

A Simulation Model for Evaluating Alarm Routing Policies in ICU Patient Monitoring Information Systems

Emergent Research Forum papers

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Abstract

Patient Monitoring Information Systems generate alarms that are designed to make the clinician aware of the condition of a patient, but frequent false alarm occurrence can result in alarm fatigue and reduce the probability of a clinician to respond to the alarms. The purpose of this paper is to develop a simulation model to investigate the effect of false alarms and different alarm routing policies on clinician workload and patient safety. In this preliminary work, we present results related to two alarm routing policies: 1) all alarms routed to the nurse, and 2) role-based routing of alarms. We modeled the alarm generation and response process and the routing policies using JaamSim, open-source discrete event simulation software. The preliminary result suggests that role-based routing of alarms can significantly reduce the time spent on false alarms, clinician workload and patient safety in terms of number of missed critical alarms.

Keywords

Alarm policy, alarm fatigue, false alarm, alarm management, role-based alarms, and simulation for alarm policy

Introduction

Clinicians employ multiple devices in Intensive Care Unit (ICU) to access information from multiple sensors and devices to understand patient health status. The information from individual devices is often aggregated, processed and displayed using patient monitoring information systems. The patient monitoring information systems generate alarms to alert clinicians so that they can provide immediate attention to a patient in need. These alarms are designed to make the clinician aware of the condition of a patient, but false alarms occur frequently. The false alarms are generated due to various artifacts like patient movements or due to noise or by generic alarming criteria. These false alarms result in alarm fatigue and reduce the probability of clinician to respond. Alarm fatigue may occur when the number of alarm overwhelm providers because of the false alarms, technical problem in alarms, inappropriate alarm settings, inappropriate protocols for inactivation, and over utilization of physiologic monitoring devices (Cvach 2012; Graham and Cvach 2010; Shrestha et al. 2013).

Alarm management has topped the chart on the list of medical device technology hazard in the year 2012, 2013 and 2014 (ECRI 2011; ECRI 2012; ECRI 2013). U.S. Food and Drug Administration (FDA) Manufacturer and User Facility Device Experience (MAUDE) database reported 566 patient deaths related to the monitoring device alarms between January 2005 and June 2010 and the Joint Commission's Sentinel Event database reported that 98 alarms related events were recorded between January 2009 and June 2012. Among 98 reported events, 80 resulted in death, 13 in permanent loss of function, and five in unexpected additional care (TJC 2013).

Given the critical nature of this issue, clinical notification systems have been developed (Wagner et al. 1999) that sends information to recipients based on roles such as physician, nurse and technician. The purpose of this research is to help understand the effect of different alarm policies and their impact on patient safety, alarm fatigue and cognitive load in clinicians. In the current paper, we develop and present

a preliminary simulation model investigating the effectiveness of role-based routing policies on patient safety and clinical workload. In the next section, we discuss relevant literature. Following this section, we describe simulation in healthcare and then present our research model. We then discuss the preliminary analysis followed by conclusions and future work.

Literature Review

The problem of unnecessary clinical alarms has been reported for several years. Imhoff et al. (2009) reported that about 359 alarms occur per cardiac surgery procedure at 1.2 per minute and about 80% of the alarms have no beneficial effect. American College of Clinical Engineering survey reports that 81% of clinicians agreed that nuisance alarms occur frequently, and 78% agreed on disabling them (Drew et al. 2004). In ICU, Lawless (1994) identified that up to 94% of the alarms are false and Siebig et al. (2010) state that only 17% of the alarms are clinically significant.

Numerous studies have been conducted to analyze the issue and reduce false alarms. Borowski et al. (2011) suggested higher rate of false alarm can be minimized using statistical signal extraction algorithm like adaptive online Repeated Mediation (Schettlinger et al. 2010), adaptive online Trimmed Repeated Median-Least Squares (Borowski et al. 2009) that separates significant signals from noise. Zong et al. (2004) developed an algorithm that reduces false alarms related to changes in arterial blood pressure (ABP) in ICU monitoring by evaluating the ABP signal quality and examining the ECG-ABP relationships using a fuzzy logic approach. Aboukhalil et al. (2008) reduced the rate of false critical ECG arrhythmia alarms from 42.7% to 17.2% by relating the ECG data with the arterial blood pressure curve. Charbonnier and Gentil (2007) developed a trend based alarm system to improve patient monitoring in intensive care units.

