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SIMULATION AND EVALUATION OF ICU MANAGEMENT POLICIES

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ABSTRACT

The intensive care unit is one of the bottleneck resources in the hospital, due to the fact that the demand grows much faster than the capacity. The pressure on intensive care unit managers to use resources efficiently and effectively increases. Therefore, optimal management policies are required. In this work, we evaluate eleven commonly referred policies from the literature and compare their performance by nine key performance indicators in different perspectives, such as utilization, patient health status, and profit of the hospital. The 30 most frequently occurring patient paths, based on the practical dataset of more than 75,000 patient records from a German teaching hospital, are simulated. According to our results, increasing the capacity and treating the patients in well-equipped intermediate care units performed better in the medical perspective, while the early discharge policy performs well when the capacity is limited. Furthermore, the COVID-19 scenario could be integrated into the model.

1 INTRODUCTION

Intensive care unit (ICU) is one of the most crucial resources in hospital (Bai et al. 2018). It provides constant, close monitoring to the most critical patients by specially trained staff. ICU is different from other regular hospital wards in its above average staff-to-patient ratio and prior access to advanced medical resources and equipment. The ICU is considered among the most expensive medical resources in a hospital, as it generally consumes more than 13% of a hospital's total budget (Halpern and Pastores 2010). Additionally, as the aging population is growing rapidly, the demand of ICUs grew 62% faster than the number of available beds (Howell 2011). Moreover, ICUs play the bottleneck role in a hospital-wide patient flow (Litvak et al. 2008). Once the admission of a patient-in-need is restricted by capacity, correlated up- and downstream departments in the hospital will be influenced. Therefore, an efficient capacity management is necessary.

From the economic perspective, a high utilization of the ICU is one of the goals of hospital managers in terms of capacity management. On the other hand, the increasing utilization level leads to a decreasing service quality, to not only the ICU, but also the up- and downstream departments, such as over-beds (a non-staffed bed which is forcefully brought into operation (Litvak et al. 2008)), surgery cancellation or postponement, and demand-driven discharge (premature diverting inpatients out). One challenge to the ICU management is to find an appropriate balance between maintaining high utilization level of ICU beds and providing sound treatment quality as well as an appropriate service level. Furthermore, optimizing the total patient flow adds more difficulty.

Plenty of different ICU capacity management policies are discussed (Bai et al. 2018). Early discharging current patients in the ICU to the downstream departments in order to create space for the new patients (Chan et al. 2012; Dobson et al. 2010), denying the admission requests from the upstream departments (Li et al. 2019), and rescheduling the operations (Chow et al. 2011; Price et al. 2011) are the most frequently discussed policies to manage the ICU capacity. They are supposed to work well, based on their own key performance indicators (KPIs). However, what are the performances of these policies in the same scenario? Which ones are better when considering different KPIs? How are the upstream and downstream departments influenced by the ICU management policies? Currently, we haven't found a paper to answer these questions.

Therefore, the patient flow centered by the ICU is simulated to evaluate the performances of eleven different management policies. Nine KPIs are compared, covering different aspects, as well as different departments. The simulation model is based on a dataset with 75,934 patient records in the year 2015 from one of the largest teaching hospital in south Germany. The dataset covers 1,215 beds in general wards, 45 emergency beds, 20 IMC beds, and 30 ICU beds. The 30 most commonly occurring patient paths are integrated from the dataset in the simulation model. The results clearly indicate that the introduction of control policies has a positive impact on patient status, length of stay (LOS), and cost when comparing to the baseline case (first-come-first-served policy, FCFS). The parameters of our model can be flexibly adjusted to the parameters from different hospitals. Therefore, it can work as managerial reference to practice. The managers can choose proper policies according to their goals (specific KPIs).

The remainder of the paper is organized as follows: After the literature review, our contribution is summarized in Section 2. In Section 3, the detailed descriptions of the eleven management policies and the definitions of the KPIs are presented. The simulation model is discussed in Section 4. Section 5 follows with an analysis of the results. Finally, in Section 6, the work is concluded and the potential future research directions are highlighted.

2 RELATED LITERATURE

Simulation is an extremely suitable method for hospital planning, in particular due to the complexity of the real-world situation (McHardy et al. 2004). There are many papers applying simulation for the optimization of different departments in the healthcare system, for example, operating room scheduling (Adan et al. 2011; Persson and Persson 2010; VanBerkel and Blake 2007), emergency department scheduling (Mielczarek and Uziałko-Mydlikowska 2012), and of course ICU planning (as described in the following).

