Real-time Simulations to Support Operational Decision Making in Healthcare

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Abstract

Long wait times lead to many important issues in the Canadian healthcare system. Emerging technologies now enable real-time measurement of wait times, leading to new opportunities for operational decision making in healthcare. This paper investigates a real-time simulation approach that exploits this information, combined with patient care process models, in order to support short-term predictions targeting the allocation of resources having an impact on wait times. A special style of modeling is used to enable real-time simulations with the Arena tool. The approach's feasibility is assessed on a realistic clinical process for cardiac patients of an Ontario hospital, with encouraging results.

1. INTRODUCTION

According to the Canadian Institute for Health Information, in 2012, among eleven developed countries, Canada had the highest patient wait times in emergency departments (ED) [CIHI 2012]. For example, according to February 2013 statistics (http://edrs.waittimes.net), the total time spent in ED on average in Ontario hospitals that month was 10.8 hours for complex conditions, for 9 out of 10 patients (with a provincial target of 8 hours). In a Gatineau (Québec) Hospital, the average length of stay in the ED was above 25 hours in 2012 (with a provincial target of 12 hours or less), with 14% of patients staying longer than 48 hours. High wait times not only cause patient inconveniences, but they also increase the risks of patients getting sicker and then staying even longer than necessary (leading to higher costs), and their consequences might be life-threatening.

Waiting occurs mostly because of insufficient resource availability compared to the large amount of service delivery requirements at a given time. In other words, because of the high variability of the care demand on a given period of time, hospitals generally attempt to adjust resource availability over that demand. However, the whole process is usually manual and involves human actors forced to make decisions under time pressure without a sound knowledge or visibility over i) the current state of their processes, and ii) the concrete impact of the possible alternatives that they have at hand. Operational decision making at that level needs to be done faster, with accurate information, and at a holistic level (i.e., targeting all departments involved in the care process, instead of targeting local optimizations that simply move the bottleneck to the next department).

In order to propose effective solutions for reducing patient wait times, the following capabilities must be enabled:

1) Predict which tasks are going to cause waiting.
2) Propose required adjustments in resource scheduling and check for impacts on upcoming results.
3) Make decisions ahead of time accordingly, in the near future, to avoid bottlenecks.

The above become possible by using *real-time simulations*, enabling *short-term* (or near future) decision making (e.g., several hours in advance), which rely on a real-time monitoring infrastructure. The main problems addressed in this paper are the construction of a simulation model that reflects the content of a process expressed with the Business Process Model and Notation (BPMN) [OMG, 2011] while incorporating the constructs necessary to support real-time simulations, and in particular the loading of the system's current state, represented by the running process instances. This paper hence presents several contributions in that area:

i) A new style of modeling that enables real-time simulations (including state loading) with a leading commercial tool, namely Arena 14 from Rockwell Automation [2013], and
ii) Modeling and analysis of a realistic healthcare process initially described with BPMN.

This research is done within the context of an ongoing collaborative project involving a community hospital in Ontario interested in reducing its wait times for a particular patient flow, namely *cardiac care*.

The next sections of this paper are organized as follows: section 2 reviews relevant background, section 3 exposes our simulation approach, section 4 presents a case study applying the approach to a community hospital, section 5 discusses our contribution and related work, and finally, section 6 provides conclusions and future work items.

2. BACKGROUND

2.1. Real-time monitoring system

Baarah et al. [2011] recently proposed the development of a system for improving cardiac patient flow. The work is centered on the design and implementation of an event-driven architecture based on complex event processing (CEP) for enabling real-time measurement of wait-times. In order to extract higher-level events (such as patient wait state events), the CEP engine correlates information from four main types of sources flow: medical equipment, physiological sensors, RFID tag readers and a business process management (BPM) system. The architecture particularly relies on the BPM engine for automation of care processes. More precisely, the authors present how orchestration of hospital activities for a given care process can be achieved in an automated way. Care processes are modeled using BPMN. The result is a system exhibiting the capability of capturing process performance data through allowing care process information to be collected in real-time. This system also enables tracking staff and patient locations and measuring accurately wait times.

