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Editorial

AI planning and scheduling in the medical hospital environment

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Abstract

Hospital management is a hard task due to the complexity of the organization, the costly infrastructure, the specialized services offered to different patients and the need for prompt reaction to emergencies. Artificial Intelligence planning and scheduling methods can offer substantial support to the management of hospitals, and help raising the standards of service. This editorial presents an overview of the achievements reported in therapy planning and hospital management together with a general roadmap of the published research in Artificial Intelligence planning and scheduling. Finally, a discussion for the future research and development in this area concludes the presentation. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

Hospitals use their medical expertise with the support of their specialized and expensive infrastructure in order to offer services of good quality to their patients. Mainly, their infrastructure includes

- *personnel*: such as physicians of various specialities, nurses, technicians specializing in specific equipment, administrative and financial clerks as well as other support personnel,
- *intensive care units*: with a complex infrastructure to support the monitoring and therapy process of an intensive care patient,
- *surgical operation units*: with dedicated equipment, tools and procedures for different type operations,

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- *specialized laboratories*: such as X-ray, ultrasound, magnetic tomography, biochemical, radiological, etc.

The infrastructure, of course, includes wards and beds for in-patient stay, ambulances for emergency transfer, pharmacy for the required drugs, restaurants for preparing food and other logistics needed to keep the hospital running.

Hospital management always seeks to maintain quality standards. This can be achieved if physicians, nurses, laboratories, surgical operation units, intensive care units, etc. are coordinated in such a way as to offer successful services on time to both routine and emergency problems. As a result, the requirements for the organization and management of a hospital in order to attain services of high quality are very demanding. Additional constraints on cost effectiveness make management in hospital environment even harder [64]. The principle of payment based on diagnosis (diagnostic related groups — DRGs [17]) adopted by the medical insurance companies in USA and other countries increases the pressure on hospital management to always be efficient both in their cost performance and the services offered.

The tight constraints under which hospital management operates make the use of management information systems essential. These systems might be general purpose applicable to different types of organisations, like logistics management, or specialised to the hospital environment, like the management of intensive care units, surgical operation units, etc. All these specialised systems belong to the category of medical information systems. Planning and scheduling systems that belong to this category have started to play an important role in the management of hospitals. They may apply to personnel management, management of care units like intensive care unit, operation theatres, various laboratories or the management of patient diagnosis and therapy. Furthermore, I should notice that the inherent uncertainty, unpredictability and the emergency of the events as referred to individual patients make the hospital environment quite different from other environments, e.g. production, air campaign, etc.

The rest of this editorial gives first an overview of the achievements of Artificial Intelligence (AI) planning and scheduling in general, as well as in therapy planning and planning and scheduling in hospital management. Then it presents a short description of the special issue papers and discusses the future perspective of the planning and scheduling systems in the medical hospital environment.

2. AI planning and scheduling

Although different definitions have been used for planning, one could broadly accept the definition that planning is the process of putting in a sequence or partial order a set of activities/actions to fulfil temporal and resource constraints required to achieve a certain goal. On the other hand, scheduling is the allocation of activities/actions over time to resources according to certain performance criteria. However, there are many researchers who consider scheduling as a special case of planning [38]. The Artificial Intelligence (AI) research community has been very active in the area of planning and scheduling, since the 1960s.

Most of the published work focused on the development of algorithms (planners) that concern a variety of planning models. For many years the planning model was considered static and omniscient with actions instantaneous and deterministic, having fixed goals. This is the so-called classical planning model, where the planning steps are kept in linear order and the search space close to the situation space [14,18]. Then, in the mid-1970s the above model expanded and the goal was considered to be achieved through the achievement of various sub-goals and therefore partial-order planners appeared [51]. Later, by the mid-1980s the model was further expanded to consider time as a major factor in the planning process [1,9,62]. Finally in the 1990s, researchers started to study models that are closer to a dynamic real world. They looked at mixed-initiative planning, distributed planning or even continual planning models. Two recent papers presented by McDermott and Hendler [38] as well as by des Jardins et al. [10] review the research on planning in an excellent way.

