing emergency facilities and the implementation of measures to preserve quality of care for consumers. Currently, there is a lack of tools for assessing the extent of waiting, particularly in Pediatric Emergency Departments (PEDs), which are a more delicate environment. In PEDs, the patients are children who are with their parents most of the time. The latter need to be well informed about what is happening: about the treatment progress of their child as well as whether the PED is in an overcrowding situation, which also reflects the remaining waiting time. This information helps patients to know whether the health institution where they are waiting is in a state of overcrowding. Thus, the waiting times, the length of stay in the PED and the interaction with care and information providers can predict the level of satisfaction of parents and patients [1] and ensure an unceasing service quality enhancement strategy. The benefits to let the parents know whether the health institution where they are waiting is in a state of overcrowding are to give them on one hand, an estimation of the waiting time of patients who are already in the waiting room and those who have just arrived, and on the other hand the possibility of reorienting them to a less overcrowded health institution in the region in case of an excessive waiting time. The PED does not operate as an isolated unit but thanks to our agent based architecture, the PED interacts with other actors in the framework of the larger hospital system. These interactions exert a significative influence on the PED. For example, the knowledge of the overcrowding level of the other PEDs, the information about the current waiting time in the services where patients are sent to undergo diagnosis tests, the knowledge of remaining beds in other services of the hospital where patients are transferred.

In cooperation with the Regional University Hospital Center (RUHC) of Lille, in order to respond to these challenges, we are interested in the development and implementation of a decision support system (DSS) based on a multi-agent approach for modeling the architecture of the PED and optimizing its functioning. This tool proposes a refined model for logistical needs under emergency conditions, taking into account existing functioning. Currently no DSS is used to get information, the PED just has tools for entering data, and no concrete measures have been adopted to address the problem of long waiting times before the first consultation. For testing, we carried out field observations and we noticed that information circulates poorly, sometimes missing or arriving late with PED actors. We therefore modeled a system with a set of autonomous and interactive entities called "agents." These latter represent the different actors of the PED environment, which is therefore represented by a set of interactive agents and so becomes a multi-agent system. A special form of interaction between these agents was set in this paper: negotiation for peak activity adjustment and waiting time minimization. This work focuses on involving management processes in the PED knowing that management activities include patients' reception, treatment task planning and resources allocation. So, in this paper we propose a distributed architecture using a multi-agent system designed for treatment task scheduling where actors provide a smart negotiation with uncertainty management in order to execute and control the scheduling of medical acts and resources during a patient's journey. The goal is to provide a high quality of care services while considering the different constraints related to the

stochastic arrivals of patients, dynamic patient pathways, sensitivity of medical tasks, emergency degrees, resources availability, etc.

In our previous study, we proposed a workflow model to identify overcrowding indicators and bottlenecks [2]. An approach based on the optimization of the patient path through the construction of a workflow model was presented. The main goal of this work is to manage patient flows by supporting and prioritizing the most serious cases. Care services must mobilize both human and material resources related to their availabilities. Human resources are the most critical resource in the scheduling process. In fact, before assigning healthcare treatment operations to medical staff members, a study must be carried out. Indeed, medical staff should be deemed “expert” for a given care task to execute it. Their availabilities and their skills must also be taken into account. Because accuracy is one of the basics of the administration of operations in health emergency organization management, most of our attention is given to multiskill tasks scheduling. This very important point was not addressed in previous works. In the next section, we present a state of the art about existing researches in the context of our work. Then we position our problem compared to the literature before presenting our proposed solution.

2. State of the art

2.1. Healthcare system management

Analysis carried out in the hospital and care sectors shows some deficiency due in part to an organization poorly adapted to the constraints and evolution of medical staff missions and poor management of patient flows [3, 4]. Thus, the optimization of the organization and information systems is an important lever for the success of this development. More generally, the implementation of control systems, strategic, tactical and operational healthcare and production systems is now inescapable. To manage the transition, it is necessary to define the new organizational paradigms, new methods for the governance and management of these new organizations as well as support mechanisms and ownership. Reconfiguring and improving the healthcare system requires an “efficient reorganization”. These are problems whose complexity appeals to an innovative, comprehensive and scientific approach: “Health Logistics,” which is the only approach capable of meeting this objective.

Today, hospital emergency services have a strategic position in modern healthcare systems and represent the main gateway to the hospital [5, 6]. This key role will be strengthened in future years due to the sustained growth in the number of patients arriving at emergency departments who are increasingly demanding [7]. These changes generate problems for different actors in public health, including operating problems in coping with this increase in consultations and a significant cost in health expenditures [7, 8, 9, 10, 11, 12]. However, if the majority of healthcare systems in the world are faced with this reality, the ways to deal with it differ from one country to another [1]. Thus, to better understand the problems and current issues, it is important first to put the emergency services in their general context in order to understand their operation and their own characteristics.

In a literature review, it is clear that despite the existence of an explicit agreement between researchers in the world on the extent and severity of the sustained increase in attendance and the consequences for emergency services, the debate still continues about the definition of, and appropriate actions for, this “overcrowding” situation [13] and its impacts on patients’ flow [14]. In literature, we find that researchers use terms such as “crowding,” “overcrowding,” “congestion” and “crisis” [5]. Regardless of the terms used in the literature, this is a situation that reflects the consequences of an imbalance between the supply of, and demand for, care in emergency departments. This imbalance is always a generator of overcrowding in the different units of an emergency service. Therefore, we use the term “overcrowding” in our research to describe the consequences of this state of congestion. In the literature, there is no definition of the overcrowding that is universally accepted by researchers [15, 16, 17, 18].

2.2. Human resources scheduling

The healthcare system is now facing a scarcity of certain resources that can be too expensive or not readily available. This has led to a need to optimize resources in healthcare facilities – hence the need to adopt management tools for an efficient allocation of resources in emergency services. The problem of assigning human resources is a problem of planning and organization of a set of tasks to be performed with a set of resources with variable performance [19]. In the literature, all authors consider two stages in its resolution: 1) task assignment to resources and 2) task sequencing [20].

Task assignment

The first stage is to judiciously assign different tasks to the proper resources. The problems of human resources scheduling, their assignments and their timetables were initially raised in business. In classical scheduling, staffing is rarely taken into account [21]. The notion of knowledge level representing the speed of an experienced person compared to another is seldom used and considered in order to balance the load between resources and to find the most appropriate resources for a task. In [22], an approach taking into account the skills needed to better distribute the workload was developed. This approach considers the experience levels of production employees in a performance model.

Task sequencing

The second step in the resolution of the resources assignment problem is task sequencing and the determination of starting times taking into account different precedence and resources constraints. Thus, several criteria can be considered in the analysis and resolution of this alternative scheduling. Indeed, two major issues arise. The first is medical staff load optimization. The second is the organization of, and compliance with, certain details that could be imposed in advance. This variety of criteria makes it difficult to assess the achievable solutions and the comparison between the methods. Metaheuristics have proved to be a class of highly adaptable approximate methods for a large number of combinatorial problems and assignment problems under constraints. These methods are very effective for providing good approximate solutions to a large number of conventional optimizations and actual applications of large problems. In Portugal, a metaheuristic based on a genetic algorithm was adopted for scheduling of nurses and the proposed solution has been successfully tested using real data from a hospital in Lisbon [23]. Hence, in spite of the variety of resolution methods and computing, difficulties related to the resolution of scheduling problems persist because of the combinatorial complexity [24]. To deal with the difficulties stated, metaheuristic methods such as evolutionary algorithms can be used. However,

given the continuous presence of uncertainty in emergency departments, healthcare problems remain hard to resolve. The uncertain aspects appear not only in the request process but also in the process of “care providing” and in the availability of material and human resources.

2.3. Simulation and modeling in healthcare organizations

As stated in the work of Taboada et al. (2012), there is still no standard model to describe complex systems and simulation is becoming a crucial tool in the hands of decision-makers for anticipating the consequences of a given situation [25].

In recent decades, there has been considerable effort in the development of simulation and optimization models for solving various problems related to the functioning of health system structures (flow management, human, technical and financial resource allocation, etc.) [26, 27]. The efforts made to improve the performance of the functioning of this service have relied largely on the mobilization of technical modeling and simulation in the field of information technology [28, 29, 30, 31, 26]. In the literature, we find some main approaches commonly used in modeling and simulation in the field of health [32], such as decision analysis, Markov chain, mathematical modeling, dynamic systems and discrete events [30, 32, 33]. However, it is clear that research fails to achieve sustainable and comprehensive solutions. Indeed, the major drawback of these common modeling approaches is that they tend to neglect the effect of human behavior on the performance of the care process [34]. In addition, the stochastic characteristics in the various stages in the healthcare process are generally not fully integrated. As such, agent-based simulation provides a complementary perspective to model the process of healthcare [34, 35]. Furthermore, if we find an extensive literature using these approaches in different areas of health, we find that the use of multi-agent systems is still in its infancy, although healthcare systems are closer to the use of this approach.

2.4. Multi-agent systems

Agent is a concept in the field of Artificial Intelligence. It can be viewed as a computer system integrated in a certain environment such as a physical system or internet, with flexible autonomous action. Agents perceive input data through sensors. Then, they perform subsequent actions to affect the environment. Agents are also able to make decisions and choose the suitable actions to reach the goal in an autonomous manner, without external intervention from other agents or human interference. Meanwhile, agents can have different actions, including responsiveness, pro-activeness and social behaviors. Each agent can receive the information from the external environment and react in a real time to affect or adapt to the environment [35].

Healthcare systems are based on human actions and interactions that are very difficult to model. In this sense, Escudero-Marin and Pidd (2011) estimate that the use of such discrete event simulation is not at all appropriate for the health sector [36]. Research conducted over the past decade highlights the growing potential of the use of multi-agent system modeling in the field of health, especially in emergency departments [33, 37, 38].

According to Taboada et al. (2012), modeling techniques based on agents would bring more benefits when applied to human systems in which the interaction between individuals is characterized by heterogeneity and complexity [25]. According to Norling et al. (2001), a multi-agent system is mainly used in situations where the use of conventional methods, such as qualitative or statistical analysis, does not predict human behavior [39].

In this perspective, some researchers have attempted to apply a multi-agent system in the health field, including planning [40], optimizing the use of resources [35] or in search of an optimal allocation to minimize the length of stay of patients [25]. In the area of health, a multi-agent system seems to be the best approach to adopt since it adapts to the distributed and dynamic nature of logistical flows in health problems. In addition, it allows the decomposition of the system into multiple agents that interact and work together to achieve a common goal.

