Online Surgery Rescheduling - A Data-driven Approach for Real-time Decision Support

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Abstract: The operating room area is still one of the most expensive sections in the hospital due to its high and cost-intensive resource requirements. Further, several uncertainties like complications, cancellations and emergencies as well as the need to monitor and control the interventions during execution distinguish the operational planning tasks of surgery scheduling from more tactical and strategical planning activities. However there are few solutions that support monitoring and decision-making in operating room management at this level since they focus on creation of initial schedules or the efficient resource allocation. In this paper we describe a solution approach for supporting online surgery scheduling by a real-time decision support system. It allows the rescheduling based on intra-surgical information about the current surgical phases and predictions about remaining intervention times and further allows replanning due to emergent or canceled patients.

1 INTRODUCTION

Many business processes on operational level are characterized by uncertainties and frequent changes in the environmental setting. Hence, online operational planning methods address the monitoring and control of the process during execution and encompass to react to unforeseen events (Hans and Vanberkel, 2012). As well in every-day hospitals operations and especially the operating room (OR) area are locations where these traits and vaguenesses are ever-present. The OR manager is responsible for operational planning in the OR area, in particular for the supervision of all surgery-related resources and the guarantee of efficient accomplishment of the initially created surgery schedule according to diverse performance indicators. Uncertainties like urgent or emergent patients require the immediate integration in the schedule and complications or cancellations lead to time delays and shifting later procedures.

By this reasons, (May et al., 2011) describe the online surgery scheduling (OSS) as an contemporaneous job with a very short-term perspective that includes the execution, monitoring and control of schedules that were constructed the day before. At the beginning of each day a surgery schedule exists but is often outdated within a few minutes and needs to be modified on-the-fly as the associated uncertainties and dynamics occur. Since complications, cancellations and emergencies happen frequently it is uncommon that a schedule stays all day through. For this reasons, the OR manager needs latest information of the situations in the ORs as well as predictive information about future states and the impact of possible decisions. Despite, the well-known and often described surgery scheduling problem, there are few systems so far that tackle intra-day surgery scheduling and allow OR managers to get necessary information and support the decisions based on this information. Accordingly, in this work we address the problem of rescheduling of surgeries and describe a solution approach. The corresponding research question reads as follows: *How should a decision support solution be designed for supporting the online surgery scheduling problem?*

In contrast to other approaches, we describe an integrated solution that allows real-time rescheduling and schedule modification based on intra-surgical information about the current surgical status and predicted future developments.

The paper is organized as follows. In section 2 we present a state of the art of approaches for operational support for real-time scheduling as well as for online surgery scheduling. Section 3 provides a description of the underlying decision and optimization problem. Subsequently in section 4 we introduce the solution

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approach and the inherent components of the decision support system. Section 5 describe the efforts so for to validate our solution and give insights into the use case setting and its impact. Finally we conclude with a discussion of our results and describe future research directions.

2 RELATED WORK

Surgery scheduling in general is one of the highly adapted problems of operations research and scheduling research community. (Demeulemeester et al., 2013) as well as (Erdogan et al., 2010) state that operational support for real-time scheduling is not researched well in contrast to other domains where real-time approaches can be found. (Atkin et al., 2008) developed an approach for operational support for online scheduling of airport runways with a deterministic scheduling algorithm. (Ngai et al., 2012) describe an approach to compose primitive context information of location sensors to support real-time accident handling in fleet management use case. The problem of monitoring and scheduling multiple production plants is tackled by a information system including a algorithmic pipeline is described by (Guo et al., 2015) Since, the OSS problem differentiates in aspects of uncertainties and unpredictablities to the characteristics of these domains these approaches cannot be replicated to the operating room area. E.g. in manufacturing use cases the production process can be paused and proceeded within the same state of the item, which is not possible within a surgery (May et al., 2011).

Nevertheless in surgery scheduling literature several papers address the OSS problem and suggest approaches for supporting decision makers. (Demeulemeester et al., 2013; May et al., 2011; Guerriero and Guido, 2011; Erdogan et al., 2010) provide comprehensive reviews of existing literature approaches tackling the various levels of the surgery scheduling problem. Further, we focus on approaches that face the OSS and are published after the mentioned reviews.

(Dios et al., 2015) provide a decision support system for operating room managers to plan different decision tasks like medium-term and short-term schedules. Further, it is focused on handling elective patients so it lacks in supporting very short-term planning tasks like handling deviations in intervention times or emergency patients.