On the other hand, based on the argument that 'there is more life than making plans' expressed by Pollak and Horty [49], researchers started looking at more practical problems and developed operational or industrial prototypes for planning, scheduling as well as integrated planning and scheduling systems. These prototypes were mainly distinguished according to the context of the application domain, the strategic approach they followed, i.e. centralized, distributed or client-server, the architecture used, i.e. multiagent, blackboard, etc. as well as the way the user was interacting with the system, i.e. in a mixed-initiative way, continually, etc.

To mention some interested operational systems or prototypes one may refer to

- O-PLAN [59], a blackboard based multiagent system that was tested in mission sequencing, planning and control of supply and distribution logistics and project management,
- Cypress [68], an integrated planning and scheduling system, successor of the previous SIPE-2 planner [66,67] applied to mobile robots, house construction, beer production as well as to military operations planning,
- CEP [4], a planning system used for the generation of plant operating procedures in chemical processes,
- Advisor [37], a planning prototype tested in the process of loading/uploading chemical product carriers.

Also during the same period scheduling or planning and scheduling systems were developed, referred to as knowledge or AI based systems. Interesting as well as critical reviews on AI based scheduling systems can be found in [2,28,36,43]. To refer to some interesting reported systems one should call

- IP3S [52], a blackboard based, mixed-initiative scheduling system applied to a highly dynamic machine shop facility,
- DITOPS [58], a mixed-initiative scheduling tool applied to transportation scheduling,
- ROSE [45], a reactive scheduling system, used for scheduling scientific instrument operations for space station and tracking and data relay satellite network control center.

Moreover, AI planning and scheduling research includes a substantial amount of work on knowledge engineering issues such as

- knowledge acquisition, with the support of machine learning techniques [11,16,25,31,70] and
- knowledge representation and reasoning [6,15,20,47,69].

Finally, having in mind autonomous robots, or robust intelligent agents in general, the requirement for a unified framework for planning and learning is apparent as described in [35] by P. Langley and J.A. Allen.

The domain of medical services in hospitals is quite a challenging one for applying planning and scheduling methodologies. This is due to its emergency, unpredictability and high demand for services at an individual patient level. Sections 3 and 4 present what has been achieved so far. Section 3 refers to the work of planning as it applies to medical therapy, while Section 4 devotes to planning and scheduling for a better hospital management.

3. Planning in medical therapy

Since the 1970s, medical scientists together with AI scientists realized the need to provide specialized tools for supporting physicians' diagnosis and therapy planning. They built expert systems like MYCIN [57], or EXPERT [27,65]. The validation of such systems has shown that apart from the inherent difficulty of knowledge acquisition it is very difficult to offer a diagnostic solution for all the cases that might occur. For this reason they decided to specify care-protocols or clinical guidelines for different medical specializations. Those protocols stand at a certain level of detail so that they can be adapted to the special case of each individual patient, depending upon the results of the laboratories examination tests as well. The description of such protocols requires languages with the ability to express, as Miksch describes in [39], at least

- temporal dependencies,
- sequential, parallel and cyclical actions, activities and intentions,
- annotations,
- knowledge roles for acquisition and maintenance.

Knowledge roles reflect the set-up, suspension, restart, completion, abort, preference, effect and revision of the overall/intermediate intentions and/or actions to achieve the expected therapy goal. Specific languages that are machine readable and machine interpretable for specifying care-protocols were issued in [22,56], having the flexibility to support for

- assessment of applicability to the patient,
- monitoring the application process,
- assessment of the results,
- critiquing the process and its results and
- modifying the original guideline.

These requirements led the AI scientists to develop either specific systems like ATTENDING [42] for critiquing a physician's management plan or general planning systems based on skeletal plan architectures [60], which have the flexibility to be evolved and refined reactively over significant periods of time, as they get applied to particular patients. EON [44] and Asgaard [54] are two of the systems that use this approach. The need for applying therapy planning systems in intensive care units deserves particular attention [7]. Such systems need to process a bulk of continuous data arising from complex monitoring systems in combination with discontinuously assessed numerical and qualitative data creating a rising information management problem. The work presented by Miksch et al. in [40] provides a good reference for the complexity one could face in such cases. Moreover, in operation theatres preoperative planning systems are becoming quite attractive especially for delegate operations. Prototypes that have been applied to cardiac surgery, neurosurgery and liver resection are presented in [21,29,53], respectively. In these systems, knowledge acquisition was made using medical experts and relevant documents.