3. Problem description

Treatment tasks have different levels of urgency. This concept of urgency springs necessarily into the consideration of tasks and medical staff assignment. In the literature, many articles discuss the arrival of patients in hospitals and many similarities can be observed. Priority is given to treatment tasks depending on their nature, the patient's condition or external constraints related to emergency department operation. The priority of tasks increases with elapsed time. The most common scheduling algorithm with dynamic priorities is the Earliest Deadline [9] wherein the priority of a task is inversely proportional to its latency. To approach the scheduling problem, it is also necessary to identify the sources of uncertainties related to scheduling and allocation in emergency department activities. A schedule of activities is carefully structured by times, depending, some of them, on the tasks themselves, and for others, on external events (such as the availability of the staff member who is charged to perform a task or the availability of equipment with which an operation must be carried out). Thus, there are three types of uncertainties:

- Uncertainties about the characteristics of tasks: The expected duration of a task depends on the diagnosis made. It is very difficult to predict the duration of the current care procedure. In addition, it will depend on the skills of the medical staff member who will intervene and his experience.
- Uncertainties about the occurrence of tasks: The main uncertainty, which particularly concerns an emergency department, is the arrival of new tasks to be performed. In fact, not only are they unpredictable, but they can also generate major disruptions in scheduling.
- Uncertainties about resources: To carry out medical interventions, healthcare tasks may need a special medical staff member. It may happen that the required medical staff member is already busy in the execution of a task whose ending time is uncertain. Staff have various medical skills and levels of experience. The processing speed depends on the choice of the staff member that will be assigned and the evolution of the patient's health state. In the sequential scheduling, schedules are organized in several steps [41] and priority tasks are allocated to the most qualified staff. Authors on [42] study task scheduling take into account information about human resources. However, even if the schedule takes into account staff skills, software production scheduling considers that task durations are known [43]. These approaches are generally associated with the production and management of noncare activities. Thus, because

of the unpredictable nature of healthcare activity, which requires dynamic information management, we propose an adaptive and dynamic system based on software agents to solve the multiskill healthcare task scheduling in PEDs. The originality of our work lies in the alliance between optimization tools and multi-agent systems in favor of health. Existing models incorporate little instant control or decision assistance while allocating dynamic resources.

4. Methods

Obviously the search field selected is specific and requires a special approach to carry out our work and to solve the problem of overcrowding in PEDs. For this, we chose a qualitative approach in order to better understand the field. In this sense, if qualitative methods are varied, it is rare that a single qualitative data collection method is sufficient to fully explore the research space. Thus, we conducted individual interviews with some experts on PEDs. The purpose of these interviews was information and understanding. Meetings were held with physicians to find out about the practices and proceedings of medical activities in treating rooms. Similarly, we organized with the medical staff of the PED visits to carry out nonparticipating direct observations in order to understand the behaviors and interactions of the actors in a natural environment without intervention.

The overall objective of our approach is therefore, first, to design a solution representing the patient journey within the PED from data collected, as well as “encrypted” data concerning hospitalized patients. This solution will represent the PED environment in terms of autonomous and interactive entities for two purposes: simulation and real-time running.

4.1. The proposed multi-agent architecture

The PED of Lille University Hospital is spread over a surface of 450 m² within the hospital of Jeanne de Flandres. While this may seem small, there are two other equivalent structures in the Lille metropolitan area: one in the Saint Vincent Hospital and the other in the Hospital Center of Tourcoing. Thus, the structure of the University Hospital of Lille remains modest in terms of annual admission. However, pediatric emergencies are often overcrowded especially in epidemic periods.

As shown in Figure 1, the architecture of the PED of Lille University Hospital includes:

- 1 reception area,
- 10 exam rooms with single or double beds,
- 1 plaster room and 1 suture room (can also be used as an exam room),
- A recovery room for patients whose condition requires great vigilance (these patients must be discharged and sent home as soon as possible),
- 1 waiting room (in the corridor).

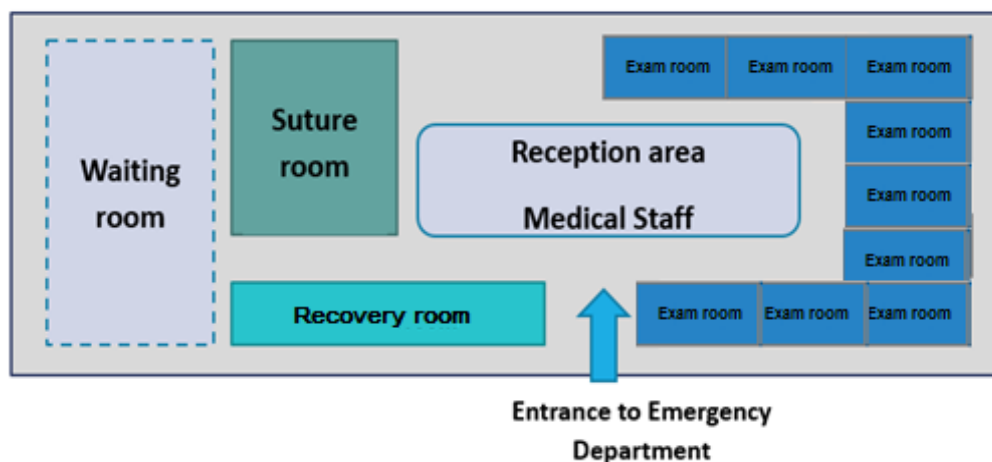


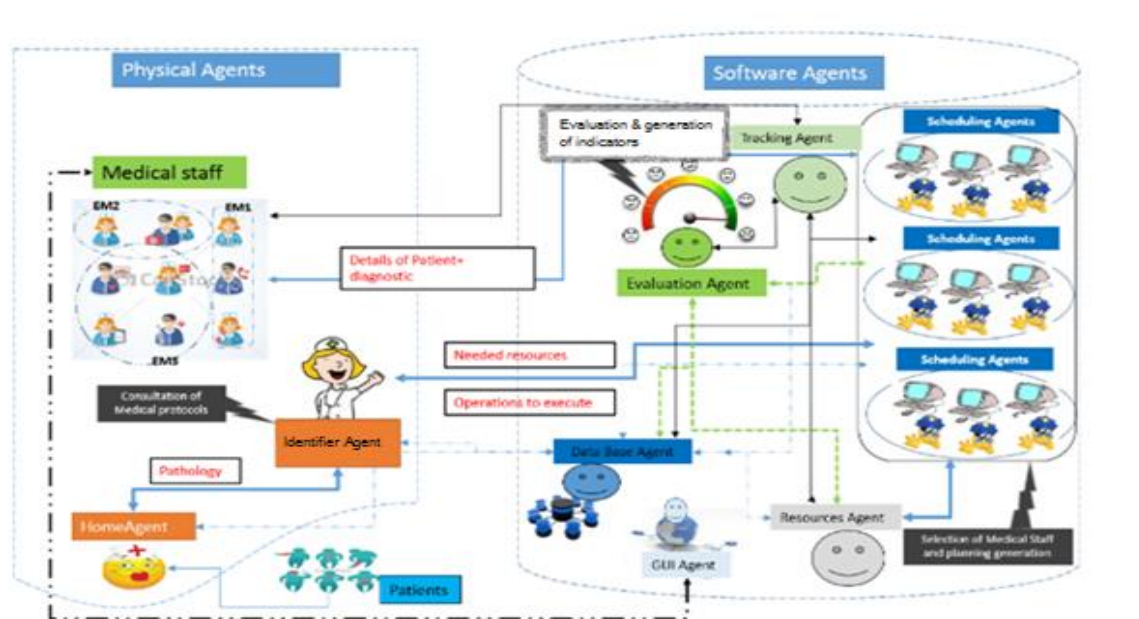
Figure 1: The PED architecture.

With regard to the staff available, the medical team of the PED is composed of:

- 2 care pediatricians (medical specialists),
- 1 intern in general medicine,
- 2 pediatric interns,
- 1 surgical intern,
- 2 to 3 nurses whose distribution is as follows: 2 in the morning, 3 in the afternoon, 2 at night,
- 2 childcare assistants.

Many interviews and meetings with the medical staff of the PED report that this latter does not have sufficient capacity to support the flow of patients in optimal circumstances and without excessive waiting times. As a result of this imbalance between existing health care capacity and patients' request, the PED is currently facing the recurrent problem of overcrowding. The overcrowding signs are the excessive number of patients, long patient stays and waiting times, and treatment in hallways. Congestion in the PED leads to decreased physicians productivity, miscommunication between working staff and dissatisfaction of patients who may sometimes leave without treatment.

In the PED, the initial patient health care orientation can be described as follows. After registering at the main entrance of the PED, the patient is evaluated in the triage post, usually by a nurse that identifies the severity of the situation. An acuity level is assigned to the patient who then proceeds to the waiting room. After triage, the consultation starts once the suitable physician becomes available. When the first assessment is made by the physician, one or more ancillary tests (radiology and/or laboratory tests) may be requested in order to confirm or refine the diagnosis. Once all the tests are accomplished, the physician analyzes the results and makes a decision about the appropriate process outcome for the patient. Finally, the patient can be admitted to another service of the hospital, shifted to another hospital, admitted to the observation unit, redirected to the waiting room, or discharged. All the already mentioned steps are separated by different waiting times that depend on the availability of the required resources.



As mentioned above, the emergency department model defined in this work is a pure agent-based model, formed entirely of the rules governing the behavior of the individual agents that populate the system. Through the information obtained during interviews carried out with the emergency department staff at the RUHC of Lille, two kinds of agents have been identified: software agents and physical agents. The physical agents represent people and other entities that act upon their own initiative: patients, admission staff, health care technicians, triage and emergency nurses, and doctors. These are mobile agents that take into account the displacements of medical staff. The software agents represent systems that add several functionalities to the proposed system, such as a patient information system, resources management and performance indicator calculation. This section is dedicated to describing the various components of the general model.

In the proposed agent-based architecture (Figure 2), there are several types of agents: first, a Home Agent (HA) for patient reception and orientation and also for pathology identification. After registration, this agent sends information about the patient to the Tracking Agent (TA), which is responsible for patients' health and location control, and to the Identifier Agent (IdA), which defines the resources needed to treat patients and the required skills for each treatment task. The IdA

then notifies the Resource Agent (RA) and the Scheduling Agent (SA) regarding information about material and human resources to be allocated. While human resources are being allocated, the SA communicates with Medical Staff Agents (MSAs) to identify the member of medical staff able to provide healthcare for a specific patient. This is related to their skills and availabilities. Each healthcare provider in the PED is modeled by an MSA corresponding to a mobile agent. The latter can move intelligently from one medical team to another in order to treat patients. While executing scheduling, patients with high degrees of emergency are given priority. Once the scheduling is accomplished, the Integration and Evaluation Agent (IEA) generates performance indicators for global schedule evaluation. We can also have a Watch Agent whose mission is to ensure that certain operating conditions are met (creation of agents, assigning their roles, etc.) in order to make sure that the system works properly. It runs in the background and is therefore invisible to the user. In the next section, we detail the behavior of the agents of our proposed system.

