



HAL
open science

An Agent-Based Metaheuristic with Cooperation Approach applied for patients'scheduling in hospital emergency department

Faiza Ajmi, Faten Ajmi, Sarah Ben Othman, Hayfa Zgaya-Biau, Jean-Marie Renard, Gregoire Smith, Slim Hammadi

► **To cite this version:**

Faiza Ajmi, Faten Ajmi, Sarah Ben Othman, Hayfa Zgaya-Biau, Jean-Marie Renard, et al.. An Agent-Based Metaheuristic with Cooperation Approach applied for patients'scheduling in hospital emergency department. 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Oct 2022, Prague, Czech Republic. 10.1109/SMC53654.2022.9945510 . hal-03977833

HAL Id: hal-03977833

<https://hal.science/hal-03977833>

Submitted on 7 Feb 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

An Agent-Based Metaheuristic with Cooperation Approach applied for patients'scheduling in hospital emergency department

Faiza Ajmi

CRIStAL CNRS UMR 9189
Villeneuve d'Ascq, France
faiza.ajmi@univ-lille.fr

Faten Ajmi

CRIStAL CNRS UMR 9189
Villeneuve d'Ascq, France
faten.ajmi@centralelille.fr

Sarah Ben Othman

CRIStAL CNRS UMR 9189
Villeneuve d'Ascq, France
sara.ben-othman@centralelille.fr

Hayfa Zgaya-biau

CRIStAL CNRS UMR 9189
Villeneuve d'Ascq, France
hayfa.zgaya-biau@univ-lille.fr

Jean-Marie Renard

Lille University Hospital Center
Lille, France
jean-marie.renard@univ-lille.fr

Gregoire Smith

Lille University Hospital Center
Lille, France
gregoire.smith@univ-lille.fr

Slim Hammadi

CRIStAL CNRS UMR 9189
Villeneuve d'Ascq, France
slim.hammadi@centralelille.fr

Abstract—In this paper, we propose an innovative metaheuristic characterized by a multi-dimensional chromosome where each dimension is driven by a rational agent. These agents have to communicate in order to implement evolving and adaptive genetic operators to accelerate the convergence towards the optimal solution. This cooperative approach is applied to solve the patient scheduling problem in emergency department (ED). This problem is NP-difficult due to the permanent interference between three types of arrival: already programmed patients, non-programmed patients and urgent non-programmed patients. Our scheduling problem has to integrate several dimensions such as medical dimensional, patient dimensional, temporal dimensional. The multi-dimensional aspect of the chromosome is crucial to model the different dimensions of the ED. The main goal of the simulation results is to assess the performance of the proposed agent driven multi-dimensional chromosome. The simulation results confirm that the intra and inter chromosomal interactions allow to avoid the blind aspect of the genetic operators and impacts the quality of solutions. The agents' cooperation and its ability to improve efficiently the quality of the solutions by exploring intelligently the research space are confirmed by the drop in average total patient waiting time by 15.09%

Index Terms—Metaheuristics, Multi agent Systems, Cooperation, Hybridization, Combinatorial Optimization, Hospital Logistics

I. INTRODUCTION

The ED is a complex system that interacts with the downstream and upstream flows of hospital services. This complexity is due to the stochastic features of the ED such as arrival times, treatment times, admission rates, triage categories and waiting time. In addition, the ED has limited resources and stochastic demand, which makes the combinatorial optimization an ideal tool/model to improve the healthcare system [1].

In this paper, we present a hybrid metaheuristics as an innovative approach for optimization using a multi dimension chromosome in with each dimension is modeled by an autonomous agent. So that each chromosome is represent by a multi agent system. This approach aims to help ED

managers in setting up strategies and management guidelines to optimize the healthcare activity of ED while assigning a dynamic priority to the patients. In this approach, each agent acts independently in the solution search space through its ability to manage its own dimension of the chromosome. Agents cooperate with each other in order to make good decisions while improving the quality of care provided for patients. This cooperation is made thanks to the well defined negotiation protocol. This protocol allows agents to make appropriate decisions based on experiences gained in interacting with other agents and the environment. This protocol mainly exploits two knowledge databases detailed in [2].

- A declarative database for describing the objectives and context of the negotiation. For example, to determine the pathology of the patients and to define the appropriate treatment rooms.
- A database for negotiation rules, for example, choosing the adequate skills of medical staff to provide care quality.

In our approach, the negotiation protocol is established to represent the genetic operators such as mutation and crossover. This protocol respects all the strong and the flexible constraints which are already fixed and published in our previous work [3]. The objective is to determine a protocol for the negotiation between agents allowing as to schedule and re-schedule in real time care tasks while minimizing the patient's Average Total Waiting Time (ATWT). Thus, our approach is based on the cooperation of agents to generate a viable chromosome in order to provide a set of a good solution in the final population.

Metaheuristics are used as one of the main methodologies to solve highly complex optimizing problems for which there is no method to efficiently find the optimal solution [28]. Metaheuristics are chosen not only for their versatility and great adaptability to solve these problems, but also for their ability to obtain, in limited computational time, good quality solutions [5]. In our case we classify hospital systems as a complex environment system since it is simultaneously inaccessible, no-deterministic, dynamic and continuous. To solve

the optimization problems in ED, a bibliographic review of concepts and approaches can generally be categorized into 3 classes: (i) those that used metaheuristics in order to schedule patient considering (or not) resources. Generally in this class, researchers do not consider the evolution in real time of the patient care state, (ii) those that use the multi agent system to help staff to make a good decision in real time (or not), and (iii) those that made a combination of two (or more) approaches to effectively schedule patients in real time. Our work belongs to this last category.

