Multi-agent System Specification for Distributed Scheduling in Home Health Care

Filipe Alves, Ana Maria A. C. Rocha, Ana I. Pereira and Paulo Leitão

Abstract Nowadays, scheduling and allocation of resources and tasks becomes a huge and complex challenge to the most diverse industrial areas, markets, services and health. The problem with current scheduling systems is that their management still occurs manually or using classical optimization methods, usually static, time-consuming and centralized approaches. However, opportunities arise to decentralize solutions with smart systems, which enable the distribution of the computational effort, the flexibility of behaviors and the minimization of operating times and operational planning costs. The paper proposes the specification of a Multi-agent System (MAS) for the Home Health Care (HHC) scheduling and allocation. The MAS technology enables the scheduling of intelligent behaviors and functionalities based on the interaction of agents and allows an evolution of current strategies and algorithms, as it can guarantee the fast response to condition changes, flexibility and responsiveness in existing planning systems. An experimental HHC case study was considered to test the feasibility and effectiveness of the proposed MAS approach, with the results demonstrating promising qualitative and quantitative indicators regarding the efficiency and responsiveness of the HHC scheduling.

Filipe Alves
ALGORITMI Center, University of Minho, 4710-057, Braga, Portugal and Research Centre in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal, e-mail: id7541@alunos.uminho.pt

Ana Maria A. C. Rocha
ALGORITMI Center, University of Minho, 4710-057, Braga, Portugal, e-mail: arocha@dps.uminho.pt

Ana I. Pereira
Research Centre in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal, e-mail: apereira@ipb.pt

Paulo Leitão
Research Centre in Digitalization and Intelligent Robotics (CeDRI), Instituto Politécnico de Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal, e-mail: pleitao@ipb.pt

1 Introduction

Over the years, it has been verified that scheduling is a problem of a highly complex nature, namely in areas like manufacturing and industry, services and/or health [15]. In this sense, scheduling has become an important topic of business and public interest, where challenging optimization problems have arisen, especially in the field of health. For example, today, long-term care supports people in the need of primary care with their activities of daily living or health problems that can be treated in the patients' homes. The problem of the management and scheduling optimization in Home Health Care (HHC) has been a growing topic of research, namely in its operational planning. Furthermore, the HHC problem involves uncertain demand and travelling restrictions, which makes the resources planning and allocation systems highly complex [9].

In practical terms, there are many HHC problems, namely the lack of distributed knowledge, the need for coordinated effort (manager or health professionals), the complex problems (scheduling management) and a great amount of dispersed information. These factors are difficult to be managed by planners because they involve several variables, constraints and dependency tasks. There are still several health units that perform this task in a manual manner, however in recent years, combinatorial optimization models (heuristics and metaheuristics) have become popular [5]. Despite their optimal solutions, these algorithms reveal some inefficiency problems, such as, the solutions need a high consuming time to be computed, the information should be aggregated and available centrally and the adaptation to condition changes is weak.

To face these problems, alternative approaches, relying in distributed structures, are needed to address the dynamics of the scheduling problem in HHC. In this context, MAS have been widely used in complex systems, being suitable to solve the scheduling problem in a distributed manner [20]. MAS, based on a set of intelligent autonomous and cooperative agents, offer a distributed capacity to design and control dynamic systems, differing from the traditional approaches, due to fast response and their capabilities to adapt to condition changes [21]. MAS can also provide smart techniques, able to coordinate a socialized solution to achieve the goals of the individual and global perspectives of a particular system.

Having this in mind, this work describes the specification of a distributed MAS, which intends to manage the HHC service with more capacity in developing scheduling solutions, even in presence of dynamic situations. The experimental scenario presents a system able of establishing communication between health professionals and patients who require a certain task (treatment). The tasks are assigned to health professionals according to an automatic and personalized match and according to their availability, taking into account proposals that imply time and distances involved in routes, work overload and/or time penalties. The results obtained show the effectiveness and high performance of the MAS system, namely the improvement of the responsiveness, less time consuming and better fitting the management of emergencies and unexpected events.