- **Home Agent (HA) behavior**

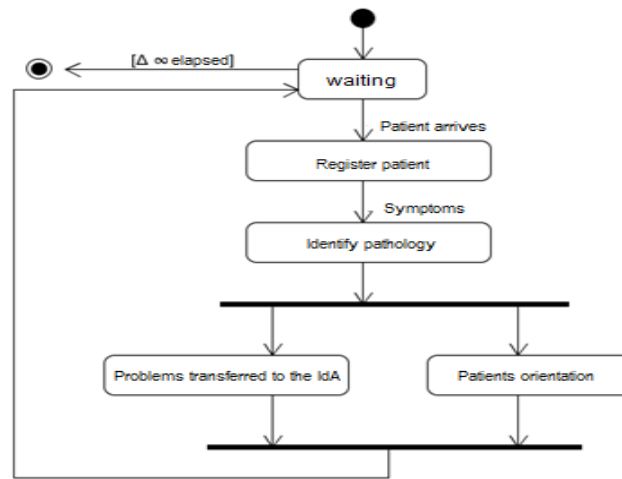


Figure 3: Home Agent behavior.

The HA behavior is described in Figure 3 and operates as follows:

A patient arriving at the PED for a consultation must be added to the hospital database by medical staff thanks to the interaction with the HA. Indeed, this data addition is carried out through the HA, which is an autonomous agent with a graphical interface allowing the RON to record to and retrieve records from the database. So, the RON (the person responsible for the reception of patients) sets the patient's social security number within the HA interface for their registration. Then, this same agent consults the medical record of a patient in the created database and registers them.

During the consultation, whose aim is to quickly assess the patient's symptoms, the doctor or nurse defines one or more diagnoses. These are recorded in the patient's medical record. Finally, the HA interacts with the IdA by transferring to them all identified patient health problems.

- **Identifier Agent (IdA) behavior**

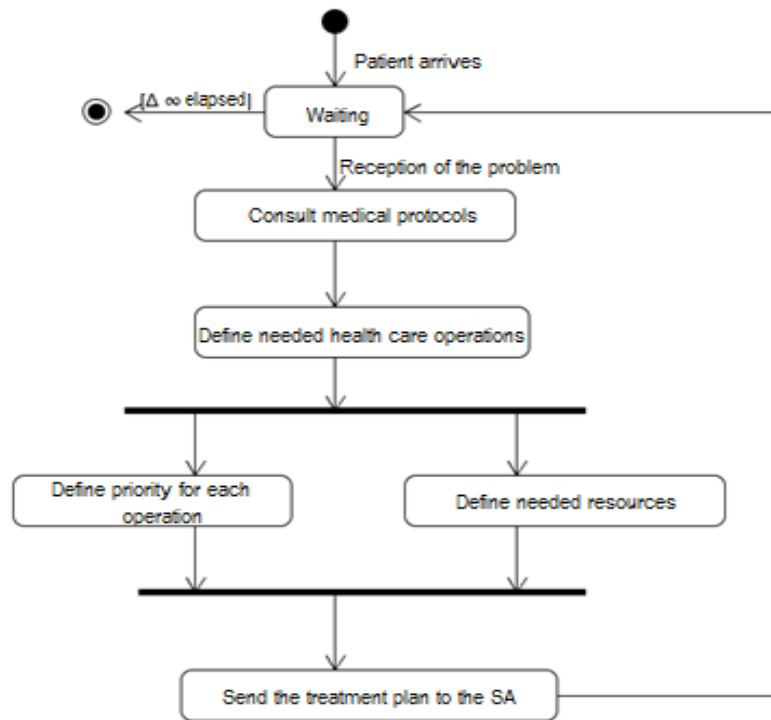


Figure 4: IdA behavior.

The behavior of the IdA is described in Figure 4 and operates as follows:

The IdA receives all the administrative information from the HA. It therefore receives the complete medical record of the patient and generates the treatment plan for the patient by creating a list of healthcare operations (measurement of temperature, measurement of blood pressure, taking a blood sample, etc.). It also identifies the medical staff required for each health care task execution and “time to first treatment” or “time to physician” which describes the time between the patient arrival and the first handling by a physician.

Finally, the IdA saves all this information in the patient medical file and transmits these data to the SA. This latter assigns human resources to the tasks, creating the schedule for each medical staff at the PED.

- **Tracking Agent (TA) behavior**

The TA mainly intervenes when patients’ medical condition or their list of operations changes, either by adding a new task or deleting an already scheduled one – for example, when the medical condition of a patient worsens. So medical staff members inform the TA about the changes to be made and the TA transmits information to the IdA. The latter has to update healthcare operations and needed resources in order to achieve them. The TA interacts with software and physical agents, informing them about the changes of actions and the patient’s status.

- **Resource Agent (RA) behavior**

This agent interacts with the MSA. It is responsible for the monitoring and management of different human and material resources available for healthcare treatment tasks. It calculates the availability date of the medical staff members and also detects whenever medicines are out of stock and informs the user through the IdA about requested supply. The availability date is the possible earliest date for the medical staff to be available to begin a care operation. The monitoring of material resources can be set manually or automatically – manually through a graphical interface, for example to update the amount of stock of medicines, or automatically thanks to system sensors.

- **Integration and Evaluation Agent (IEA) behavior**

This agent is responsible for the whole system performance control. It checks and controls the overcrowding indicators. It also calculates the performance indicators of the system, such as patient waiting time and treatment costs, in order to evaluate the overall patient schedule in the PED.

- **Medical Staff Agent (MSA) behavior**

An MSA is a mobile software agent. The integration of the mobile paradigm into our agent-based system enables the possibility of migrating towards the different medical teams. The MSA represents a physical medical staff member through a graphical interface integrated within their mobile device (i.e. smartphone). So this agent can move from one medical team to another in the PED in order to treat patients. Thanks to this graphical interface, the medical staff member can set or get information about the healthcare of patients. For example, they can validate or cancel a medical care operation. The interaction of the MSA with the TA ensures effective care tracking. The interaction of the MSA with the RA ensures effective information about the availability of medical resources.

Healthcare tasks can be related to one or various patients. MSAs receive many requests for the treatment of different patients, and depending on their availability and the degree of emergency of patients, they carry out treatment in the different exam rooms of the PED. This special kind of agent is composed of data, states and a code and has a smart behavior. They are especially characterized by two variables (skills and availability). Once the MSA achieves a treatment task, it can shift to another team to carry out a new task. Therefore, the SA must take this aspect into account while assigning human resources to tasks. Each task represents a service that can be performed by different possible MSAs, with different delays. To respond to tasks, it needs data about the availability of MSAs and available skills through the RA. Therefore, the SA agent must optimize the assignment of resources to tasks. For this assignment problem, we adopt an optimizing solution based on the alliance between multi-agent systems and optimization tools. The scheduling behavior and the different optimizing tools will be described in the next section.

- **Scheduling Agent (SA) behavior**

The SA behavior is described in Figure 5 and operates as follows:

This agent has to optimize the choice of resources for patients' treatment taking into account some of the constraints of our system (precedence constraints and resources constraints (skills, availabilities, etc.)). It has to assign resources to patients' treatment tasks minimizing the total cost and patients' waiting time. This agent organizes the queue of patients who need treatment taking into account their degrees of emergency, then it assigns resources to different tasks.

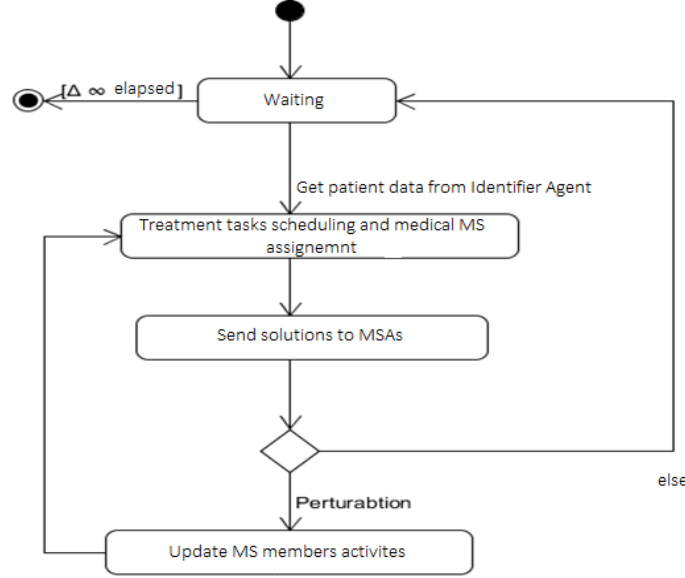


Figure 5: SA behavior.

Patients are triaged using a scheduling algorithm (see Figure 8) in order to decide who will get priority. The problem is solved by static or dynamic priority rules (emergency degree, arrival time, etc.). Specifically, at a given time t_0 , among the patients to be treated, the patient with the highest emergency degree is treated first.

In the next section, we focus on the negotiation between the SA and MSA to manage uncertainty related to the availability of resources and to find an optimal solution for the medical staff scheduling problem in the PED. Indeed, the problem stated above cannot be solved using basic communication between agents because it is not good enough to deal with the highly stochastic environment.

5. Uncertainty management through agents' negotiation

The aim of the studied problem is to organize the execution of a set of healthcare operations by medical staff members. Each health treatment task T_j corresponds to a patient waiting for treatment in the PED and is a sequence of n_j healthcare operations. Each operation i of a task T_j (noted $O_{i,j}$) may be performed by one or more medical staff members. The assignment of an operation $O_{i,j}$ to a medical staff member MS_k ($MS_k \in U$) entails the occupancy of this medical staff member for a period $d_{i,j,k}$ (we assume that $d_{i,j,k} \in \mathbb{N}^*$).

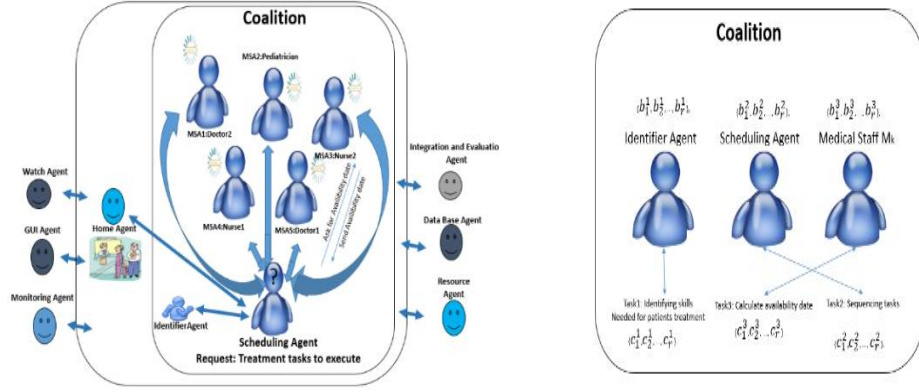


Figure 6: Multi-agent system coalition.

To solve the studied scheduling problem, we propose a negotiation process based on the formation of a coalition. Coalition formation is a different approach in terms of how the interaction between agents operates. It is about a group of agents facing the same request. Agents have to make individual compromises to find a satisfying agreement for all actors. If more than two agents are involved, alliance methods can be useful to reach consensus. The difficulty here is defining the communication protocol between agents. The protocol must allow agents to exchange their current choices, and these choices change to consensus.

