An Evaluation of the Risk Impact of Device Heterogeneity on Critical Care Delivery

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***Abstract*—Hospital care facilities often make use of non-interoperable devices produced by many different vendors to monitor the state of patients. The heterogeneity of these devices makes it difficult to synthesize multivariate monitoring data into a unified array of real-time information regarding the state of patients in a care unit. Without an infrastructure for data integration, the assignment of caregivers to patients cannot be optimized to reflect the relative urgency of patient needs. This is an especially serious issue in critical care units (CCU). In this work, we evaluate the hypothesis that the integration of vital sign data can yield a significant positive impact on the efficiency and outcomes of critical care delivery, via a computer simulation of a CCU. Within our simulated CCU, an infinitely replenishable finite set of patients are being monitored, while a small set of caregivers is addressing patient alarm conditions. Patients who experience an alarm accumulate injury exponentially during the time that they are without care. Once a caregiver arrives at a patient, the time it takes to treat the underlying disturbance is assumed linear in the patient's accumulated injury. If a patient accumulates more than a threshold level of injury, a fatality occurs. Fatalities require the execution of close out procedures, which take a specified period of time (and must be given precedence over living patients).**

Through simulation we compare the current defacto scheduling processes in use within CCUs, against a new scheduling algorithm that makes use of an integrated array of patient information collected by a hypothetical vital sign integration infrastructure. Our simulation study provides quantitative evidence from which we can measure the extent to which such an infrastructure reduces risk to CCU patients and lowers operational personnel costs.

I. INTRODUCTION

Medical related errors, occurring frequently in hospitals may result in catastrophic consequences. Some studies [13] found that in the United States, medical errors resulted in between 100,000 and 200,000 of deaths that could have been prevented. In [19] Schroeder described a case of patient fatality linked to a nurse delayed response to a cardio alarm. This catastrophic loss could have been prevented if the nurse have postponed stabilizing a patient with a less critical alarm and handled a more severe cardio alarm. In the effort of determining the causes of this breakdown, the Joint Commission, a non-profit organization seeking to improve safety through healthcare accreditations recently released a report that investigated incidents of serious injuries related to ventilation [10]. It was found that approximately 20-35% of these incidents were associated with a delayed response to an alarm; none of the cases were found to be related to a hardware malfunction.

In order to assess the human body functions, health professionals need to monitor the state of the patient *vital signs* such as body temperature, pulse rate, blood pressure, and respiratory rate [22]. In CCU, these are collected and monitored through a set of sophisticated *heterogeneous* devices produced by a number of distinct vendors with, often proprietary system of cabling, data protocols, etc. The heterogeneity of these devices has added more challenges to caregivers to monitor, integrate, aggregate, and more important prioritize the multivariate alarms reporting the patient's overall health which has a direct impact on the health professional response time.

The extent to which we can mitigate patient risks caused by delayed responses rests on addressing the problem of effective caregiver scheduling. Caregiver scheduling has received considerable attention in recent years. Researchers have proposed different approaches on how to tackle this problem. The first major approach suggests to start with data from existing facilities and analyze the data to build a model and determine how it responds to various stresses. For instance, McManus et al [17] and Zai et al [25] have used queuing theory to model the operation of existing healthcare facilities and admission procedures. The existing practices of "manpower allocation" in respiratory care is considered Matthews et al. in their 2006 study [16], while Gajc et al. examine the effects of having 24-hour (mandatory) versus on-demand critical care specialists on staff. The second major approach suggests using data mining techniques to improve workflow and decision making processes (e.g. Gallivan et al [8] and Shahani et al. [21]).

The third major approach consists of standardizing medical device interfaces, so as to allow for easier integration in both critical care and operating rooms. Most of these efforts (e.g. COSMOS [11]) have sought to define data standards for interconnectivity between heterogeneous systems in healthcare [7]. A recent RFID-based effort to device integration was demonstrated in pilot project in a Taiwan hospital [24]. Such ongoing efforts aim at developing an infrastructure capable of integrating vital sign data streams, thereby providing a unified view of a collection of patients, synthesized from a diverse collection of medical devices. Proponents of such infrastructures claim they would yield great positive impacts on the delivery of critical care. Here we seek to verify such claims, quantitatively.

The remainder of the paper is organized as follows. We begin in Section II with a description of the system model. Then, in Section III we define the proposed simulation frame-

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work. In Section IV we present our simulation results. Finally, in section V we present our concluding remarks and future work.