The paper is organized as follows: Section 2 describes the related work and some MAS background. Section 3 presents the system architecture for the distributed scheduling, namely the entities, interactions and intelligent mechanisms embedded in agents and used during the allocation process. Section 4 presents preliminary results of the developed experimental testing. Finally, Section 5 rounds up the conclusions and future work ideas.

2 Related Work

HHC scheduling problem, requires the vehicle routing, the allocation of resources and professionals, and the optimal sequencing approaches combination, making this problem too complex for institutions, public or private, that provide these health care services, often performed manually and without using any computational support. Some of the differences between the scheduling in health and especially in HHC, when compared to other applications, are the implications of the routes combination, variable distance/times, resource allocation, several variables, real-time emergence's, priorities and other assumptions and requirements [9]. Traditionally, the research carried out today applies optimization algorithms to classic HHC problems, usually in a centralized mode that considers only the static problem settings, where they present high time-consuming in obtaining solutions and only consider static and deterministic data that are often outside the dynamics of the current context.

Thus, there is a need for intelligent, reactive, and adaptive systems to deal with the distributed and increasingly dynamic context of HHC scheduling. For that reason, distributed artificial intelligence (DAI), highlights the efficacy and potential of MAS systems to solve large and complex problems.

The MAS paradigm is one example of DAI [8], composed of an intelligent society, based on entities, especially cooperatives and autonomous, called agents. These entities coordinate and interact according to their tasks and resources, making use of their knowledge and skills, in order to achieve their goals in a global or local way. These agents can be mechanized for a given domain, in this case health and especially HHC, especially to try to achieve common goal or separate goals. The agents are characterized by a set of properties that determine its behavior, namely, autonomy, social ability, reactivity, mobility and pro-activity [21]. On the other hand, some tasks need to be performed by more-than-one agent due to their size and/or complexity, giving rise to the concept of MAS. Thus, a MAS system has features, such as, modularity, adaptation, cooperation, coordination and negotiation [16]. MAS systems seek to intelligently coordinate the optimization of an objective(s) offering interesting possibilities and solutions with re-usability and according to a distributed control paradigm with an important fact, the decentralization of information [12]. The decentralization of intelligence, information and/or control suggests reconfiguration tolerances and rapid and variable dynamics of interaction protocols between autonomous agents and modes of operation of individual agents [7]. The easy automation of agents also convinces the MAS specification to become more reliable for application in complex problems. In this sense, it is necessary to provide distributed controls for the MAS, in an attempt to assess the degrees of decentralized decision-making (MAS) versus centralized (traditional optimization methods).

For that reason, to ensure this distributed control and agents interaction, normally are used communicative acts of communication languages [11], that allows agents to interact while hiding the details of their internal workings. In agent communication languages (ACLs), the best known and widely used, is FIPA-ACL (Foundation for Intelligent Physical Agents) [16]. One of the best mechanisms used to implement the agents' coordination is the Contract Net Protocol (CNP) [19]. In general, the CNP works like a business market where an initial agent (initiator) asks for bids (proposals) from the contractor agents (responders) and then awards tasks (accept or reject proposals) to suitable contractor agent. In this protocol it is possible to highlight the attributes of responsiveness, balancing the fairness of acceptance, communication overload, robustness and mutability.

In general, looking at some of the aspects of MAS background and their interactions, these distributed systems have many fields of application, such as manufacturing [13], market simulation [6], resource management [18], production planning [4], health applications [17], and many others domains. In terms of HHC applications, MAS have contributions in routing problems [14], planning [3], medical data management [10], and many others decision support systems in smart health applications. Some of these applications show hybrid behavior, where the system is often not fully distributed, with excesses of external communication that often hinder decision-making in a more socialized and coordinated way with the agents involved. Therefore, the idea of this work is to provide a MAS system for distributed scheduling with decentralized performance, where each agent attempts to optimize its own use of resources and coordinate/interact with the others will be the basis.

3 System Architecture for Distributed Scheduling

The approach of this research work tries to get the best of both worlds for scheduling, optimal solutions from centralized and optimization algorithms, and MAS to support the fast response to condition changes by using distributed solutions [1]. However, this paper only focuses on the specification of the MAS system for the distributed scheduling.