There are a lot of scientific papers with the intention of finding better solutions for ICU capacity planning (Bai et al. 2018). Most of the ICU simulation papers try to figure out the ideal number of beds in ICUs (Barado et al. 2012; Cahill and Render 1999; Costa et al. 2003; Lamiell 1995; Ridge et al. 1998; Troy and Rosenberg 2009; Zilm and Hollis 1983). Another stream is applying simulation for staff scheduling (Duraiswamy et al. 1981; Hashimoto et al. 1987). In addition to patient care and nurse monitoring, Villa et al. (2009) also examined the LOS of patients. All these objects can be improved through better ward designing, capacity planning, and management of patient flows. Furthermore, there are many papers simulating the operating theatres scheduling policies (Akkerman and Knip 2004; Astaraky and Patrick 2015; Chow et al. 2011; Marmor et al. 2011; Marmor et al. 2013; Troy and Rosenberg 2009; Yang et al. 2013). In these papers, ICUs are not the primary target, but are nevertheless considered in the optimization models or simulations.

Looking at the papers, it is obvious that a gap in comparing different control policies for admission to ICUs exists, especially when considering the complete patient flow centered around the ICU. Mahmoudian-Dehkordi and Sadat (2017) present a detailed work on the effects of management guidelines for ICUs. They simulated a disaster with extraordinary emergency patient arrivals. In their paper, they describe eleven different control policies, six of which are ultimately used in the simulation. A simulation with a simultaneous implementation of all six control guidelines was carried out. Kim et al. (2015) also examine various admission guidelines in their simulation study. Different policies are always applied in the appropriate cases based on observed measurements. They are able to achieve better results than the clinic's own regulation. However, the simulation model is very limited with the admission and discharge rates of patients. Both are constants in the study. This limits the evaluation of the influencing factors and reduces the meaningfulness of the effects of the control guidelines in different scenarios.

Our work extends the existing research by evaluating different ICU control policies not only inside the ICU, but in the complete patient flow (including emergency department (ED), intermediate care unit (IMC), ward, and operating theatre (OT)). Rather than focusing on one specific type of patients like Mahmoudian-Dehkordi and Sadat (2017) did, we simulate 30 different patient paths covering almost all types of patients. Furthermore, medical and monetary KPIs are used to evaluate the performance. On top of that, our model is flexible to adjust the parameters. Therefore, it can be easily applied in different hospital settings.

3 ICU CONTROL POLICIES AND KPIS

Patient flows connect the ICU with other departments inside and outside the hospital. All the decision policies implemented in the ICU also influence the up- and downstream departments (Bai et al. 2018). Vice versa, control policies applied in the up- and downstream departments can also help to optimize the utilization and service quality in the ICU. For example, IMC is logistically located between the ICU and the general ward. It can work as a physically independent unit or as a dedicated section, incorporated within the ICU (Plate et al. 2017). Therefore, increasing the capacity in the IMC is an option to relieve the stress from the ICU. Additionally, rescheduling surgeries in the OT is another frequently applied method.

3.1 Control Policies

In order to figure out the best performance using simulation, various control policies are evaluated. When the ICU is fully occupied, the patients will be arranged according to the policies. Any of the policies result in different consequences, such as the patient's health condition, the occupancy at other departments, etc. Most hospitals have no regulated process when it comes to making decisions on patient transfers, since it usually depends on the situation, such as the current utilization of the ICU. Our cooperating hospital has a list of patients who are less critical. They can be early discharged when it is necessary. Sometimes when the ICU is full, the new patients are immediately rejected and transferred to the next station in their paths (after the ICU). We model the FCFS policy as the baseline case. The control policies evaluated in the simulation and the respective implementation procedures are described below.