In this regard, several strategies for alarm management have been suggested to reduce alarm fatigue and improve patient safety. Changing the alarm default settings and customizing the alarm parameters according to the patient have resulted in decrease of false alarms rate (Graham and Cvach 2010; Phillips 2006). Research has shown that changing the heart rate alarm from 120 bpm to 130 bpm has resulted in a 50% decrease in the number of alarms (Gross et al. 2011). Similarly, when default alarm parameters were changed including customization of the alarms, 43% reduction in critical monitor alarms was observed (Graham and Cvach 2010). Delaying the setting on the SpO₂ alarm to 15 seconds (Welch 2011) or 19 seconds (Görgeş et al. 2009) can reduce the frequency of alarms by 50% and 70%, respectively. Setting the alarm threshold based on each patient's condition can also reduce the frequency of alarms resulting in decrease of alarm fatigue. Welch (2011) reduced the SpO₂ alarm threshold from 90 % to 88%, and the alarm rate was decreased by 45%.

While various solutions have been suggested for reducing false alarm rate in healthcare, there is very limited research that models the effect of various alarm policies on patient safety and clinician workload. Given the nature of healthcare, which prevents live testing of policies or strategies, simulation models are often used in healthcare to evaluate the impact of alternative strategies.

Simulation in Healthcare

Healthcare systems are complicated with numerous stakeholders involved where significant decisions are made on routinely basis. Simulation has been a beneficial tool to conduct virtual experiments (Winsberg 2003). In general, modeling is a popular tool to support decision-making. There are various techniques used in healthcare modeling such as Markov modeling (Bauerle et al. 2000), Monte-Carlo simulation (Sebillé and Valléron 1997), discrete event simulation, and many more.

The most extensively used simulation approach in healthcare is discrete-event simulation (DES) method. Jun et al. (1999) review the literature regarding applications of DES modeling to healthcare clinics. Fone et al. (2003) perform an extensive review on the use of simulation in healthcare. Sobolev et al. (2011) analyze the use of simulation for modeling patient flow. Harper and Shahani (2002) presented the various types of patient flows when simulating bed occupancies and patient rejection rates. Shahani et al. (2008) developed a simulation model for a critical care unit to implement changes in bed numbers, patient length of stay, discharges in order to explore their effects on bed occupancy and refused admissions. Investigating the flow of patients (Caro 2005; Davies and Davies 1994; Sobolev et al. 2011), studying

healthcare workflows (Sarnikar 2010), and resource allocation (Steins and Walther 2013) are most common examples of use of discrete event simulation in healthcare.

Research Model

In this section, we present our research model for evaluating the impact of alarm policies on patient safety and clinician workload. Specifically, we extend the approach proposed by Gupta et al. (2005) that includes discrete event simulation for modeling email interruptions based on email policy, task complexity, and workload level in the workplace to the context of alarm interruptions in ICU. An overview of our proposed model is shown in Figure 1. The simulation model is designed to study different alarm policies in varying clinical contexts and its effect on patient safety and various performance variables in clinicians.

