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Simulation-Based Optimization for Improving Hospital Performance

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Abstract

Background and Objectives: Hospitals are the final stage of health services delivery supply chain, and thus the quality of health services offered by hospitals directly impacts the well-being of individuals. Application of efficient operations research (OR) tools has proved powerful in finding non-intuitive solutions for enhanced hospital performance. The aim of the present study was to develop a design-of-experiments (DOE) model based on computer simulation to optimize key factors influencing health services quality, including queue length, patient waiting time, departure rate, and productivity.
Methods: The study was designed and implemented in Shomal hospital situated in Northern of Iran. The response surface methodology (RSM) was adopted as the DOE technique. The proposed simulation model considered all wards and their interactions together.
Findings: Our method demonstrated feasibility of reducing the decision-making risk and decreasing queue length and patient waiting time by evaluating and analyzing different scenarios.
Conclusions: Our study indicates the usefulness of adopting simulation-based approach in identifying bottlenecks of achieving high health services performance.
Keywords: Hospital performance, Medical processes, Simulation, Design of experiments, Response surface methodology

Background and Objectives

Recently, improving health services has become much important and has drawn attention among researchers. In this regard, quality of services provided for patients have been improved and is still improving due to its significance. Hospitals, which are considered as the substantial parts of the health service supply chain are not exempt from the mentioned improvements. Therefore, improving performance of hospital procedures has a major influence on the productivity and efficiency of the health care industry. Hence, researchers in various fields are moving toward improving the health service quality, for the purpose of meeting the requirements of physicians, nurses and patients. Recently, the major part of attention is only focused on emergency wards of health care centers and hospitals. In this regard, different patients with critical conditions referring to emergency ward should be prioritized according to the type of health service they need. However, according to patient movements between various hospital wards, optimizing this supply chain by individually improving the performance of a specific ward is impossible and would not be an efficient strategy. Therefore, simultaneously optimizing the entire hospital procedures should be taken into account (comprising all movements done by patients between different wards, from his primary entrance until he exits the hospital). Hence, by taking advantage of this comprehensive approach, health service procedures will be improved in a continuous manner by concentrating on more critical hospital wards. On the other hand, hospital resource management is another important concept which should be addressed as well as possible by assigning the appropriate number of facilities, physicians, nurses, etc.[1] Besides, optimization of some queueing theory parameters such as patient waiting time is of crucial importance. Therefore, by considering all the above mentioned concepts the satisfaction rate of patients could be increased and consequently the performance and productivity of the specific hospital will be improved. This paper aims at determining the appropriate number

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of physicians, nurses and other crucial resources and decreasing the unnecessary movements of patients between different hospital wards due to hospital resource restrictions. The main advantages of this approach are achieving customer satisfaction, higher profit margins, capacity prediction and finally patient health level enhancement as the most important achievement. In this regard, hospitals should focus on reliability of health care procedures and patient's health, in order to gain higher profit margins and competitive advantages.

Computer simulations reproduce the behavior of a system using a model and could be used to evaluate the system outputs. The purpose of this research is optimizing the hospital procedures in addition to hospital resource management by presenting an integrated approach, by combing design of experiments (DOE) and computer simulation. This research concentrates on modeling the specialty and subspecialty wards of a specific hospital by utilizing discrete-event simulation. Then, with the purpose of identifying potential bottlenecks of hospital the simulation model has been run several times by ARENA version 14 software and different scenarios are proposed for the sake of improving hospital procedures. Afterwards, by the application of design of experiments (response surface methodology [RSM] in this study) Pareto optimum solution sets are obtained, according to available resource constraints and four predefined objective functions. The predefined objective functions are, namely queue length, productivity of resources, number of exits in the system and waiting time in queue. Finally, beneficial analysis is done by taking advantage of the outputs of Expert Design version 10.

This study is organized as follows: in Section 2, the literature review and previous conducted researches associated with the application of simulation methods in health service is presented and the research gap is identified in this area. In Section 3, theoretical foundations of our research, comprising simulation, design of experiments and RSM is gathered. In Section 4, the proposed approach is investigated. Section 5 covers studying a subspecialty hospital as our research case study. The results obtained from computer simulation and RSM outputs are analyzed in Section 6, and optimum resource levels are specified according to predefined objective functions. Finally, future research paths are gathered in Section 7.