3.1 MAS Entities and Behaviors

The HHC scheduling is a complex and very dynamic process, not only due to the requirements, several variables, temporal dependencies, matching of skills and needs, and also restrictions imposed. However, this work aims to specify the MAS layer, illustrated in Fig. 1, that will be responsible for simplifying, through fast and intelligent decisions, solutions able of being put into practice in the daily service. The distributed scheduling provided by the MAS system will allow to obtain solutions through the interaction among the involved agents, aiming to search to find the best offer of proposals that meet the objective(s) in the shortest running time.

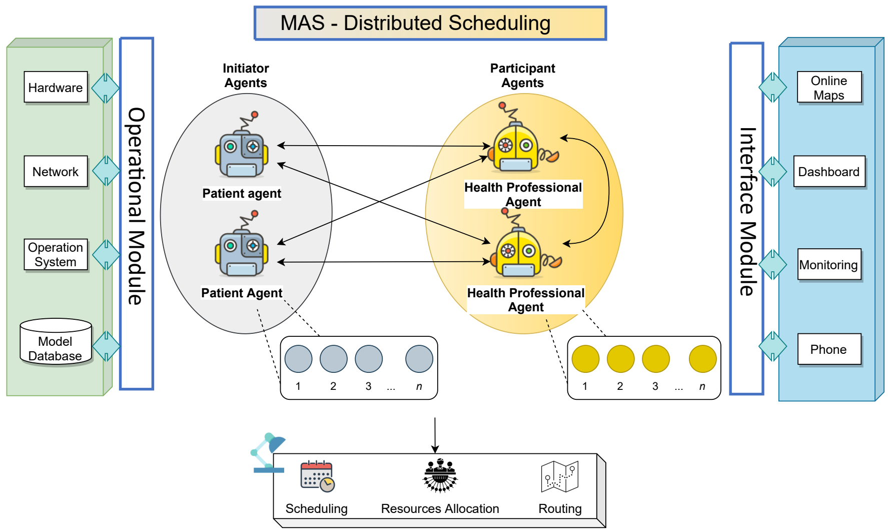

Fig. 1 System architecture for distributed scheduling based on MAS.

The MAS architecture considers a network of intelligent and autonomous agents each one exposing its functionality as local schedule. According to the specification, two types of agents were designed, namely the patient agent and the health professional agent, each one possessing different objectives and responsibilities, as illustrated in Table 1. The agents belong to the home healthcare center, which, not being an agent, represents the entity providing the service.

Table 1 Types of agents and their functional goals and responsibilities.

Agent Type	Responsibility
Patient agent	Has a need for the execution of a treatment, and starts a negotiation when it desires to schedule a treatment. Initiates a call for proposals by setting the search parameters and selects the best proposal for the desired treatment.
Health Professional agent	Has skills to execute a treatment. Respond to calls for proposals by determining if it has the necessary skills to execute the target treatment and in affirmative case makes a bid.

Each agent type has embedded proper behaviors to execute the associated functionalities and aiming to achieve its objectives, which may include the management of the negotiation process, the determination of interaction parameters using intelligent mechanisms (e.g., determining the price to be included in the bids or the selection of the best proposals), as well as the execution of the treatment tasks.

3.2 Agent's Interaction

As previously referred, the distributed scheduling emerges from the interaction between the agents. In this work, the negotiation between patient agents and health professionals will following a CNP-based protocol, supporting the interaction and message exchange between agents and their environment, in an attempt to cooperate and negotiate the best solutions, optimizing, whenever possible, the internal goals. The idea is to consider agents as pieces of autonomous code, able to communicate with each other, considering their specification and/or rational properties. Therefore, interactions between the agents will have specified responsibilities where, for example, the interacting agents and protocol function (e.g., patient and health professional agents), reference and/or triggering conditions and state change will be defined. For this purpose, the negotiation protocol will be modelled using the Agent Unified Modelling Language (AUML) that extends the UML to design the interaction between agents through an intuitive graphical representation of the processes.

The proposed CNP-base protocol is illustrated in Fig. 2. Briefly, the interaction starts when a patient agent has a need to schedule a treatment, where after discovering the available health professional agents, it sends a call for proposals (*cfp*) to this list of available agents.

