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An analytical model based on simulation aiming to improve patient flow in a hospital surgical suite

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Abstract

Surgical suits allocate a large amount of expenses to hospitals; on the other hand, they constitute a huge part of hospital revenues. Patient flow optimization in a surgical suite by omitting or reducing bottlenecks which cause loss of time is one of the key solutions in minimizing the patients' length of stay[1] (LOS) in the system, lowering the expenses, increasing efficiency, and also enhancing patients' satisfaction. In this paper, an analytical model based on simulation aiming at patient flow optimization in the surgical suite has been proposed. To achieve such a goal, first, modeling of patients' workflow was created by using discrete-event simulation. Afterward, improvement scenarios were applied in the simulated model of surgical suites. Among defined scenarios, the combination scenario consisting of the omission of the waiting time between the patients' entrance to the surgical suite and beginning of the admission procedure, being on time for the first operation, and adding a resource to the resources of the transportation and recovery room, was chosen as the best scenario. The results of the simulation indicate that performing this scenario can decrease patients' LOS in such a system to 22.15%.

Keywords: Simulation, discrete-event modeling, patient flow, hospital, surgical suite

1-Introduction

At present, optimizing health care centers encounter problems more than any other time (VanBerkel and Blake, 2007). All human beings have been part of this system from birth to death, and healthcare is considered as one of the influential factors affecting the economic growth rate of countries (Najmuddin et al., 2010). The systems in the healthcare area have many complexities at all levels (Hamrock et al., 2013). A complex system is a set of factors with indefinite relationships which its functionality is not generally predictable (Santibanez et al., 2009).

Hospitals are considered one of the most important sections of healthcare area, and they allocate more than 36% of the state expenses to themselves (Pham and Klinkert, 2008). Likewise, the surgical suite as the most important hospital department comprised of operating and recovery rooms, owns 40% share of total hospital expenses (Ozcan et al., 2017). Also, around 60 to 70 percent of the hospital admission is for surgeries (Hans and Nieberg, 2007). On the other hand, surgical suites are closely related to other hospital departments and improving their efficiency will have a significant effect on increasing the total efficiency of the hospitals (Ozcan et al., 2017). Thus, the importance of surgical suites and also the necessity of regarding patients as the center of attention in healthcare centers have made optimization of patient flow in the surgical suite a necessary work to do (Ozcan et

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al., 2017). Patient flow optimization is considered a key solution for increasing efficiency, reducing operating costs, and enhancing the quality of care in surgical suits (Georgievskiy and Georgievskaya, 2018).

Patient flow is attributed to the sequence of processes ahead of a patient, from admission to discharge from the system (Ballard and Kuhl, 2006). In previous studies, for modeling patient flow in surgical suits, two methods of queue theory and simulation of processes models have been utilized (Kolker, 2009). Regarding queue theory point of view, a healthcare unit is considered as a network of queues and different types of service providers (Kolker, 2009). In this system, those customers are considered who arrive at the system for receiving of a specific service (Salleh et al., 2017). If the service is unavailable, they have to wait and then, leave the system after receiving the service. In the queuing theory, it is assumed that the arrival time of customers complies with Poisson distribution and service time conforms to the exponential distribution and in some cases, conforms to the Uniform or Erlang distribution (Salleh et al., 2017). Although these assumptions are rarely valid in processes of the healthcare area, even with regard to limited applications of Poisson process and queuing theory (due to nonconformity to the real world situation), they are extensively used in different papers (McManus et al., 2004, McManus et al., 2003, Harrison et al., 2005, Green et al., 1991, Green et al., 2001, Green et al., 2006).

Utilizing queuing theory in the patient flow modeling has two main challenges:

- If the patient flow arrival rate is not random, the queuing theory cannot be used. (E.g. Since patients' arrival time for elective surgeries is not random, proposed formulae in queuing models are not satisfied in these situations) (Oh et al., 2016).
- The workload in hospitals is high during morning and evening hours, and is low at night hours. This situation indicates high changeability in workload. As a result, Poisson distribution is not a suitable distribution for approximating patients' arrival pattern (Green et al., 2006).

In contrast to the inadequacies of the queuing theory, simulation models are preferred for patient flow modeling (VanBerkel and Blake, 2007). Simulation models are a kind of auxiliary tool for decision making which enhances our conception of the problem and different solutions for it by considering the dynamism of the healthcare systems (Taylor and Kuljis, 1998). Moreover, simulation is considered one of the most important tools for patient flow optimization (Norouzzadeh et al., 2015). In recent years, the application of this tool in the healthcare department has increasingly extended (Bard et al., 2016, Bal et al., 2017, Pan et al., 2015). The reason for this extensive application is, on the one hand, success in studies carried out by using simulation for recognizing and solving the healthcare problems, and on the other hand, significant advancements in the simulation software (Swisher et al., 1997, Vissers, 1998). In spite of this, utilizing the simulation models in the healthcare area, as well as, other areas such as industrial, military, and support has not extended enough, and thus it seems to be a suitable areas for study in this field (Barnes et al., 1997).

1-1-Discrete-event simulation

A simulation model is a tool for modeling complicated systems which analyses their behavior during the time and under specific conditions (Banks, 2001). By replicating logic and unsystematic nature of the processes, simulation is useful for comparison and evaluation of the suggested changes in the studied systems(Banks, 2001). By creating and validating a simulation model, it can be used for probing different questions such as "what-if" about a real system. We can first simulate practical changes in the system so that the effect of every one of them on the functionality of the system is predicted (Banks, 2001).

Simulation models have different types. A simulation model can be stochastic or deterministic, dynamic or static, and discrete or continuous. Time has no role in static models, but it plays a significant role in dynamic models. In continuous models, the state of the system continuously changes during the time. But in discrete models, a change in the state of the system is only possible in discrete points of time. These models having no random admission are deterministic. In stochastic models, at least some of the admission rates will be random (Banks, 2001).