From these results, an opportunity is envisioned which relies on real-time process data about current state of processes fed to a simulation engine in order to enable computer-aided short-term decision making.

2.2. Real-time simulation in healthcare

There are various applications of simulation in healthcare, which can be categorized into two main groups: the use of real-time simulation for clinical and medical purposes, and simulation for analyzing operations and business processes. There are different objectives in using real-time simulation for each of the mentioned categories.

In the first category, real-time simulation is mostly used for increasing patient safety and quality of medical results with a minimum number of medical errors. For instance, the ability to monitor the health state of the patient or analyzing the requirements of designing new medical devices could be explored using real-time simulation [Barjis, 2011]. Exposing clinical trainees to virtual environments for experimenting the simulated version of physical objects is another application [Samosky et al., 2011].

The second category focuses on the application of simulation to medical processes with a business point of view [Gaba, 2007]. The main objective here is to be able to capture, analyze and investigate the healthcare operational processes and provide the means to facilitate managerial decision making in an organization. Simulation has mainly been applied as a support for strategic decision making for the organization that provides clinical services.

2.3. Real-time simulation for short-term decision making

The uses of simulation for long-term or strategic decision making generally requires that non-terminating systems always reach a steady state. However, the systems of interest that are being studied (and simulated) here are usually of a stochastic nature and thus exhibit random behavior. As a result, simulation parameters can present significantly dynamic values when observed over time. Therefore, the long term simulation approach is not really suitable in our context. Short-term decision making is a possible alternative.

Short-term decision making is about making decisions for the near future (e.g., planning 4 to 8 hours ahead). In this context, the simulation behavior is closer to the real behavior because the simulation occurs over a short period of time (minutes or even seconds). This makes the use of real-time simulation much more valuable in term of results accuracy. The idea to simulate the system for a short period of time becomes a valuable approach for decision support.

3. REAL-TIME SIMULATION APPROACH

In our research project, we (in collaboration with healthcare partners) have extended and prototyped the architecture proposed by Baarah et al. [2011]. Figure 1 gives an overview of the various elements involved for measuring wait times accurately and managing patient flows, including a BPM engine that interacts with existing healthcare systems, a business intelligence tool, a home-made patient monitoring tool, and a real-time location system via a CEP engine (and a message broker). The BPM engine contains a BPMN model of the patient flow and manages the various interactions with doctors, nurses and others via a mobile user interface. Our focus here is however on the highlighted part, where a simulator (Arena): i) is fed with the current state of patient flow instances from the BPM engine, ii) performs real-time simulations based on scenarios, and iii) reports results/recommendations through a decision support system.

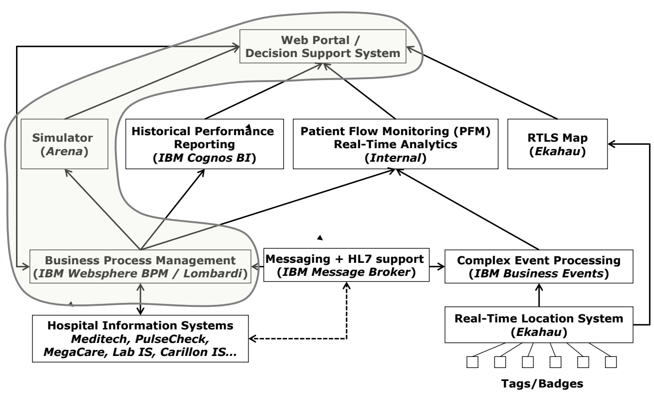

Figure 1. Simulation model using Arena.

The main idea of our approach is to support the short-term decision making process using real-time simulations. Decision making usually involves the evaluation of different possible scenarios and of their performance against a set of criteria and the selection of the alternative that maximizes the objectives of interest. The fast and dynamic pace/nature of healthcare and the non-predictability of patient issues ask for complex decisions about processes involving clinical activities, patients in needs, and human/material resources distributed over large areas, to be made in a timely manner.