(Erdogan et al., 2015) describe a stochastic integer programming model for dynamic sequencing and scheduling of appointments in hospitals with the goal to minimize the weighted sum of direct waiting time and waiting time until appointment for patients. Though, they include different kinds of uncertainties like process durations or number of customers, the model isn't directly portable to OSS since it doesn't involve important surgical characteristics like urgency.

(Riise et al., 2016) propose an approach for a generalized operational surgery scheduling problem that is able to support decision making on different planning levels and with different characteristics. Hence, it helps planning elective patients as well as rescheduling by integrating urgent and emergent patients. Since, they argue that it is also applicable for intra-day rescheduling, the evaluation only focuses on scheduling on a weekly or daily level.

(Samudra et al., 2016) used a discrete event simulation model for the patient scheduling model considering uncertainties like varying estimations and arrivals of unplanned surgeries to avoid excessive overtimes in the OR area. They handle rescheduling of elective patients as well as including non-electives in the current surgery schedule since it represents the hospitals reality. They also use a estimated surgery duration model based on mean values of similar OR sessions but without feature-based machine learning model. As well it doesn't include real-time remaining intervention time estimations based on current phases.

(van Essen et al., 2012) developed a DSS that is providing the three best adjusted OR schedules according to variability in surgery duration and emergencies. This system is based on a linear integer programming model with the goal to accomplish the preferences of all stakeholders and departments as good as possible. Further, the objective function includes penalties for canceling surgeries or overtime minimization. It doesn't include the reassignment of surgeries to different ORs which leads to a reduced flexibility in scheduling and hence reduced efficiency.

The previously presented approaches treat the OSS problem on an algorithmic level, but don't take into account that information collection and DSS architecture considerations could also show improvements. This research papers assume that necessary information is already present in the scheduling system and further exclude the aspect of real-time information systems.

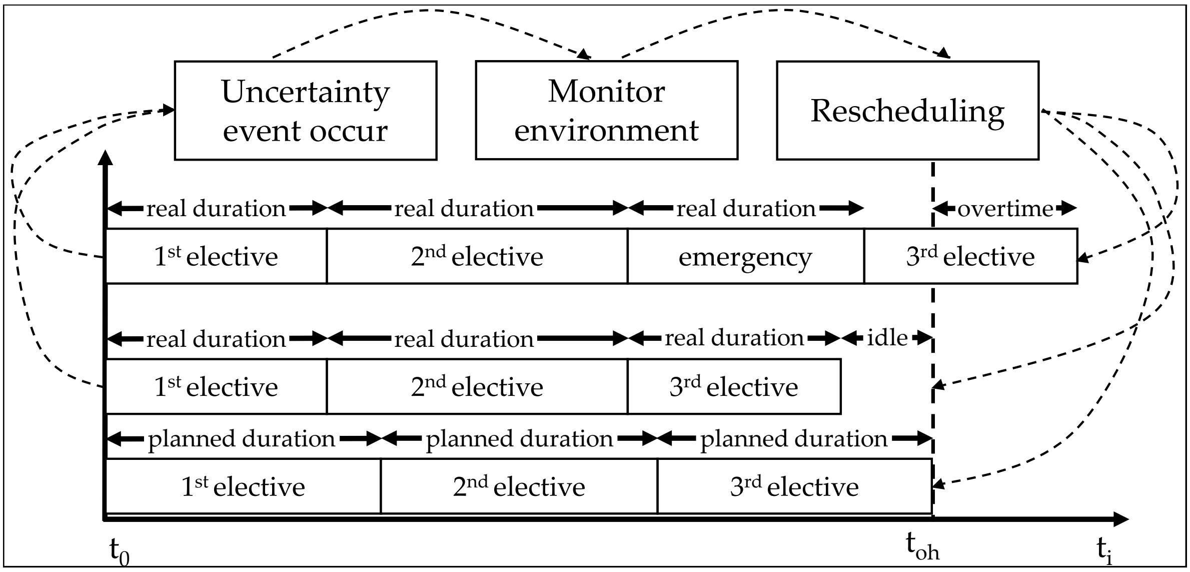

Figure 1: Model of the OSS problem for a single operating room including the challenges due to changing intervention durations and introducing emergent cases (extension of (Hans and Vanberkel, 2012)).