II. System Model

A **vital sign** is a real-time measurement of a patient, e.g. heart rate, blood pressure, etc. Many classes of vital signs arise in practice, because of biological and vendor diversity. A **patient** p, then, is a collection of k vital signs. An **alarm** is a triple (p,i,t) consisting of a patient p, a vital sign i, and a time t. The occurrence of alarm (p,i,t) is an assertion that the state of vital sign i in patient p has attained a value, which *if left unattended*, is expected to lead to increasing patient injury (and ultimately death). Post-alarm, a patient accumulates **injury** as exponential in elapsed time, following prior research [4], [12], [3]), according to

$$I(p_a,t) \stackrel{def}{=} \begin{cases} 0 & t < t_a \\ e^{\alpha_a \cdot (t-t_a)} & t_a \leqslant t \leqslant \ln(100)/\alpha_a \\ 100 & t > \ln(100)/\alpha_a \end{cases}$$

If the patient remains unattended for longer than $D_a = \ln(100)/\alpha_a$ post-alarm a, injury reaches 100, signifying death.

We model the alarms events for each vital sign as an independent Poisson process, i.e. the alarm inter-arrival time for alarm events concerning vital sign i are distributed according to a Poisson distribution of intensity λ_i. Once vital sign intensities λ_i have been specified, concrete alarm event sequences can be generated independently for each patient using a Poisson sampling process. A **caregiver** is an individual capable of attending to the conditions underlying patient vital sign alarms. The assignment algorithm which dynamically assigns caregivers to patients is subject to the following conditions:

1) A caregiver c *cannot be assigned to two distinct patients at the same time* t;
2) Caregivers assigned to a patient must remain there for a half-open interval of time $[t_1,t_2)$;
3) At most one caregiver may be assigned to a patient p at any given time;
4) Once assigned to a patient, a caregiver must stay with the patient until all alarms have been resolved (i.e. pre-emption of assignment is not supported). The time required for treatment is linear in the injury level that the patient has accumulated (across all vital signs), with the constant of proportionality being denote T_{max}. Once treatment is completed, the patient's injury is reset to 0;
5) If a fatality occurs, the expired patient is removed from the bed immediately, and placed in the "Code-Blue" (CB). The expired patient's now-vacant bed is immediately populated with a new critical care patient. This new patient is the source of future alarms that are attributed to "patient p". Each fatality in the CB require special close out procedures be carried out by a caregiver. If a caregiver is assigned to the CB, they must complete the close out procedures before handling any new alarms. Close out procedures require a fixed time T_{fatal}.
6) Assignment of caregivers must give higher priority to handling unprocessed fatalities in the CB than to existing critical care patients.

We now turn to the problem of evaluating the operation of a given caregiver assignment algorithm A. If caregiver c is assigned to (living) patient p, then the cost incurred by the caregiver is the total injury due to unhandled vital sign alarms at p (measured at the moment that the caregiver arrives at the patient). If a caregiver is assigned to the Code-Blue CB, then the cost incurred to carry out closeout procedures is C_{fatal} (a specified parameter). Over the lifetime of the simulation, and the operation of the caregiver assignment algorithm, each caregiver c accumulates costs based on its assignments, and the algorithm as a whole is charged the total cost accumulated by the caregivers.

Evaluating an algorithm will consist of conducting multiple independent simulations in which its caregiver scheduling processes are subject to alarm conditions. We will draw error bars at each point on the performance curve to show the mean/variance of the algorithm's performance across multiple trials. In comparing two algorithms, if we find that the mean curve of an algorithm lies within the error bars of its competitor, then it is inconclusive which algorithm is superior (if any). In such cases, we consider the **relative costs** of the two algorithms by considering the ratios of their costs (on identical alarm sequences), and seeing if the mean value of these ratios is well-separated from 1.

III. Simulation Framework

The first set of inputs to each assignment algorithm is a set of static configuration parameters. These include, the patients P, the caregivers C, the uniform time to death D_i for alarms concerning vital sign i; the maximum time to process an injury T_{max}; the time (resp. cost) to process a fatality T_{fatal} (resp. C_{fatal}). The second set of inputs is dynamically generated, and consists of the entire sequence $\widehat{A}$ of vital sign alarms that will be raised (for all vital signs, and all patients) in the course of the simulation. To generate $\widehat{A}$, the simulator needs to be informed of the patients P, the number of patient vital signs k, the intensity λ_i of the Poisson process governing alarms for each vital sign i, and lastly, the duration of the simulation T_{sim}. It then generates the alarms set $A(p,i,0,T_{sim})$ by sampling an independent Poisson processes of intensity λ_i, and the cumulative set of alarms $\widehat{A}$ for a trial is then taken as the union of $A(p,i,0,T_{sim})$ over all patients and their vital signs.