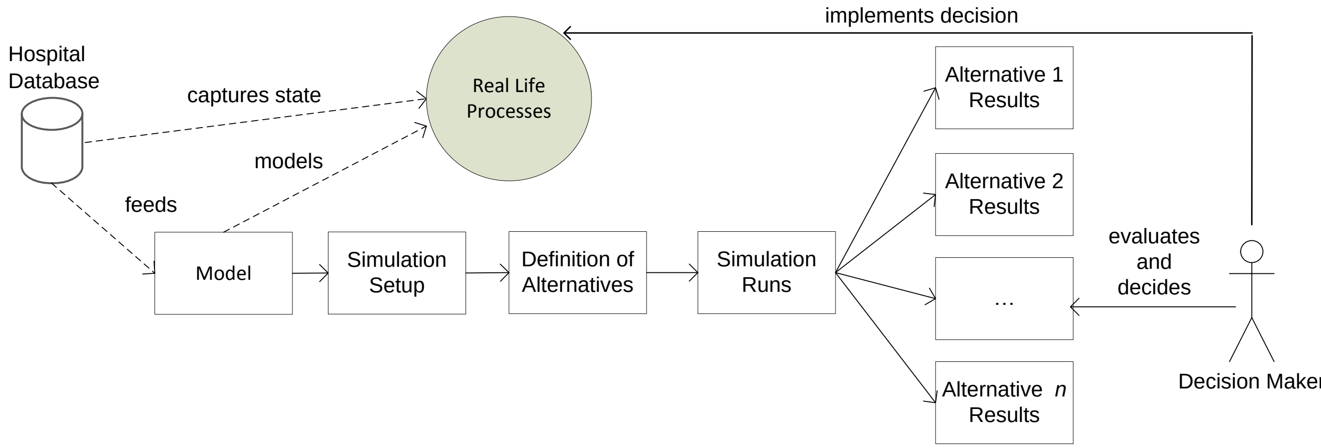

Figure 2. Operational decision making process aided by real-time simulations.

The decision maker (e.g., a senior nurse) needs to quickly yet accurately evaluate her alternatives to maintain a healthy state of the process she manages. In our approach, a simulation models reflects real-life processes and is fed two types of information from the enterprise databases (Figure 2): historical data is used to compute the characteristics of arrival functions, while BPM data is used to feed the current state of running processes. The simulation is then used for prediction of near future outcomes of candidate alternative scenarios, allowing the best decision to be made promptly by comparing the simulation results on criteria of interest (e.g., total wait times, resource utilization, cost, etc.).

The two main challenges in this approach are: the design of a simulation model complying with the corresponding BPMN patient flow (but abstracting from details irrelevant from a simulation viewpoint), and the injection of input data to initialize the state of the simulation model to be run. The latter is necessary because an accurate short-term simulation needs to start from an initial state identical to the current state of the physical process in the hospital at that time, that is, its real-time state. Short-term simulations can be initiated in a timely manner (periodically or upon demand) and possible outcomes of each alternatives can be observed (directly or via a more comprehensive decision support system). Eventually, among all the feasible candidate choices, the one that performs the most desirably will be chosen as the best case. The decision maker (e.g., a nurse) can then implement the decision in the real field. The real-time monitoring engine can enable process changes to be clearly observed and validate predictions of the simulations. The system is meant to be used in a closed loop fashion, meaning that the simulation data will be updated with real-time data of the hospital so the decision maker can run simulations to predict the outcome state of the process in a near future (e.g., 4 or 8 hours ahead). Real-time simulations are computed quickly and can be used to provide an accurate evaluation of the impact of alternatives on process performance.