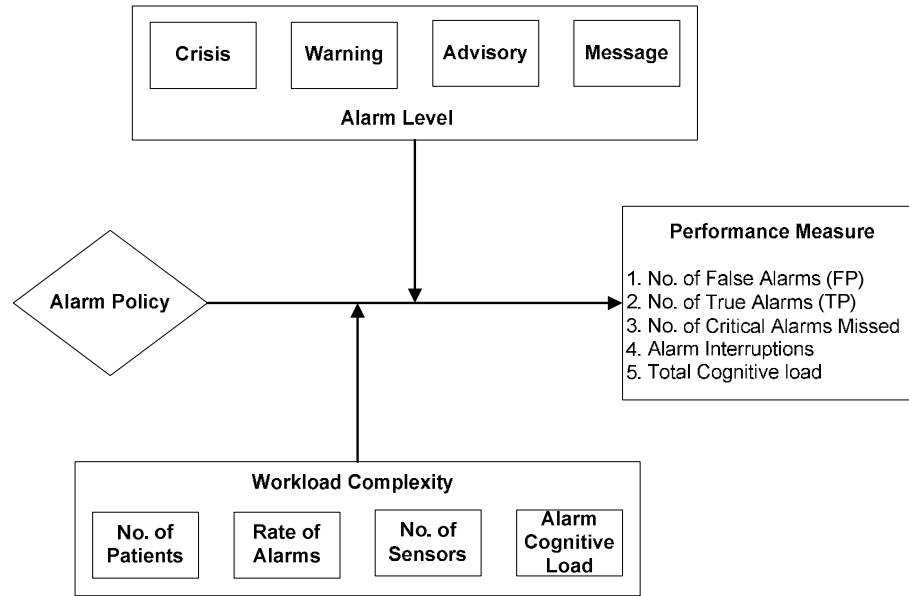


Figure 1: Research Model

The research model consists of four major components:

- **Alarm Level:** Alarm levels are categorized as crisis, warning, advisory, and message alarms (Graham and Cvach 2010). Crisis alarms are most serious alarms such as Asystole (a state of no cardiac electrical activity i.e. flat line), Extreme Tachycardia (heart rate is dangerously high, typically above 200 beats per minute). Warning alarms are to alert the clinicians that the condition is likely to occur and clinicians should take preventive actions such as Tachycardia (heart rate is faster than normal range), Bradycardia (heart rate is slower than normal range). Advisory alarms are meant to advise the condition such as Low Pulse Oximetry (low oxygen level in blood), Premature Ventricular Contractions (PVC - abnormal heartbeats from the ventricles of the heart). Message alarms are common notification to clinician such as Atrial fibrillation (rapid irregular heartbeat).
- **Workload Complexity:** Workload complexity can vary from low, medium to high. Workload complexity is directly proportional to the number of patients in ICU, number of sensors attached to the patient, rate of alarms, and increase in cognitive load because of alarm.
- **Alarm Policy:** Alarm policies guide the process of alarm notification including thresholds, routing, formats etc. For instance, policy outcomes guide which patients to monitor and suggest parameters to optimize the alarm systems that can reduce false alarms. In this paper, we explore the alarm policy related to role-based routing of alarms.

- **Performance Measure:** The performance measures are the number of true alarms in ICU, total number of false alarms, number of critical alarm missed, alarm interruptions, and total cognitive load of the clinician.

The two policies we explore in this paper are described below.

Policy 1: All Alarms routed to Nurse

In policy 1, all the alarms are routed to a nurse for response. When a sensor triggers the alarm and alarm notification enabled, the alarm is sent to a nurse. If nurse is available, the nurse responds to the alarm by monitoring the patient's vital signs and other physiologic parameters to determine the patient condition. If the alarm is assessed to be valid, the nurse takes appropriate patient care actions and records the alarm in documentation. If the alarm is identified as false, the nurse ignores the alarm or may switch the alarm off based on a threshold value signifying too many false alarms. A flow chart depicting this process flow in more detail is presented in Figure 2.