Furthermore, new tools and methodologies specialized in therapy planning have been developed to help in the knowledge acquisition task. To mention a few of them one could refer to PROforma [63], KBTA [55], the work by Pattison-Gordon et al. [47] as well as to Arden Syntax and its improvements in [56]. Apart from these acquisition methodologies, machine learning techniques have been applied to large amounts of data concerning the clinical status, the diagnosis and the therapy process followed for past cases. Such efforts are described in [11,31].

Recently, Dr. S. Miksch in [39] presented a comprehensive overview of the work being done worldwide in the field of therapy planning. Furthermore, efforts to allow hypertext browsing of clinical guidelines via World Wide Web have already been announced [50].

In general, one can expect that the appearance of such therapy planning systems for use in Hospital intra-networks would result in

- gradual development of international standards,
- improvement of the information infrastructure on clinical guidelines worldwide and
- gradual development of well trained medical experts to serve the world community.

4. Planning and scheduling in hospital management

As mentioned above, hospitals are complex organizations and thus their management is a hard task. It has to integrate and coordinate a number of internal and external entities, taking into account the relationships among them. The main target is always to offer high quality services at an acceptable budget cost. Hancock et al. in [23] show that well designed patient-scheduling systems can contribute to the improvement of hospital services.

Simulation techniques have been used to address problems of space organisation or bed allocation [13,33,34,61], and Operations Research (OR) techniques have been used to look at the problems of

- personnel shift allocation (i.e. nurses) [12,26,41],
- drug logistics [24],
- ambulance scheduling [3],
- operation theatres scheduling [5,46], etc.

It is only in the last decade that published work started appearing more regularly on scheduling of hospital entities using AI techniques and sometimes in combination with OR techniques.

Expert or knowledge based systems have been developed for personnel scheduling [8,19]. Kumar et al. in [32] proposed a dynamic distributed system, based on multi-agent technology, for coordinating schedules at hospital laboratories. Their approach tries to optimize laboratory resource utilization. On the other hand, the work of Kokkotos et al. [30] proposes a patient-wise knowledge-based dynamic distributed system, for allocating requests for examination tests to various laboratories. A similar problem was examined by Podgorelec et al. [48] and they developed a prototype with interactive capabilities using a genetic algorithm and machine learning techniques.

5. Overview of the special issue papers

The papers appearing in this issue primarily present planning and scheduling methods, approaches and prototypes that deal with problems of hospital management.

A. Oddi and A. Cesta in their paper, 'Toward interacting scheduling systems for managing hospital resources' explore constraint-based scheduling techniques and implement a mixed-initiative problem solving approach in order to achieve interactively satisfactory solutions to the problem of managing medical resources in a hospital environment. They used a temporal modeling scheme for defining medical protocols and resources. Medical protocols are treated as regular activities that require the reservation of relevant resources of a specific laboratory in order to be executed. A medical protocol is represented as a direct acyclic graph. The resources are considered as unary dedicated ones being either relaxable or non-relaxable during the scheduling procedure. They develop a greedy constructive algorithm to produce a partial non-feasible solution first and then a local search algorithm is applied to reduce violations in the solution and make it feasible. This was realized using the tabu search algorithm with the appropriate meta-heuristics. Finally, they present the interactive module they developed to support the mixed-initiative facility of the so-called Interactive Scheduler prototype. The information the system visualizes helps the responsible manager to take decisions and initialize moves to the system in order to reduce the violated constraints.