- P1. **Increasing ICU capacity**: Increasing the capacity is supposed to be a simple and intuitive policy to overcome the capacity shortage. For instance, in the current COVID-19 crises the ICU capacity in Germany has been doubled. Many researchers suggest that increasing the capacity is necessary (Daly et al. 2001; Lyons et al. 2000). However, higher fixed costs for additional beds and instruments will incur and more staff will be needed. In the long run, inefficiency might be another problem (Kim et al. 2015). De Bruin et al. (2005), however, show that increasing the capacity of expensive beds in ICUs is ultimately more cost-effective than investing in cheaper beds at general wards.
- P2. **Early discharging the patient with the lowest remaining LOS to the next station in the path**: If a patient urgently needs to be admitted into the ICU due to his/her critical condition, another patient in a more stable condition can be discharged from the ICU and transferred to the next department. However, an early discharge is proven to cause a higher readmission rate and to increase mortality (Daly et al. 2001; Dobson et al. 2011; Marmor et al. 2011). As customary applied in hospitals, the patient with the expected lowest remaining LOS is transferred. This has the advantage that the patient is already in a good condition compared to the other patients in the ICU and therefore the negative consequences are minimized.
- P3. **Early discharging the patient with the highest remaining LOS to the next station in the path:** Complementary to the previously described policy P2, the patient with the highest remaining LOS is discharged prematurely. This policy is inspired by a popular rule in manufacturing, which gives the shortest processing time (i.e., short LOS) highest priority (Yang et al. 2013). It reduces occupancy in the long run, as the other patients remaining in the ICU will be regularly discharged soon. However, the fact that the patient would be expected to have a long LOS ahead of him/her

suggests that his/her state of health is not even stable at all. This control policy can have serious negative consequences for the early discharged patients.

P4. **Early discharging the patient with the highest LOS in the ICU to the next station in the path**: This control policy could compensate for disadvantages of the policy P3 where the remaining LOS has been considered. The patient benefits from the fact that he/she has already been treated the longest time in the ICU.

P5. **Early discharging the patient with the lowest remaining LOS to IMC**: In this policy, if there is no capacity for a new patient left in the ICU, the patient with lowest expected remaining LOS is discharged early to the IMC, regardless of the next station his/her patient path.

P6. **Early discharging the patient with the lowest remaining LOS to home**: In the special case that all departments are completely busy, a relatively stable patient can be discharged straight back home. A lack of monitoring of the health state can lead to a high possibility of readmission, which is not only undesired to the health of the patient, but also inefficient to the system in a long run.

P7. **Boarding in IMC or ward**: If the ICU is fully utilized, boarding the new patient in the IMC or the general wards is another option. The patient waits in IMC or ward until a bed in the ICU becomes available. However, depending on the urgency and condition of the patient, this can lead to negative health consequences. This control policy might also lead to queuing in the IMC and general wards. Because the ICU patients are normally not allowed to wait for a long time for the ICU bed, after more than two periods (6 hours per period), he/she will be transferred to another hospital with free capacities.

P8. **Increasing IMC capacity**: Similar to the first policy P1, the number of beds in the IMCs can also be increased. In this policy the fixed costs, such as personnel and equipment costs, are not as high as in the ICU. Likewise, this rule is only effective in combination with other control policies that involve IMC and general wards.

P9. **Rescheduling of planned surgeries**: If a patient's surgery is planned to be performed on a certain date, a transfer to the ICU afterwards is also planned in advance. If the utilization level is already high in the ICU, this surgery can be postponed to keep a certain number of buffer beds free for emergencies. Kolker (2009) find a reduction in patient deflections from 1.5 percent to 10 percent when up to four operations are postponed on a single day.

P10. **Transferring to IMC**: Since IMCs are roughly classified between ICUs and general wards in terms of care and costs, moving the new patient to the IMC is supposed to be an acceptable emergency solution in case of a full ICU. In this policy, the patient will receive the entire treatment in the IMC, without the intent of going back to ICU later on.

P11. **Transferring to another hospital**: Normally transferring the potential ICU patient is not desired (Litvak et al. 2008). However, when the health status permits a transfer, it might be a better option than waiting for an available ICU bed.

In order to generalize our model and make it more adjustable to different scenarios, some other more complex policies, which are based on the personalized condition of each patient, are not taken into account. For instance, the policy might consider the disease or the required treatment (e.g., cancer, cardiovascular disease, obstetrics etc.).