Within a trial, each online algorithm $A[i]$ must assign caregivers in response to an identical random sequence of alarms $\widehat{A}$, based on its own logical criteria. The statistical analyzer collects data on the cost incurred by each algorithm for each trial, repeating this so as to be able to analyze the algorithms' relative performance across a set of trials.

A. Scheduling Algorithms

The **Cyclic Scan** algorithm (CS) represents a formalization of the de-facto modus operandi of the majority of critical care units today. First, it reflects the absence of interoperability between vital sign monitoring devices: each device produces data in its own proprietary format, and heterogeneous devices cannot be integrated. Second, it reflects the relative absence of a wireless data communication infrastructure. These two features are unfortunately the norm in the healthcare system

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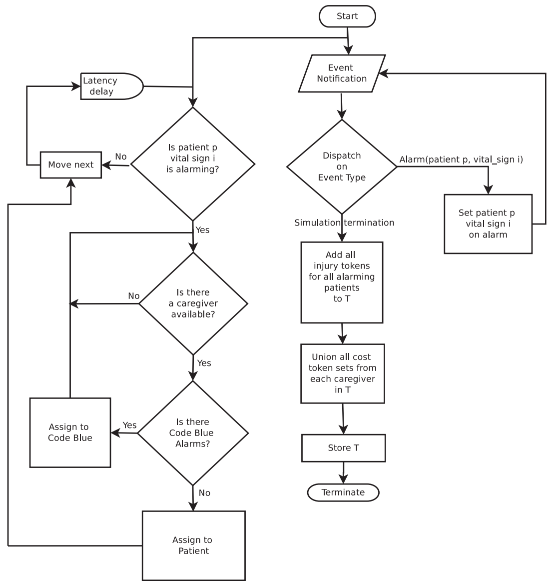

Fig. 1. The Cyclic Scan algorithm flow chart.

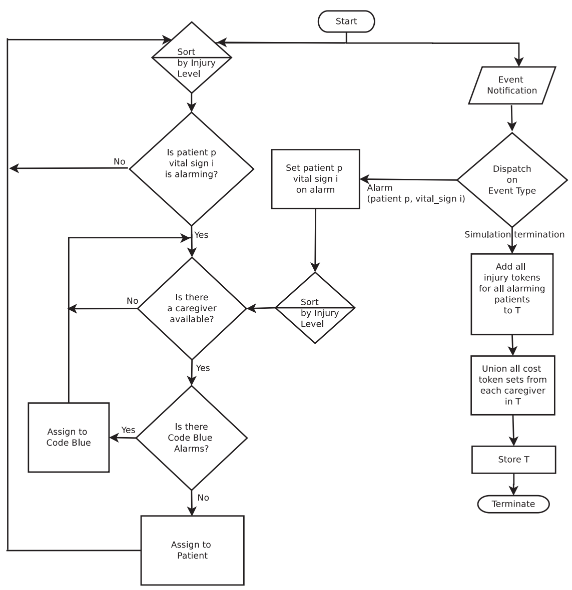

Fig. 2. The Greedy algorithm flow chart.

today, and taken together, they reduce the task of monitoring patient vital signs to a process in which caregivers "scan" among the devices to collect the presented data and status information.

B. Greedy

The **Greedy** algorithm is the first algorithm which is made possible by a vital sign integration infrastructure. Alarm data is consolidated at a central location, and the algorithm dispatches each caregiver, as they become available, to the alarm which reports the highest injury level at that precise moment. Greedy selection is admittedly shortsighted, in that it focuses on alarms which have the highest risk or harm of injury *at the present moment*. It is designed to prioritize (triage) handling of alarms.

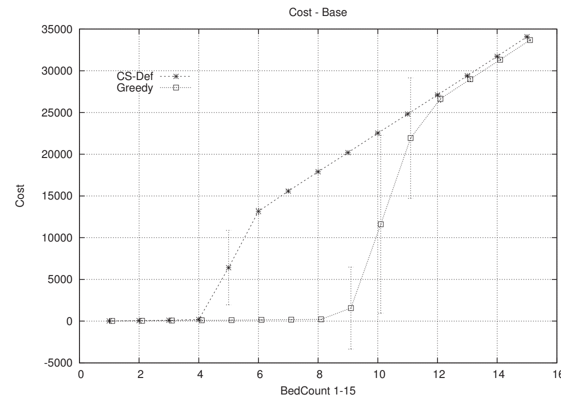

Fig. 3. Baseline (absolute) costs for Greedy and Cyclic Scan.