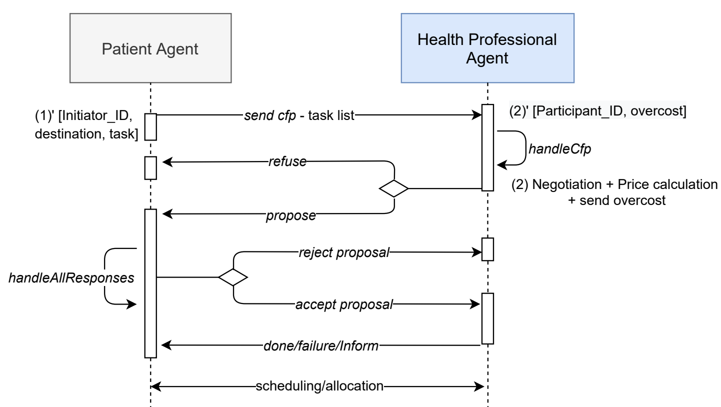

Fig. 2 Agents interaction based on CNP sequence diagram.

When receiving a *cfp*, the health professional agents can send (or not) their proposals to the agent who requested the tasks and needs. For this purpose the health professional agents verify if they have the required skills to execute the treatment and if yes they need to calculate the price to execute the treatment and send a (*Propose*) to the patient agent.

The patient agent receives the different proposals from the health professionals and determines the best proposal that maximizes/minimizes its utility function. Once the optimal proposal is selected, the patient agent sends an acceptance message to the agent that provided the best offer and a rejection message to the others. The agent that receives the acceptance message, commits itself by sending a confirmation message (*Done*). In turn, the resource is allocated to the tasks and the scheduling starts.

In these interaction protocols, the agents share a social and cooperative state that contains commitments and/or messages, relevant to the interaction. Therefore, after some patient agent activates the CNP and performs a *cfp*, the health professional agents will handle the task proposals by performing a matching protocol (Fig. 3).

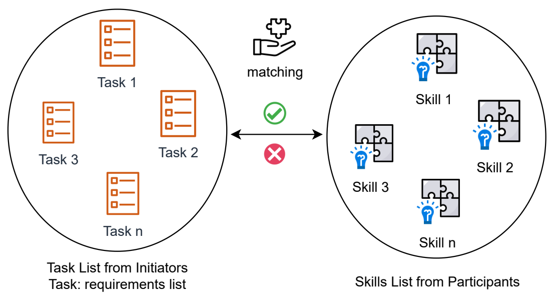

Fig. 3 Matching protocol between task requests and responses based on skills and resources.

A matching scheme in MAS allows, for example, with a vector $Z(x;y;a;b)$ to demonstrate a contractual relationship between an patient x and a health professional y, with x being committed to y to fulfill the condition or task b when antecedent task a is deemed valid or completed. For instance, suppose that we have a patient agent that tries to assign a certain task x, and that the health professional agent ($P1$) has the capacity and skill to execute it. Bearing in mind that the health professional agent is probably already registered, and that the CNP for communication has already instantiated, the current state of the system has confirmed that the patient agent is currently null, and the health professional are named $P1.AID$, where AID is the identifier. In this sense, for cooperation to take place between the agents involved, the health professional agents after receiving the *cfp* and before sending any response (proposal or rejection) perform the matching according to them with requests for tasks (treatments) and the existing kills. Thus, if there is a match the system allows it to calculate a price and make an offer to continue the CNP. If there is no match between the agents, the health professional agent sends a refuse message.

It should be noted that, after and/or during the scheduling, there is a need to reschedule in case of any unexpected event (new order, delay, accident) or failure of the health professional, the patient will be notified and, in turn, it will start o again the *cfp* to request a new allocation with the available health professionals, that is, the CNP will be restarted. Another aspect to highlight of the assembled structure is the existence of a dynamic that allows that when a new patient agent is added with additional work, it can be easily added to the execution plan of the system with automatic start and on-time transmission of information. Anyway, the specification developed are prepared to handle with unforeseen exceptions during the execution of agent systems. A business logic will always be considered since each method of the behavior is only executed after the exit of the previous method.

In summary, the proposed CNP-based protocol presents powerful benefits in terms of sharing tasks and smart resolution mechanisms in different nodes of distributed systems, being an excellent alternative when compared, for example, with traditional auctions.