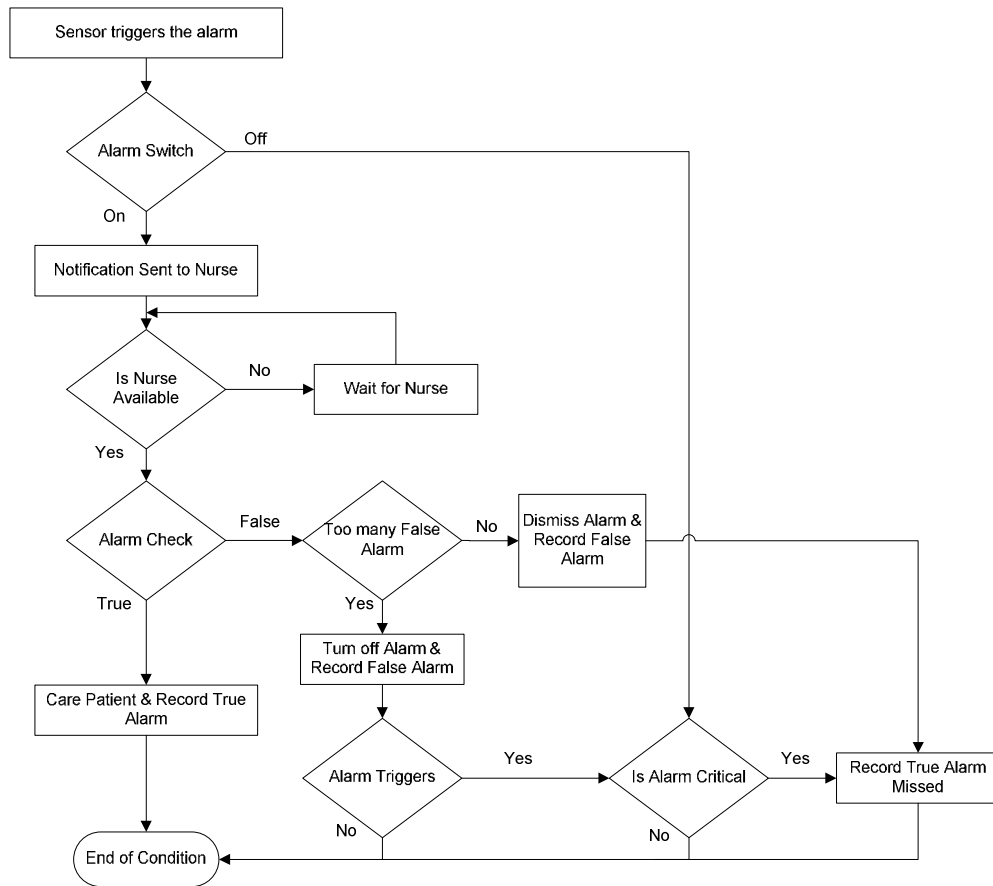


Figure 2: Process Flow for Policy 1

*Alarm Triggers -> Alarm occurrence after the alarm is switched off.

* Is Alarm critical -> Alarm of crisis level.

Policy 2: Role-based Routing of Alarms

In the policy 2, alarms are routed based on role of nurse and technician in ICU. The role of physician is not considered in this scenario, but we plan to model it in the future.

The policy 2 is similar to policy 1 with the addition of role of technician. When sensor triggers the alarm and alarm switch is on, alarm notification is sent to technician if the alarm is classified as a technical

alarm or non-clinical alarm by the alarm notification system. A detailed overview of policy 2 is presented in Figure 3.