Patient flow in the surgical suite has a dynamic, discrete, and stochastic state. Simulation models with these features are called discrete-event simulation in which the state of the system functionality is displayed according to the time sequence of events (Jacobson et al., 2006). Every event occurs at a time instance and changes the state of the system. In the surgical suite, events can be either patient's admission to the system or their discharge from the system. The state of the system can be determined based on busy or free conditions (as a service provider), and also the length of queues. We will also have a set of random variables like the time of providing the services and the time between admissions of two consequent patients (Sobolev et al., 2011). Researchers have determined the position of discrete-event simulation according to Fig 1(Sobolev et al., 2011).

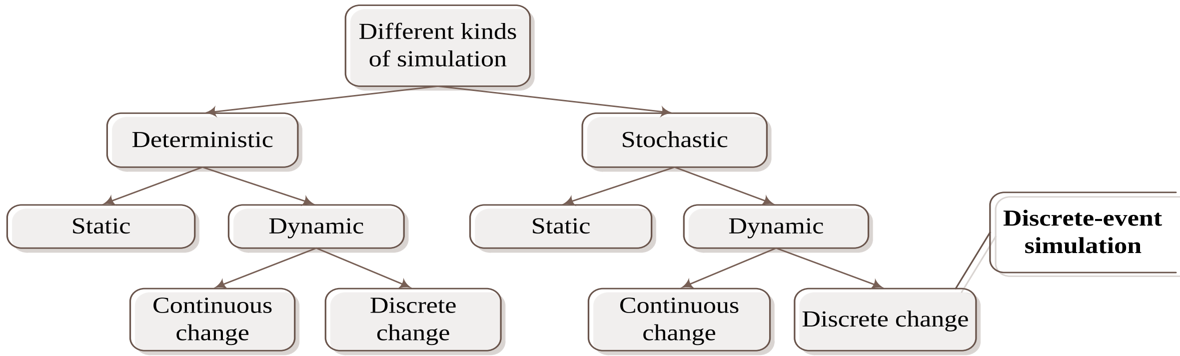

Fig 1. Different models of a system and the position and discrete-event simulation

Discrete-event simulation allows hospital managers to examine the efficiency of the operating rooms and pose questions like "What-if". This model allows users to virtually make changes in the surgical suite and see the results and finally can design a new and desirable system (Jacobson et al., 2006). Also, discrete-event simulation is an effective tool for assigning rare resources for improving patient flow, minimizing the costs, and enhancing patient's satisfaction in the surgical suits (Law, 2006).

The expressed background indicates the use of effective techniques for patient flow optimization is necessary because it leads to efficient usage of the surgical suite and its valuable and expensive resources. This optimization has a significant effect on the total efficiency of the hospital and increases the revenue of this department, and bless with patient satisfaction and saving more people's lives. As a result, the main objective of this paper is the patient's flow optimization in surgical suits using discrete-event simulation.

2- Materials and methods

2-1-Study area and setting

Shariati Hospital affiliated with Tehran University of Medical Sciences is a teaching, research, and therapeutic hospital established in 1974. This hospital contains 857 fixed beds. The number of outpatients and inpatients reaches about 136000 people yearly. Shariati hospital's surgical suite currently possesses 15 operating rooms, two recovery rooms, and two sterilization rooms. These rooms are in two stories. Surgical services provided for patients in this hospital are such as General surgery, Urology surgery, vascular surgery, Neurosurgery, Orthopedic surgery, Oral surgery, Cardiac surgery, Gynecology surgery, Thoracic surgery, and Emergency surgery. This study was conducted in cooperation with this hospital, and the required data were collected from the patients admitting to the surgical suite. As a result, in the present study, several executive steps were necessary. Fig 2 shows these steps in the form of a flowchart.