3.3 Agents' Functionalities in the Allocation Process

As previously referred, during the allocation process, based on the well-known CNP, the agents need to apply intelligent capabilities to perform decisions, namely in terms of price calculation with workload-balancing and evaluation of the proposals.

3.3.1 Calculation of the Price with Workload-balancing

As mentioned earlier, there are two key points for the functionality of agents, including the price calculation.

In this way, after their verifying the matching between the proposed treatment requirements and the existing skills to execute the treatment, the health professional agents should calculate the conditions to elaborate the offer/proposal. The final value of the proposal, designated in the literature as cost or price, is calculated based on a multi-criterion. The price function determines the value, e.g., based on two components, namely the costs that are already fixed and the profit margin. Fixed costs involve the costs necessary for a given execution/order (e.g., investment in the resources and costs associated to the duration of the treatment) and the profit margin is the value to be adapted by current market laws.

The *price* to be proposed by each health professional agent i to perform some task (treatment), is calculated using the following Equation 1:

$$Price(i) = \frac{C_i * T_t + [C_i * Time + C_{ci} * Distance]}{100} \tag{1}$$

where C_i is the health professional cost per hour (execution cost) and T_t refers to the cost of task time (duration of treatment). In turn, the parameter $Time$ refers to the distance time involved in the visit route, the C_{ci} identifies the fuel costs (unit per km) and the $Distance$ criterion comprises the distance involved in the trip and consequent return to the health unit. It should be noted that each agent has a different C_i (agent's hourly cost) and C_{ci} (agent of fuel and/or transport cost).

In order to have a dynamic price, the cost of a health professional agent i is not always the same, as the price margin may increase or decrease according to the allocations already made. Therefore, the C_i parameter may present itself with dynamic variations, where the final cost will depend on the actual work/resource load (or overload) and the offer acceptance rate, and thus manage to distribute and balance the workload among the participating agents. In this sense, the agent i is aware of previous bids and adjusts the final price to be proposed, being able to reduce the price if the bid acceptance rate is greater than one or increase if the price is otherwise. The function specializes the health professional agents already with schedules performed, balancing the workload by "penalizing" future values.

3.3.2 Evaluation and Selection of the Proposals

The evaluation and decision of the best proposal (*handleAllResponses*), elaborated by the patient agent, can combine two strategies, one of them simpler and the other more complex. In the simple strategy, the patient agent selects the proposal that only considers the final price, that is, it can choose the proposal with the lowest or highest price. The more complex strategy combines a multi-criteria function, where the patient agent will analyze different parameters with different weights considering the preferences of the patient, such as, the proposed price, the trust/reputation in the health professional, among others. This last strategy will be the most interesting to support the patient with decision making, where the function will be as follows (Equation 2):

$$ScoreRate(i) = \frac{W_1 * C_1 + W_2 * C_2 + ... + W_n * C_n}{100} \tag{2}$$

where i is each of the proposals and W_1 represents the weight of trust given to the criterion C_1 (e.g., price), and W_2 the weight given to the criterion trust in the health professional (C_2). The function allows the inclusion of more criteria and parameters with the consequent assignment of weights (W_n and C_n), taking into account the patient agent's preferences. It should be noted that the sum of the various $W(s)$ must give 100% (weights). When evaluating the proposals, it is necessary to be aware that it is necessary to normalize the prices of the multi-criteria in order to standardize different intervals. Another important aspect is the fact that the multi-criteria must follow the same direction, that is, they will either maximize or minimize. In order to achieve the best proposal, it is necessary to minimize the function $ScoreRate$.

Another aspect that was considered in the selection of bids is the possibility of proposals that have the same value, especially in the initial call for proposals and due to the fact that many of the health professionals' agents have similar criteria, data and skills. For that reason, and if a decision needs to be taken in case of equal proposals, the first come first served (FCFS) function was programmed, that is, in a generic way, the proposal/offer that arrives earlier is attended to or dealt with before that whoever arrives later.