IV. Experimental Results

Objective. We seek to determine the maximum number of patients $|P|$ that can be satisfactorily served by a *single* caregiver, and the dependency of this value on the alarm frequency λ and the maximum service time $T_{\max}$. We seek to quantify the impact of integrated vital sign data on the *efficiency* of a single caregiver.

Parameters. Thirty simulations were conducted for each system configuration. Each simulation was for 480 minutes (a standard work shift) in a facility having just $|C| = 1$ caregiver. All patients had one $k = 1$ vital sign, exhibiting alarms with a time to fatality of $D_1 = 6$ minutes.

The simulation has three parts. In Part 1, we varied $|P|$, the number of patients, while fixing the Poisson alarm process intensity $\lambda_1 = 20$ minutes, and the maximum service time $T_{\max} = 25$ minutes and Code-Blue processing time $T_{fatal} = 25$ minutes. The results of Part 1 are considered the "baseline". In Part 2 of the experiment, we varied the intensity $\lambda_1 = 7.5, 15, 40, 80$ minutes and studied the effects on performance against the baseline. In Part 3 of the experiment, we varied $T_{\max} = T_{fatal} = 6.25, 12.5, 50, 100$ minutes, and studied the effects on performance against the baseline.

Part 1: Here, we seek to quantify how increasing the workload of a caregiver (i.e. the number of patient beds) impacts the emergence of injury within the critical care unit. Figure (3) shows that initially the cost of all algorithms are in agreement, since the workload of the caregiver is so low that optimization is unnecessary. This parity breaks down when the number of beds exceeds 4, as the Cyclic Scan sees a dramatic rise in cost from 0 to 17000 as the number of beds increases from 4 to 8. During this same interval, the Greedy algorithm maintains its lost cost. Finally, when the number of beds increases beyond 8, the Greedy algorithm begins to experience non-zero cost; at such high workloads, greedy scheduling cannot avoid the occurrence of patient injury. Finally, when the number of beds is sufficiently high,in excess of 13, the costs of the algorithms once again coincide, since greedy optimization is now no better than Cyclic Scan at circumventing patient injuries.

The error bars (across multiple trials) tend to be small outside of the phase transition, but grow during phase transitions. This may lead the reader to question whether, the

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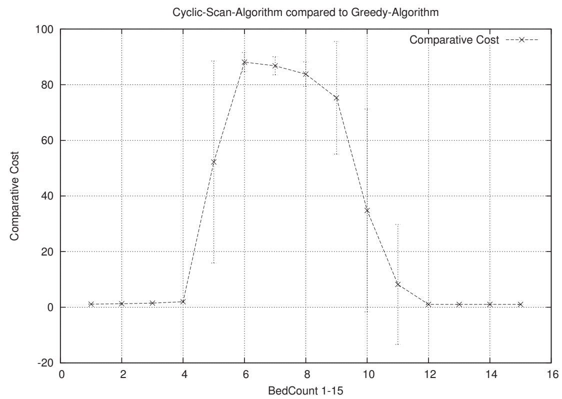


Fig. 4. Baseline (relative) costs for Greedy and Cyclic Scan.

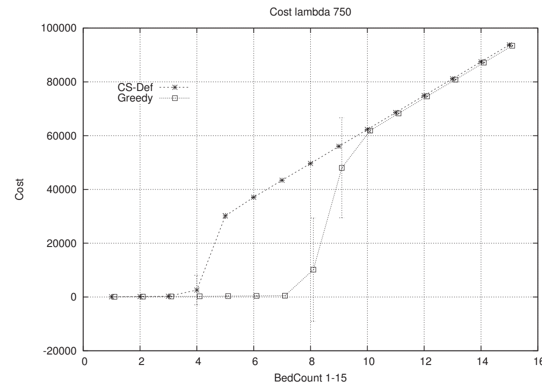
Greedy algorithm really outperforms the Cyclic Scan (for example in the 10 bed scenario), since the curves lie within a standard deviation of each other. The graph of Figure (4) seeks to address this concern. It depicts the *relative* performance of Greedy normalized against the Cyclic Scan. Note that the normalized performance is computed for *each trial*, and the graph depicts the mean and standard deviation of these normalized values.