3 PROBLEM FORMULATION

In this section we give a short formulation of the OSS (rescheduling) problem for a particular day and the corresponding mixed integer linear programming (MILP) model that can be used to generate valid OR schedules within a surgery day. Since, it is a dynamic scheduling problem, it implies updating the schedule defined the previous day in reaction to external effects like incoming emergencies or internal changes like deviations (see figure 1). According to the rescheduling framework of (Vieira et al., 2003) the OSS problem described in this work can be seen as a dynamic scheduling problem with variable arrivals of patients. The OSS problem consists of a number of characteristics, assumptions, resources and constraints that are introduced next. The corresponding MILP model to solve the OSS problem is formulated by:

A set of indices with capacities and resource requirements:

- I: Set of interventions to be performed within the day, with elements i ∈ I
- O: Set of operating rooms available for surgeries, with elements o ∈ O
- S: Set of surgeons, with elements s ∈ S
- T: Set of available time slots within the day, with elements t ∈ T =1,...,X

A set of parameters describing properties of resources related to the OSS:

- $l_{o,t}$: Available time of OR o in working hours
- $c_{s,t}$: Time capacity surgeon s is available for performing interventions
- d_i: Estimated duration of Intervention i
- u_i: Urgency status of intervention i
- m_i: Modification status of intervention i

Two planning variables are available to optimize the schedule according to the given constraints, assumptions and resources:

- t_i: Assigned starting time of intervention i
- o_i: Assigned OR o of intervention i

The number of surgeries to be scheduled on the tagged day is not known in advance, since it is likely that emergencies occur. A surgical intervention i is characterized by its surgeon s_i, the estimated duration d_i before or during the intervention and its urgency u_i according to the scale elective, urgent and emergent. Further, a modification parameter is introduced to block interventions in a specific OR at a specific time manually or after start. For each surgeon indexed s, I_s denotes the set of jobs that are performed by that surgeon. Several assumptions are made to reduce complexity and develop a sparse model of the OSS problem:

Assumption 1: ORs are interchangeable, e.g. there are no equipment constraints.

Assumption 2: Unexpected incoming patients receive preferential treatment in case they have higher priority than scheduled elective patients.

Assumption 3: There are enough surgeons and surgical teams to treat electives, as well as accommodate non-electives.

Assumption 4: Surgery durations are estimations that change during interventions.

The above assumptions and the following constraints represent some of properties of the rescheduling process resulting from the situation in the OR area. Some hard constraints are defined, which, if they are violated, lead to an invalid surgery schedule.

Constraint 1: Only one surgery at the same time in a operating room. A surgery cannot be assigned to a OR that is occupied.

Constraint 2: A surgeon/surgical team can perform only one surgery at the same time.

Constraint 3: Surgeries tagged as not movable must not be reassigned to other ORs or time slots

Further, four soft constraints are modeled:

Constraint 4: Don't assign elective intervention after operating room working hours.

Constraint 5: Do urgent and emergent interventions as soon as possible.

Constraint 6: Avoid reassigning or canceling already assigned surgeries.

The problem is now to find an assignment $\sigma : I \times T \mapsto O$ of interventions to available time slots of operating rooms and surgeons according to the intervention duration. Hence, the solver optimizes the rescheduling result according to the following goals.
The most important optimization criteria for the OR manager (besides treatment quality) is maximizing OR utilization of each operating room $\omega_u(o_\sigma)$ (1). Since, there are several methods to calculate OR utilization we use the definition of (Hans and Vanberkel, 2012).

$$Max\ \omega_u(o_\sigma) = \sum_{i=1}^{I} \frac{d_i}{l} \tag{1}$$

The 2nd objective minimizes waiting time $\omega_w(\sigma)$ and should lead to fast integration of non-electives:

$$Min\ \omega_w(\sigma) = \sum_{i=1}^{I} uc^w \tag{2}$$

c^w describes the cost efficient for the waiting time of an intervention, while u means the urgency factor (higher urgency, higher integer value). The solver should minimize the penalty costs for waiting, so more urgent interventions are assigned fast (2). Further, all types of surgery are assigned as early as possible, thus a by-product is minimized overtime $\omega_o(\sigma)$.

$$Min\ \omega_o(\sigma) = \sum_{i=1}^{I} \beta_u l_{canc} \tag{3}$$

Adding penalty costs β_u for each canceled or reassigned intervention should lead to the effect that valid schedules with fewer reassignments/cancellations are preferred (3). Canceled interventions have a higher penalty beta than the reassigned and urgent interventions have higher β_u then electives.