4 Preliminary Data Analysis Experiments

The proposed approach was implemented to solve the scheduling management of health professionals to perform health treatments in a set of patients distributed in a HHC unit of the district of Porto. However, the experiments can be easily replicated in other regions or countries. This case study comprises 10 patients distributed in an area of 50 km^2, two different types of treatments (curative and rehabilitation tasks), and 3 health professionals. It should be noted that some of the patients require more than one treatment due to the need-to-need tasks that would precede other treatments or requirements (e.g., Task 2 after completing Task 1). Each health professional, based on cumulative skills, might not be able to carry out all treatments. The price calculations of distance and time in the proposals, use the Google Maps cloud, which provides locations and routes through real-time traffic.

The MAS solution was implemented by using the JADE framework [2] and comprise 10 patient agents with their needs and preferences and 3 health professional agents, implemented according to the described specifications. The proposed CNP-based protocol was implemented by following the FIPA-ACL[1] language.

The experiments were conducted on a Huawei Matebook, with an Intel(R) Core(TM) i7 CPU 1.80 GHz with 16GB of RAM. The results are summarized in Table 2 in terms of percentage of allocation (that allows to verify the resource allocation distribution) and the makespan (time complete the several allocated tasks).

Table 2 Summary of experimental results in terms of allocation and scheduling.

Agents	Allocation (%)	HHC schedule (minutes)
Health Professional #1	40	163
Health Professional #2	30	135
Health Professional #3	30	145

Based on the achieved results, it was possible to observe that the scheduling solution is efficient since it was computed correctly (all treatments required by patients were allocated to health professionals and the precedence among treatments were respected). The treatments were uniformly distributed by the health professionals (see allocation percentage column) which is a very important aspect to be considered in this kind of problems. For example, the health professional agent #1 was assigned with a total of 4 patients, and his schedule ended after 163 minutes (that comprises the execution of the treatments, the travel between patients and the return to the health unit).

In practical terms, in the implementation of the specified MAS, JADE is executed through a micro-service, using JADE in an algorithm-like typology. The quantitative results allow us to verify that each solution (HHC schedule) obtained for the allocation of the HHC problem has a response time of at most 2 seconds, from the registration of agents, followed by the interaction and result information (all lo-

[1] http://www.fipa.org/

cally). Furthermore, in terms of performance and productivity in case of failure there was a clear responsiveness to change, especially when new requests or agents' who request tasks and eventually emerge in the system, which generated instantaneous interactions and dynamic allocations, which without human intervention begin to negotiate and reach solutions faster than a centralized approach.

In addition to the fast computed scheduling solutions, the MAS approach allowed to conclude that the system is also endowed with scalability (qualitative result). It was found that there was no need to change the implemented code, and that easily went from 13 to 100 agents and the system worked. For this purpose, it was only necessary to launch 100 instances of the same code (related to each agent). In terms of the response time, the system was able to register, interact and solve the scheduling after 10 seconds, showing a high modular capacity and good scalability. Still in qualitative terms, the specified MAS showed robustness in critical domains, since the injected failures in a patient agent or health professional implied that specific agent was not attended to participate in the scheduling process, but all the other agents worked correctly, and the scheduling application run without interruption. In this way, the system ended up working properly under disturbances or conditions of uncertainty, whereas, for example, a centralized approach (using only optimization methods) would fail to obtain any solution.

5 Conclusions and Future Work

The scheduling in several domains, e.g., HHC, require the dynamic and fast reaction to condition changes, which is not addressed currently by the traditional centralized optimization algorithms. MAS solutions offer a new way to design these systems based in the interaction among individual agents, each one contributing with its own knowledge and skills.

The MAS approach described in this work contributed to design a distributed scheduling solution for HHC problems, with the fast response to condition changes or new incoming orders, performing a personalized and high-level allocation and scheduling. The distribution nature associated to the MAS architecture highlights the qualitative and quantitative aspects, namely the response time, productivity, robustness, and scalability of the experiment carried out.

The limitation of the current implementation is related to the lack of optimization, mainly in temporal aspects in tasks that may arrive later. The idea will be to combine this decentralized and distributed MAS solution with the centralized system of optimization algorithms. This combination will make it possible to solve the main gaps mentioned by both strategies and thus obtain the best of both worlds.

Future work prospects will also involve the analysis of other parameters for the negotiation process, such as proposal load balancing, trust, and confidence in decision-making. Although this work focuses more on agents and interactions between them, in the future it is important to combine centralized and distributed approaches and involve the home healthcare center in decision process.