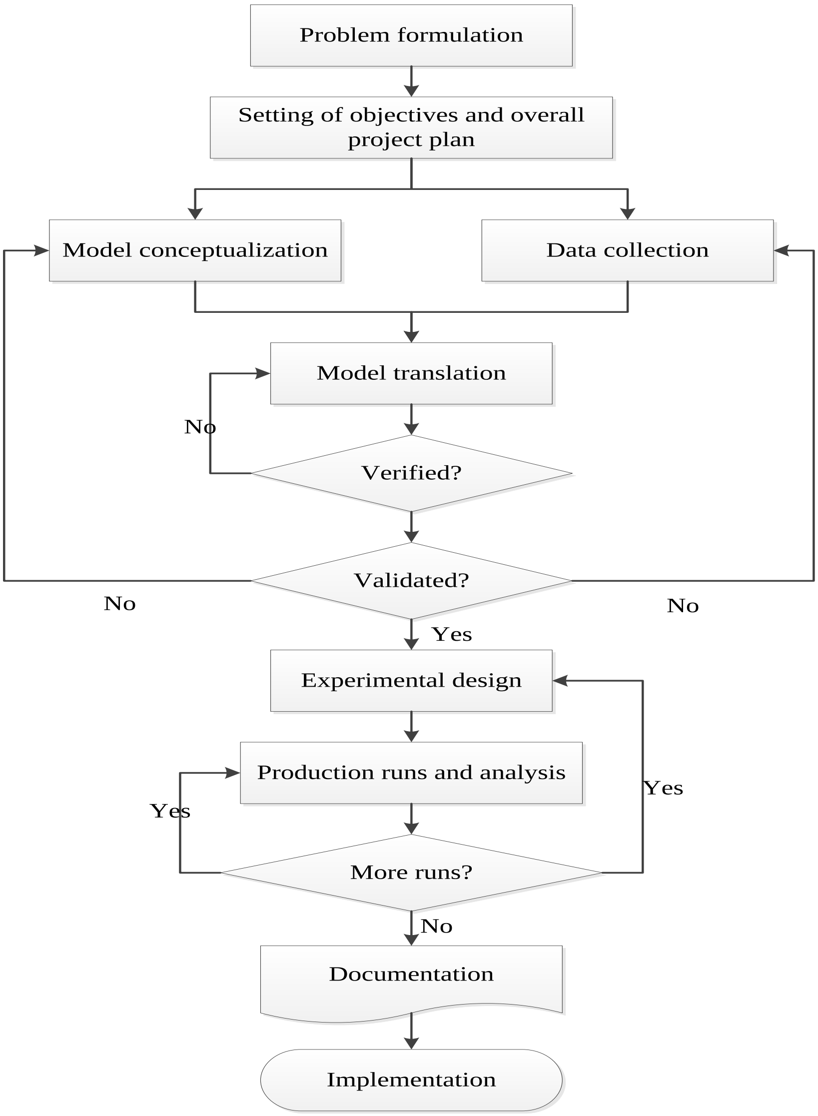

Fig 2. Steps of the present study

2-2-Recognizing of the patient flow in surgical suite

To recognize patient flow, we were present at the surgical suite of Shariati hospital and directly observed the processes. Then, the available processes, time sequence, and the relationships among them were identified with the help of surgical suite's head nurse. The surgery process can be divided into three distinct phases which all of the patients will pass these phases including pre-operative phase, operative phase, and post-operative phase.

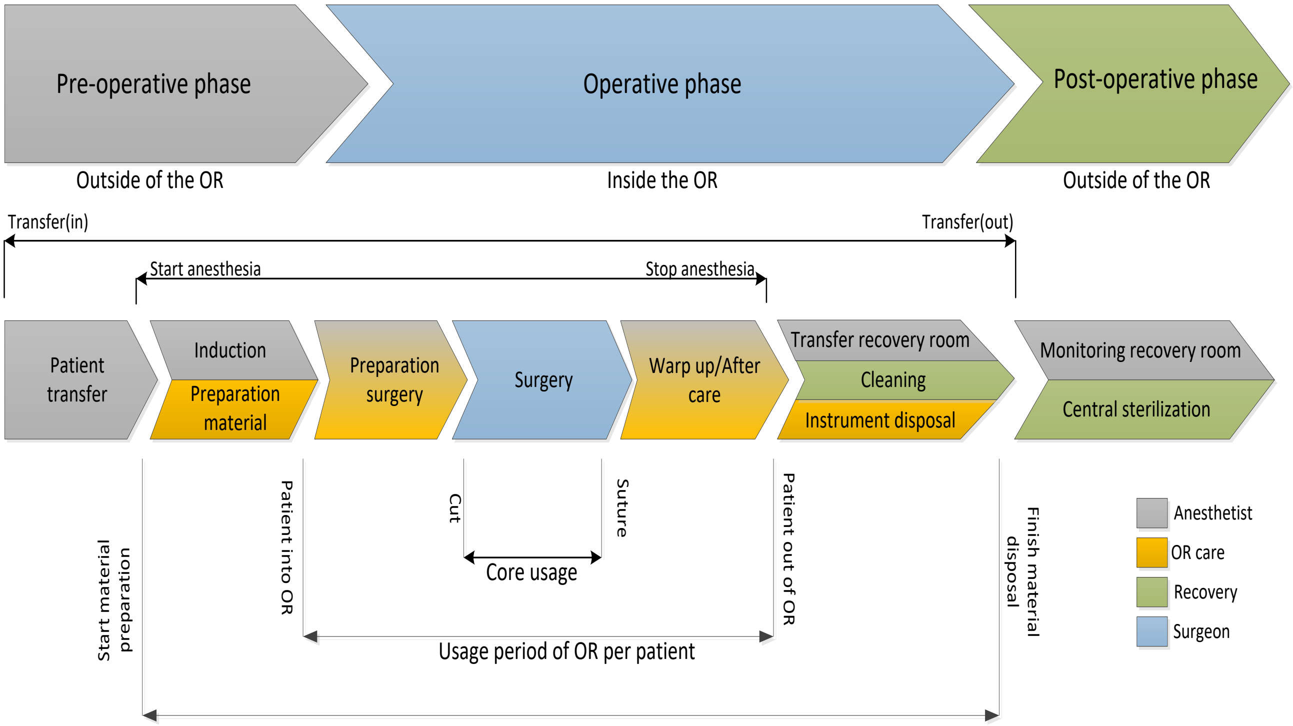

Fig 3 schematically shows these phases:

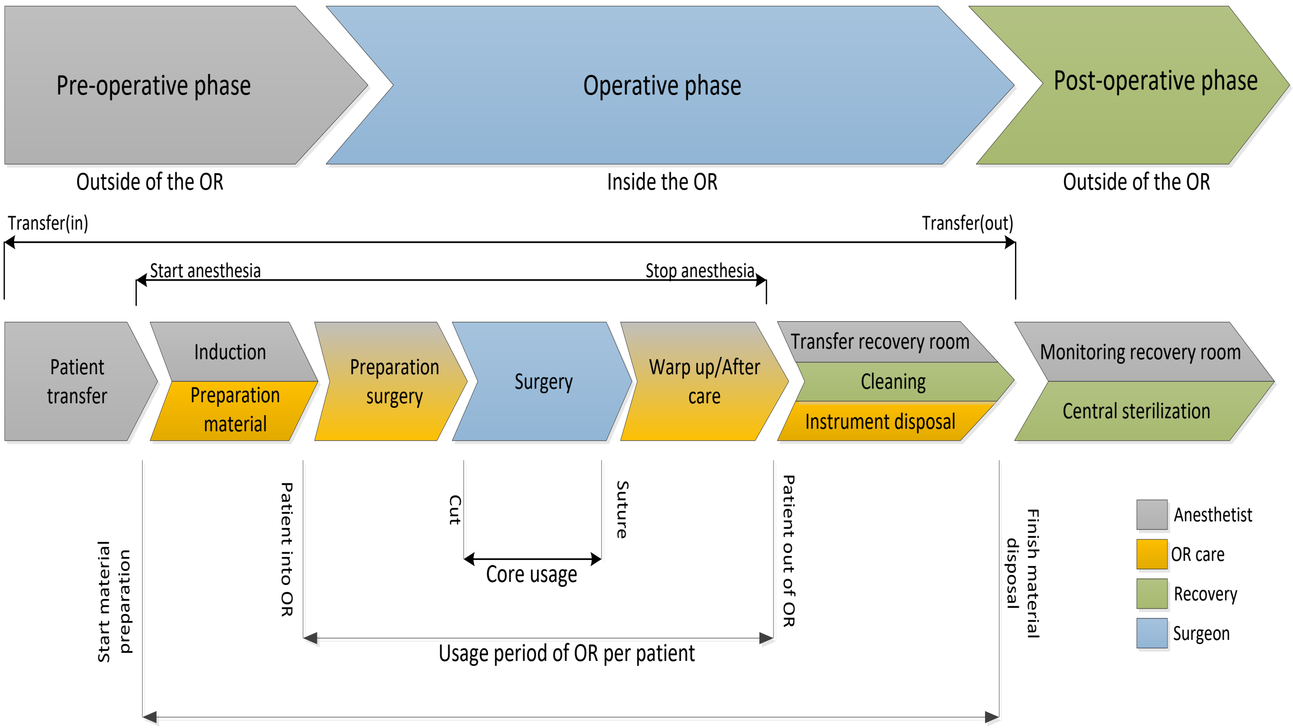

Fig 3. Three main phases of the surgery process in the surgical suite of the hospital

Every patient to be admitted to the surgical suite for performing pre-scheduled surgery operations passes pre-operative stages such as examining the availability of different medical tests and examining the general condition of the patient. The nurse or anesthetist evaluates the patient situation and examines the type of anesthesia which will be used. In the operative phase which is completely occurred inside the operating room, the patient is first prepared and anesthetized and then operates. In the post-operative phase, inpatient will be taken care of in the recovery room. If the inpatient becomes wake up without any problem, depending on his or her general conditions and the specialist opinion, the patient is transferred to the surgical ward or intensive-care unit. Fig 4 shows the patient workflow in the surgical suite of this hospital in detail.

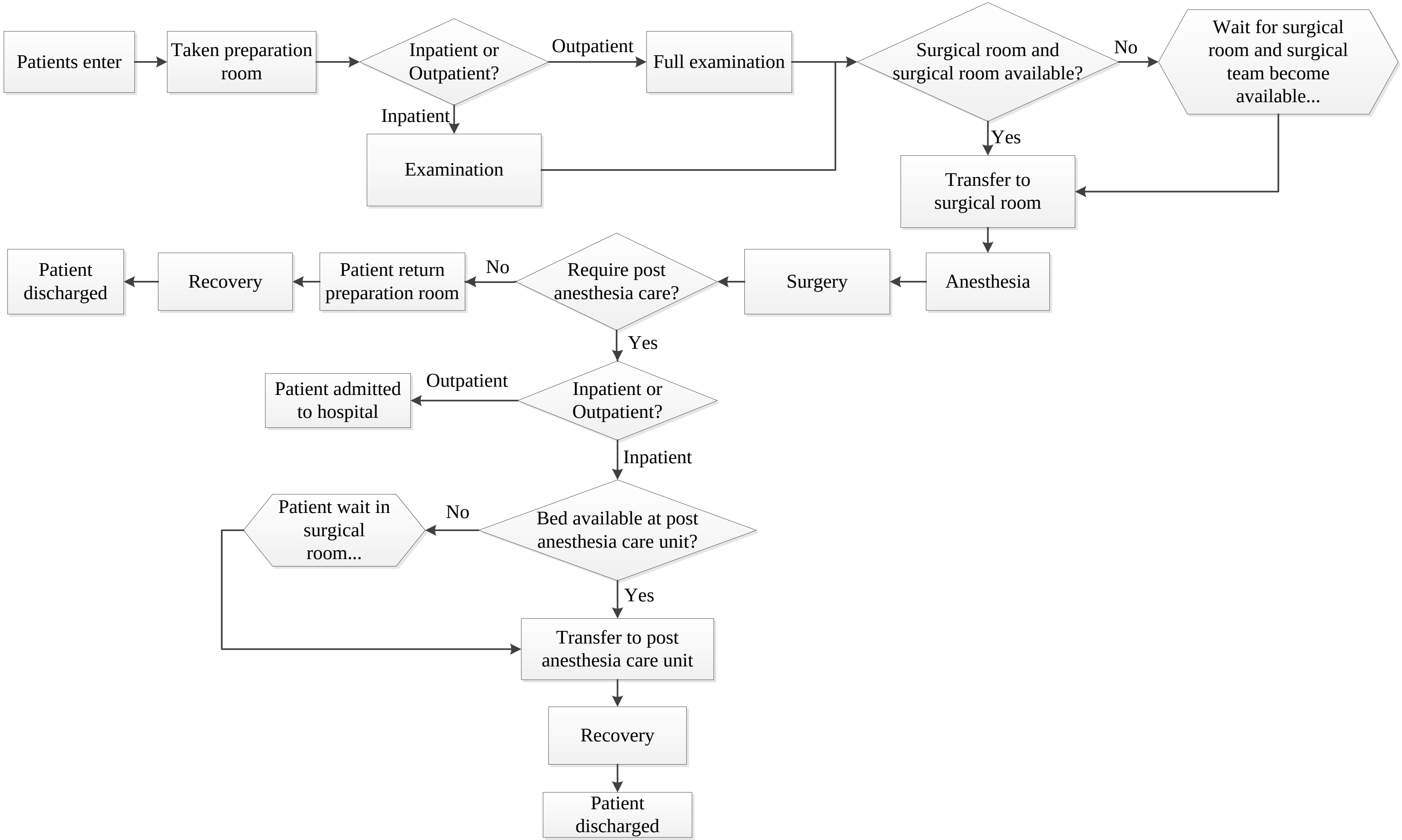

Fig 4. Patient workflow in the surgical suite

2-3-Collecting the required data

Required data are collected by using data collection form, during three weeks in 15 days from Saturday to Wednesday, from 7:00 AM until 8:00 PM which consisted of two shifts of morning and evening (data are related to 643 surgery procedures). 70% of total collected data were used to compute stochastic distribution of servicing times, and 30% were used to verified and validate the simulated model. Data extracted via the form of data collection consists of the following items:

- Operating room preparation time
- Admission time
- Patient preparation time (for anesthesia and positioning)
- Surgery time
- Wake up time
- Recovery time
- Cleaning and sterilization time

Other collected data fields consist of:

- Patient admission time and discharge from the surgical suite
- Operating room number
- Type of patient (outpatient, inpatient, emergency)
- Type of surgery (general surgery, cardiac surgery, gynaecology surgery, etc.)
- Patient's next destination after surgery (post-surgery care unit, ICU, CCU, discharge, etc.)

In this paper, time is considered regarding minutes. With the help of collected data, the percentage of patients for each surgical service was calculated according to Table 1:

Table 1. The percentage of patients for each surgery type

Surgery type	Percentage
General	%14.77
Urology	%15.09
Vascular	%1.24
Neurosurgery	%7.15
Orthopaedic	%11.66
Oral	%13.06
Cardiac	%9.33
Gynaecology	%17.73
Thoracic	%2.49
Emergency	%7.47

In the next step, with the help of 70% of the collected data, stochastic distribution of servicing time for each of the processes is computed and is shown in Table **2**. The stochastic distributions are chosen based on P-Values less than 0.05.

Table 2. Stochastic distribution of servicing time for each process in operating rooms

Process / Surgery type	Admission	OR Setup	Anaesthesia	Surgery	Wake up	Recovery	OR Cleaning
General	-0.5 + LOGN (8.01, 3.14)	4.5 + 46 * BETA (1.02, 3.35)	NORM(10.9, 3.86)	NORM(128, 56.8)	TRIA(-0.5, 10, 20.5)	NORM(50.3, 22.6)	4.5 + 26 * BETA(1.02, 3.35)
Urology			NORM(11.7, 4.81)	TRIA(25, 110, 300)	4.5 + 16 * BETA(0.827, 1.57)	15 + WEIB(45, 1.6)	
Vascular			4.5 + 11 * BETA(0.398, 0.317)	TRIA(55, 180, 185)	4.5 + 11 * BETA(0.398, 0.317)	UNIF(19.5, 85.5)	
Neurosurgery			4.5 + LOGN(20.1, 20.6)	15 + 105 * BETA(1.12, 1.42)	4.5 + 56 * BETA(0.369, 1.96)	15 + 105 * BETA(1.12, 1.42)	
Orthopaedic			TRIA(4.5, 10, 20.5)	TRIA(40, 136, 180)	4.5 + 11 * BETA(0.764, 0.937)	NORM(47.7, 17.4)	
Oral			TRIA(4.5, 10, 25.5)	NORM(126, 48.7)	NORM(10.1, 3.56)	NORM(50.7,19.4)	
Cardiac			4.5 + ERLA(4.5, 3)	TRIA(20, 205, 390)	4.5 + 26 * BETA(0.853, 1.98)	TRIA(-0.001, 70, 140)	
Gynaecology			4.5 + 11 * BETA(0.685, 0.843)	NORM(89.2, 40.5)	NORM(8.95, 3.83)	9.5 + 61 * BETA(1.64, 2.16)	
Thoracic			4.5 + WEIB(13.6, 1.13)	35 + EXPO(81.9)	4.5 + 26 * BETA(0.463, 1.61)	14.5 + 86 * BETA(0.627, 0.828)	
Emergency			TRIA(4.5, 10, 20.5)	15 + WEIB(71.5, 1.16)	4.5 + 26 * BETA(0.63, 2.53)	NORM(35.6, 19.2)	

Moreover, the histogram for the arrival rate of elective patients (outpatient and inpatient) and emergency patients are separately extracted. **Error! Reference source not found.** exhibits the histogram for the arrival rate of elective and emergency patients from 7:00 AM until 8:00 PM:

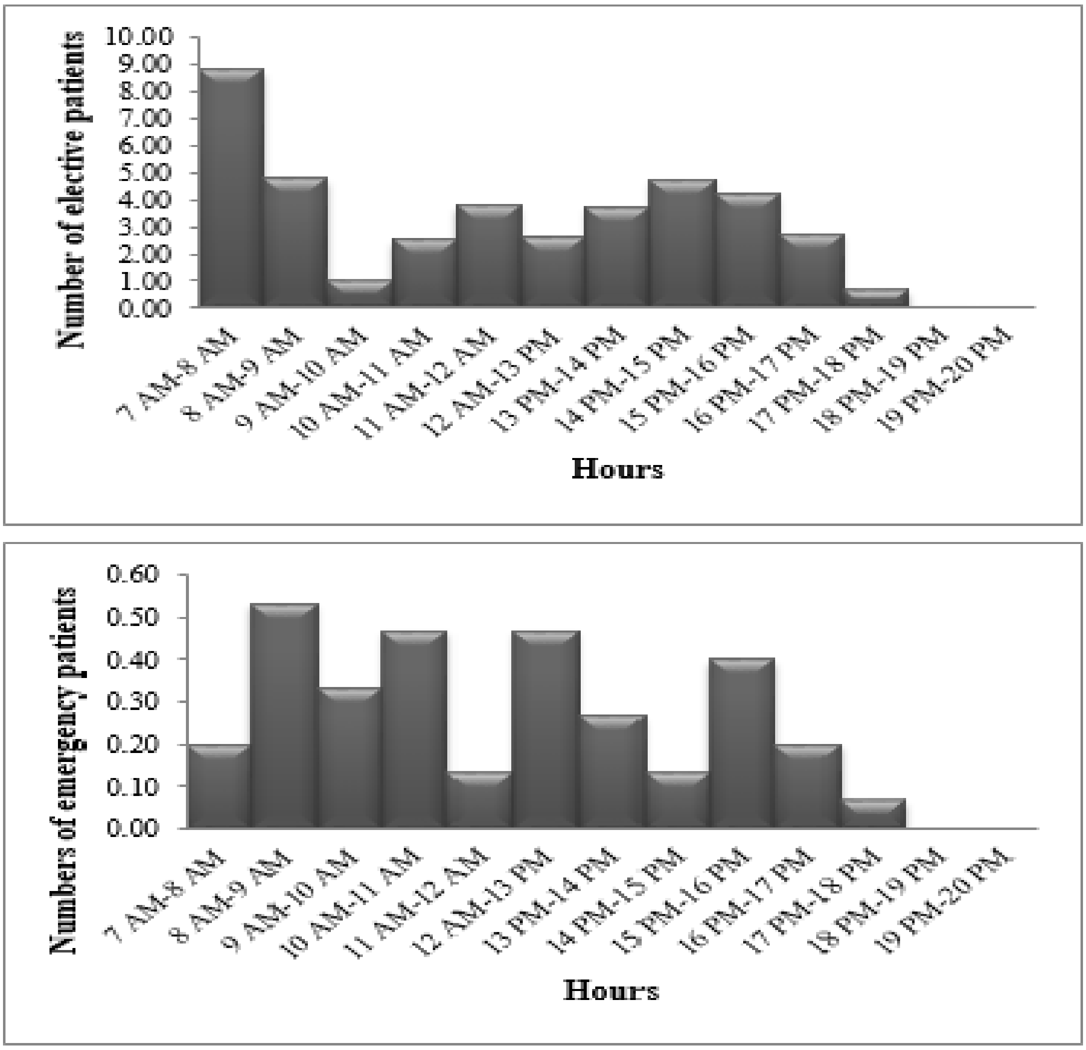

Fig 5. Histogram for the arrival rate of elective and emergency patients in each of day hours

To conceptualize the simulation model, in addition to the event time-instances, required resources for surgical operations and other complementary data are needed. There are 15 operating rooms, 14 recovery beds, two recovery staffs, 18 nurses, 15 operating room technicians, eight stretchers, and eight transport personnel in this hospital. Also, these 15 operating rooms are designated for a specific surgery type. Also, the information on allocating operating rooms to any surgical service is available.

2-4-Building the simulation model

To conceptualize a simulated model, surgical suite is divided into three main sections including admission room, operating room and recovery room. In Fig 6, visual display of surgical suite in the first and second floors of this hospital is exhibited.

Fig 6. Visual display of operating rooms in the first and second floor

After preparing the simulated model, there are two basic steps in simulation studies including verification and validation steps (Banks, 2001):

- Simulated model verification: The purpose of simulated model verification is to determine whether the simulated model matches the conceptual model (current condition) or not. For this purpose, a head nurse checked the simulated model with surgical suite processes part by part and process by process, to assure that each patient proceeds his/her supposed processes in the simulated model.
- Simulated model validation: The purpose of simulated model validation is determining that whether the simulated model matches the real system or not to make sure relations and complexities of a real system are applied in the model appropriately. For this purpose, the LOS of patients in the simulated model was compared with those obtained from the real system. The reason for using this performance measure was that we could validate the whole model by its help. For investigating simulated model validation, 30% of the collected data and two methods were considered.

In the first method, the average LOS of patients for each surgical service is calculated in the real system and then is investigated whether this measure is within the confidence interval or not. Table 3 displays the comparison between average LOS of patients in two stages of real and simulated. The difference between average LOS of patients in the system in two stages of real and simulated is statistically insignificant and also the average LOS of patients in the system in the state of real, for each surgical service is placed within the confidence interval. Therefore, by using the first method, it is approved that the simulated model matches the real world.

Table 3. The comparison of average LOS in two stages of real and simulated

Surgery type	Real system	Simulated system	
	Average LOS of patients	Average LOS of patients	Confidence Interval of average LOS of patients
General	242	244.735	[237.22,252.25]
Urology	260.41	257.235	[249.13,265.34]
Vascular	203.125	201.2	[194.1,208.3]
Neurosurgery	307.84	312.905	[303.23,322.58]
Orthopaedic	233	232.355	[224.4,240.31]
Oral	243.56	241.025	[233.07,248.98]
Cardiac	348.37	341.72	[326.85,356.59]
Gynaecology	180.39	181.21	[176.96,185.46]
Thoracic	239.69	235.7	[226.785,244.615]
Emergency	181.41	190.755	[185.035,196.475]

In the second method, the t-student test is applied which test the Statistical hypothesis for a small number of samples. The level of significance and the sample size (means the number of simulated model iterations) be determined. In this paper, α is considered as 0.05 and n is considered as 9. Sample mean ($\bar{x}$) and its standard deviation (s) are calculated per iteration of the simulation model. Table 4 indicates average LOS of patients in the system per iteration of the simulated model and also mean and standard deviation of LOS of patients in the system per 9 iterations of the simulation model. In the next step, the statistical hypothesis testing is applied separately for each surgical service. The statistical hypotheses H_0 and H_1 are shown in (1). The test statistic t_0 is calculated for each surgical service ((2)).

$$H_0: E[X] = \mu_0$$
$$H_1: E[X] \neq \mu_0 \qquad (1)$$

$$t_0 = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \qquad (2)$$

On the other hand, μ_0 or average LOS of patients in the system in the real state is extracted from Table 3. The test statistics calculated for each surgical service using (2) are listed in Table 4.Then, it is investigated whether the test statistic for per surgical service is placed within the confidence interval mentioned in (3) or not.

$$\left[-t_{\frac{\alpha}{2};n-1}, t_{\frac{\alpha}{2};n-1}\right] \quad (3)$$

If test statistics are placed within the range of $[-2.306, 2.306]$, the simulated model is valid. As the indicated by Table 4, the test statistic for each surgical service falls in the calculated confidence interval. Thus, the simulated model is valid, and improvement scenarios can confidently be implemented on the simulated model.