(i) In the literature, several researchers have adopted the metaheuristics approach and they qualified it as part of machine learning and soft computing technologies [6], [7], [8]. Indeed, metaheuristics have been used by several recent studies to solve healthcare system problem. For example, In [9] the authors propose an original model based on an evolutionary memetic algorithm in order to solve the often contradictory multi-objective home care problems (which require considerable time to obtain a fair and valid calendar) minimizing the total working time of nurses while maximizing the quality of service. In [10], the authors, propose a multiobjective stochastic genetic algorithm approach to obtain a real-time, single-score-based prioritization scheme optimization in the context of healthcare resource allocation. In [11] a simulated annealing framework and an adaptive large neighborhood search procedure are used to solve the dynamic patient admission scheduling problem, they report improvements in the range of 3–14% for the large instances. Metaheuristics offers a solution to healthcare staff, however, combined them with intelligent methods can further improve its solution in order to provide needed services to any health care organization.

(ii) Other research works focus on the multi agent system (MAS) which is used to model, optimize and schedule complex systems. For example, the authors in [12] proposed a review offering several agent-based solutions in the healthcare field, highlighting that such an approach can generate advantages in terms of modularity, efficiency, decentralization, flexibility, personalization, distributed planning, monitoring, pro activity and security. In [13] the authors present a medical decision support system for a rectal cancer center. It is a multi agent system, able of manage the entire radiomic process. Indeed, from medical images, the system can extract a set of characteristics to be analyzed in order to generate an optimized predictive model. In [14], the authors propose a multi agent planning framework for the automatic reconciliation of clinical directives dealing with both medical interactions and patient preferences. In [15], an agent approach is used to develop a personal health system adapted to follow-up of first-level diabetic patients. Each of these last three references is the result of international effort and cooperation between researchers from different institutions with healthcare institutions in different countries. This underlines the need and the importance of implementing such a system to solve optimization problems in hospitals. Indeed, agents can communicate with each other in the form of negotiation and coordination in order to accomplish beneficial tasks to users. They are able to take initiatives and perform actions proactively in order to reach their goal. Agents work together using a cooperative and/or collabora-

tive strategy to solve problems. Therefore, the multi-agent approach is considered as an effective approach to modeling and implementing health care systems. On the one hand, because of the complex environment of hospitals, on the other hand, because of the need to establish constant and effective coordination between different staff with several skills and functions to provide effective care to patients.

(iii) In recent years, the combination of two or more approaches for solving optimization problems has been growing [16] explaining the rising interest for this hybridization method. In fact, the hybridization is considered as a good technique to overcome the specific limitations of a single evolution strategy in the evolutionary algorithms [17]. Hybrid metaheuristics or hybrid evolutionary algorithms combine features of different techniques in order to exploit the asset of the several algorithms and get better algorithmic improvements [17]. There are some hybridizations proposed in the literature, among them, several researchers highlight the interest of combining optimization algorithms with MAS in order to resolve complex problems such as in [18], [19], [20], [21]. In this context, several researchers apply the use of multi-agent concepts in the hybridization of metaheuristics through the collaborative strategy, such as in [22], [18], [23], [17]. Authors in [22] used a multi-agent system approach on a framework called Collaboration of Metaheuristic Algorithms. The results of their work show that this collaboration method achieve better results for solving problems of combinatorial optimization. Other researchers realised this hybridization through the cooperative strategy, such as [24], [25], [19]. In the literature the cooperation strategy is defined as a set of highly autonomous programs, each one implementing a particular solution method, and then a cooperation scheme combining these programs into a single solution strategy [26]. In this article, we focus only on this type of hybridization where cooperation is used in the context of optimization, through the use of different agents working together by exchanging information to achieve a common goal. Here, each agent participates in problem solving autonomously. The originality of our approach comes on one hand, from the development of a Metaheuristics driven by Multi Agents Systems (MMAS). In MMAS, the blockage in a local minimum is avoided thanks to the cooperation between agents controlling the genetic operators. This will limit, even eliminate the blind research aspect in the MMAS steps by converging in the most efficient way to the optimum solution. On the other hand, from the application of our MMAS in the hospital field, and in the ED in particular.

II. MMAS DESCRIPTION FOR PATIENT SCHEDULING

The patient scheduling in Adult ED (AED), as it is mentioned in the literature, is an NP-hard combinatorial optimization problem. In this context, each time a new patient arrives to the AED, a sequence of healthcare treatment tasks is updated and adapted to the care needs of new arrivals. This involves generating real-time activity plans for each member of the medical staff. Thus, a multidisciplinary medical team is made up and a treatment role is then assigned to each member of the medical team in one of the structures of the AED. To solve the problem described above, the proposed

MMAS has a chromosome code adapted to the considered problem. The main goal of MMAS is to optimize the patient treatment process by assigning effectively the set of patients to the right medical staff and the right structure of the AED, while minimizing the ATWT.

A. MMAS chromosome coding

In our approach, the chromosome is composed of a four-dimensional hypercube with the following four axes (Medical Staff), (Patients), (Time) and (ED Structure). The time axis is defined by several optimization horizons. The idea of dividing the time axis into many slots allow to assign each resource (physician and box) to the right patient during a given period. Each axis or dimension is controlled by autonomous agent (APA : Agent of the Patient Axis ; AMSA : Agent of the Medical Staff Axis ; ASA : Agent of the ED Structure Axis ; ATA : Agent Time Axis). Each agent knows, thanks to the real database and the structural architecture of the AED, the different characteristics of the points that compose its axis. For example, the APA knows the arrival time of each patient and his pathology, the AMSA knows in real time the availability and skills of each medical staff, etc (figure 1). These information are useful for the negotiation protocol between the agents and the generation of a solution population. Indeed, each agent thus has a dynamic knowledge base enabling it to cooperate with the other agents to make the population evolve over the generations.