4 SOLUTION APPROACH

According to this problem, formulation a predictive-reactive rescheduling strategy is utilized and supported with software tools to generate and partially update the current schedule based on incoming events with planning-relevant information. In this section we propose an architectural approach with an online surgery rescheduling engine. To realize this approach several software components are needed to collect and enhance the necessary information (see figure 2). The segmentation of the solution approach into three parts is because of separation of concerns. Nevertheless they build on top of another each subsystem uses different type of data and information.

4.1 Situation Detection Subsystem (SDS)

This component supports the information gathering tasks of the OR manager and automatizes it to ease and advance this process. Based on low-level real-time data of e.g. cameras, surgical devices, OR equipment or other connected devices information about intra-surgical phases in running interventions can be gathered. Besides processing the incoming data streams, SDS realizes methods for the phase detection. Lots of research exists for surgical phase detection methods. Some are image- or video-based, e.g. (Dergachyova et al., 2016). Others relying on electronic signals of surgical devices are described for example by (Padoy et al., 2012; Spangenberg et al., 2017). All of these methods have their pros and cons, e.g. some detect minimal invasive surgical phases better then others and vice versa. We used Complex Event Processing (CEP) for modeling surgical phases based on surgical device data and operating room equipment e.g. OR lights. According to the taxonomy proposed in (Lalys and Jannin, 2014) this component classes into the data-to-model analysis methods.

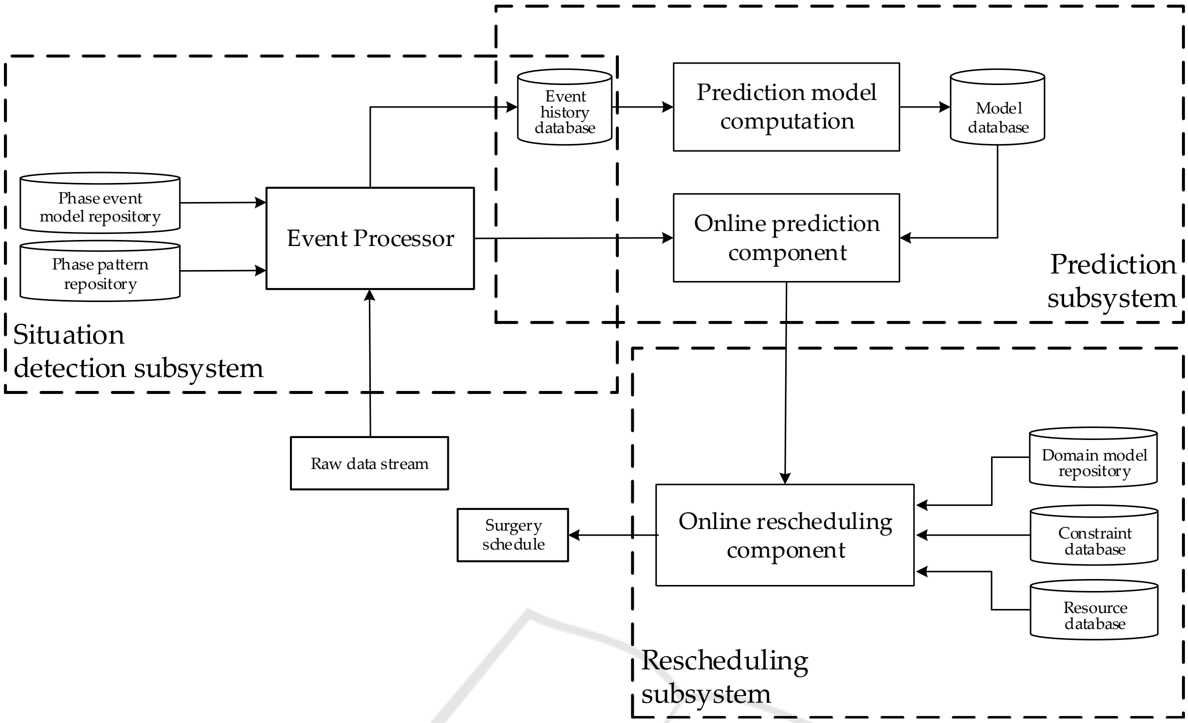

Figure 2: Components of the solution approach and their interactions.

4.2 Prediction Subsystem (PS)

PS utilizes the data of the SDS two-fold: First, a batch layer that uses historic surgical phases and other features to create a machine learning model that predicts the remaining intervention time of running surgeries. This model is built with a random forest algorithm based upon five features: an identifier for the surgery type based on the official German classification of medical procedures (OPS), a time stamp representing the time passed since start and the operating room. Further, the current phase as well as an event history based on previously detected phases is factored into the model. Second, an online prediction layer (speed layer) that loads the model and aligns detected phases in running surgeries with the model to update the estimated intervention time. Further, this starts triggering the rescheduling process.