Blasak et al applied simulation models for emergency department and medical telemetry units at Rush North Shore Medical Center. Their proposed model provided a better perception of the operations of both units as well as the interactions between the mentioned units.[2] Yeh and Lin used an integrated approach of simulation and genetic algorithm (GA) to improve the service quality of a hospital emergency ward. After analyzing results, it was revealed that by appropriate scheduling of nurses, patient waiting times will be decreased and as result patient satisfaction is enhanced.[3] Hongqiao et al simulated the complicated hospital systems considering a multi-agent technology and satisfactory achievements were gained, such as minimized costs and maximized health service quality.[4] Brenner et al carried out a research in the emergency department at the university of Kentucky Chandler hospital and were capable of identifying the bottlenecks, thereby assigning the appropriate number of resources in hospital departments.[5]

Steins et al concentrated on scheduling operating rooms in a regional hospital in Sweden and were seeking to obtain higher resource utilization.[6] Simulation results revealed that implementation of proposed scenarios would increase resource utilization as well providing a more efficient scheduling for nurses. Günal and Pidd presented a paper providing a comprehensive literature review on the application of discrete event simulation models in health care.[7] Their research revealed that there was a wide diversity in the objectives of previous researches. In this regard, the reasons why specific models are more prevalent in previous studies than generic approaches were discussed. Reynolds et al utilized a discrete event simulation model to simulate hospital pharmacy outpatient dispensing systems.[8] Potential impacts of changes in prescription workload, staffing levels, etc. were estimated by examining different scenarios. Günal and Pidd presented a generic, discrete event simulation model for investigating aspects of hospital performance. In their research, it was demonstrated how the proposed approach was utilized to investigate entire performance of a hospital, located in England.[9]

Gunal carried out a research with the purpose of highlighting the important areas of interest in hospital simulation.[10] In the first part of this study the information associated with conceptual simulation models is gathered and in the second part simulation models are categorized in three main groups, namely discrete event simulation, system dynamics and agent-based simulation. Zeng et al applied a simulation model to improve the health service quality in emergency ward of a specific hospital.[11] Their introduced model provided a quantitative tool for continuous improvement and flow control, also applicable in other hospitals. Chetouane et al[12] took advantage of sensitivity analysis for simulation-based decision making in a hospital emergency department service design. In their research, different design alternatives were compared according to total time-in-system performance metric. Holm et al investigated bed utilization rate of a hospital in Norway through simulation and optimization.[13] Their approach provided a strong tool for optimizing bed utilization rate in hospitals, thereby indicating a dramatic decrease in number of utilized beds, in case of encountering a large flow of patients in hospital.

Van Buuren et al presented a discrete event simulation model for emergency medical service (EMS) call centers. Their approach provides a clear perception of EMS call centers and could be utilized in strategic issues.[14] Shukla et al[15] proposed a systematic methodology to develop a discrete event simulation model based on role activity diagram (RAD), capable of addressing bottlenecks, low throughputs, low resource utilization and long waiting times. Raja proposed a framework to forecast the possible future state of a hospital by combing two concepts of times series forecasting and simulation. Furthermore, this framework was capable of predicting inpatient unit (IN) length of stay (LOS) at the time of admission, by applying data mining techniques.[16] Gateri predicted the number of patients in the queue by making use of Monte Carlo simulation.[17] Their presented model, after conducting experiments, revealed that it could be implemented to enhance resource utilization and decrease operating costs. Brahma developed a technique based on queueing theory and simulation to optimize the hospital central laboratory sample collection room.[18] Devapriya et al developed a decision support system tool based on a discrete event simulation model, to address issues such as bed capacity,[19] validation of their simulation model proved its accuracy, consistency and generic nature. Wang et al presented a hypothetical inpatient flow process model based on discrete event simulation in a large acute care hospital. Multi-objective simulation and MO-COMPASS approach were examined to investigate Pareto optimal solutions.[20]