B. MMAS initial population

The performance of our MMAS depends on many factors such as population size, number of generations, crossover and mutation operators, probability, etc. Generating a good initial population is one of the important steps in MMAS. A poor initial population may increase the search space or make MMAS converge at a local optimum. We initially developed two different initial population generation methods:

- random negotiation agents (figure 2): each chromosome i is generated as follows: the APA_i generates a list of patients in a random way. This list is sent to all the agents' chromosome i , where each agent assigns through negotiation, the appropriate medical staff in the available slot and AED structure to this list.
- heuristic negotiation agents (figure 3): each chromosome i is generated as follows: each agent exploits its own heuristic and negotiates with other agents to generate viable solutions in the initial population. For example, the APA_i generates a list of patients by applying a heuristic. This generation is based on dynamic priority rules [28].

Our main motivation is to use the agent knowledge basis to analyze its empirical results in order to negotiate efficiently with other agents.

C. Fitness function

The fitness function is essentially the objective function for our patient scheduling problem. It provides a means of evaluating the search chromosome. A well formulated fitness function is necessary to reach success. The fitness value

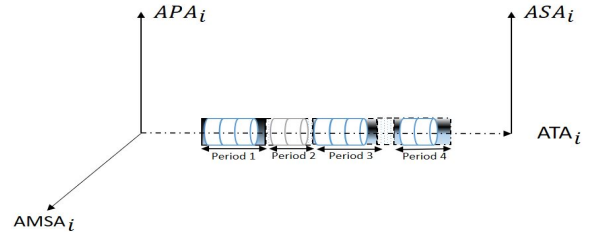


Fig. 1. Multi agent system chromosome i

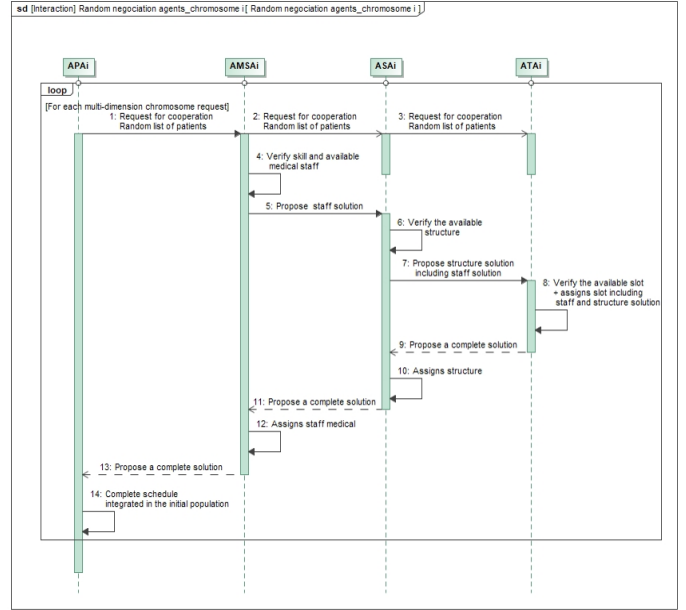


Fig. 2. Random negotiation agents to build the initial population (RNAIP)

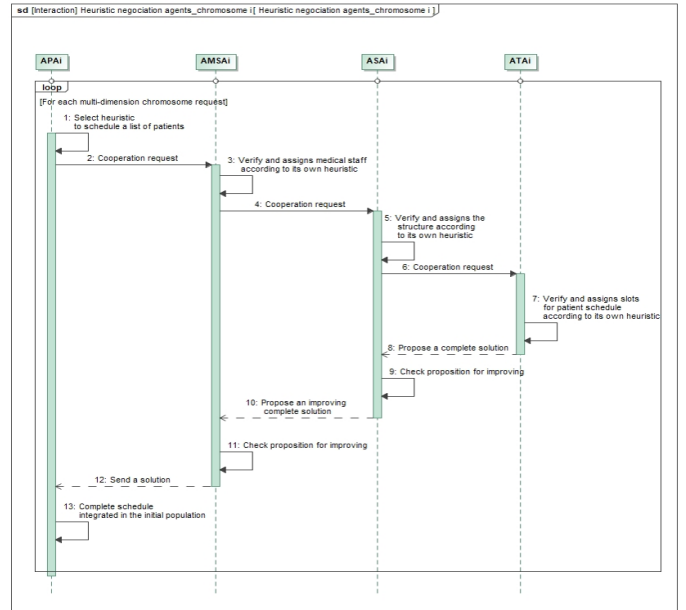


Fig. 3. Heuristic negotiation agents to build the initial population (HNAIP)

of each multi-dimensional chromosome is computed by the fitness function. A good solution is one that scores a high fitness value.

In this paper, the fitness function is the average total waiting time for patients belonging to a best scheduling s^* noticed $ATWT_{s^*}$, which is typically defined as:

$$ATWT_{s^*} = \min_s \left(\frac{\sum_{p=1}^P \sum_{k=1}^K \max(0, t_{s,p,k+1} - t_{s,p,k})}{P} \right) \quad (1)$$

Where :

- s is the current schedule belong to the current population to be assessed;
- P is the total number of patients to be treated;
- K is the total number of care tasks to be scheduled for the patient p ;
- $t_{s,p,k}$ is the ending time of the care tasks k for the patient p in the current schedule s ;
- $t_{s,p,k+1}$ is the starting time of the care tasks $k+1$ for the patient p in the current schedule s ;

According to the dynamic knowledge basis integrated into the APA_i , this agent has some information about the total number of patients to be scheduled, the total number of care tasks of each patient p , etc. Therefore, the APA_i has the ability to compute for each solution the fitness function as mentioned above.