Table 4. Average LOS of patients in the system per 9 iteration and standard its deviation and the test statistics for each surgical service

Surgery type	Iteration									Mean	SD	Test statistic
	1	2	3	4	5	6	7	8	9			
General	241.23	242.67	247.90	250.34	246.89	243.45	239.31	248.12	242.70	244.73	3.69	2.220
Urology	251.21	262.30	253.14	260.12	257.98	255.67	264.96	250.19	259.53	257.23	5.11	-1.860
Vascular	200.32	205.23	195.12	199.54	207.54	202.45	199.23	201.41	199.93	201.2	3.60	-1.600
Neurosurgery	314.34	319.29	321.93	304.47	311.27	303.39	316.55	320.10	304.78	312.90	7.24	2.097
Orthopaedic	230.65	237.90	228.21	236.58	226.32	239.10	231.25	228.34	232.84	232.35	4.58	-0.422
Oral	238.91	245.23	240.53	247.07	245.81	241.03	235.20	239.24	236.19	241.02	4.21	-1.804
Cardiac	329.14	348.29	355.94	345.23	337.82	342.92	349.19	339.46	327.49	341.72	9.32	-2.138
Gynaecology	177.12	182.3	181.21	185.43	179.43	180.29	182.01	178.65	184.45	181.21	2.67	0.918
Thoracic	229.19	233.12	241.94	238.43	239.43	240.13	231.12	240.2	227.74	235.70	5.40	-2.215
Emergency	188.12	192.32	195.69	189.34	192.46	194.58	187.39	189.1	187.78	190.75	3.08	2.281

3-Results

3-1-Running the simulation model

Since time duration for data collection from the system has been three weeks (15 work days from Saturday to Wednesday), the simulated model; likewise, is run 15 days and each day 13 hours (two work shifts of morning and afternoon). To obtain the number of model runs, In the first stage, the model is run once, and the LOS of patients in the system for each surgical service is recorded. Then in each stage, we add 1 to the number of iterations and we continue until the difference between the LOS of patients in the system in a new stage and the previous stage becomes less than a small enough definite threshold and after that the system becomes stable (Law, 2006). Table 5 displays the LOS of patients in the system for per simulated iteration.

Table 5. LOS of patients in the system per simulated iteration

Surgery type	Iteration								
	1	2	3	4	5	6	7	8	9
General	240	251	238	250	248	246	240	243	244
Urology	255	260	262	251	254	256	256	257	257
Vascular	196	204	207	199	196	205	201	202	201
Neurosurgery	309	314	304	309	317	320	315	313	313
Orthopaedic	227	235	228	229	228	238	233	232	233
Oral	238	245	240	237	235	248	244	241	241
Cardiac	329	344	330	356	350	344	342	341	342
Gynaecology	181	184	179	177	183	181	179	182	181
Thoracic	235	228	243	241	229	239	237	236	236
Emergency	190	195	196	189	187	194	191	191	191

As indicated by Table 5, there is no significant change in the LOS of each group of patients in the system up to stage 9, and the simulation runs will be terminated in this stage. The results of the simulated model listed in Table 6 are regarded as the current condition of studied hospital's operating rooms and are considered as base scenario.

Table 6. The statistics for different runs of the designed simulation model

Surgery type	Average LOS of patients	Average waiting time in queue	Average waiting time in Admission	Average waiting time in transport queue	Average waiting time in recovery queue	Number of surgeries per Day
General	244	32	22	14	17	6.33
Urology	256	34	21	14	19	6.33
Vascular	201	31	21	15	16	1.53
Neurosurgery	312	38	27	16	20	3.06
Orthopaedic	231	35	22	14	21	4.93
Oral	241	34	22	14	19	5.6
Cardiac	342	37	32	14	23	4
Gynaecology	181	35	12	12	21	7.6
Thoracic	236	36	21	12	24	1.06
Emergency	191	31	25	12	19	3.2

3-2-Implementing the improvement scenarios

Regarding the obtained results from simulation runs, improvement scenarios are defined. They are compared with base scenario based on performance measures. The scenario which creates the maximum percentage of improvement in the simulated model, is chosen as the best scenario. To compare improvement scenario with the base scenario, three performance measures are used as follows:

-Performance Measure 1: Average LOS of patients in the system

-Performance Measure 2: Average of patients waiting time in queue

-Performance Measure 3: Average of number of performed surgeries per day

Now the scenarios are implemented respectively:

Scenario 1: *Omitting waiting time between patient arrival to the surgical suite and the start of the admission process*

Regarding the base scenario, the maximum waiting time is observed in the process of patient admission. After interviewing operating room's experts, they declared that the most important factor in creating waiting time is the poor relations between surgical ward and operating rooms. If the surgical ward checks prerequisites of surgery before patient arrival to the surgical suite (e.g., checking whether the patient has got all required tests), the patient will not experience waiting time for admission. It can considerably be decreased by designing a readiness assessment checklist, a checklist in which all prerequisites for surgery is included. As a result, scenario one is defined as an omission of waiting time between patient arrival at the surgical suite and the start of the admission process.

Scenario 2: *On time start of the first surgery operation (for each surgical service) in the morning*

Another identified bottleneck by interviewing hospital experts is delayed the start of the first operation. The start time of the morning shift in Shariati hospital is at 7:00 AM. Delay in the first surgical operation (That is often due to the surgeons are not present on time in the surgical suite) causes a delay in other surgeries and also cancelation of preplanned surgeries in the evening shift owing to lack of enough time. This problem also causes a reduction in the number of preplanned surgeries for a day because of cancelation in preplanned surgeries. As a result, scenario two is defined as starting the first surgery operation (for each surgical service) on time.