Mathews proposed a simulation model for intensive care unit (ICU) patient flow with the purpose of improving ICU throughout and planning hospital capacity. According to their results, ICU admission waiting time was decreased by reallocating beds and unit occupancy was increased.[21] Kadı et al modeled a university hospital blood laboratory by discrete event simulation to identify bottlenecks and examine hospital processes.[22] The obtained simulation results revealed that proposed scenarios were capable of decreasing the throughput time. Silva et al utilized a simulation model to facilitate health service management in a hospital.[23] Their purpose was offering a discrete event simulation model representing a hospital subsystem, thereby revealing the advantage of the proposed model in reconfiguring service portfolio provided by the medical unit. DeRienzo et al conducted a research in a hospital neonatal intensive care unit, aiming at prediction of staffing needs.[24] Achieved results, demonstrated the capability of the model in estimating annual admissions, transfers and deaths, on the basis of two different staffing levels. Demir et al[25] developed a decision support tool (DST) for the sake of management purposes in a National Health Service (NHS) in England.[25] The tool allows decision makers to appreciate system operations according to its simplicity and applicability.

By taking into consideration all the above-mentioned papers, it could be understood that all of these researches are focusing on only a single hospital ward, thereby neglecting the total relationships between hospital wards. In other words, management of all hospital wards along with utilized resources, has not been considered in a comprehensive manner. Hence, in this study by presenting an integrated model of DES-DOE (discrete event simulation-design of experiments), the possibility of optimizing all hospital processes comprehensively is provided. In this research, DOE has been utilized for the sake of preventing a large number of experiments and determining levels of input factors simultaneously. In addition, RSM as one of DOE techniques, is beneficial in case of investigating interaction between experiments. Furthermore, utilizing simulation approaches has facilitated management of hospital processes, demonstrating interactions between hospital wards in real cases. In this research, a discrete event simulation model has been integrated with a DOE approach, utilizing computer simulation outputs as inputs of DOE approach. This proposed integrated approach is of significant importance, due to its capability of pausing the system or even reallocating resources, according to factors such as time, cost, individuals, etc. The novelty of this research is based on integrating a computer simulation model with RSM technique, providing a predictive model for optimization and selecting the best possible scenarios for the entire hospital processes/wards.

Methods

Simulation

Simulation models are an emulation of the real system performance over a specific time span, providing insight into the operations of those systems. In this regard, discrete event simulation is one the most useful operations research (OR) techniques serving managers, which could be used to compress a time frame. Furthermore, a simulation model run on a computer system can be used to investigate quickly the effects of a change in a real life situation that take place over several years. Finally, because of its understandable structure and available computer simulation languages such as Arena, it is beneficial for a majority of groups. Simulation models are defined as tools for predicting the effects of changes made in existent systems, also as designing tools for predicting performance of new systems.[26] Recently, application of simulation models has increased dramatically in health service affairs. The main reasons of these frequent applications are the increasing complexity of health care systems, wide capability of simulation models in modeling complex systems and finally the dramatic development of simulation soft wares. However, the application of simulation modeling in health care affairs is definitely less than in industrial areas. Simulation is an appropriate tool for precise decision making based on observations and provides exceptional results for examining complex systems. In this regard, complexity is known as one of the evident features of health care systems. This technique, provides us fascinating insight into the problem, by modeling and visualizing health care systems. In fact, simulation provides a real visualization of the system for the researcher, by performing a dynamic analysis of it. This process, improves the researcher's perception of the real system and this clear understanding is very valuable for making improvement in the studying system.[27] A major part of simulation models has been applied in emergency wards of hospitals for the purpose of enhancing efficiency. Many hospital simulation models allow managers to observe applicability of the model in real systems, before implementing them in real systems. Hence, managers would be given the chance of selecting the most satisfactory scenarios. The mechanism of simulation is based on predicting future by utilizing historical data. Therefore, application of simulation models in health care has drawn attention among researchers due to its significance and accuracy. In this regard, precise input data is substantial and required, given that people's lives are influenced directly by taken decisions.

Simulation models are categorized according to different factors such as time, status and probabilistic components. Static simulation model is a representation of a system at a particular point in time. However, dynamic simulation models are used to model systems which time evolution is considered. Whenever simulation of dynamic behavior of the entire system is under consideration, these models are applied. On the other hand, simulation models could be categorized as discrete event simulation or continuous simulation, depending on system status. Continuous simulation models are attributed to modeled systems which vary continually with time. On the contrary, in discrete event simulation models the system can change only at a countable number of points in time. In this case, events change system status, in which event is defined as an instantaneous occurrence (e.g. arrival of a new customer). This kind of simulation is utilized whenever a precise statistical analysis is required. Finally, models, depending on whether they contain probabilistic components or not, are categorized into stochastic models or deterministic models, respectively. To clarify, stochastic simulation models have at least one random input component and are presented by utilizing statistical distributions. In our research, according to the random arrival of patients, it is considered as stochastic simulation model; and due to considering time evolution, it is a dynamic simulation; and according to our queueing theory approach and related applied analysis in a specific hospital, this model fits into the category of discrete event simulation.