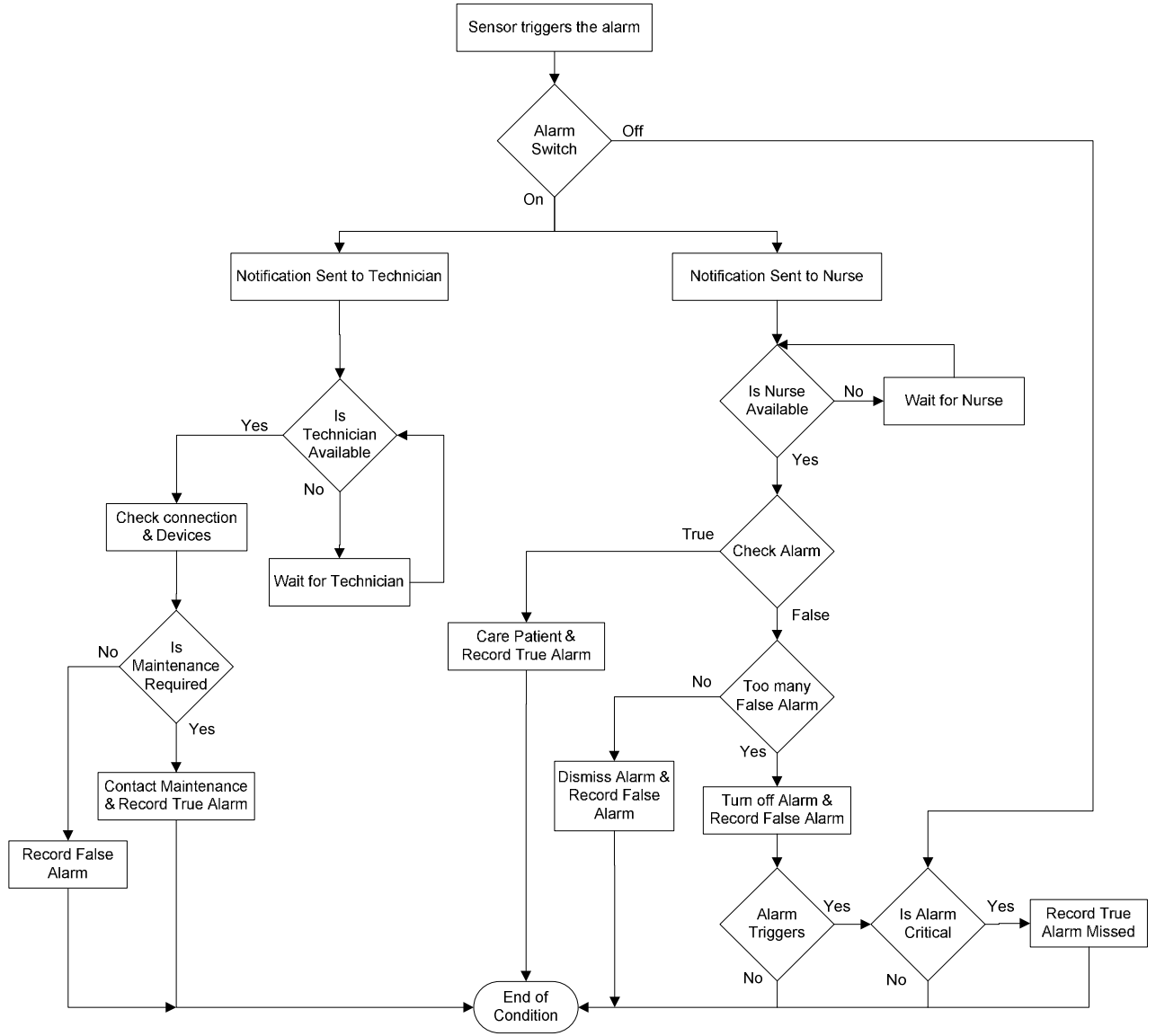


Figure 3: Process Flow for Policy 2

Simulation Model

Designing the simulation model advances our understanding of the complex nature of healthcare processes, and helps develop insights that otherwise would be expensive and time consuming. It allows testing different scenarios, and the result evaluates various strategies for effective operation of the system. In this context, we build a simulation model on two policies mentioned above to investigate the routing of alarms based on roles.

Simulation Software

We use JaamSim simulation software developed by Ausenco for modeling which is an open source simulation package coded in the Java programming language (King and Harrison 2013).

Simulation Parameters and Preliminary Analysis

AAMI (2012) reported that 771 alarm conditions occur per bed per day on average in one ICU i.e. an alarm occurs on an average of every 112 seconds. The inter-arrival time for an alarm is used as exponential distribution (Ricciulli and Shacham 1996), so the mean of 112 seconds of exponential distribution is used as inter-arrival time for alarm for simulation purpose. Lawless (1994) suggested that up to 94% of the alarms are false in ICU, so the alarm generated is set using discrete probability distribution of 0.06 and 0.94 for true and false alarms respectively. Since, the alarms are generated only for a patient, the capacity of the resource “Nurse” is assigned 1. Pergher and Silva (2014) stated that average respond time for alarms was 2 minutes and 45 seconds, so the entity delay of 165 second is used to respond to alarms after the nurse is available. Upon available, nurse monitors the vital sign, examines different parameters and determines the condition of a patient, and identifies the true alarm, takes care of the patient and then documents it. Tang et al. (2006) suggested that nurses spend 46% of time monitoring and caring patient and 30% of time documenting it in 6 hours shift when workload for each nurse was 35 patients. So, the time spent on caring a patient was used 4.73 minutes and for documenting was 3.08 minutes. The processing time to care a patient in simulation model is used 283.8 seconds and the nurse is released in 184.8 seconds after documentation. If the nurse identifies the alarm is false, it goes through a counter that keeps the track of false alarms. AAMI (2011) stated that alarm fatigue is when a nurse is overwhelmed with 350 alarm conditions per patient per day, or 0.004 false alarms per second. In our model, when there are too many false alarms, i.e. the rate for false alarm goes higher than 0.004, then the nurse is overwhelmed and alarm is switched off, and the alarms generated subsequently are recorded as missed alarms. After switching it off, the rate of false alarm starts decreasing, as the processing rate goes below then 0.004, the alarm is switched back on again. A serious problem may occur in patient’s health when true alarm is missed so, the model also captures how many true alarms are missed when the alarm is switched off.