3.2 Performance Indicators

Providing care is very complex and cannot be evaluated by a single indicator (see Table **1**). The utilization level, the service quality, as well as the economic perspectives are all needed to consider. Therefore, several KPIs are measured in our work. First of all, the utilization rates of the individual departments, which are the most frequently applied metric in practice, are monitored. To prevent hospital employees from being overstaffed or understaffed, patients from waiting, and the beds from idling, the utilization rates should be in an appropriate range. Although we agree that the LOS in the hospital itself has no direct correlation with patient satisfaction (Borghans et al. 2012), a shorter average LOS goes hand in hand with a better efficiency of the respective hospital (Herr 2008). Likewise, a longer LOS is associated with a greater likelihood of complications (Cohen et al. 2009). Therefore, in our model, the average LOSs of the entire hospital stay and of the ICU stay are recorded. For the next indicators we look at patients that are discharged from or even rejected right before the ICU. We want to measure how many patients are influenced by the policies. Therefore, we define two KPIs. The first KPI is the number of patients rejected by the ICU. The number of early discharges is defined as the second KPI. What is naturally a top priority in the healthcare system and needed to be accurately recorded and evaluated is the health condition of the patient. The health state is quantified on a scale from zero to one hundred. It is similar to the Quality-Adjusted Life Year (QALY) approach, which represents values between zero and one (Drummond and McGuire 2011). Proper treatments increase the value of health state, and meanwhile delayed treatments lead to lower value. If the score is less than 5 when the patient leaves the hospital, he/she is declared to be dead. The increased number of deaths, which are caused by the management policies, is considered as another evaluation criterion. This number is independent of the mortality that occurs in the hospital anyway (average 2.65% of all discharges). A last key aspect to be evaluated is profit. The hospital can lose revenue if patients are rejected from the ICU or have to leave the hospital to early. In this monetary perspective, profit and revenue loss are considered as separated indicators. However, neither profit nor revenue is known in our practical dataset. By means of appropriate literature, we have obtained the parameters and summarize them in Table **2** (Bai et al. 2018; Bertolini et al. 2005; Correia and Waitzberg 2003; Encinosa and Bernard 2005; Kahn et al. 2008; Lone and Walsh 2011; Ryan et al. 2019; Sznajder et al. 2001; Williams 1996).

Table 1: Summary of the KPIs.

ID	KPIs	ID	KPIs	ID	KPIs
K1	Mean LOS – system	K4	Rejections	K7	Increased deaths
K2	Mean LOS – ICU	K5	Early discharges	K8	Profit
K3	Mean utilization – ICU	K6	Health	K9	Revenue loss

Table 2: Estimated profit and revenue loss.

	Profit (/day)		Revenue loss (Euro)
ICU stay	75	Reject normal patient	6,000
ED stay	15	Reject emergency patient	4,950
IMC stay	38	Early discharge	3,600
Ward stay	13		

4 SIMULATION MODEL BY ANYLOGIC

A discrete event simulation model is developed on the platform AnyLogic, which is a multi-method programming and simulation environment. The details of the input data, simulation model, and case study are discussed in this section. In order to keep the simulation as realistic as possible, but at the same time as generic as possible, distributions of arrival times and LOSs in different units are fitted by RStudio (see Table **3**). All admissions follow Poisson distributions and the most of the LOSs can be modelled by Lognormal distributions.

Table 3: Summary of the parameters.

Parameter	Admission (per hour)				LOS (day)			
	Weekday daytime	Weekday night	Weekend daytime	Weekend night	ICU	Ward	ED	IMC
Distribution	Poisson	Poisson	Poisson	Poisson	Logn	Weibull	Logn	Logn
Average	15.78	4.41	6.36	4.03	3.23	0.82	1.50	3.74

In the dataset, each patient has a personal ID during his/her stay. The detailed information of each event (time stamps, departments transferred from and to) in the hospital stay are recorded. Based on the data, the paths for each patient are created and analyzed. In order to achieve the most precise and meaningful results of various management policies, the structure of the simulation model is kept as realistic as possible, but at the same time as minimalistic as possible. To this end, not all of the patient paths from the dataset are taken into account. The 30 most commonly occurring paths (Figure 1), which cover more than 95% of all patients, are simulated in our model.