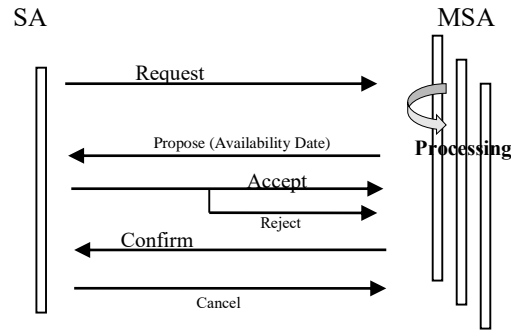


Figure 7: Negotiation protocol.

We suppose we have n agents $\{A_1, A_2, \dots, A_n\}$, each having certain capacities represented by a vector of capacity, where for an agent i the capacity vector is $B_i = \{b_1^i, b_2^i, \dots, b_r^i\}$, which is divided into r units. On the other hand, there are m tasks $V_m = \{T_1, T_2, \dots, T_m\}$, each with a certain requirement. Like agents, each task is represented by a vector of requirements. For a task j , this vector is $C_j = \{c_1^j, c_2^j, \dots, c_r^j\}$. Each task requirement vector is divided into r units.

We are interested in this work in a coalition composed of three types of agents: IdA, SA and MSA. Each agent has a local technique to improve decision-making. The aim is to meet rapidly the demands of patients with existing human resources,

which entails the minimization of the time spent by agents forming a coalition. Agents considered here are cooperative in the research and application of solutions.

The first actor of the coalition is the IdA. It is charged with the assignment procedure. The second actor is the SA, responsible for receiving queries and processing to provide execution plans for tasks. However, to carry out the scheduling, the SA needs information about medical staff availabilities to execute treatment tasks. The SA then sends a request to the MSA for the execution of the processing task. Then, negotiations between the SA and the various mobile agents modeling the medical staff members take place.

The SA is the initiator of the negotiation. It knows all information about patients, their pathologies and their needs. The initiator (SA) sends a request to the MSA deemed qualified to carry out the healthcare operations. The message form is as follows: $\langle SA, MSA_k, Request, AvailabilityDate(k), V_m(t) \rangle$, where ; $AvailabilityDate(k)$ corresponds to the earliest time at which a medical staff member MS_k is able to execute the set of treatment tasks $V_m(t)$. When an MSA receives a query, it analyzes it and sends a request to the RA in order to calculate and update in real time its availability. The RA sends back the calculated availability date to the MSA, which in turn sends a response to the SA. The latter makes a comparison between the availability dates provided by all the MSAs then decides (accepts or rejects the proposal). The MSA with the earliest availability date is chosen. The availability date of each medical staff member depends on their skills as well as the quality of the current healthcare operation progress. To determine the availability date, it is hard for experts to afford exact values due to the uncertainty involved. Besides, the evaluation is not the same in the eyes of the decision-makers [45], it depends on human feeling and recognition. Such problems are resolved using fuzzy logic, which has the advantage of dealing with uncertainty concepts. The execution time of healthcare operations depends on the skills' level of medical staff members. So, to determine $AvailabilityTime(k)$ of each MS_k we propose a simple application of fuzzy logic in order to find the best compromise value of execution time [46].

5.1. Behavior of agents involved in the negotiation

- **IdA: Assignment**

This technique allows each healthcare operation to be assigned to the most qualified medical staff member taking into account their skills. This procedure leads to the creation of a set E of assignments ($E = \{S^z / 1 \leq z \leq cardinal(E)\}$). For each healthcare treatment operation $O_{i,j}$, we associate the frequency $S^h_{i,j,k}$ to be assigned to a medical staff member MS_k then it condenses the set U to a subset where the probabilities of having a good scheduling are higher.

As an example, for the following treatment task scheduling (see Table 1), we obtain the scheme S^h as follows:

Table 1: Example of treatment task scheduling

$$C = \{C_{i,j,k} / 1 \leq j \leq N ; 1 \leq I \leq n_j ; 1 \leq k \leq M\}$$

MS Tasks		MS1	MS2	MS3	MS4
T 1	O 1,1	0.2	0.6	0.5	0.2
	O 2,1	0.4	0.9	0.3	0.2

	O 3,1	0.4	0.6	0.5	0.8
T 2	O 1,2	0.5	0.2	0.2	0.5
	O 2,2	0.3	0.4	1	0.4
	O 3,2	1	0.2	0.3	0.3
T 3	O 1,3	0.9	0.7	0.4	0.6
	O 2,3	0.5	0.6	0.9	0.2

Table 2: Assignment S^{ch}

$$S^{ch} = \{ S^{ch}_{i,j,k} / 1 \leq j \leq N ; 1 \leq i \leq n_j ; 1 \leq k \leq M \}$$

MS Tasks		MS1	MS2	MS3	MS4
T 1	O 1,1	0	*	*	0
	O 2,1	0	1	0	0
	O 3,1	0	*	*	*
T 2	O 1,2	*	0	0	*
	O 2,2	0	0	1	0
	O 3,2	1	0	0	0
T 3	O 1,3	*	*	0	*
	O 2,3	*	*	*	0

We consider that the assignment of a healthcare operation $O_{i,j}$ to a medical staff member is possible when the skill $C_{i,j,k} \geq 0.5$. The value " $S^{ch}_{i,j,k} = 0$ " indicates that we cannot assign the operation $O_{i,j}$ to the medical staff member MS_k . It means they are not sufficiently qualified for this healthcare operation. The value " $S^{ch}_{i,j,k} = 1$ " indicates that the assignment of the operation $O_{i,j}$ to the medical staff member MS_k is obligatory because they are the only one whose $C_{i,j,k} \geq 0.5$; in this case, all values of the rest of the line (i, j) are equal to "0". The symbol "*" indicates that the assignment is possible, i.e. ($C_{i,j,k} \geq 0.5$). We cannot have the value "1" and the symbol "*" at the same line. The application of the assignment procedure described above gives as a result the assignment S^{ch} (Table 2). In this table, we have for each healthcare operation one or more medical staff members who have the needed skills and are therefore qualified for its execution.

In the next section we will describe the procedure of finding out the most suitable human resource for a healthcare operation execution based on the calculation of availability dates.

- **RA: Fuzzy logic calculation**

This consists in calculating availability dates for each medical staff member in order to execute the healthcare operation $O_{i,j}$ in the same assignment table S^{ch} . We replace each $S_{i,j,k}=1$ and $S_{i,j,k}= *$ with the couple ($C_{i,j}, Ev_{i,j}$) where $Ev_{i,j}$ is the quality of the progress of the current healthcare operation $O_{i,j}$ being executed by MS_k . The cells where $S_{i,j,k} = 0$ are unchanged.

Table 3: Assignment by the couple (C_{ij}, Ev_{ij})

MS Tasks		MS1	MS2	MS3	MS4
T 1	O 1 ,1	0	(0.6, 0.5)	(0.5, 0.7)	0
	O 2 ,1	0	(0.9, 0.7)	0	0
	O 3 ,1	0	(0.6, 0.8)	(0.5, 0.9)	(0.8, 0.3)
T 2	O 1 ,2	(0.5, 0.6)	0	0	(0.5, 0.8)
	O 2 ,2	0	0	(1, 0.6)	0
	O 3 ,2	(1, 0.5)	0	0	0
T 3	O 1 ,3	(0.9, 0.3)	(0.7, 0.4)	0	(0.6, 0.8)
	O 2 ,3	(0.5, 0.9)	(0.6, 0.8)	(0.9, 0.5)	0

We choose to calculate the availability dates of the MSA by analyzing the progress of the current treatment task and the affordable skills, which are the inputs (C_{ij}, Ev_{ij}) . Then, we define for each input three subsets {"Low," "Medium" and "High"}. Each subset is characterized by its trapezoidal Membership Functions (MFs), while the passage from one state to another happens gradually. So, we begin with the definition of the MF of the variables or inference, which is based on decision rules depending on experts' views and historical data.

- Example of rules: **if** (the medical staff is "highly qualified") **and** (the progress of the current act is "high") **then** (the medical staff is "highly available").

After the inference step, the overall result is a fuzzy value. This result should undergo defuzzification to obtain an exact number as the final output. This is the objective of the defuzzification of a fuzzy logic system. It is done according to the membership of the output function. We apply the Center of Area method (COA). The outputs of this fuzzy logic calculation are fuzzy values corresponding to the availability of each medical staff member. The application of the fuzzy calculation procedure yields the following results:

Table 4: Assignment resulting from fuzzy availability processing

MS Tasks		MS1	MS2	MS3	MS4
T 1	O 1 ,1	0%	50%	83.3%	0%
	O 2 ,1	0%	83.3%	0%	0%
	O 3 ,1	0%	83.3%	83.3%	16.7%
T 2	O 1 ,2	50%	0%	0	83.3%
	O 2 ,2	0%	0%	50%	0%
	O 3 ,2	50%	0%	0%	0%
T 3	O 1 ,3	16.7%	50%	0%	83.3%
	O 2 ,3	83.3%	83.3%	50%	0%

As a final result, we choose the maximum values given by fuzzy logic calculation and we obtain the table below (Table 5). If we have 2 equal values we make a random assignment. Otherwise, an optimization of the total workload of each member of the medical staff is possible.

Table 5: Final assignment

MS Tasks		MS1	MS2	MS3	MS4
T 1	O 1,1	0	0	1	0
	O 2,1	0	1	0	0
	O 3,1	0	1	0	0
T 2	O 1,2	0	0	0	1
	O 2,2	0	0	1	0
	O 3,2	1	0	0	0
T 3	O 1,3	0	0	0	1
	O 2,3	1	0	0	0

- **SA: Scheduling Strategy**

BEGIN Scheduling_Agent Algorithm

Initialize the vector of Treatment Task availabilities $Dispo_Task[j]=0$ for each task j ($j \leq N$);

FOR ($i=1, i \leq \text{Max}_j(n_j)$)

- construct the set E_i of operations to schedule from S :
 $E_i = \{O_{i,j} / S_{i,j,k}=1, 1 \leq j \leq N\}$;
- classify the operations of E_i according to the chosen priority rule;
- **FOR** ($j=1 ; 1 \leq j \leq N$)
 - calculate starting times by following the same order given by the classification of E_i according to the formula:
 $Dispo_Staff[k] = \text{Fuzzy Availability Processing}(C_{i,j,k}, E_{v_{i,j,k}})$;
 $t_{i,j} = \text{Max}(Dispo_Staff[k], Dispo_Task[j])$ such that $S_{i,j,k}=1$;
 - updating of the vector of medical staff members' availabilities:
 $Dispo_Staff[k] = t_{i,j} + \text{Fuzzy Availability Processing}(C_{i,j,k}, E_{v_{i,j,k}})$;
 - updating of the vector of treatment task availabilities:
 $Dispo_Task[j] = \text{Fuzzy Availability Processing}(C_{i,j,k}, E_{v_{i,j,k}})$;

End FOR

End FOR

End Scheduling_Agent Algorithm

Figure 8: Scheduling algorithm used by the SA.