Measure	Policy 1	Policy 2	
	Nurse	Nurse	Technician
Total Number of Alarms	769	769	
Alarms State Time	24 hours	24 hours	
Number of Critical Alarm Missed	18	0	
Number of True Positive Alarms	16	6	6
Number of False Positive Alarms	348	98	119
Number of Unprocessed False Positive Alarms	385	6	
Number of Alarms in middle of Simulation	2	534	
Number of Nurse/Technician Seized to process Alarm	365	105	126
Maximum Number of Alarms in Queue	21	532	4
Average Number of Alarm in Queue	4.29	271.75	0.288
Total Time spent on False Alarms	5.76 hours	1.632 hours	1.97 hours

Table 1: Comparison of Policy 1 and Policy 2

The role of technician is added in the scenario in the Policy 2. When the alarm is switched on, the alarms are distributed based on roles of nurse and technician. Konkani et al. (2012) addressed that 17.5% of alarms are due to technical problems. So, we use the discrete probability distribution of 0.175 for technician alarms and 0.825 for alarms to nurse. Since, the alarms are generated only for a patient, the capacity of the resource “Technician” is also assigned 1. We use the same average time for nurse and clinician to respond to alarms i.e. 2 minutes and 45 seconds, so the entity delay of 165 seconds is used. Upon available, technician checks the connection problem, medical equipment and instrument. The processing time of 3 minutes is used for the scenario. If the maintenance is required, technician contacts

the maintenance department. We used 195 seconds as time to contact technical support and report a problem and then release the technician for other work.

The Table 1 illustrates that nurse administered 348 false alarms in Policy 1 and 98 false alarms in Policy 2. It implies that implementing routing of alarms based on role eases the workload on the nurse and helps to reduce alarm fatigue. The total time spent on false alarms in Policy 1 is 5.76 hours, and 1.632 hours in Policy 2. This allows the nurse to spend adequate time in caring for a patient when role-based routing of alarms is implemented. The other significant measure is number of critical alarm missed. 18 critical alarms are missed in Policy 1 compared to none in Policy 2. It increases patient safety, which is the ultimate goal of setting up alarms. But at the same time, we also identified that there are numerous alarms waiting in queue to be responded by nurse in Policy 2 and continue to investigate the cause of this backlog.

Conclusion & Future Works

This paper explores the role-based routing processes involved in responding to alarms on ICU and develops a simulation model that helps to better comprehend the effect of alarm policies on patient safety and cognitive load in clinicians. We have proposed a research model to allow for the comprehensive analysis of the phenomena. However, in this paper we present a preliminary implementation of the model and its results. The preliminary result suggests that the total amount of time spent on false alarms by nurse is significantly reduced when role-based routing of alarms is implemented. The model also implies that such an approach would increase patient safety.

The data used for the simulation model was extracted from various time and motion studies and research reports. This is a limitation of the current paper, but in future, we plan to collect estimates of all parameters based on a single context. We also intend to add the role of physician, and model the cognitive load as well. We plan to enhance the process by modeling alarm levels, and workload complexity in future for the role-based routing of alarms.