1	47.62%	Admin	Ward	Discharge					
2	30.89%	Admin	ED	Ward	Discharge				
3	9.95%	Admin	ED	Discharge					
4	2.65%	Admin	ED	ICU	Ward	Discharge			
5	1.93%	Admin	Ward	ICU	Ward	Discharge			
6	1.73%	Admin	ED	Ward	ICU	Ward	Discharge		
7	0.94%	Admin	ED	ICU	Discharge				
8	0.46%	Admin	Ward	ICU	OT	Ward	Discharge		
9	0.36%	Admin	ED	ICU	OT	Ward	Discharge		
10	0.27%	Admin	ICU	Discharge					
11	0.25%	Admin	ICU	Ward	Discharge				
12	0.23%	Admin	Ward	OT	Ward	Discharge			
13	0.23%	Admin	ED	Ward	ED	Ward	Discharge		
14	0.21%	Admin	ED	Ward	ICU	Discharge			
15	0.19%	Admin	ED	OT	Ward	Discharge			
16	0.16%	Admin	ED	ICU	Ward	ICU	Ward	Discharge	
17	0.14%	Admin	ED	Ward	ICU	Ward	ICU	Ward	Discharge
18	0.14%	Admin	Ward	ED	Ward	Discharge			
19	0.12%	Admin	Ward	ICU	Discharge				
20	0.11%	Admin	ED	Ward	ICU	OT	Ward	Discharge	
21	0.11%	Admin	Ward	ICU	Ward	ICU	Ward	Discharge	
22	0.08%	Admin	ED	Ward	OT	Ward	Discharge		
23	0.07%	Admin	ED	ICU	OT	Discharge			
24	0.06%	Admin	ICU	OT	Ward	Discharge			
25	0.04%	Admin	ED	Ward	ICU	Ward	ICU	Discharge	
26	0.04%	Admin	OT	ICU	OT	Ward	Discharge		
27	0.03%	Admin	OT	ICU	Ward	Discharge			
28	0.03%	Admin	OT	Discharge					
29	0.03%	Admin	ED	ICU	Ward	ICU	Discharge		
30	0.02%	Admin	Ward	ICU	Ward	ICU	OT	Ward	Discharge

Figure 1: The 30 most frequently occurring patient paths.

To model the patient flows, a recursive network (see Figure **2**) is set up that uses the patient paths in Figure 1. The patient (agent) enters the system with a specified patient type, which is either a normal or an emergency patient. Then based on the empirical probabilities the admission station is determined. The LOS in each department depends on distributions given in Table 3. When a patient arrives to a fully occupied ICU, different control guidelines, i.e., the eleven management policies P1 to P11, are applied. When the other units are full, the patient waits for a certain period of time and is then transferred to a downstream department (e.g., from IMC to ward). Finally, the patient leaves the hospital.

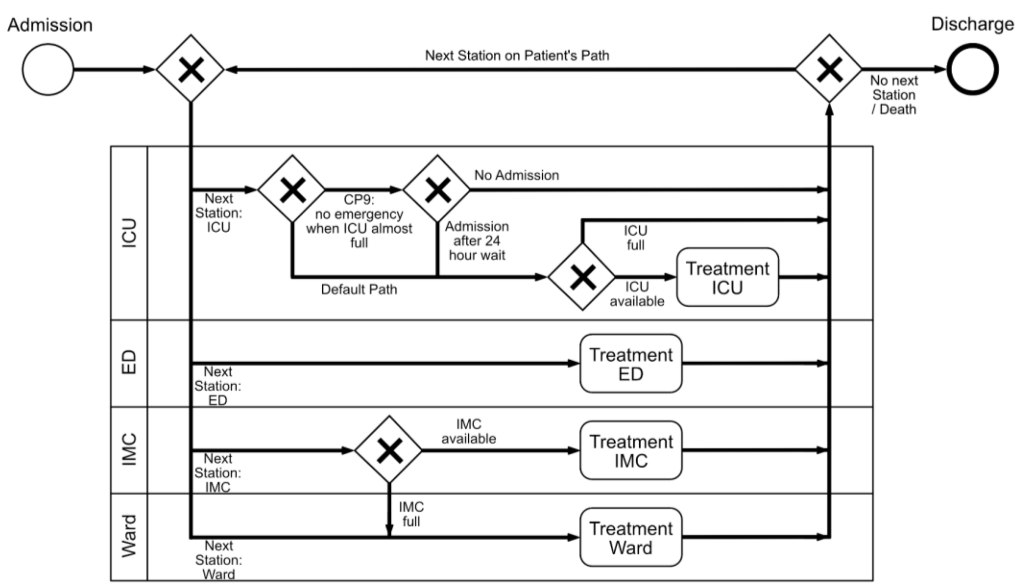

Figure 2: The flow chart of the simulation model.

5 RESULT DISCUSSION

Eleven different management policies P1 to P11 are compared and parameter variations are investigated. The FCFS policy, which is used widely in practice, is marked as policy zero (P0). It is used as the baseline case to evaluate the relative performance of the other policies. The simulation period length is set to be 6 months, and 100 replications are implemented for each run.