Part 2: Here, we seek to quantify how varying the mean inter-arrival time of the vital-sign generated alarms (i.e. the Poisson process) impacts the emergence of injuries within the critical care unit. In effect, we seek to quantify the impact of varying λ_1 on the conclusion of Part 1.

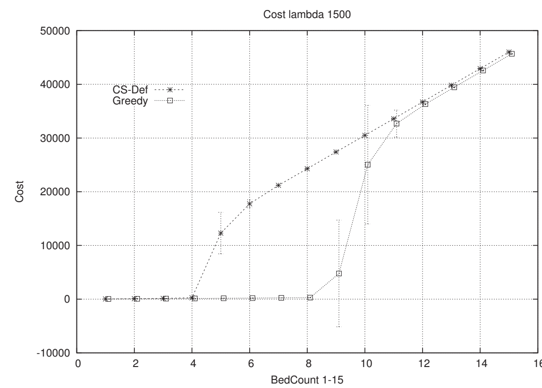
Graph (a) - (d) of Figure (5) consider alarm sequences in which the mean inter-arrival time set to 7.5 minutes, 15 minutes, 40 minutes, and 80 minutes. The Greedy algorithm incurs injuries when the bed count exceeds 7, 8, 9, and 10, for each of the respective scenarios. By comparison, the Cyclic Scan consistently incurs injuries whenever the bed count exceeds 4-5. The experiment demonstrates that using the Greedy algorithm enables us to leverage alarm sparsity towards an increased capacity to handle more patients in an injury-free manner. The conclusion is further supported by considering the upper boundaries of the phase transition where the performance of two algorithms once again coincides. This occurs at bed counts 10, 11, 15, and 19, for each of the respective scenarios. This shows us that the interval (in terms of bed count) for which the Greedy algorithm maintains an advantage over Cyclic Scan, increases as alarm events become more scarce.

Part 3: Here, we seek to quantify how varying the treatment times (for injured patients) and processing times (for patients in Code-Blue), impacts the emergence of injuries within the critical care unit. In effect, we seek to quantify how varying parameters $T_{\max}$ and T_{fatal} (which we assume to be equal), impacts the conclusion of Part 1.

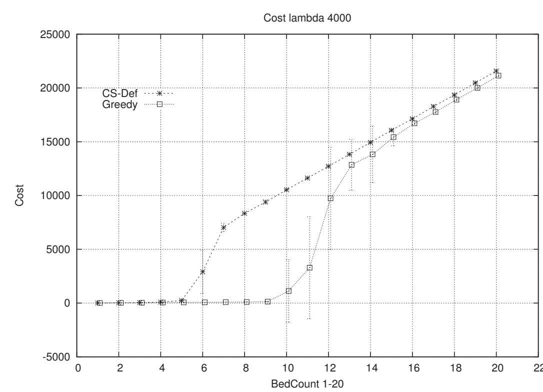
Graph (a) - (d) of Figure (6) consider alarm sequences in which the mean inter-arrival time set to 7.5 minutes, 15 minutes, 40 minutes, and 80 minutes. The Greedy algorithm incurs injuries when the bed count exceeds 32, 10, 5, 3, for each of the respective scenarios. By comparison, the Cyclic Scan consistently incurs injuries whenever the bed count exceeds 8,



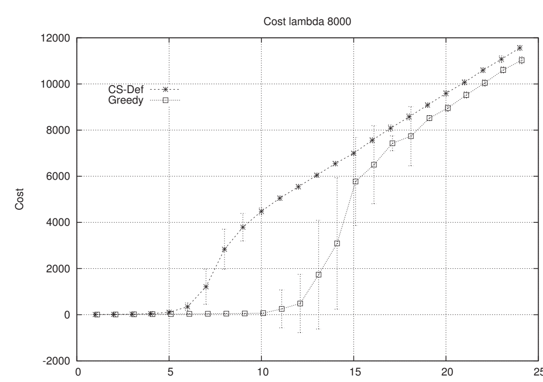
(a)



(b)



(c)



(d)

Fig. 5. Part 2: λ 7.5 min, 15 min, 40 min and 80 min.