The SA solves the problem of task sequencing through a scheduling algorithm. It calculates the starting time of execution $t_{b,j}$ regarding the availability of medical staff members and their skills. The SA receives this information in the messages delivered by the different MSAs, which, after receiving the SA request, go for processing, then answer the request by sending the fuzzy value of their availabilities calculated and updated by the RA (Figure 8).

Conflicts are resolved by applying conventional priority rules (SPT, LPT, FIFO, etc. [47]), so we get a set of plans according to the applied priority rules. In emergency departments, priority is given first to the most urgent cases, then to the operation related to the patient who has arrived first.

6. Results

6.1. Data analysis

number	Arrival Date	Exit Date	duration	MD	diagnostique	echographie	scanner	radiologie	biologie	nbreTests	codeN
69453	28/11/2013 08:13:00	28/11/2013 13:18:00	305	3091	Autres pneumopathies bactéri	0	0	0	0	0	0
69454	28/11/2013 08:19:00	28/11/2013 16:44:00	505	3091	Gale	0	0	1	1	2	0
69455	28/11/2013 08:33:00	28/11/2013 08:35:00	2	3092	Intoxication par autres analgés	0	0	0	0	0	0
69456	28/11/2013 09:14:00	28/11/2013 12:25:00	191	3091	Fractures multiples des méta	0	0	0	0	0	0
69457	28/11/2013 09:27:00	28/11/2013 15:41:00	374	3091	Gastroentérites et colites d'éc	0	0	1	1	2	0
69458	28/11/2013 09:31:00	28/11/2013 14:30:00	299	3091	Nausées et vomissements	0	0	0	1	1	0
69459	28/11/2013 09:34:00	28/11/2013 14:24:00	290	3091	Morsure de la joue et de la lè	0	0	1	0	1	0
69460	28/11/2013 09:34:00	28/11/2013 11:57:00	143	3091	NA	0	0	0	0	0	0
69461	28/11/2013 09:40:00	28/11/2013 11:19:00	99	3092	Autres difficultés liées à l'em	0	0	0	0	0	0
69462	28/11/2013 09:42:00	28/11/2013 14:57:00	315	3091	Contusion de(s) doigt(s) sans	0	1	0	0	1	0
69463	28/11/2013 09:59:00	29/11/2013 09:59:00	1440	3092	Laryngite (aiguë)	0	0	0	0	0	0
69464	28/11/2013 10:13:00	28/11/2013 13:02:00	169	3091	Malaise	0	0	0	0	0	0
69465	28/11/2013 10:14:00	28/11/2013 11:36:00	82	3092	Diabète sucré insulino-déper	0	0	0	0	0	0
69466	28/11/2013 10:21:00	28/11/2013 13:43:00	202	3091	Asthme, sans précision	0	0	0	0	0	0
69467	28/11/2013 10:35:00	29/11/2013 10:16:00	1421	3092	Gastroentérites et colites d'éc	0	0	0	0	0	0
69468	28/11/2013 10:50:00	28/11/2013 17:27:00	397	3091	Pyélonéphrite (non obstructi	0	0	0	1	1	0
69469	28/11/2013 10:52:00	28/11/2013 14:27:00	215	3091	Autres conjonctivites	0	0	0	0	0	0
69470	28/11/2013 10:59:00	28/11/2013 15:07:00	248	3091	Inquiétude et préoccupation	0	0	1	1	2	0
69471	28/11/2013 11:02:00	28/11/2013 20:14:00	552	3091	Plaie ouverte d'autres parties	0	0	1	0	1	0
69472	28/11/2013 11:05:00	28/11/2013 15:21:00	256	3091	Bronchiolite (aiguë), sans pré	0	0	0	0	0	0
69473	28/11/2013 11:07:00	28/11/2013 15:54:00	287	3091	Bronchiolite (aiguë), sans pré	0	0	0	0	0	0
69474	28/11/2013 11:15:00	28/11/2013 15:05:00	230	3091	Rhinopharyngite (aiguë) [rhu	0	0	1	1	2	0
69475	28/11/2013 11:32:00	28/11/2013 23:02:00	690	3092	Convulsions, autres et non pr	0	1	0	1	2	0
69476	28/11/2013 11:47:00	28/11/2013 14:57:00	190	3091	Rhinopharyngite (aiguë) [rhu	0	0	0	1	1	0
69477	28/11/2013 11:50:00	28/11/2013 15:19:00	209	3091	Hernie inguinale, (unilatérale	0	0	0	0	0	0
69478	28/11/2013 11:58:00	28/11/2013 17:54:00	356	3091	Rhinopharyngite (aiguë) [rhu	0	0	1	0	1	0
69479	28/11/2013 12:12:00	28/11/2013 17:11:00	299	3091	Douleur aiguë	0	0	1	0	1	0
69480	28/11/2013 12:30:00	28/11/2013 16:43:00	253	3091	Néphrite tubulo-interstitielle	0	0	1	0	1	0
69481	28/11/2013 12:36:00	28/11/2013 18:28:00	352	3091	Entorse et foulure de la chevi	0	0	0	0	0	0
69482	28/11/2013 12:46:00	28/11/2013 15:44:00	178	3091	Malaise	0	0	0	0	0	0

Figure 9: The 3-year database of the PED.

We have the real 3-year database collected in 2011–2012–2013. During this period from 2011 to 2013 we noted 47,188 visits; 19% of them were hospitalized in the Short-stay Observation Unit (SOU), and the other 81% were patients of the Outpatient Care Unit (OCU). We are concerned with the second population's responsibility for the overcrowding phenomenon. Usually, their length of stay (LOS) does not extend beyond 8 hours, otherwise they are transferred to the SOU.

Following an initial exploration of data available at the PED (2011, 2012 and 2013), we were able to highlight some key figures of the pathway of patients at the PED of Lille University Hospital:

- 5.5 is the average number of changes of place for a patient entering the PED;
- 25,000 people is the average annual number of incoming patients to the PED;
- 2 hours is the average waiting time for a patient at the PED, including examinations and results.

According to data collected, we noted that the patient flow coming to the service is totally random. However, the average figures are cyclical and sufficiently redundant so that we can generate a model of the incoming flow, and several temporal scales – depending on the time of year, the time of day, certain particular events, etc. For example, in winter, the diseases treated are frequently infectious, while in the summer, patients rather suffer from trauma due to falls while playing sport outdoors. In this context, the months November to February recur frequently in attendance statistics as very busy months. This is due to the upsurge of infectious diseases such as gastroenteritis, bronchiolitis and influenza during the winter period. On the other hand, some periods of the day are busier than others. Thus the service is seen to be overloaded daily between 18 h 00 and midnight, with waves of arrivals of patients around 18 h 00, then 20 h 00 and finally 23 h 30 to midnight.

These peaks are due to the fact that the PED deals, as the name suggests, with young patients, and therefore they come with their parents in the afternoon, after school and after leaving work. During epidemic episodes, the usual flows are complicated by epidemic-related flows. This increasing flow has an impact on the use of structures dedicated to emergencies welcoming emergencies within 24 hours. It also affects the capacity of the University Hospital to receive patients and sometimes induces a redistribution of patients to other hospitals in the metropolis. In times of normal affluence, that is to say during the day and in the early hours of the morning, the waiting of patients is no longer due to the overcrowding situation, but the normal processing time for patient medical examinations.

Figure 10 shows three curves of the total number of patients in service per month for three years of the study. These curves evolve around the average to indicate increases and decreases in demand.

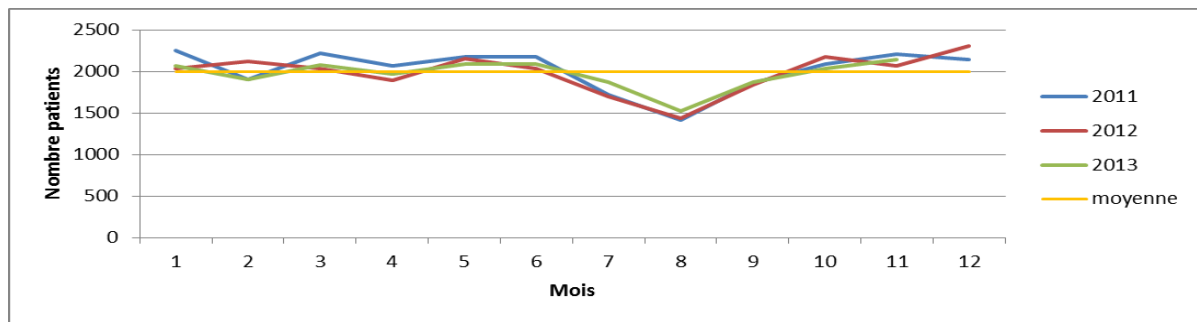


Figure 10: Total number of patients per month.

We can see that the variations are almost the same every year and depend on certain periods. We can conclude from this graph that the number of arrivals per month in the PED is a stable phenomenon in which seasonality seems obvious for each 12-month period.

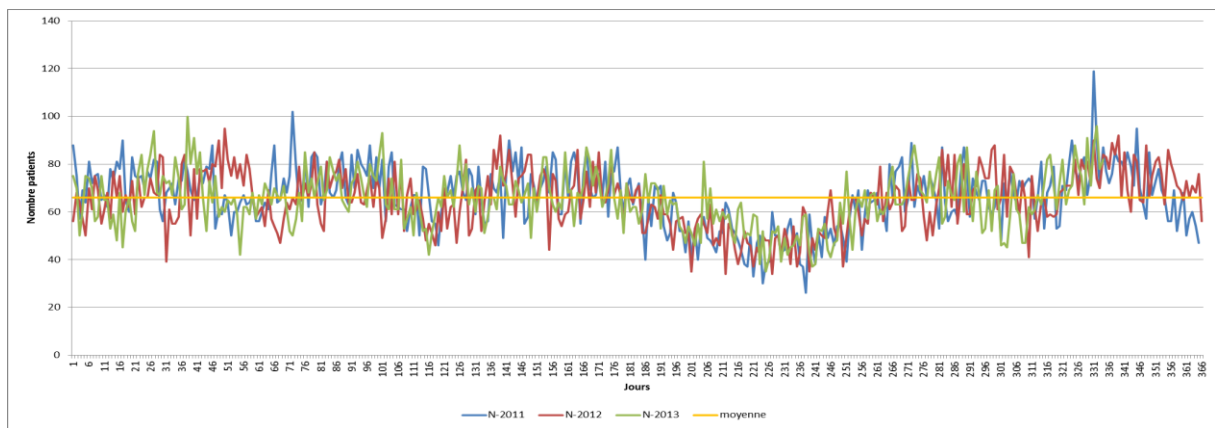


Figure 11: Total number of patients per day.

Making predictions at the horizon of one month could be interesting in terms of monitoring, observation and organization, but we do not have relevant information reflecting the overcrowding situation. So we need to refine the horizon to a day as shown in Figure 11.

By refining the horizon to one day in Figure 11, the phenomenon becomes less stable due to the appearance of the details of the variations that were previously absorbed. We also find some daily peaks. The 3 most prominent peaks for each year are noted as 119 patients on 27/11/2011, 97 patients on 19/02/2012 and 100 patients on 02/07/2013, against the daily average of 66 patients.