5.1 Results from the Default Settings

In this part, the parameters of patient arrivals and LOSs are kept the same as summarized in Table **3**. Except P1 (increasing ICU capacity) and P8 (increasing IMC capacity), the capacities in the other policies are constants as well (1,215 beds in general wards, 45 emergency beds, 20 IMC beds, and 30 ICU beds). The ICU and IMC capacities are increased 20% in P1 (36 ICU beds) and P8 (24 IMC beds). The dashboard in Figure 3 shows box plots for each KPI and control policy. The performance indicators of the polices are recorded from the simulation and summarized in each histogram. The best management policy of each KPI can be found in the upper right corner. For instance, the shortest system LOS (K1) results from applying P11, and the highest profit is obtained by P10. We assume when the utilization level is lower than 0.9, then the higher the better. The table below shows how often a policy is evaluated as the best one. The same information is given in the frequency chart below for a quick evaluation.

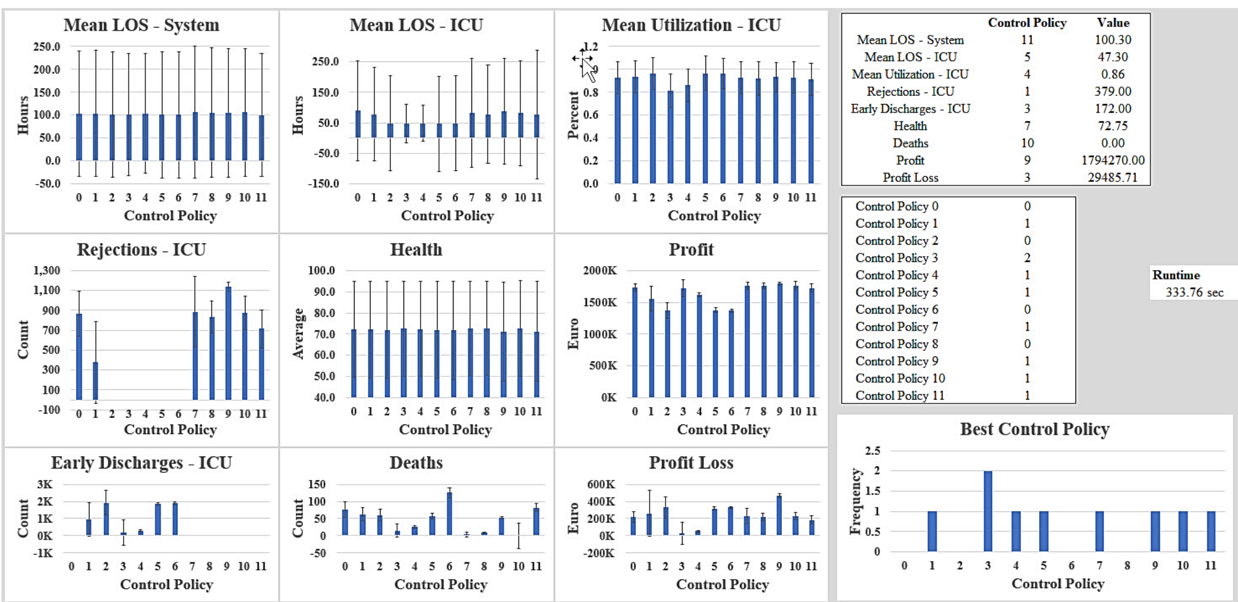

Figure 3: Dashboard of the simulation results.

From the histograms in Figure **3**, we can see that no policy is dominant in all KPIs. From a service quality perspective, the two most important criteria to be evaluated are the average patient health condition (K6) and the increased number of deaths caused (K7). When looking at the increased number of deaths (K7), transferring the patients to IMC (policy P10) is optimal. If the ICU is fully utilized, no additional deaths incur. In this case, instead of waiting and then eventually being rejected, or early discharging other patients, the patients who arrive at a peak time are treated directly to the IMC, which can provide lower level of care. Similarly, boarding and queuing the patients in the IMC (P7 and P8) lead to the best performance in average patient health condition (K6). On the contrary, early discharging the patient with lowest remaining LOS to home (P6) and transferring patients to other hospitals (P11) put the patients in higher risk and result in extra deaths, even more than the baseline case (P0). Rescheduling of planned surgeries (P9) is evaluated to be the worst by looking at the health condition (K6). Let the patients waiting longer for a surgery might not cause additional death, but the health condition of these delayed patients will be deteriorated .