4. CASE STUDY

This case study covers the implementation of a simulation-based short-term decision making process in the context of an Ontario hospital interested in reducing wait times. The entire clinical process for cardiac patients of the hospital was chosen for this study. That healthcare process selected involves several units, including the emergency department (ED), the cardiac catheterization laboratory (CCL), the test laboratories (TL), and the cardiology ward (CW). In a nutshell, a patient arrives at the ED and is triaged, then a physician consults with the patient and orders tests from TL. TL provides test results, and then the physician does a second consultation and admits the patient. The patient is moved to CW, then undergoes surgery in CCL, and finally returns to CW until he/she is discharged. Various delays can occur and influence different wait times. Several alternatives and potential concurrency are also considered along the way.

The main steps of Figure 2 were followed in order to prototype a real-time simulation environment in such a context. The main problem to solve (i.e., the simulation's objective) is to reduce wait times in the cardiac care process.

4.1. Model

The simulation model covers a subset of a clinical pathway of a cardiac patient. Arena v.14 was used for modeling the real-time simulation of the cardiac patient flow. The BPMN model of this process (already created jointly with the hospital staff) was mapped to the simulation model using novel guidelines that help focus on the relevant aspects of the BMPN model while enabling this tool to load the current state of running processes, an essential capability that is not supported out of the box in Arena. Among the guidelines we can find the following important ones:

i) The BPMN model captures the care process from a system point of view. The information captured at that level reflects two types of interactions: between the system and the user, and within the system itself.

As Arena is an entity-driven application, only the tasks that directly impact the entities are modeled. Therefore, the first type of interactions is modeled indirectly in the simulation model while the second type is not included at all.

ii) In BPMN, activities are being assigned to actors, hence capturing the authority of the different actors. In a simulation model however, the capacity and availability of the resources must also be captured since these parameters are of concern for calculating patient wait times. These must come from outside the BPMN model (e.g., from experts or logs).

iii) Some nodes are used in a BPMN model to record the real-time tracking information of the entities, for real-time monitoring. Such nodes are ignored in the mapping because the simulation model collects and generates the predicted statistical information automatically by the end of each simulation run.

iv) For enabling the injection of the initial state into the simulation model, additional modules and connections are required for each task. This more or less doubles the size of the model, but this is essential for near-future, real-time simulations.

Figure 3 shows a simple extract of the resulting simulation model, where the tasks at the top exist only to enable loading the initial state (as per the last guideline above).

4.2. Simulation setup

The next step involved feeding the required *historical* and *state* data to the model and setting the number of replications and the length of simulation runs. The historical data relates to the duration of the activities involved in the patient flow as well as to the patient arrival rate to the emergency department. Such information is represented in the form of statistical distributions extracted (manually for the moment from hospital databases or from discussions with experts. The *Input Analyzer* is an external application in Arena through which the distributions were set and defined from the raw data. This information can be updated at a low frequency, e.g., every few weeks or months. The initial state of the hospital however should be injected to the simulation model from the database, every time a short-term simulation is initiated (in our case every 8 hours, however this can be adjusted to the needs of decision makers). The precision of the initial state information is of significant importance, since the warm-up period is to be avoided by loading the initial state of the simulation at each run. The historical data related to the *duration of the activities* is less likely to change in a short period of time. However, the parameters of the *arrival rate* distribution should be calculated and fed into the model as often as the initial state of the hospital. This is because of the unpredictable and random nature of the patient arrivals in ED during different days of the week and hours of the day. The resource capacity related to each activity was also defined according to the current schedule of the resources.

Each simulation run should be initiated from a state that corresponds to the current state of the hospital. The simulation setup was configured to read the initial state from an external comma-separated value file (e.g., generated by the BPM engine, which knows about all running processes), which initializes all resources via the supplemental tasks and connections found in the simulation model.