III. MULTI AGENT GENETIC OPERATORS

The multi agent system used to limit/even eliminate the blind research aspect of the evolutionary algorithm steps. The idea is that each agent searches iteratively among the solutions neighboring to its axis for the best solution and then communicates it to all agents through the agent negotiation protocol. The generation of neighboring solutions is carried out by keeping the same neighborhood (the same axis) and by varying only one component at a time of the solution (change of coordinates) or by changing the axis (change of neighborhood) until the obtaining a local optimum. The crossover and mutation operators are applied to generate new solutions. These steps are controlled by the agents' negotiation protocol where each agent manages a full part of chromosome gene, thanks to the multi agent coding. The cooperation takes place through the exchange of information of axes, avoiding premature convergence.

A. Mutation operator

In order to diversify the solution population; four different mutation algorithms are developed based on neighborhood approach. The idea is that we choose randomly one multi-dimensional chromosome i and one agent within it to search a neighborhood solution through its axes and decide if it keeps this solution or not. Indeed, the mutation operator proceeds on intra-chromosome. Therefore, the agent that was chosen to generate the neighboring solution is called the mutation director agent.

- swap-intra-chromosome i when the mutation director agent is APA_i : neighborhood function that performs the exchange move of the patient with another patient of the same solution.
- shift-intra-chromosome i when the mutation director agent is APA_i : neighborhood function that performs

the relocation move of one patient to another position into the same schedule.

- reassignment-intra-chromosome i when the mutation director agent is $AMSA_i$: neighborhood function that performs the exchange move of the medical staff with another medical staff who has the same skills of the same solution. For example, if the care task is to give a shot to a patient who has been assigned to a doctor through this mutation this task is assigned to a nurse so that the doctor's skill is used to perform another consultation task.
- location-change-intra-chromosome i when the mutation director agent is ASA_i : neighborhood function that performs the exchange move of a medical structure with another medical structure into the same zone or into another zone of the same solution.

B. Crossover operator

In the literature there are many crossovers operators used for combinatorial problems whose solutions are represented by the order sequences, especially in TSP and scheduling problems. Among these crossover operators we cite: partially mapped crossover (PMX) [29], order crossover (OX) [30] and cycle crossover (CX) [31]. The PMX manages the important similarities of parents and the child generation and needs a correction process to generate a viable solution. The OX crossover emphasizes that the sequence order is very crucial and no correction process is needed. The CX crossover reserves the absolute position of the elements in child's generation. In the literature it is indicated that OX is 11% better than PMX and 15% better than CX [31].

So, in our crossover operator the director crossover agent is the APA_i for multi-dimensional chromosome i and uses the OX crossover operator. During the search process of the offsprings, the agents of MMAS should explore a multi agent system environment. In this case, the multi agent environment is defined by the chromosome search space. We choose randomly 2 chromosomes i and j which represent the parents in crossover. The latter produces offsprings by recombining parental genetic material. In this paper, the crossover operators are made by the protocol negotiation between agents. Figure 4 details this negotiation. In fact, it is mainly based on the request to crossover OX from APA_i to APA_j . Once the APA_j confirms this request, it sends a crossover operator solution. Based on this confirmation the APA_i selects randomly two crossover points and executes OX crossover operator, then it sends that to APA_j for confirmation. Once again confirmed by APA_j the intra and inter chromosome negotiations will start as described into the same figure until the building of two new viable offsprings. At the end of the protocol negotiation the newly formed offsprings replace the 2 chromosome parents. This means that the agents constituting the chromosomes parent are destroyed.

C. MMAS algorithm

In the MMAS approach, the multi agent environment is characterized by a solution search space of the addressed problem, as presented in figure 5. The perception and action capabilities of the agents are determined in this environment as:

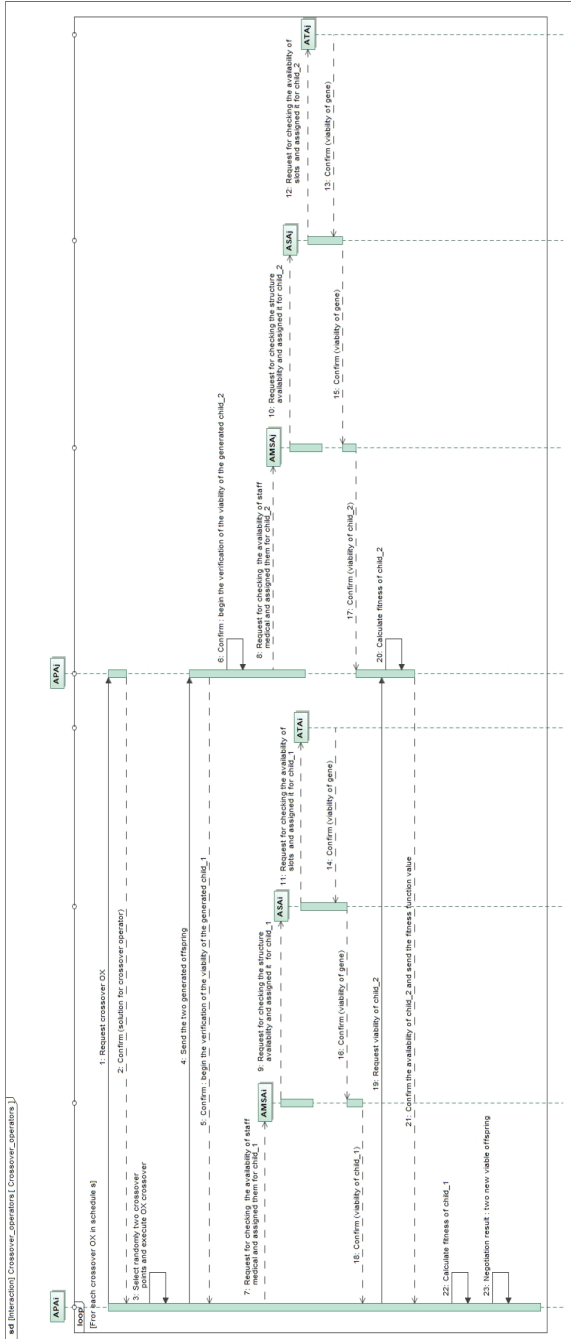


Fig. 4. Negotiation agents protocol for the crossover operator

- perception of the environment: thanks to the knowledge basis integrated in agent memories the agents are able to access information about the patient scheduling problem;
- positioning: thanks to their autonomy, agents are able to precise their positions in the environment and to build a new solution or choice of available solutions;
- move: the ability of the agent to move from one solution to another in both intra-chromosome and in inter-chromosome;
- cooperation: is the main characteristic of our approach, it shows the ability of the agents to share and provide a partial solution (gene) for the other agents of our approach.

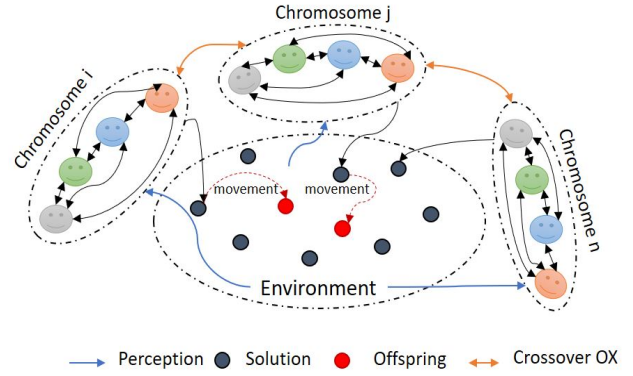


Fig. 5. Agent interaction

All these characteristics are included in the behaviors of agents handled by our MMAS algorithm 1.

Algorithm 1: MMAS algorithm

- input** : RNAIP (figure 2), HNAIP (figure 3), N is the global size of initial population
- output**: a set of N good scheduling solutions
- 1 **Initialization** : generate a NL feasible RNAIP solution
 - 2 generate a N-NL feasible HNAIP solution
 - 3 Merging of NL feasible RNAIP and a N-NL feasible HNAIP (N agents multi-dimension chromosome is obtained)
 - 4 **while** *stop criterion is not reached* **do**
 - 5 **for** $i = 1$ **to** N **do**
 - 6 calculate the fitness function in the behaviour of APA_i
 - 7 **end**
 - 8 select randomly 2 parentes P1 and P2;
 - 9 Apply a protocol negotiation between concerned agents to execute crossover operator with a probability P_{cross} in order to obtain offspring 1 and offspring 2 (figure 4) ;
 - 10 Apply a protocol negotiation between concerned agents to execute mutation operator with a probability P_{mut} ;
 - 11 Select N new chromosome and built a new population;
 - 12 update the stopping criterion
 - 13 **end**

IV. RESULTS

A. MMAS implementation

In order to implement MMAS the use of a software infrastructure adopted as an environment for executing and deploying agents is required. Indeed, there are several multi agent platforms, such as JADE, AgentBuilder, Jack, ZEUS, Madkit. In this context, we must choose the multi agent platform that best adapts not only to the healthcare constraints, but also which is growing and has possibilities to be extended in the future. So, for the development of our system and to obtain the simulation results of our MMAS we chose JADE (java agent development framework). The

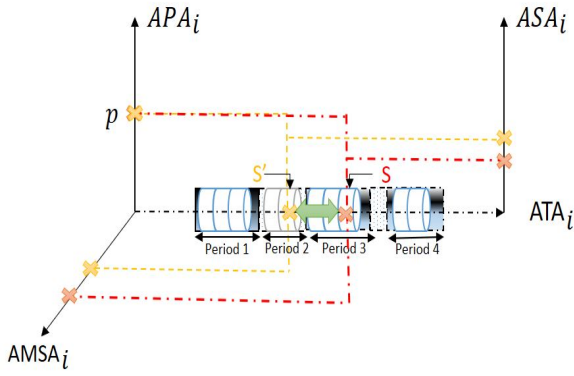


Fig. 6. multi dimension chromosome solution after crossover and mutation operators

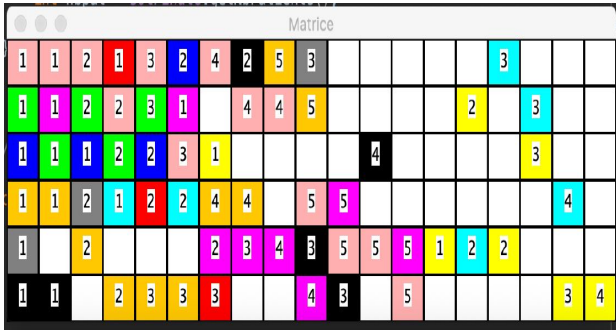


Fig. 7. Current practice solution for the simple test instances

main reason for this choice is that JADE is one of the best modern agent environments [32] and it has interesting characteristics such as the extension of a good medium for content languages and ontologies. This framework is a middleware that enables flexible implementation of interoperability between agents through efficient transfer of Agent Communication Language (ACL) messages, according with FIPA norms, which is in perfect adequacy with the proposed approach.