Besides the above discussed criteria, the number of patients influenced by the policies (e.g., K4 and K5) is important. For instance, early discharging the patient with highest remaining LOS (P3) can release more capacity in the long run, and therefore prevents more patients from early discharge (K5). Furthermore, early discharging the patient with the highest LOS (P4), which is widely implemented in practice, results in relative lower number of early discharging as well. Increasing ICU capacity (P1) leads to the lowest rejections (K4). This is naturally due to the increased number of beds in the ICU, which ultimately enables to accept more patients. Three of the remaining early discharge policies (P2, P5, and P6) influenced more than 1,800 patients in our case, which is around 200% of the baseline case (P0). In the monetary perspective, rescheduling surgeries (P9) results in the highest profit (K8) without a large advantage compared to P7, P8 and P10. Early discharging the patient with highest remaining LOS (P3) leads to the lowest revenue loss (K9), which is consistent with K5. As a general trend, profit (K8) is positively correlated with the LOS in the system (K1), while revenue loss is correlated with the number of influenced patients (K4 and K5).

In general, the results indicate that the introduction of management policies has a positive impact on patient status, LOS and/or costs. Since the assessment of the effects of control policies is carried out by comparing simulation results under the same general conditions, and thus comparability is given, valid decisions can be made. Finally, the managers can also make the decisions based on their own priorities and weighting of the KPIs .

5.2 Performance under Different Parameters

In order to figure out the influence of parameter variations on the results, different ICU and IMC capacities, as well as different combinations of profit and revenue loss for each management policy are simulated in this section.

5.2.1 Policy Performances under Different Capacities

We model the ICU capacity with 80%, 100%, and 120% (thus 24, 30 and 36 beds) and the IMC capacity with 100% and 120% (20 and 24 beds). In most of the cases, when increasing capacities, the total LOS in the hospital and in the ICU both increases. Only by boarding in the IMC or the ward (P7), the total LOS in the hospital decreases, because the patient recovers sooner. By P9, P10, and P11, the patients are delayed or transferred, so that there are sometimes free capacities in the ICU which cause the average LOS in the ICU to decrease. The LOS in the ward changes slightly with the increasing capacities. At the same time, the utilization levels of the ICU and IMC decrease. Having more capacity is beneficial to the service quality and the monetary KPIs. For instance, if the capacities in both ICU and IMC increase, by early discharging the patient with the highest remaining LOS (P3), the total increased deaths can be reduced by 25%, from 96 to 72, meanwhile, the revenue loss can be reduced to 0 from 0.3 million (M).

Consequently, different policies are preferable under different scenarios (Figure **4**). In general, P3 and P10 perform good in almost all the cases we simulated. Specifically, if the manager focuses on the medical outcomes, transferring the patients to the IMC (P10) is a good choice to implement. Similarly, in case of ICU shortages increasing the capacity in the IMC can improve the performance. Additionally, the differences between increasing IMC beds and increasing ICU beds are not significant, especially when comparing to the increased costs. Therefore, the importance of the IMC should not be underestimated. Besides, in the ICU capacity shortage (decreasing the capacity) scenario, early discharging the patient with the highest LOS (P4) is worth to be considered. When the capacities in both ICU and IMC are increased, then early discharging the patient with the highest remaining LOS (P3) should be preferred. In particular, when the capacity shortages are small, most of the patients can receive proper treatment. Please remember that this policy might lead to severe negative consequences to the few early discharged patients.

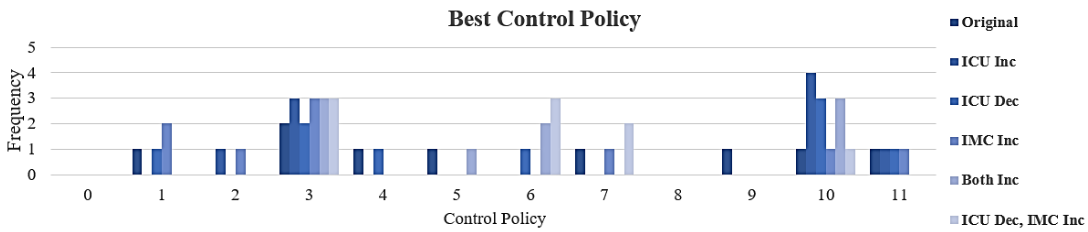

Figure 4: Frequency of best policy under different capacity assumptions for ICU and IMC.