4.3 Rescheduling Subsystem (RS)

After collecting information of the PS, the RS starts to adapt the current schedule to events and changes in surgeries. The RS is responsible for the generation of valid surgery schedules based on the resources and constraints described in section 3. Rescheduling is triggered by several factors, for example changes in remaining durations of running interventions based on the machine learning model. Further, the adding of emergent or urgent patients to the set of interventions leads to the execution of the rescheduling procedure. We use a metaheuristics approach for solving the optimization problem of the rescheduling task. Metaheuristics don't guarantee finding an optimal solution for the optimization problem, but find an appropriate solution in a given amount of time, which is necessary for our goal to give real-time decision support. The search space is defined by two vectors: One for the OR assignments of each surgery and second a vector for non-overlapping time-slots including surgeons, surgical team and ORs. Hence, the planning variables are operating room and the combination of starting time slot and the intervention duration. The cost function incorporates all cost factors of the constraints described in 3. Violations of the hard constraints, e.g. two surgeries at the same time in the same OR, are not allowed. The quality of a valid schedule is determined by the minimization of the soft constraints. Our metaheuristic consists of the following computational steps, based on the principle of local search. The used algorithm is Simulated Annealing, described in more detail by (Kirkpatrick et al., 1983). Since, it has been successfully used in dynamic scheduling domain before it is as well scalable and finds near optimal solutions (Ceschia and Schaerf, 2016).

4.3.1 Initial Solution

To get a satisfying, but non-optimal and mostly not feasible solution, initial solution of a schedule that afterward could be optimized, we use the First Fit Approximation algorithm. The algorithm assigns the interventions to a available planning value (in our case ORs and available time slots) and further takes the already initialized interventions into account. Since, First Fit doesn't change an planning entity after assigning, it terminates after initializing all interventions.

4.3.2 Move Selection

Moves are chosen indiscriminately as it is common for Simulated Annealing algorithm. A move is selected if it is equal or greater than the best move. Furthermore, non-improving moves are also picked with a certain probability according to its score and the time gradient. In the early phase of the calculation process the probability of selecting sub-optimal moves is higher than in later phases.

4.3.3 Cooling Schedule

Since, an ideal cooling method cannot be determined in advance, a cooling calculation for temperature is used. Depending on a time gradient decreases from time to time by a constant quantity.

4.3.4 Acceptance and Stop Criterion

Moves are accepted in every case if they improve the solution. Moves leading to a worse solution the acceptance probability is determined by $e^{\frac{-f}{temp}}$, where f describes the cost function and $temp$ the current temperature. The whole procedure stops when the calculation gains a final temperature or exceeds a given amount of time due to the near real-time requirement of the system.

5 EVALUATION

The evaluation of the solution approach and its implementation in a case study in a real-world setting is planned for advanced research. So far we used a simulated environment of an operating room area representing 10 operating rooms each with 10 hours of operation/day and 4 starting time slots/hour. We used a data set of 15 surgeries with real-world data that produce a low-level events stream to simulate a surgical day and feed the SDS. The detected intra-surgical phases trigger the calculation of remaining intervention times and use this information afterward to start rescheduling. In this stage the interventions can have five different states:

- Planned: Are introduced to the system, but OR or time slot are not assigned yet.
- Scheduled: OR or time slots are assigned, but intervention didn't start already.
- In progress: Intervention is running and changes in running intervention time are likely but OR isn't moveable.
- Reassigned: Scheduled intervention is reassigned to other OR or time slot.
- Canceled: Are delayed with higher priority for next day.

Observations showed that each running intervention updates its predicted remaining time on an average of 20 times so the rescheduling is triggered the same number. Further, the observations indicate that the metaheuristic provides good solutions according to tardiness and schedule stability. Few reassignments or cancellations are done by the algorithm and non-elective interventions, that are fed into system as well, are assigned fast (see figure 3).

First implications of the proposed system for productive operations are that the notable number of updates of the surgery schedule will increase. This is because that domain knowledge of the OR manager , e.g. for remaining intervention times, is now modeled and leads to a higher degree of transparency, since less information and thus decisions are based on experience-based knowledge and human estimations. For the main user of the system (the OR manager) two major improvements can be noted. First, the whole process for information collection in the operating room area is simplified. Second, the cognitive efforts for combining current states, estimations, available resources and potential emergencies, which is done without software support so far, is reduced significantly. These performance aspects will later be investigated in more detail by comparing it to decisions made by the OR manager.