The communication between agents and their behaviors in JADE are presented by graphical tools, which are themselves agents:

- remote management agent (RMA) : represents the main administrative interface;
- introspector : allows viewing for an agents, the sent/received messages, the active/inactive behaviors and controls its life cycle;
- sniffer: allows to interactively view the sequence of messages (ACL) and the correction of protocols (figure 10);
- directory facilitator agent (DF): it is the main container, manages the yellow pages service and allows the association between description of proposed services and agents.

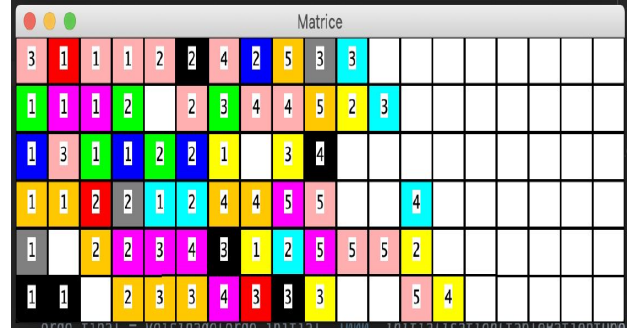


Fig. 8. MMAS solution for the simple test instances

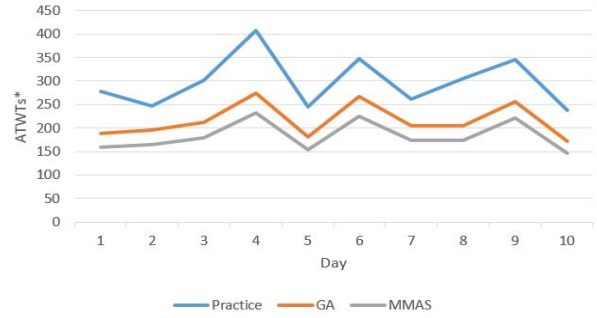


Fig. 9. Comparison of $ATWT_s^*$ using MMAS vs. AG and current practice

B. Computational results

The communication protocol between agents search to continuously improve the current solution by comparing it with the neighboring solution into each axis thanks to the crossover and mutation operators. In our case, we can find four types of neighboring solution, i.e. we can change the assignment of medical staff or we can switch patients and thus check if they are better compared to the current solution. For example, the transition from solution S to S' in figure 6, shows that for the patient p changing the solutions on the 2 axes ($AMSA_i$ and ASA_i) allowed improvements in terms of waiting time (ATA_i).

To perform the simulation studies, we firstly define the genetic algorithm parameters which are the size of population (set by 30), the number of generations (set by 5000), the crossover probability (P_{cross} : set by 70%), the

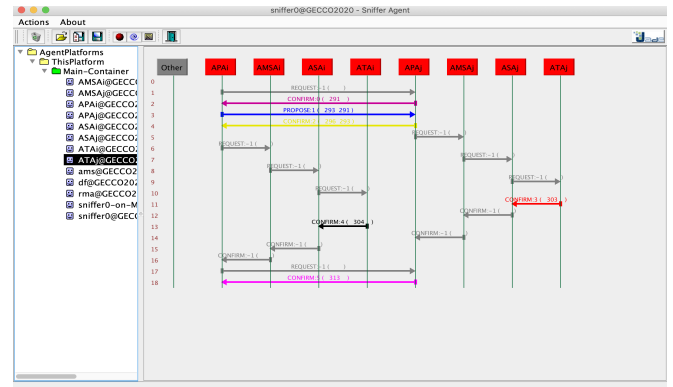


Fig. 10. Sniffer tool

TABLE I
SIMPLE TEST INSTANCES

Patients	task 1	task 2	task 3	task 4	task 5
P1	C1*2	C1 and C2	C1 and C3	C1 and C2*2	C4, C5*2 and C6
P2	C2 and C3	C2 and C3	C2	-	-
P3	C3*2	C3	-	-	-
P4	C4*2	C5 and C6	C6*2	C4*2	C1 and C2
P5	C2*2	C5	C5 and C6	C4 and C5	C3
P6	C1	C4	C6	-	-
P7	C6*2	C1	C5 and C6	C3	-
P8	C3 and C5	C2 and C5	C3 and C6	C6	-
P9	C5	C4	C1	-	-
P10	C4	C4 and C5	C1 and C2	C4	-

TABLE II
COMPLEX TEST INSTANCES

2*Instances	Number of patients	Practice	Genetic algorithm			MMAS approach	
			$ATWT_{s*}$ (min)	$ATWT_{s*}$ (min)	Computation time (s)	$ATWT_{s*}$ (min)	Computation time (s)
1	56	278.39	188.46	9.76	159.63	8.78	
2	67	247.52	195.16	11.02	165.31	9.91	
3	64	301.81	211.59	81.83	179.28	73.64	
4	59	406.83	274.01	126.69	232.10	114.02	
5	64	244.32	181.30	14.62	153.57	13.15	
6	117	345.62	266.40	126.27	225.65	113.64	
7	82	261.76	204.34	84.98	173.08	76.48	
8	52	306.10	205.17	97.27	173.78	87.54	
9	39	345.84	255.57	73.74	220.80	66.36	
10	42	237.50	172.21	10.07	145.87	9.06	

mutation probability (P_{mut} : set by 4%), the number of instances (set by 10). Here, we chose to define two types of simulation tests, a simple test instances with a sample of 10 patients (small size optimization problem) and a complex test instances with a larger number of patients (big size optimization problem).