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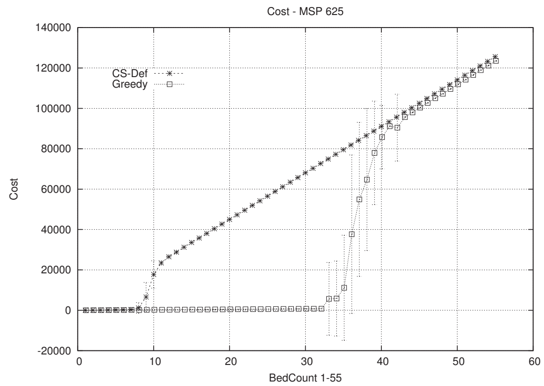
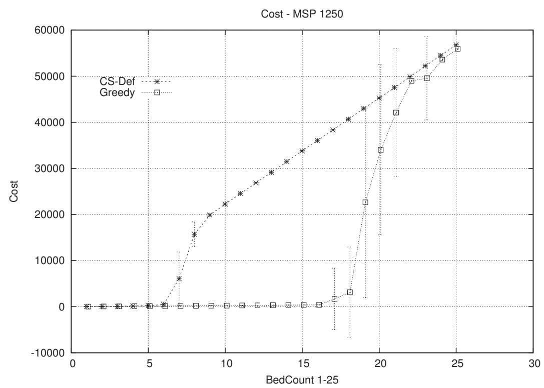


(a)



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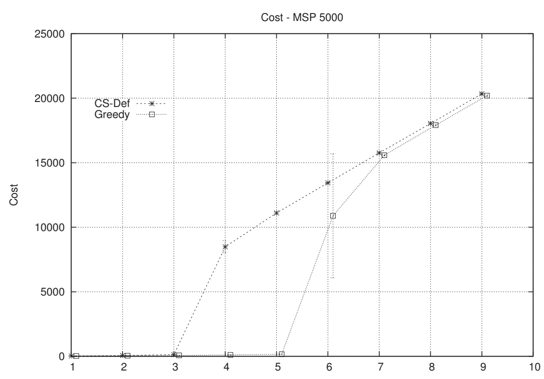

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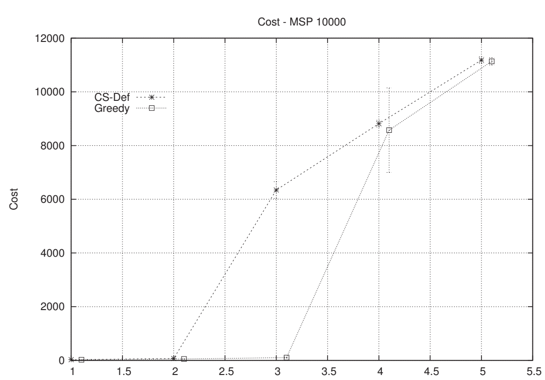

(d)

Fig. 6. Part 3: $T_{\max} = T_{fatal} = 6.25$ min, 12.5 min, 50 min and 100 min.

5, 3, 2, for each of the respective scenarios. The ratios of these values are 4, 2, 1.6, 1.5. The experiment demonstrates that using the Greedy algorithm enables us to leverage reductions in treatment/processing time towards an increased capacity to handle more patients in an injury-free manner. The conclusion is further supported by considering the upper boundaries of the phase transition where the performance of two algorithms once again coincides. This occurs at bed counts 41, 22, 7, and 3, for each of the respective scenarios. The intervals in which the Greedy algorithm outperforms Cyclic Scan is then 8-41, 5-22, 3-7, and 2-3. This indicates that the interval (in terms of bed count) for which the Greedy algorithm maintains an advantage over Cyclic Scan, increases in scenarios where treatment/processing times are lower.

V. Conclusions

In this paper, we propose a new scheduling algorithm that makes use of an integrated array of monitoring information (and alarms) provided by a vital sign data integration infrastructure. A simulation framework was developed to measure the performance of our proposed Greedy algorithm against the current defacto Cyclic Scan algorithm under which caregivers routinely operate today within CCUs. The latter is only feasible at medical institutions where a vital sign data integration infrastructure is available.

Simulation study provides clear evidence that such an infrastructure reduces risk to patients, and lowers operational costs. We showed that the cost associated with the adoption of such infrastructure are offset by the benefit of the healthcare delivery efficacy consisting of a considerable reduction to systemic risks for patients.

These conclusions are based on compelling evidence based on simulations grounded in a precise formal model: A facility that uses Greedy scheduling will make more effective use of its caregivers than the Cyclic Scan (Part 1). This advantage becomes more pronounced whenever alarm frequencies drop (Part 2), or treatment time decreases (Part 3).

In future work, we intend to extend the simulation to consider algorithms which will take into account multiple vital signs with disparate injury accumulation curves, and multiple caregivers within the facility. In addition, we plan to incorporate more realistic models of alarm sequences, generated by mining real historical data from vital sign streams.

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