6.2. System performance through agents' orchestration

The approach already presented can give a scheduling solution that represents a good compromise between the various criteria (minimization of waiting time and medical staff workload). The scheduling established provides a GANTT for medical staff and a running order between the optimized operations. But this ordering, although it is optimized, does not take into account the evolution of the health status of patients, particularly after additional tests such as a blood test, MRI, X-ray, etc. Therefore, in order to be effective, this scheduling must be coupled with a dynamic patient pathway orchestration approach to further improve the criteria. We therefore need a dynamic orchestration workflow architecture modeling the patient journey through agents. The alliance between a multi-agent approach and workflow is interesting in terms of performing a dynamic orchestration in order to provide high-quality healthcare services in the PED. Through the agent-based modeling, we have optimized the pathway of patients. In fact, agents are responsible for the orchestration of patients' movements, which are modeled by a workflow approach already mentioned in [2], within the departments of the PED. This orchestration enables validation of the decisions made by the different interacting agents in the proposed system. These decisions concern the dynamic reorientation of patients, the real-time transfer of information between the PED medical staff members thanks to the interaction between agents (information about medical staff availability, beds availability, etc.), pathology identification, the assignment of the healthcare provider who is deemed the most expert, etc.

Negotiation protocols of agents in the coalition allow the distributed execution of a workflow instance. We propose a two-step approach for the management of a collaborative workflow. The interest of this division into two stages lies in separating, thanks to a coalition of agents, a first phase of assignment and care task scheduling, which is then used by the SA to control the second phase of dynamic orchestration, based on a process of negotiation between agents in the coalition (e.g. between the SA and the MSA). The idea is to separate coalitions depending on the nature (predictability) of the knowledge they handle.

During the scheduling and task assignment phase, the SA analyzes the description of a workflow scheme that defines the inherent properties complying with healthcare treatment protocols set before execution. It includes specifications on existing resources, and a list of tasks to be performed respecting the precedence constraints between tasks.

The dynamic orchestration phase is based on a dynamic scheduling methodology. In addition to time constraints, real-time resources availability is also taken into account. During this phase, tasks are scheduled according to the priorities calculated while executing the workflow.

The proposed agent-based architecture has enabled the dynamic reorchestration of the patient pathway modeled by a workflow in the different services of the PED. This has led to reduced patient waiting time during their journey.

Our agent-based approach enables orchestration and reorchestration in the case of overcrowding situations to support patients in the most efficient way possible by reducing the total waiting time of patients. The figure below demonstrates the effectiveness of our resolution architecture in terms of Global Patient Waiting Time (GPWT).

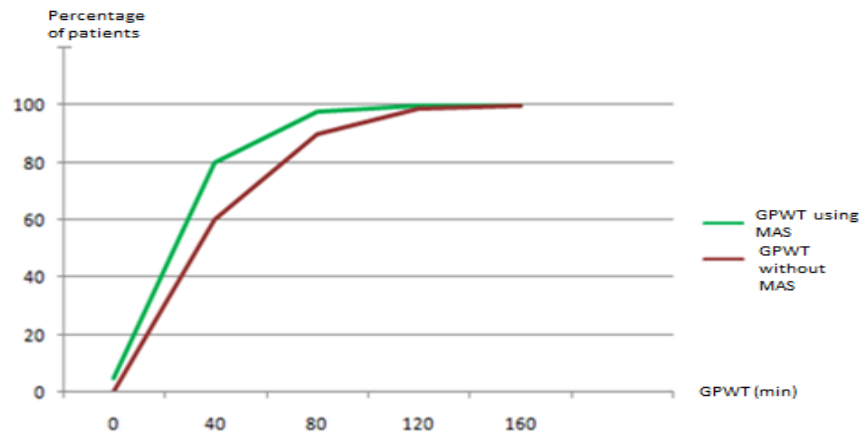


Figure 12: Distribution of the average waiting time using multi-agent system.

Thanks to the interaction between agents, the GPWT studied in the PED becomes less than one hour for 79% of patients whereas it was initially greater than 2 hours (without multi-agent system) for 72% of these patients. A total of 98% of patients had an overall length of stay of less than 4 hours with our resolution algorithm instead of 93%.

The GPWT is generally lower in the morning (before 9 am) and at night (after midnight). It is more than one hour for patients enrolled in the workload period (from 18 h). The GPWT is determined according to the degree of severity. According to experts in medical care, 61% of those who have spent more than two hours had at least one healthcare treatment without additional examinations. The majority of patients (86%) who spent more than 2 hours in the PED had one or more additional examinations such as X-ray, etc.

Thanks to the dynamic orchestration, our simulation affirmed the several factors which were determined by the IEA and may be responsible for the variation in GPWT:

- The waiting time: A patient can spend the majority of their stay in the PED waiting for their first healthcare treatment. This waiting time is very high during periods of overcrowding.
- Severity of the pathology: The time spent in the PED varies according to the severity of the patient's health condition. The results showed that a serious condition is likely to lead to a longer stay because this situation requires more complex care including complementary examinations.
- Ask for expert advice: Waiting for the arrival of a medical specialist appears to increase the GPWT.
- Request for additional radiological and biological examinations: The demand for additional tests is quite common in the emergency department. These examinations extend the length of stay of patients since obtaining the results requires a long time.

6.3. The management decision support system implementation

Our system is a management decision support system designed for medical staff members to manage and monitor patients in order to improve their healthcare treatment process. It helps the PED staff make decisions about patients' orientation and management and control PED performance. Indeed, thanks to this system, each medical staff member can have information about the number of patients in the PED, both being treated and waiting for treatment. It also allows better coordination and communication within medical teams and between different teams and patients. It is a flexible tool, scalable and interactive. It has several ergonomic interfaces that allow PED managers to intervene and act on its functionalities.

We have developed our system with the JADE (Java Agent DEvelopment framework) platform, which supports coordination between several agents and provides a standard implementation of the communication between agents.

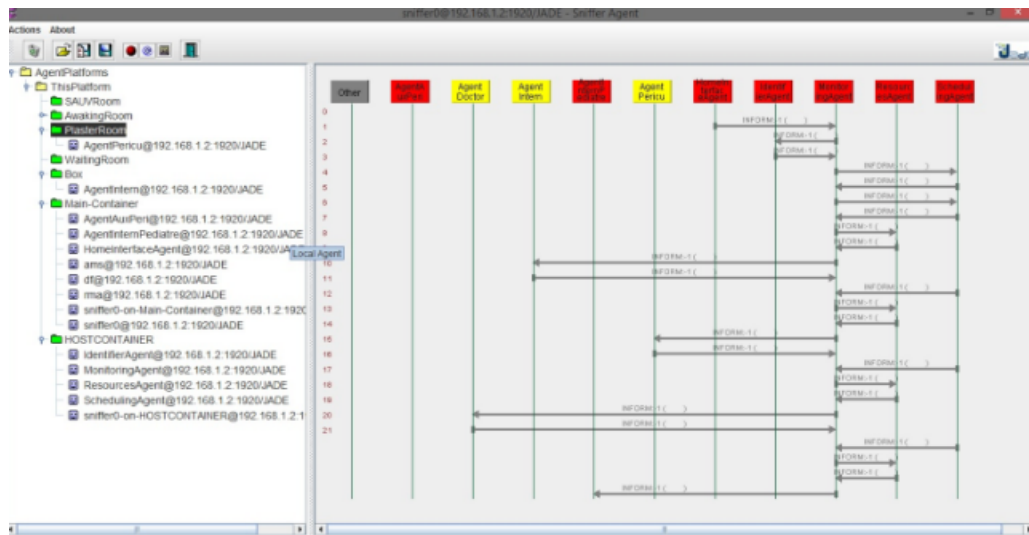


Figure 13: Communication between agents.

In this paper, to view agents' communication we used a JADE graphical tool that sniffs message exchanges and debugs a conversation between agents. Figure 13 shows the evolution of message exchanges between the different agents through the "sniffer" tool that is useful for debugging.

When we start the simulation the real PED database is loaded. Our management decision support system already running in Lille University Hospital includes managing interfaces covering essentially:

- **Registration and authentication interfaces**

When we launch the system, the interfaces for the user registration or identification appear. This step is important for the privacy of information related to patients.

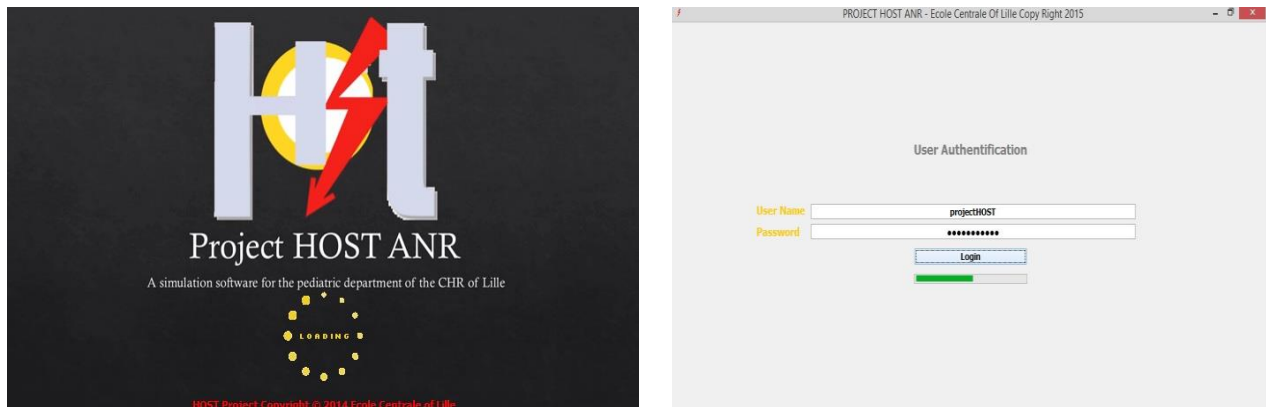


Figure 14: Authentication interface

- Main interface

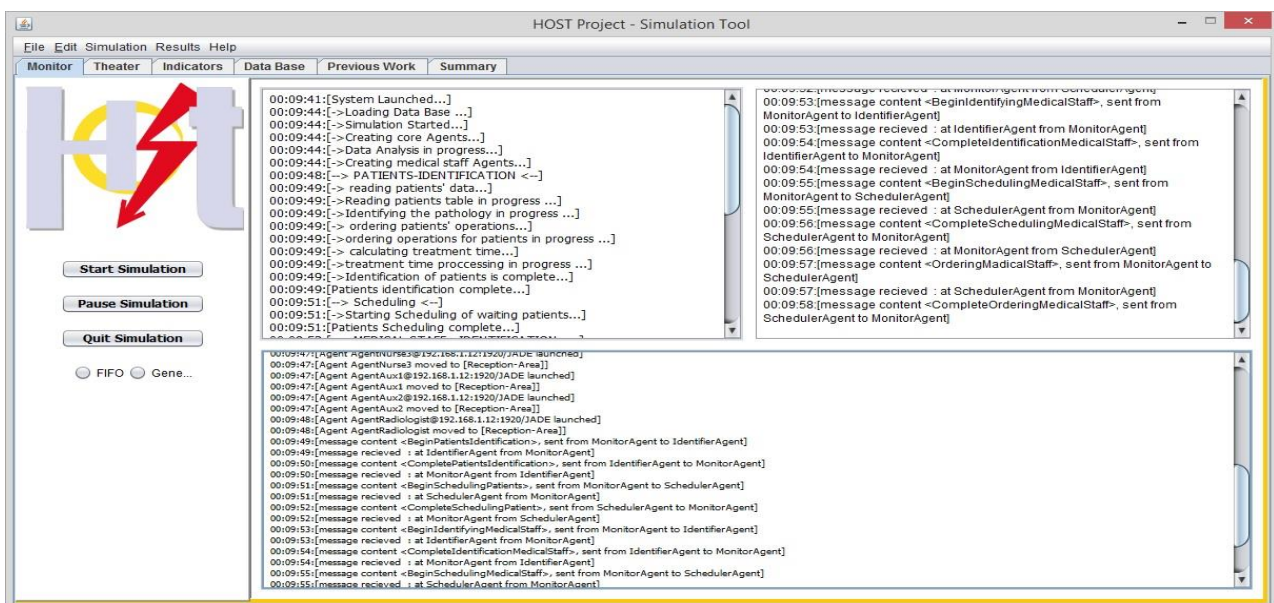


Figure 15: Main interface.