Table I presents a simple test instances presenting a sample of 10 patients based on the real database provided by the AED of Lille in France which is our partner in this work. Into this test, we simplify the execution of the MMAS by fixed input of the algorithm in matrix form (id-patient, num-task) which set by APA_i allowing the $AMSA_i$ to fix the required skills. This matrix fixes the order of healthcare tasks and its needed skills thanks to the knowledge databases of APA_i and the $AMSA_i$. For example, the first care task for patient 6 requires a medical personnel skills C1 to be executed and the first care task for patient 1 requires two medical staff members who have the same skills C1. This task must be treated in two successive slots. Figure 7 and 8 reflect: on the abscissa, time (5 min/slot). In ordinate, there are the skills needed (doctor, nurse, etc.). Each color represents a patient, and the numbers represent the healthcare task corresponding to each patient. Figure 7 presents the solution in current practice (according to the AED database used by the medical staff). This solution is based on triage process which gives a simple scheduling without taking into account dynamic information such as, the evolution of the patient healthcare status. By applying MMAS, and thanks to the crossover and mutation operators based on the negotiation protocol the best scheduling among the solutions of the final population is selected. In fact, MMAS chooses the optimal neighboring solution, which corresponds to the scheduling closest to

the predetermined criteria (fitness function). The results obtained into figure 8 show that MMAS reduces the total treatment time of all patients by 25 min, which implies a decrease in terms of waiting time.

The complex test of instances is shown by simulated 10 instances of randomly generated problems with a different number of patients. These instances were generated from the real database of AED of Lille. To evaluate the performance of our MMAS we compare the results obtained with those obtained in practice (according to the database) and with those generated by the genetic algorithm (table II).

Table II shows that the proposed approach works much better than the genetic algorithm in terms of computation time and works better than current AED practice as well as the genetic algorithm in terms of $ATWT$ which has drop of 15.09% (figure 9). The MMAS computation time is much shorter in the majority of cases than that of the GA. Table II also, indicates that the difference in computation time between the MMAS approach and the GA is less than one minute. This time gap is sufficient to allow our approach to generate high-quality solutions minimizing the $ATWT$, by exploring other research areas.

V. CONCLUSIONS

In this paper, we have produced a multi dimensional chromosome driven by multi agent system integrated in our metaheuristic to solve patient scheduling in the ED. This approach models each dimension by autonomous agents making a chromosome more alive and ready to cooperate. Our metaheuristic based on agents cooperating in the search space is an important and original concept in scheduling

optimization in health care systems. The proposed approach, called MMAS, uses agents as a link between different chromosomes and defines the interaction and negotiation between them in order to obtain a final population of good solutions. The originality of our MMAS consists of the development of mutation and crossover operators as a negotiation protocol which ensures the convergence to an optimal solution. To evaluate our approach, a two simulation tests of the ATWT before and after applying MMAS are done and show a decrease of 15.09% in the ATWT within the AED. Future work will focus on the improvement of agents' interactions by using the concepts to reinforcement learning resulting from past experience.