The setup also includes setting the number of replications and the length of run. In this study, the number of replication chosen was 10, in order to get a sufficient *confidence level* and a reasonable amount of *coefficient of variation* (CV) for the output values. The output that Arena generates is within a 95% confidence level, meaning that in 95% of the repeated trials, the mean would be reported within the interval of the mean ± half width [Kelton et al., 2010]. For ensuring the precision of the output data, we calculated the coefficient of variation, a common sampling error measurement approach. CVs were calculated for all of the outputs and finally averaged. The maximum acceptable average CV was chosen to be 5%, with condition upon the lowest percentage of error on the average wait times. Satisfying the minimum sufficient confidence level (95%) and the maximum error calculated by the average CV (5%) with a minimum number of replications results in a minimal running time, and this was the main objective we followed while choosing the number of replications. The choice of the run length depends on the specific characteristics of the patient flow processes in the hospital and is a user's choice. A length of 8 hours was chosen here as this corresponds to two consecutive clinical shifts. The run length should be chosen short enough to fulfill the objective of short-term decision making for proper resource scheduling. For reducing patient wait time, we believe that short-term decision making would be much more effective rather than medium-term or long-term decision making due to the unpredictability of the hospital events.

The simulation model, including the tasks, resources, distributions and scenarios, was validated by a hospital qualified manager who was knowledgeable of the entire clinical pathway elements and of the process models.