Compared to other approaches tackling the OSS our work provides some benefits. (Li et al., 2016; Riise et al., 2016; Dios et al., 2015) also address short-term scheduling, but focus on optimization and manual adjustments on the day before. Hence, intra-day rescheduling is still unsupported and conducted by the OR manager. (Bruni et al., 2015) and (Heydari and Soudi, 2015) describe a similar problem of handling emergencies and uncertainties in surgery rescheduling and formulate new solution strategies from a algo-

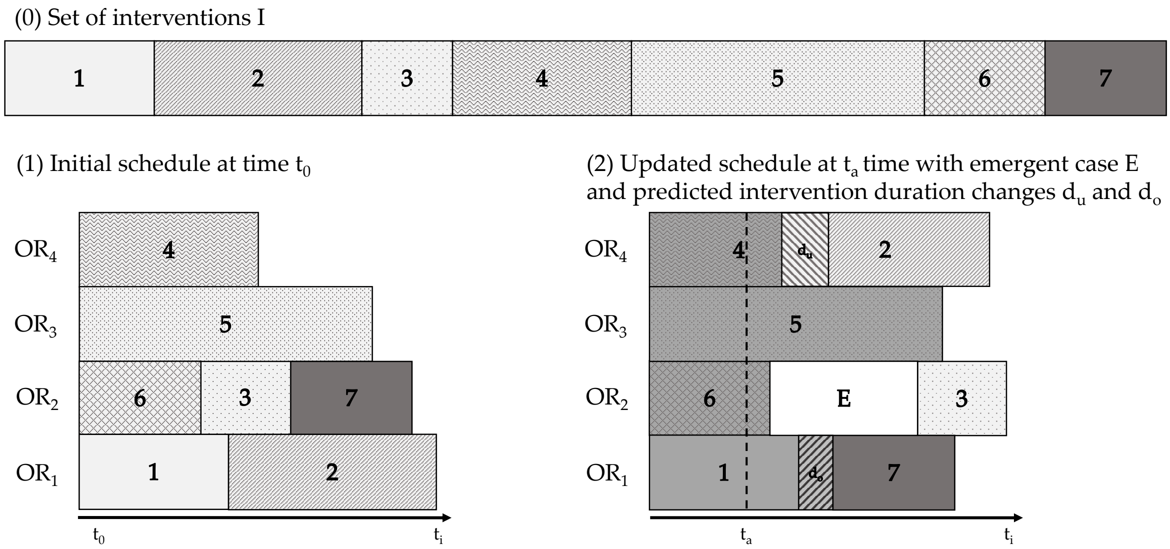

Figure 3: Components of the solution approach and their interactions.

rithmic point-of-view but lack with an integrated architectural approach and implementation details that would lead to simplifications for decision maker.

6 CONCLUSION

In this paper we presented a new solution approach for supporting the OSS problem by a real-time decision support system for rescheduling. Based on intra-surgical information about the current surgical phases and predictions about remaining intervention times it allows updating the surgery schedule and replanning due to emergent or canceled patients. The proposed approach denotes an innovative solution since most of the current approaches operate on the tactical and strategical planning and scheduling with longer time horizons. We focused in this work on modeling OR-related resources and constraints and for now omit other related entities like intensive care (ICU) unit or the like. But the approach can easily be extended in this directions, e.g. by modeling other personnel resources (nurses, porters, anesthetists) or facilities (equipment, devices, ICU capacities). It was shown that the benefits of our approach focus on the support of the OR manager and improve his daily tasks twofold. First, the process for information collection in the operating room area is simplified since it reduces communicative efforts, e.g. for monitoring current system status the status of running interventions in particular. Second, the cognitive efforts for combining current states, estimations, available resources and potential emergencies, is reduced significantly. The prediction and the rescheduling subsystem provide an automatized solution for tasks which so far are dispatched without software support.

In future work, we will focus on methodologies for the appropriate delivery of information to the OR manager. For instance a situation-aware user interface would benefit our approach concerning for better representation and prevention of information overload. Further, modeling more resources and constraints would lead to a more realistic Finally the evaluation of the integrated system in a real-world setting in a operating room area will be done to compare the performance of the system against human decision makers.

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