REFERENCES

- [1] Juan, A. A., Faulin, J., Grasman, S. E., Rabe, M., & Figueira, G. (2015). A review of simheuristics: Extending metaheuristics to deal with stochastic combinatorial optimization problems. *Operations Research Perspectives*, 2, 62-72.
- [2] Ajmi, F., Ajmi, F., Othman, S. B., Zgaya, H., Renard, J. M., Smith, G., & Hammadi, S. (2021, October). Friends and enemies agents collaboration protocol to optimize multi-skills patient scheduling in emergency department. In 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 1677-1684). IEEE.
- [3] Othman, S. B., Ajmi, F., Zgaya, H., & Hammadi, S. (2019). A cubic chromosome representation for patient scheduling in the Emergency Department. *RAIRO-Operations Research*, 53(5), 1453-1474.
- [4] Ramos-Figueroa, O., Quiroz-Castellanos, M., Mezura-Montes, E., & Schütze, O. (2020). Metaheuristics to solve grouping problems: A review and a case study. *Swarm and Evolutionary Computation*, 53, 100643.
- [5] Silva, M. A. L., de Souza, S. R., Souza, M. J. F., & Bazzan, A. L. C. (2019). A reinforcement learning-based multi-agent framework applied for solving routing and scheduling problems. *Expert Systems with Applications*, 131, 148-171.
- [6] Blum, C., & Roli, A. (2003). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM computing surveys (CSUR)*, 35(3), 268-308.
- [7] Blum, C., Puchinger, J., Raidl, G. R., & Roli, A. (2011). Hybrid metaheuristics in combinatorial optimization: A survey. *Applied soft computing*, 11(6), 4135-4151.
- [8] Borne, P., & Tangour, F. (2007). Metaheuristics for the Optimization in Planning and Scheduling. *IFAC Proceedings Volumes*, 40(18), 1-7.
- [9] Decerle, J., Grunder, O., El Hassani, A. H., & Barakat, O. (2019). A memetic algorithm for multi-objective optimization of the home health care problem. *Swarm and evolutionary computation*, 44, 712-727.
- [10] Feng, W. H., Lou, Z., Kong, N., & Wan, H. (2017). A multiobjective stochastic genetic algorithm for the pareto-optimal prioritization scheme design of real-time healthcare resource allocation. *Operations Research for Health Care*, 15, 32-42.
- [11] Lusby, R. M., Schwierz, M., Range, T. M., & Larsen, J. (2016). An adaptive large neighborhood search procedure applied to the dynamic patient admission scheduling problem. *Artificial intelligence in medicine*, 74, 21-31.
- [12] Isern, D., Sánchez, D., & Moreno, A. (2010). Agents applied in health care: A review. *International journal of medical informatics*, 79(3), 145-166.
- [13] Gatta, R., Vallati, M., Dinapoli, N., Masciocchi, C., Lenkiewicz, J., Cusumano, D., ... & Valentini, V. (2019). Towards a modular decision support system for radiomics: A case study on rectal cancer. *Artificial intelligence in medicine*, 96, 145-153.
- [14] Fdez-Olivares, J., Onaindia, E., Castillo, L., Jordán, J., & Cózar, J. (2019). Personalized conciliation of clinical guidelines for comorbid patients through multi-agent planning. *Artificial intelligence in medicine*, 96, 167-186.
- [15] Falcionelli, N., Sernani, P., Brugués, A., Mekuria, D. N., Calvaresi, D., Schumacher, M., ... & Bromuri, S. (2019). Indexing the event calculus: towards practical human-readable personal health systems. *Artificial intelligence in medicine*, 96, 154-166.
- [16] Ghanes, K., Wargon, M., Jouini, O., Jemai, Z., Diakogiannis, A., Hellmann, R., ... & Koole, G. (2015). Simulation-based optimization of staffing levels in an emergency department. *Simulation*, 91(10), 942-953.
- [17] Silva, M. A. L., de Souza, S. R., Souza, M. J. F., & de Franca Filho, M. F. (2018). Hybrid metaheuristics and multi-agent systems for solving optimization problems: A review of frameworks and a comparative analysis. *Applied Soft Computing*, 71, 433-459.
- [18] Malek, R. (2010, October). An agent-based hyper-heuristic approach to combinatorial optimization problems. In 2010 IEEE International Conference on Intelligent Computing and Intelligent Systems (Vol. 3, pp. 428-434). IEEE.
- [19] Fernandes, F. C., de Souza, S. R., Silva, M. A. L., Borges, H. E., & Ribeiro, F. F. (2009, October). A multiagent architecture for solving combinatorial optimization problems through metaheuristics. In 2009 IEEE International Conference on Systems, Man and Cybernetics (pp. 3071-3076). IEEE.
- [20] Souza, G. R., Goldberg, E. F., Goldberg, M. C., & Canuto, A. M. (2012, October). A multiagent approach for metaheuristics hybridization applied to the traveling salesman problem. In 2012 Brazilian Symposium on Neural Networks (pp. 208-213). IEEE.
- [21] Wang, D., Wang, W., Liu, Y., & Alsaadi, F. E. (2018). A modified distributed optimization method for both continuous-time and discrete-time multi-agent systems. *Neurocomputing*, 275, 725-732.
- [22] Malek, R. (2009, August). Collaboration of metaheuristic algorithms through a multi-agent system. In *International Conference on Industrial Applications of Holonic and Multi-Agent Systems* (pp. 72-81). Springer, Berlin, Heidelberg.
- [23] Milano, M., & Roli, A. (2004). Magma: A multiagent architecture for metaheuristics. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 34(2), 925-941.
- [24] El-Abd, M., & Kamel, M. (2005, August). A taxonomy of cooperative search algorithms. In *International Workshop on Hybrid Metaheuristics* (pp. 32-41). Springer, Berlin, Heidelberg.
- [25] Martin, S., Ouelhadj, D., Beullens, P., Ozcan, E., Juan, A. A., & Burke, E. K. (2016). A multi-agent based cooperative approach to scheduling and routing. *European Journal of Operational Research*, 254(1), 169-178.
- [26] Crainic, T. G., & Toulouse, M. (2003). Parallel strategies for metaheuristics. In *Handbook of metaheuristics* (pp. 475-513). Springer, Boston, MA.
- [27] Ahmed, M. A., & Alkhamis, T. M. (2009). Simulation optimization for an emergency department healthcare unit in Kuwait. *European journal of operational research*, 198(3), 936-942.
- [28] Ramos-Figueroa, O., Quiroz-Castellanos, M., Mezura-Montes, E., & Schütze, O. (2020). Metaheuristics to solve grouping problems: A review and a case study. *Swarm and Evolutionary Computation*, 53, 100643.
- [29] Gorges-Schleuter, M. (1989). ASPARAGOS an asynchronous parallel genetic optimization strategy. In *Proc. 3rd ICGA* (pp. 422-427).
- [30] Davis, L. (1985, August). Applying adaptive algorithms to epistatic domains. In *IJCAI* (Vol. 85, pp. 162-164).
- [31] Oliver, I. M., Smith, D., & Holland, J. R. (1987). Study of permutation crossover operators on the traveling salesman problem. In *Genetic algorithms and their applications: proceedings of the second International Conference on Genetic Algorithms: July 28-31, 1987 at the Massachusetts Institute of Technology, Cambridge, MA*. Hillsdale, NJ: L. Erlbaum Associates, 1987..
- [32] Bellifemine, F., Bergenti, F., Caire, G., & Poggi, A. (2005). JADE—a java agent development framework. In *Multi-agent programming* (pp. 125-147). Springer, Boston, MA.