This interface (Figure 15) allows the system user to see the different transactions and interactions between agents in our system.

- Theater

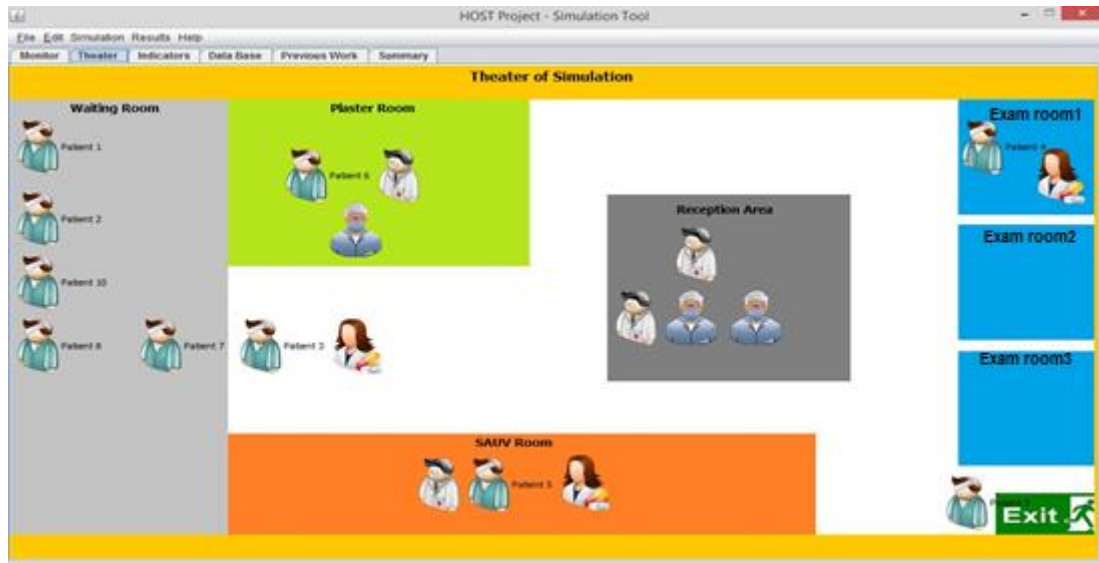


Figure 16: Theater (PED) interface.

This interface (Figure 16) emulates the architecture of the PED including exam rooms, waiting rooms, etc. It is used to track the movements of medical staff members in the PED, modeled by mobile agents in the proposed multi-agent architecture, while performing healthcare tasks.

- Criteria evolution interface

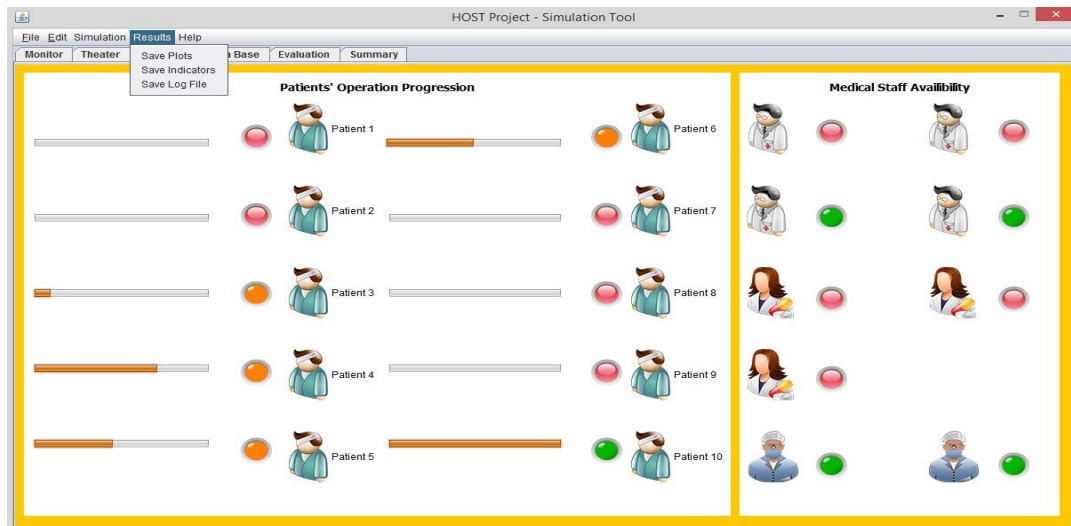


Figure 17: Indicators interface.

This interface is used to monitor the availability of medical staff and the patient journey. The left panel regards monitoring patients' healthcare treatment process. For example, upon their arrival, waiting for the first patient support is indicated by

a red LED and the corresponding progress bar is empty (0%). Once the first healthcare operation is performed, the indicator turns orange. Each time a treatment operation is performed on a patient the progress bar is filled with a percentage, which depends on the remaining operations to be performed (x%). When the patient treatment process is completed, the light turns green and the progress bar is completely filled (100%). The right panel shows schematically the green lights and red lights respectively indicating the availability and unavailability of medical staff. This task is the role of the SA.

- **Patient tracking interface**

This is the task of the IEA. This interface helps the medical staff members to take decisions about patients' treatment management and evaluates the performance of the PED. Thanks to the proposed management decision support system, each healthcare provider knows the number of patients in the PED, both waiting for treatment and being treated. They can also, through this interface, follow the evolution of patients' treatment process. Thus, the PED actors are more likely to be able to satisfy patients' needs.

Counting patients in the PED with certainty is already a first step toward viewing the occupied volume and the overcrowding level of the service, but following in real time the progress of various treatments is better for assessing carefully the remaining load at time t . So in order to avoid being limited to the physical presence of patients and because a high occupancy rate does not necessarily mean that there is a strong demand for care, we choose to assign to each patient a time counter that is triggered upon entering the service as shown in the figure below.

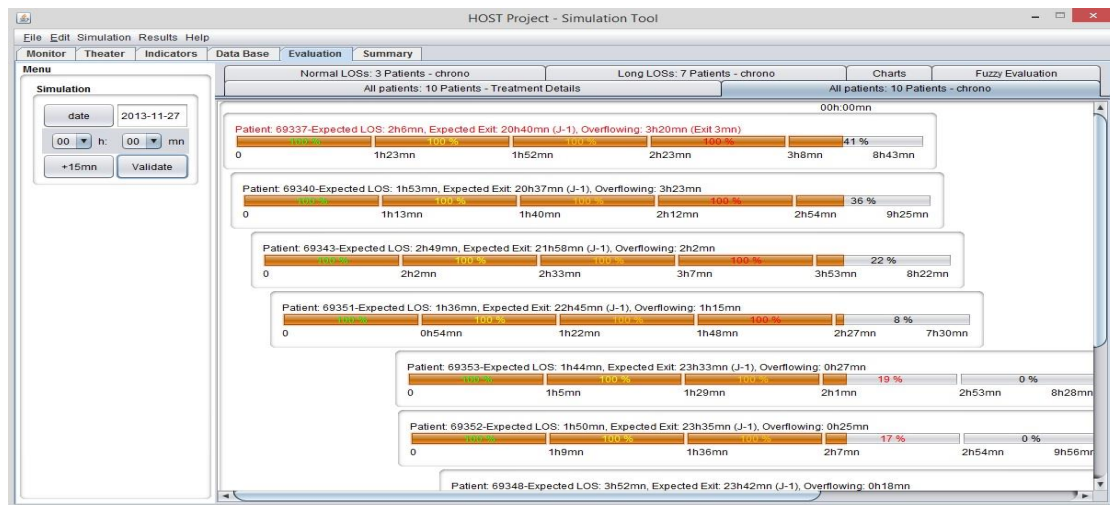


Figure 18: Patient tracking interface.

Thanks to the interaction between the SA, TA and RA, we get a visualization interface of the evolution of the healthcare treatment process of different patients in the PED. This allows us to have in real time an idea about the current situation in the PED. Progress bars give the SA a clear idea about the decisions concerning the next patients to treat and medical staff assignments. These progress bars indicate the remaining healthcare operations to be performed on patients. Thus, we assess the state of overcrowding according to the progress of patients' treatment and the exact percentage of what remains to be done, and not according to the number of patients in the waiting room. This interface gives the user a general idea about

the situation in the PED by indicating the cumulative percentage of the remaining healthcare operations to be performed on patients.

6.4. Agents' activities

All the actors of the proposed multi-agent system modeling the PED, because of their different properties (autonomy, communication and interactions, cooperation, etc.), can have different activity features. Indeed, at a given time t , agents can negotiate or transmit instructions while others are executing scheduling tasks. As shown in Figure 19, we have identified four types of activity:

- Staggered activities: All the medical staff members (MSA) work with a lag. An agent is able to start a new scheduling activity even if an earlier activity (a healthcare task) is still being performed.
- Parallel activities: In the example shown below, the four medical staff members are functioning simultaneously, nonsequentially. Each agent must wait until the end of an activity before beginning another.
- Interruption: An agent can stop an activity already started if it receives an update or a more urgent healthcare task to execute.
- Different durations: The activities of agents can have different durations, which depend on the category of the healthcare task being carried out.