REFERENCES

- AAMI. 2011. "A Siren Call for Action: Priority Issues from the Medical Device Alarms Summit," Association for the Advancement of Medical Instrumentation, Arlington, VA.
- AAMI. 2012. "Using Data to Drive Alarm System Improvement Efforts - the John Hopkins Hospital Experience," AAMI Foundation HTSI, Baltimore, MD.
- Aboukhalil, A., Nielsen, L., Saeed, M., Mark, R.G., and Clifford, G.D. 2008. "Reducing False Alarm Rates for Critical Arrhythmias Using the Arterial Blood Pressure Waveform," *Journal of Biomedical Informatics* (41), pp. 442-451.
- Bauerle, R., Rucker, A., Schmandra, T.C., Holzer, K., Encke, A., and Hanisch, E. 2000. "Markov Cohort Simulation Study Reveals Evidence for Sex-Based Risk Difference in Intensive Care Unit Patients," *The American Journal of Surgery* (179), pp. 207-211.
- Borowski, M., Schettlinger, K., and Gather, U. 2009. "Multivariate Real Time Signal Processing by a Robust Adaptive Regression Filter," *Communications in Statistics—Simulation and Computation* (38:2), pp. 426-440.
- Borowski, M., Siebig, S., Wrede, C., and Imhoff, M. 2011. "Reducing False Alarms of Intensive Care Online-Monitoring Systems: An Evaluation of Two Signal Extraction Algorithms," *Computational and Mathematical Methods in Medicine* (2011), p. 11.
- Caro, J.J. 2005. "Pharmacoeconomic Analyses Using Discrete Event Simulation," *PharmacoEconomics* (23), pp. 323-332.
- Charbonnier, S., and Gentil, S. 2007. "A Trend-Based Alarm System to Improve Patient Monitoring in Intensive Care Units," *Control Engineering Practice* (15:9), pp. 1039-1050.
- Cvach, M. 2012. "Monitor Alarm Fatigue an Integrative Review," *Biomedical Instrumentation & Technology* (46:4), pp. 268-277.
- Davies, R., and Davies, H. 1994. "Modelling Patient Flows and Resource Provision in Health Systems," *Omega (Oxford)* (22), pp. 123-131.
- Drew, B.J., Califf, R.M., and Funk, M. 2004. "Practice Standards for Electrocardiographic Monitoring in Hospital Settings," *Circulation* (110:17), pp. 2721-2746.