The next paper entitled, 'Continual planning and scheduling for managing patient tests in hospital laboratories' and authored by C. Marinagi, C.D. Spyropoulos, C. Papatheodorou and S. Kokkotos, gives emphasis on patient test management. They consider the patient as the entity that evaluates hospital services and therefore the one that admits the quality of service. So, they look at managing the problem of patient test requests as they are issued by specialized physicians and have to be realized at the hospital laboratories. The objective is to minimize the patient stay in hospital while at the same time maximizing the utilization of resources. An objective function is issued with the appropriate weights being introduced by the management, in order to evaluate and rank the resulting schedules. They implemented an integrated planning and scheduling approach based on multiagent technology, using a blackboard architecture and sharing a set of knowledge sources. As soon as a request is inserted in the system, a new agent is initialized and using the sharable sources, i.e. a planner, scheduler, solution assessment and the common knowledge base, as well as the requested tests and the snap-shot of the resources database, tries to find the most promising solution. The agent remains live till the complete execution of the request. The planner, called TRL-planner, is a temporal hierarchical planner that manages dedicated, sharable and consumable resources and on the other hand, accepts interventions from the user or the system. This facility together with the ability to activate an agent on test request availability or violation of previously scheduled request(s) leads the proposed system to be categorized as a continual planning and scheduling one.

Finally, C. Valouxis and E. Housos present the paper, 'Hybrid optimization techniques for the work shift and rest assignment of nursing personnel'. They issue a hybrid methodology that combines the strengths of operations research solutions with heuristic search alternatives of artificial intelligence in order to provide high quality solutions for the problem of nurse scheduling. A solution to the problem is approximated at the beginning using an integer linear programming (ILP) model. Then Tabu search strategies and other neighborhoods defined by local search procedures are integrated with the approximated ILP model in order to reach a highly quality solution. The presented approach successfully solves problems with up to three work shift types per day for up to 50 personnel in a monthly roster planning horizon, although larger groups of people and possibly larger periods could also be managed.

6. Looking at the future

So far one could say that AI planning and scheduling has not offered measurable, substantial results to the management of the hospital environment. However, the medical AI research community has studied many models, methods and techniques for a variety of medical problems within the laboratory environment. This has resulted in a rich background experience which has started to be gradually exploited in operational prototype systems for practical applications [30,32,44,54].

According to the author's view this exploitation could become more active by defining fixed but comprehensive model scenarios for different problems as well as specific measurement criteria to be used as benchmarks for the evaluation of the proposed prototype solutions. These problem scenarios should either refer to specific problems like scheduling the nurse personnel, the radiological laboratory, defining a therapy planning for breast cancer, pneumonia, etc. or refer to more complex problems like management of intensive care units, surgical operation theatres or even the medical management of a whole hospital. This is a really hard task and requires experts from hospitals and the medical AI community to participate actively in common workshops.

It is expected that the results will be realized gradually. However, the main target is always an integrated medical plan management support for the entire hospital. We should never forget that the medical hospital environment is continuously evolving due to the requirement of dealing with unpredictable emergency events resulting from patient requests or the progress of patient therapy. Thus, it is clear that medical environment is different from other environments concerning production, air campaign, etc. and need special attention. This difference does not mean at all that achievements reported in AI planning and scheduling for other application domains will not be taken into consideration. They will be critically evaluated and used appropriately.

Therefore, the author believes that a continual planning and scheduling model is the most appropriate one to attract the attention of the medical AI community. In the future it is expected this model will be tested in therapy planning as well as in patient examination tests planning and scheduling or in integrated medical plan management. The paper presented in this issue by Marinagi et al. could be a starting point but it needs further exploration. The control mechanism in the paper of Oddi and Cesta, also in this issue, is of interest for aggregating conflict resolution as well as for its mixed-initiative approach. It will also be of interest to evaluate such a multiagent architecture with a therapy planning model and vice versa, i.e. to evaluate architectures used in therapy planning for patient test management as well.

The development of the appropriate knowledge engineering tools for managing therapy planning procedures for different diseases is of great importance. Also, their availability through hospital intra-networks will greatly help the development of a medical expert community with equal access to a standard information infrastructure to the benefit of the patients worldwide.

Moreover, the machine learning methods should be further explored towards the adaptation of clinical guidelines in the therapy planning process taking into account past patient medical records, as well as toward the development of a general autonomous agent, i.e. a medical service robot, where planning and learning evolve interactively.

Concluding, the author believes that the AI medical planning and scheduling research is at a quite mature level and it is expected will soon be applied to practical systems.

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