Acknowledgements This work has been supported by FCT – Fundação para a Ciência e a Tecnologia within the R&D Units Projects Scope: UIDB/00319/2020 and UIDB/05757/2020. Filipe Alves is supported by FCT Doctorate Grant Reference SFRH/BD/143745/2019.

References

1. Alves, F., Rocha, A. M. A., Pereira, A. I., Leitao, P.: Distributed scheduling based on multi-agent systems and optimization methods. In International Conference on Practical Applications of Agents and Multi-Agent Systems **(pp. 313-317)**, Springer, Cham (2019)
2. Bellifemine, F. L., Caire, G., Greenwood, D.: Developing multi-agent systems with JADE. John Wiley & Sons, **Vol. 7** (2007)
3. Becker, C. A., Lorig, F., Timm, I. J.: Multiagent systems to support planning and scheduling in home health care management: A literature review. In International Workshop on Artificial Intelligence in Health, **(pp. 13-28)**. Springer, Cham (2018)
4. Caridi, M., Cavalieri, S.: Multi-agent systems in production planning and control: an overview. Production Planning & Control, **15(2)**, 106-118 (2004)
5. Cissé, M., Yalçındağ, S., Kergosien, Y., Şahin, E., Lenté, C., Matta, A.: OR problems related to Home Health Care: A review of relevant routing and scheduling problems. Operations Research for Health Care, **13**, 1-22 (2017)
6. Confessore, G., Giordani, S., Rismondo, S.: A market-based multi-agent system model for decentralized multi-project scheduling. Annals of Operations Research, **150(1)**, 115-135 (2007)
7. Dorri, A., Kanhere, S. S., Jurdak, R.: Multi-agent systems: A survey. Ieee Access, **6**, 28573-28593 (2018)
8. Ferber, J., Weiss, G.: Multi-agent systems: an introduction to distributed artificial intelligence. Reading: Addison-Wesley, **Vol. 1** (1999)
9. Fikar, C., Hirsch, P.: Home health care routing and scheduling: A review. Computers & Operations Research, **77**, 86-95 (2017)
10. Jemal, H., Kechaou, Z., Ayed, M. B., Alimi, A. M.: A multi agent system for hospital organization. International Journal of Machine Learning and Computing, **5(1)**, 51 (2015)
11. Labrou, Y., Finin, T., Peng, Y.: Agent communication languages: The current landscape. IEEE Intelligent Systems and Their Applications, **14(2)**, 45-52 (1999)
12. Leitão, P.: Agent-based distributed manufacturing control: A state-of-the-art survey. Engineering applications of artificial intelligence, **22(7)**, 979-991 (2009)
13. Leitão, P., Barbosa, J., Trentesaux, D.: Bio-inspired multi-agent systems for reconfigurable manufacturing systems. Engineering Applications of Artificial Intelligence, **25(5)**, 934-944 (2012)
14. Marcon, E., Chaabane, S., Sallez, Y., Bonte, T., Trentesaux, D.: A multi-agent system based on reactive decision rules for solving the caregiver routing problem in home health care. Simulation Modelling Practice and Theory, **74**, 134-151 (2017)
15. Pinedo, M.: Scheduling: Theory, Algorithms, and Systems **74** (Vol. 29), Springer (2012)
16. Russell, S., Norvig, P.: Artificial intelligence: a modern approach. (2002)
17. Shakshuki, E., Reid, M.: Multi-agent system applications in healthcare: current technology and future roadmap. Procedia Computer Science, **52**, 252-261 (2015)
18. Skobelev, P.: Multi-agent systems for real-time adaptive resource management. In Industrial Agents, **(pp. 207-229)**, Morgan Kaufmann (2015)
19. Smith, R. G.: The contract net protocol: High-level communication and control in a distributed problem solver. IEEE Transactions on computers, **29(12)**, 1104-1113 (1980)
20. Wooldridge, M., Jennings, N. R.: Intelligent agents: Theory and practice. The knowledge engineering review, **10(2)**, 115-152 (1995)
21. Wooldridge, M.: An introduction to multiagent systems. John wiley & sons (2009)