- ECRI. 2011. "Top 10 Health Technology Hazards for 2012," *Health Devices Journal* (40:10), pp. 1-16.
- ECRI. 2012. "Top 10 Health Technology Hazards for 2013," *Health Devices Journal* (41:11), pp. 1-23.
- ECRI. 2013. "Top 10 Health Technology Hazards for 2014," *Health Devices Journal* (42:11), pp. 1-13.
- Fone, D., Hollinghurst, S., Temple, M., Round, A., Lester, N., Weightman, A., Roberts, K., Coyle, E., Bevan, G., and Palmer, S. 2003. "Systematic Review of the Use and Value of Computer Simulation Modelling in Population Health and Health Care Delivery," *Journal of Public Health* (25:4), pp. 325-335.
- Goerges, M., Markewitz, B.A., and Westenskow, D.R. 2009. "Improving Alarm Performance in the Medical Intensive Care Unit Using Delays and Clinical Context," *Anesthesia & Analgesia* (108:5), pp. 1546-1552.
- Graham, K.C., and Cvach, M. 2010. "Monitor Alarm Fatigue: Standardizing Use of Physiological Monitors and Decreasing Nuisance Alarm," *American Journal of Critical Care* (19:1), pp. 28-37.
- Gross, B., Dahl, D., and Nielsen, L. 2011. "Physiologic Monitoring Alarm Load on Medical/Surgical Floors of a Community Hospital," *Biomedical Instrumentation & Technology*, pp. 29-36.
- Gupta, A., Sharda, R., Greve, R., and Kamath, M.C., Mohanraj. 2005. "How Often Should We Check Our Email? Balancing Interruptions and Quick Response Times," in: *BigXII+ MIS Research Symposium*. Norman, Oklahoma.
- Harper, P., and Shahani, A. 2002. "Modelling for the Planning and Management of Bed Capacities in Hospitals," *Journal of the Operational Research Society* (53:1), pp. 11-18.
- Imhoff, M., Kuhls, S., and Gather, U. 2009. "Smart Alarms from Medical Devices in the OR and ICU," *Best Practice & Research Clinical Anesthesiology* (23), pp. 39-50.
- Jun, J., Jacobson, S., and Swisher, J. 1999. "Application of Discrete-Event Simulation in Health Care Clinics: A Survey," *The Journal of the Operational Research Society* (50), pp. 109-123.
- King, D.H., and Harrison, H.S. 2013. "Open-Source Simulation Software "Jaamsim"," in: *2013 Winter Simulation Conference*, R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill and M.E. Kuhl (eds.).
- Konkani, A., Oakley, B., and Bauld, T.J. 2012. "Reducing Hospital Noise: A Review of Medical Device Alarm Management," *Biomedical Instrumentation & Technology* (46), pp. 6478-6487.
- Lawless, S.T. 1994. "Crying Wolf: False Alarms in a Pediatric Intensive Care Unit," *Critical Care Medicine* (22:6), pp. 981-985.
- Pergher, A.K., and Silva, R.C. 2014. "Stimulus-Response Time to Invasive Blood Pressure Alarms: Implications for the Safety of Critical-Care Patients," *Rev Gaucha Enferm* (35:2), pp. 135-141.
- Phillips, J. 2006. "Clinical Alarms: Complexity and Common Sense," *Critical Care Nursing Clinics of North America* (18:2), pp. 145-156.
- Ricciulli, L., and Shacham, N. 1996. "Modeling Correlated Alarms in Network Management Systems," *Western Simulation Multiconference*.
- Sarnikar, S. 2010. "Using Simulation and DEA for Optimizing Post-Emr Workflows," in: *5th INFORMS Workshop on Data Mining and Health Informatics*. Austin, TX: INFORMS.
- Schettlinger, K., Fried, R., and Gather, U. 2010. "Real-Time Signal Processing by Adaptive Repeated Median Filters," *International Journal of Adaptive Control and Signal Processing* (24:5), pp. 346-362.
- Sebille, V., and Valleron, A.J. 1997. "A Computer Simulation Model for the Spread of Nosocomial Infections Caused by Multidrug-Resistant Pathogens," *Computers and Biomedical Research* (30), pp. 307-322.
- Shahani, A., Ridley, S., and Nielsen, M. 2008. "Modelling Patient Flows as an Aid to Decision Making for Critical Care Capacities and Organisation," *Anesthesia* (63:10), pp. 1074-1080.
- Shrestha, S., Sarnikar, S., and Timsina, P. 2013. "Data Integration in CDSs for Alerts & Reminders: A Review," in: *Eighth Midwest Association of Information Systems (MWAIS)*. Normal, IL: pp. 1-6.
- Siebig, S., Kuhls, S., Imhoff, M., Langgartner, J., Reng, M., Schlmerich, J., Gather, U., and Wrede, C.E. 2010. "Collection of Annotated Data in a Clinical Validation Study for Alarm Algorithms in Intensive Care: A Methodologic Framework," *Journal of Critical Care* (25:1), pp. 128-135.
- Sobolev, B., Sanchez, V., and Vasilakis, C. 2011. "Systematic Review of the Use of Computer Simulation Modeling of Patient Flow in Surgical Care," *Journal of Medical Systems* (35:1), pp. 1-16.
- Steins, K., and Walther, S.M. 2013. "A Generic Simulation Model for Planning Critical Care Resource Requirements," *Anaesthesia* (68), pp. 1148-1155.
- Tang, Z., Mazabob, J., Weavind, L., Thomas, E., and Johnsin, T.R. 2006. "A Time-Motion Study of Registered Nurses' Workflow in Intensive Care Unit Remote Monitoring," in: *2006 AMIA Symposium* Washington D.C.: pp. 759-763.

- TJC. 2013. "Sentinel Event Alert," The Joint Commission, pp. 1-3.
- Wagner, M.M., Tsui, F.-C., Pike, J., and Pike, L. 1999. "Design of a Clinical Notification System," *AMIA Annual Symposium*, pp. 989-993.
- Welch, J. 2011. "An Evidence-Based Approach to Reduce Nuisance Alarms and Alarm Fatigue," *Biomedical Instrumentation & Technology*, pp. 46-52.
- Winsberg, E. 2003. "Simulated Experiments: Methodology for a Virtual World," *Philosophy of Science* (70:1), pp. 105-121.
- Zong, W., Moody, G.B., and Mark, R.G. 2004. "Reduction of False Arterial Blood Pressure Alarms Using Signal Quality Assessment and Relationships between the Electrocardiogram and Arterial Blood Pressure," *Medical and Biological Engineering and Computing* (42:5), pp. 698-706.