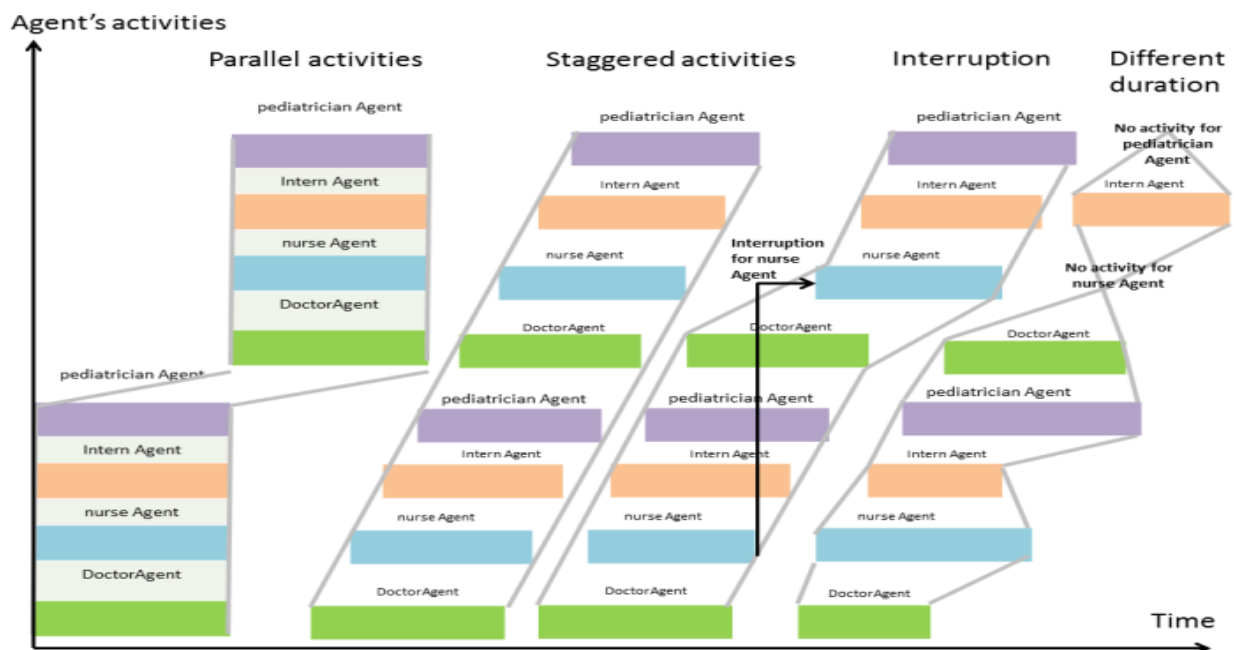


Figure 19: Agents' activities.

7. Discussion

Health logistics aims to efficiently deploy technical and IT tools to optimize time management, reduce the risk of errors and anticipate the overcrowding situations in an area where the human factor is strongly present. The state of overcrowding within healthcare institutions can be described by indicators related to internal factors such as the increasing number of patients; the lack of beds; the proliferation of diagnostic tests, the waiting time of patients, etc. Our field of study is the PED, in which the patient journey is complex. The largest cause of delay is the waiting time, which represents 70% of the total time spent in the PED. The direct causes of this waiting time are the bottlenecks that disrupt normal traffic flow within the process, leading to overcrowding. We noted typical days in 2011–2012–2013 characterized by overcrowding. Unfortunately, waiting times in the PED can reach up to 5 hours with the strong incoming flows. For a long time pediatric emergency services have been trying to organize themselves by increasing the number of caregivers, adapting certain work schedules, etc.

Unfortunately, in the current state of things, there is no reliable system to effectively manage the availability of human or material resources, whether for the PED exam room itself, or for beds. Moreover, an additional problem is “falsely free” beds, i.e. the beds are unusable due to the presence of a contagious patient in the same room, or the fact that the room has not been cleaned after the stay of a patient. We can also add to this the fact that there is no centralized alarm or monitoring of rooms for patients who need to be placed under observation (short hospitalization periods). Nevertheless, the PED has already experienced over the years many upgrades, which have already enabled it to consistently improve the management of peaks of activity within the service.

The research conducted in this paper concerns the design, the development and the implementation of models and innovative methods to effectively manage the PED logistics flows. Numerous reports and studies include a review of the state of health systems in demographic and financial crisis. We found a synthesis in the work of Guinet et al. (2008). This is due to the accumulation of new constraints, combined with highly rigid structures [44]. According to Benjamin et al. (2013), the expenditure in the health field depends on the organization budget [8]; however, we think that it is possible to optimize healthcare organization functioning to reduce costs related to patients’ treatment. In fact, a mismanagement can engender economic losses. So, in order to reduce costs, it is necessary to optimize the healthcare organization’s resources management and communication between its different actors. Thus, hospital systems and emergency sectors are facing increasing difficulties in carrying out their tasks. However, there is an overall continuous mutation of the health system. The culture of the health sector and in particular public and private hospitals is facing new concepts. These initiatives have a beneficial effect but analysis of needed changes in the health system shows that the key to achieving this is the optimization of the organization that leads to optimization of the information systems. Thus, dysfunctions observed at present in hospital services and care pathways are largely due to an organization poorly adapted to the constraints and the evolutions of their missions as well as the mismanagement of patient flows, which usually leads to overcrowding situations.

The overcrowding concept, as defined by Moskop et al. (2009), depends only on load indicators (number of patients, number of available resources, etc.) [13]. Yet, it is defined as part of our work as the imbalance between the flow of care

of patients and the capacity of the healthcare organization (emergencies or hospital) for a sufficient period to cause adverse consequences for proper functioning. In addition, it depends not only on load indicators but also on the Health Care Load Indicator (HCLI) (progress of patient treatment process, i.e. remaining healthcare operations related to patient to treat). However, it remains crucial to understand the causes of this overcrowding in order to avoid it. In this perspective, Asplin et al. (2003) developed a conceptual model for understanding these causes throughout the care process [45]. Some research has adopted this model to identify the causes, which the authors grouped into three categories:

- Problems due to inflow (input),
- The problems encountered during the processing (throughput),
- Problems due to outflow (output).

Kadri et al. (2013), based on a cause-effect diagram, identified the main causes of overcrowding in an emergency department. In our work, thanks to the multi-agent system these causes are controlled and updated through agents' behaviors [5].

Healthcare actors must master the process flow issues (patient information, products and equipment) and the issues related to restructuring leading to the pooling of resources, particularly by technical platforms. However, health professionals are neither prepared nor trained to solve such problems; it appears that they have no methodologies or management decision support tools adapted to the requirements involved in their future operating modes.

In recent decades, there has been considerable effort in the development of simulation and optimization models to solve various problems in the functioning of the healthcare system structures. Efforts to improve the operating performance of these services are based on modeling and simulation approaches in the field of information technology. In literature, we find the main approaches commonly used in modeling and simulation in the field of healthcare. However, it is clear that research does not come up with generic, global and sustainable solutions. Indeed, the major disadvantage here is that modeling approaches do not take into account the impact of human behavior on the performance of the healthcare process. For instance, Fone et al. (2003), through the use of the Markov Chain, did not consider the impact of human behavior on the performance of the care process [32]. Pato and Moz (2007) used metaheuristics to solve the human resources scheduling problem without taking into account the skills. Metaheuristics ensure only local optimization without considering the interaction and the information exchange between medical staff members [23]. In this paper, we use conjointly the multi-agent system and optimization algorithms in order to optimize the scheduling taking into account the skills of care providers and the communication and coordination between them. We aim in this work to contribute to the study and the development of modeling, optimizing and implementing a management decision support system to evaluate the overcrowding level in the hospital in order to improve the care process of patients in the different departments of the hospital. This system must be the logistic engine of healthcare facilities for a better efficiency of care perspective, human and material resources management, pricing of medical activities and anticipating risks. The system must interact with a distributed, uncertain and dynamic environment, enabling simulation, as faithfully as possible to reality, of logistics flows, medical staff activities, behaviors and shifts in healthcare organizations.

Currently, in healthcare organizations there is a lack of communication between the different hospital actors, especially in emergency departments. Information about patients is not exchanged in real time between healthcare providers and sometimes arrives late or is forgotten. For example, doctors sometimes forget to inform their colleagues of chronic patient illness while this information is very important for the administration of medicines. For this reason, we propose using an multi-agent system as an adequate approach to ensure communication, coordination and negotiation between the different medical staff actors, to enhance the care quality provided to patients and to guarantee their safety [50]. There are two categories of intelligent agents: “stationary” agents and “mobile” agents. To model medical staff members’ activities, doctors, nurses and medical assistants are represented by mobile agents, which, unlike other agents known as “stationary,” have mobility. The goal here is to simulate the behavior of healthcare providers, which can move from one medical team to another alternately to treat different patients, according to the skills needed for the corresponding treatment tasks. Agent-based technology is a useful concept in healthcare applications. In fact, it allows better analysis and characterization of the operation of the emergency department, which is a complex system. Agent-based modeling is able to explicitly model the complexity arising from medical staff members’ interactions that arise in the real world. Simulation using a multi-agent system allows healthcare providers to model their real-world activities, which is not possible through traditional modeling techniques such as discrete event systems. A multi-agent system is therefore the best approach to adopt since it can deal with the distributed and dynamic nature of logistic flows in health problems. In addition, it enables the decomposition of the system into multiple agents that interact and work together to achieve a common goal, which is the optimization of healthcare organization and patients’ management. The interaction between the different agents is carried out through communication which can be explicit or implicit. A physical agent can be continuously emitting messages with regard to its location and visible physical position; other software agents may act according to their environment, certain circumstances and goals to achieve.

8. Limitations

We have proposed in this study a management decision support system providing support services for practitioners and managers in the PED in order to reduce and anticipate the peaks of activity and overcrowding phenomenon. Nevertheless, this system does not offer any final decisions. It has additional support to provide greater visibility on activity and detect any abnormalities.

The agent-based model was limited to the PED itself. Hence, the results are valuable, mainly, for internal PED management. However, the optimization approach does not take into account external factors such as the availability of beds.

Another limitation concerns the fact that our system, in the case of an overcrowding situation, cannot orientate patients to other less crowded PEDs in the neighborhood.

The data were collected in 2011–2012–2013 and do not contain all the needed information. Some details are missing, especially those concerning the medical staff members as well as the waiting time between each step of the treatment process. We therefore tried to get approximate information through meetings established with some practitioners.

9. Conclusion

During our study, we noticed difficulties in the management of patients, especially in the case of an overcrowded PED. So healthcare specialists should get involved in new actions aimed at improving care services. Our target is to provide intelligent management of the healthcare process based on artificial intelligence. A distributed decision-making agent-based paradigm provides an interesting approach to improving the quality of care services provided by healthcare facilities. In this paper, a dynamic approach based on a multi-agent system was proposed as a methodology for the intelligent management of PEDs, patient scheduling, improving healthcare services provided to patients and minimizing costs related to delays. These delays are due to the complex patient pathway, human and material resources allocation and patients' waiting time. It is important to emphasize that this methodology has proven its efficiency in reaching the global objective of the whole healthcare process in the PED.

For future work, generalizability and transfer to other healthcare systems are possible. Indeed, if we generalize this approach, the calculation is adaptable to any connected database respecting the study protocol. Furthermore, the scheduling and evaluation methods can be adapted depending on the service and the region.

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