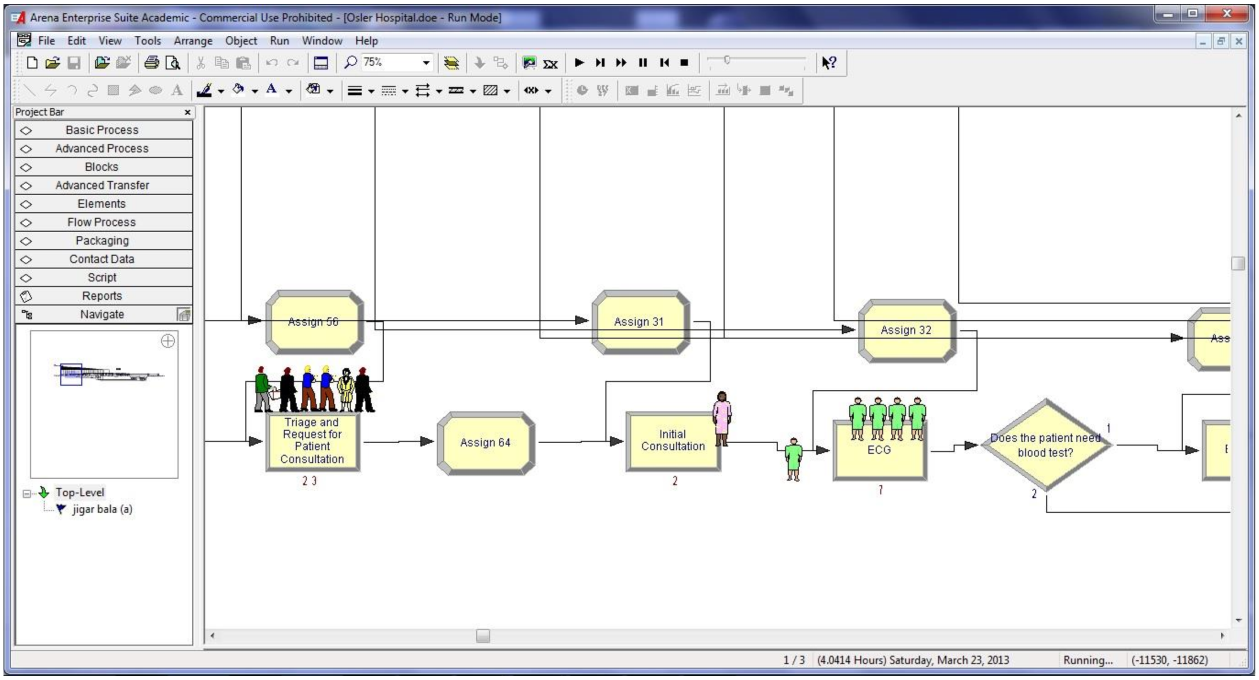

Figure 3. Simulation model using Arena

4.3. Alternatives, Runs, and Results

The next step involves defining different candidate alternatives by configuring different resource allocation combinations and assessing their impact through multiple simulation runs. The main objective here relates to the reduction of patient wait times, and the decision maker has to decide whether to bring/release staff, open/close beds, etc. We want to assess the tradeoffs between different business outcomes and to choose the best option among the possible alternatives according to the objective. The criteria chosen for this case are "patient total wait time", "total (hospital) cost" and "percentage of patient discharged". The different combinations of resource allocation leading to operational decisions were set in the scenarios and the outcome for each scenario was analyzed. The best scenario would be introduced as the one with the best expected outcome values from the access and flow manager's point of view (i.e., a senior nurse who is here the main decision maker).

Figure 4 shows a subset of the scenarios (seven in the figure), the controls available (ED/CW/CCL/Discharge secretaries, nurses, physicians; CW beds, transport, etc.), and the results. The decision maker does not necessarily have to create the scenarios as the latter can be predefined (hence capturing recurring patterns of decisions), or selected from a list. The resource values are computed from the current state, plus or minus desired variations. Results can be turned into recommendations in a decision support system where weaker alternatives are eliminated and only the 2-3 best options are shown, together with their tradeoffs in terms of costs, wait times, etc.

Such real-time simulations are fast enough (a few seconds) to be used on demand or periodically by decision makers who want to predict what-if situations several hours in advance, in order to avoid bottlenecks altogether.

	Scenario Properties				Controls									Responses		
	S	Name	Program File	Reps	ED sec_Cap(1)	ED_Nu_Cap(1)	ED_Ph_Cap(1)	CW_Sec_Sch(1)	CW_Nu_Cap(1)	CCL_Su_Cap(1)	Sec_Dis_Cap(1)	Bed_Capacity(1,1)	Transport_cap(1,1)	Average Waiting Time	Total Resource	Percentage Discharged
1		BaseCase	772 : Osler	10	1	7	4	2	7	4	2	32	2	8.752	18138.723	48.938
2		Add ED staff	772 : Osler	10	2	8	5	2	7	4	2	32	2	8.078	18742.392	52.782
3		Add CW staff	772 : Osler	10	1	7	4	2	7	5	3	32	3	8.144	18395.356	47.912
4		Add ED and CW staff	772 : Osler	10	2	8	5	2	7	5	3	32	3	7.279	19228.822	55.606
5		Remove CW Nurse	772 : Osler	10	2	8	5	2	5	5	3	32	3	7.279	19092.822	55.606
6		Add 8 beds	772 : Osler	10	2	8	5	2	5	5	3	40	3	6.882	19124.420	58.541
7		Add More ED Phy & CCL Surg	772 : Osler	10	2	8	6	2	5	6	3	40	3	4.854	19972.192	56.429

Figure 4. Simulation results for several scenarios, with controls and responses.

5. DISCUSSION AND RELATED WORK

There exist previous research contributions targeting the use of real-time simulations for enabling short-term decision making. Marmor et al. [2009] focused on online prediction of current and near future states with the objective of adjusting resource scheduling in emergency departments. This model only takes, as real-time input data, the patient arrival to the ED from an external database, and then injects it into the model. The model is hence initiated with an "Empty and Idle" state and in turn the model must be run for a long enough period of time to overcome the warm-up period and reach a steady state. One drawback in this study is that the warm-up period differs from run to run, and it is required to be calculated before each run. Computing the steady state (when it exists) takes a long time, and not having a way to save and load steady states makes such an approach unusable in our context. Moreover, the scope of this study is limited to ED, thus resulting in calculations related to the patient wait times to exclude the information related to an entire patient journey in a hospital. In our approach, we bypass the warm-up period altogether by having a simulation model whose system's current state can be loaded dynamically (and quickly), with accurate information.