5.2.2 Policy Performances under Different Monetary Settings

According to section 3.2, four parameters of profit (the profits in ICU, ED, IMC, and wards) and three parameters of revenue loss (the cost to reject an normal case, to reject an emergency case, and to early discharge a patient) are used in the monetary perspective. When defining these parameters, we refer to several published papers. Therefore, it's practical to figure out how these parameters influence the performance of the different policies. As a reminder, if parameter variations are implemented for profit (K8) and revenue loss (K9), the best policies under the other KPIs (K1 to K7) are not influenced. In the variation of both K8 and K9, each parameter has two possible values, which are the original one (factor 1.0) and 150% (factor 1.5) of the original value. All possible combinations ($2^4 = 16$ combinations for K8 and $2^3 = 8$ combinations for K9) are evaluated. Considering the parameter variation for profits, the policies P1, P3, P7, and P10 are selected to be the best performing ones, i.e., the other policies are never chosen (see Table 4). Surprisingly, when increasing the profits of ICU and wards together, the FCFS policy (P0) performs the best. However, P0 is never selected by the other KPIs in any other setting.

Table 4: Results of policy performance under different parameters of profit.

Profit settings				Best	Profit settings				Best
ICU	ED	IMC	Ward	Policy	ICU	ED	IMC	Ward	Policy
1	1	1	1	P10	1.5	1	1	1	P10
1	1	1	1.5	P3	1.5	1	1	1.5	P0
1	1	1.5	1	P7	1.5	1	1.5	1	P1
1	1	1.5	1.5	P1	1.5	1	1.5	1.5	P1
1	1.5	1	1	P10	1.5	1.5	1	1	P10
1	1.5	1	1.5	P3	1.5	1.5	1	1.5	P3
1	1.5	1.5	1	P7	1.5	1.5	1.5	1	P3
1	1.5	1.5	1.5	P1	1.5	1.5	1.5	1.5	P3

When comparing different combinations of parameter variations for revenue loss, P3 performs always the best. The total revenue loss depends on the cost for each rejected or early discharged patient and the total number of patients affected. Because of discharging the most serve patients with longest remaining LOS (P3), much more capacities are released. Therefore, the total number of affected patients is less than 50% compared to the other policies. As a result, we see low sensitivity to the parameters' settings. Of course, when the difference between the parameters are much larger, the best policy might change.

6 CONCLUSION

Health care is facing great challenges to make processes more efficient and meanwhile provide better service to patients. The management of the ICU, which is one of the most critical departments in terms of patient status and patient flow, also tries to provide better service and reduce the mortality rate. In particular during COVID-19, the effective and efficient management is of utmost importance. Our simulation model allows a comprehensive evaluation of eleven different management policies for controlling ICU admissions when facing capacity shortages.

In comparison to the baseline case running on a FCFS rule, we show that any management policy is superior regardless of the evaluation criteria. Increasing the capacities of the ICU is obviously beneficial to all the patients but depend on structural circumstances. Generally speaking, it makes sense to discharge patients early when the ICU is fully loaded, i.e., all KPIs indicate an advantage. This ensures that most of the patients receive the appropriate level of care in the ICU. It remains to be decided whether the patient with the highest remaining, the highest elapsed, or the lowest remaining length of stay should be discharged. The simulation results with the data from the University Hospital Augsburg suggest the early discharge of patients with highest remaining LOS, especially in the peak time, when considering the overall impact instead of individual patient's consequences.

Currently, the COVID-19 is spreading all over the world. This disease is severe because of the high infection rate and the speedy spreading. Implementing efficient policies to manage ICU capacities is critical. The COVID-19 scenario can also be simulated by our model. With roughly approximated parameters, it can be shown that at the beginning of pandemic, postponing the scheduled surgery is an option. In the long run, increasing the ICU as well as IMC capacities should be definitely implemented. In extreme cases, early discharging the patients having the lowest survival probability is cruel but efficient.

With the attempt to model the problem as realistic as possible, we rely on the 30 most frequently occurring patient paths based on real data. However, there is still room for improvements. The type of disease, the type of treatment and its impact on the patient are possible variables for a future consideration. Furthermore, the readmission of the patients is not considered in our model which might be another direction to investigate. Additionally, the performance of each single policy is evaluated one by one. The combination of different management policies also offers the potential to make hospital processes even more effective. Last but not the least, to generalize the findings of our model, an application to other hospital settings might be necessary.

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