Scenario 3: *Increasing number of recourses in the recovery room by adding a bed and a nurse*

The third identified bottleneck is the lack of sufficient resources related to recovery room which a part of patients waiting time in recovery room's queue is also due to lack of sufficient resources. The recovery room contains 14 beds and two nurses. In some cases, due to the occupation of recovery beds, patients are kept in the operating room until recovery bed is evacuated. It causes waiting for the mentioned patient and the next patient also has to wait in the admission queue until the occupied bed in the operating room is evacuated. On the other hand, in this hospital, the admission room and recovery room are shared and, two staff members of this room perform both tasks simultaneously. This problem causes a workload for them and thus results in waiting for patients. As a result, scenario 3 is to increase recovery room resources by adding a recovery bed and a nurse.

Scenario 4: *Increasing the number of required resources for transportation by adding a stretcher and a stretcher service staff*

The fourth identified bottleneck is the shortage of resources related to transportation process which makes patient wait for transportation process. For this process, a stretcher and a stretcher service staff are required. Inside the surgical suite, the transportation process occurs twice. That is transferring from admission to operating room and also from the operating room to recovery room. The operating rooms in the hospital contain eight stretcher service staff members and eight stretchers which are used interchangeably. As a result, scenario four is defined as increasing the number of required resources for transportation by adding a stretcher and a stretcher service staff.

Scenario 5: *Combination of the four scenarios mentioned above*

In this scenario, a combination of scenarios 1-4 is implemented simultaneously. Scenarios one and two do not charge the system with any expenses, but scenarios three and four charge it with costs.

Table 7 displays the amounts of performance measures 1, 2 and 3 due to the implementation of improvement scenarios for all surgical services in the simulated model and the comparison between improvement rates resulting from implementation of each of these five scenarios. As indicated by Table 7, scenario five which is a combination scenario has the greatest improvement based on the considered performance measures. This scenario is comprised of omission of waiting time between patient’s arrival at the surgical suits and start of the admission process, on time start of the first surgery operation and adding a resource to the resources of transportation and recovery room.

Table 7. The values of performance measures in base scenario and improvement scenarios and improvement rates resulted by implementing defined scenarios in surgical suite

Scenario	Performance measure 1 (% of Improvement)	Performance measure 2 (% of Improvement)	Performance measure 3 (% of Improvement)
Current-state	243.5	34.3	43.64
Scenario 1	223.25 (%8.31)	32.06 (%6.53)	49.9 (%14.34)
Scenario 2	242.2 (%0.53)	31.9 (%6.99)	47.69 (%9.28)
Scenario 3	205.91 (%15.43)	13.7 (%60.05)	47.7 (%9.3)
Scenario 4	229.97 (%5.55)	19.03 (%43.73)	45.95 (%5.29)
Scenario 5	189.56 (%22.15)	7.21 (%78.97)	53.1 (%21.67)

4-Conclusions

Surgical suits are considered the most important hospital departments and improving patient flow in this department is a key goal of surgical suits managers. Since this department deals with human lives, the smallest mistake in the implementation of its change projects may cause irreparable losses. Therefore, it is necessary to prepare a simulated model of the surgical suite before implementing improvement scenarios in the real world. We test improvement scenarios in the simulated system, and if the expected results gained, we will implement it in the real world. In this case, the costs are reduced (because the project of improving surgical suits processes is not done by trial and error), and the irreparable losses such as the death of patients are prevented.

For this purpose, in this paper, a discrete-event simulation was used to improve patient flow in the surgical suite. To achieve these goals, we first collected the required data by using a data collection form. These data include patients servicing time in different stages of the surgical process and arrival rate of patients in the system, etc. By using Arena software, the stochastic distribution functions of processes were identified. Afterward, the simulated model was conceptualized, and to be reliable for the user of the model, it is verified and validated. It this paper, in conceptualizing the simulation model, the both elected and non-elected patients were considered, and an effort was made to consider all processes of the surgical suite, both processes with value-added and processes without value-added. As a result, a comprehensive simulated model is created. After passing these stages, the improvement scenarios are suggested and implemented in the simulation model. These scenarios were compared based on three performance measures, including LOS of patients in the system, waiting time of patients in the queue, and number of performed surgeries. The best scenario chosen is scenario 5 resulting 22.15% improvement in LOS of patients in the system.

To implement the chosen improvement scenario, the participation of the final users in the simulation process is considered as a success factor. If final users engage with the simulation process from the beginning of the study, they will apply the research results in the real world with more likely. In this study, for identifying patients' workflow in the surgical suite and also for collecting required data and designing a form for this purpose, recovery staff members and surgical suite nurses were contributed in the course of actions and their ideas were paid attention by the researchers of this study.

Another important point for a manager in implementing a research's output in the real world is considering cost measures. If the proposed scenarios are economical, the manager will be ready to spend required money for improving efficiency in his or her surgical suite. Therefore, for implementing the superior scenario examined by this study, after meetings of counseling with hospital management, it is necessary to consider cost measures in suggested scenarios and then implementation will be done the in the surgical suite. But unfortunately the information related to the costs of implementing each scenario were not available when the research was carried out, and thus comparing those by using performance measure related to cost was not possible.

On the other hand, time-consuming process of collecting required data for conceptualizing simulated model, time-consuming process of identifying the workflow of surgical suite considering related details, unfamiliarity with jargons of healthcare area and surgical suits and limitations in the modeling of the real system are considered as some of the major limitations of this study.

Some of the key suggestions for further related researches include:

- Utilizing other measures such as cost measures for evaluating scenarios
- Optimizing the flow for surgeons, nurses, staff members, equipment and materials
- Redesigning the surgical suite layout to eliminate bottlenecks related to this area
- Rescheduling all existing resources in the surgical suite
- Considering some of the limitations which are not considered in the simulated model.

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