Rozinat et al. [2009] highlight the possibility of using simulation systems for operational decision making, rather than using them for strategic decision making. As a case study, a credit card application process has been modeled, and the historical data as well as the initial state have been injected into the model. What-if scenarios have been defined for finding out the outcome of different staff scheduling alternatives. However, the focus of the study is not specific to healthcare processes, and is quite far from capturing the information required to measure and reason about wait times. Due to the complexity and human-related nature of patient flows, in our study, we found the discrete-event approach to be ideal for modeling and analyzing patient wait time problems in healthcare.

In most of the studies previously done with the objective of reducing patient wait times, strategic long-term decisions have been made by conducting a one-time simulation run. Real-time simulations might not be a vital component for long-term decision making in healthcare domain. However, their significant role cannot be denied in enabling short-term decision making in that context. Coats and Michalis [2001] have used a mathematical model to explore the impact of different shift patterns on future wait times. Even though their main intent was to improve future wait times, it is assumed that the system is going to behave in a steady way for a long period of time. This conclusion seems not be to reflecting the actual reality. For instance, when a crisis occurs, the arrival rate of the patients would quickly increase due to many patients being referred to the hospital, and this cannot be reflected within a one-run, long-term simulation setup. In fact, in all of the clinical processes inferred with unpredictable and unexpected patient arrivals, using simulations for long-term decision making might not be the most accurate approach, because of the continuous dynamic changes in the state of the hospital.

6. CONCLUSIONS AND FUTURE WORK

In this paper, the application of real-time simulation in healthcare for short-term operational decision making has been investigated. We have modeled and prototyped an end-to-end clinical pathway for cardiac patients of a community hospital. With the help of guidelines, a BPMN operational model of the patient flow was mapped to a simulation model for Arena v.14, in a style that enables the current state of the tasks and resources to be loaded. This simulation model is populated with historical data and the initial state data from a real-time monitoring engine powered by BPM technology. The model then evaluates alternative what-if scenarios and predicts the hospital state in the near-future. Bottlenecks and inacceptable trade-offs related to desired outcomes are easily detected in the generated reports. The decision maker (typically a senior nurse) is then able to make accurate and timely decisions for the near future, based on a set of likely alternatives that better satisfy the overarching objective.

Our study concretely shows how real-time simulation can be implemented in a healthcare context to support operational decision making. Particularly, we have demonstrated the benefits of the instrumentation of simulation techniques in the critical area of short-term decision making for wait times management.

Future work items include the consideration of scheduled patients in our simulation model, the use of an optimizer for full automation of the decision process, and further validation. *Scheduled patients* are an important factor related to wait time prediction that needs to be considered in our model. Supporting both walk-in patients and scheduled patients will better reflect the reality of hospitals and thus improve the accuracy of simulation models. Full automation of the decision process could make the system easier to use. As presented in our methodology, alternative scenarios currently need to be set manually by the decision maker, or selected from recurring patterns. Those alternatives are not necessarily the optimal ones, and better options might be missed. The use of an *optimizer tool* to automatically identify and propose the *n* most optimal alternatives to the decision maker is a possible solution. Better alternatives might hence be proposed, but the time required for such simulation and the complexity of creating/choosing appropriate optimization functions (which might also change from time to time) must be studied further. Finally, although we have used a real clinical pathway, with realistic data and models validated by a domain expert, much validation remains to be done before deploying this approach in hospitals.

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Biographies

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Daniel Amyot is Professor at the School of Electrical Engineering and Computer Science of the University of Ottawa, which he joined in 2002 after working for Mitel Networks as a senior researcher. His research interests include scenario-based and goal-based requirements engineering, business process modeling, healthcare informatics, aspect-oriented modeling, and legal compliance. He has over a hundred publications in these areas. For the past decade, Daniel has led the evolution of the User Requirements Notation as Associate Rapporteur for requirements languages at the International Telecommunication Union. He has a Ph.D. and a Master's in Computer Science from the University of Ottawa (2001 and 1994), as well as a BSc from Laval University (1992).