Response Surface Methodology

RSM is a branch of statistical and mathematical methods for improving, developing and optimizing processes. a Process could be defined as operations needed for converting a set of input variables to output variables (response variables). RSM methodology, is a technique used for estimating a relationship between some response variables and some independent variables, by applying a set of designed experiments and regression analysis.[28,29] Furthermore, RSM methodology is an important branch of DOE, which implements a collection of statistical and mathematical techniques (encompassing statistical design of experiments, statistical modeling, preliminary optimization) for the purpose of developing a new process and production optimization.[28,30] RSM is utilized in many industrial cases and other research areas such as[31]:

1) Designing a response procedure for the intended area
2) Optimization of the response or qualitative characteristic (discovering the best factor levels for optimum production)
3) Joint optimization of several qualitative characteristics.

RSM consists of a group of mathematical and statistical techniques for developing and optimizing processes. This approach, also has a significant application in designing and developing new products, in addition to improving existent products. Suppose, for instance, a researcher or engineer is considering a system or process consisting a response of interest, y and a number of associated control variables denoted by, $x_1, x_2, \ldots, x_k$. In this case, the relationship between the response variable and the control variables is approximated by the function presented in equation (1).[28]

$$y = f(x_1, x_2, \ldots, x_k) + \varepsilon \tag{1}$$

The exact form of response function *f* is unknown and could be very complicated. ε, is a random experimental error assumed to have a zero mean. In this case, the expected value of y is denoted by equation (2).

$$E(y) = E[f(x_1, x_2, ..., x_k)] + E[\varepsilon] \tag{2}$$

$x_1, x_2, \ldots, x_k$ variables are measured according to natural units and are called natural variables. There are special cases of model (1), in case of having two independent variables, the fist-order model is as equation (3).

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \tag{3}$$

If the interactions between variables exists, they could be simply added to equation (3). The added interactions are defined as surface curvature. A general second-order design model is defined as:

$$\eta = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i<j}\sum \beta_{ij} x_i x_j \tag{4}$$

Where x_i and x_j are design variables and β are tuning parameters.

Research Methodology

First, indoor hospital processes are simulated via discrete event simulation. In fact, the main purpose of providing a simulation model in this study is modeling simultaneously different hospital wards and developing different scenarios, to examine patient waiting time, queue length, productivity and departure rate. After providing a computer simulation model, the next step is sampling and gathering data. The required data were randomly gathered according to each hospital ward's entrance and are presented in Table 1. Main steps of the proposed integrated approach, achieved by combing RSM and discrete event simulation are outlined as follows. A) determining distribution functions of hospital wards. B) screening and merging defined wards to achieve main hospital wards based on decision maker's opinion. C) utilizing computer simulation for generating 40 distinct scenarios. D) Optimization in order to determine optimum levels of input variables by RSM.

In fact, in order to determine more efficiently optimum values of input factors (variables), only main hospital resources are considered (or some resources are merged) according to the decision maker's opinion. Main input resources of the under investigation hospital consist of operating room, labor room, ICU, CCU, specialist, general practitioner, physiotherapy, pharmacy, radiology and sonography. According to the levels of input variables and different outputs, RSM is applied to determine the Pareto optimum solutions. To clarify, in this research, outputs are queue length, departure rate, patient waiting time and productivity. The conceptual model of research is illustrated in Figure 1.

Case Study

This research was conducted at a specialty and subspecialty hospital, named Shomal located in North of Iran. The wards of the hospital consist of clinic, paraclinic, inpatient, intensive care, surgery, etc. The clinic consists of ENT, orthopedics, internal, obstetrics and gynecology, neurosurgery and surgery. The paraclinic consists of imaging, pharmacy and laboratory. The inpatient ward consists of maternity, internal surgery, pediatrics and labor room. The intensive care ward consists of ICU, CCU, etc. the surgery ward consists of operating room, outpatient operating room, emergency, labor room, etc. this mentioned hospital is considered as a system, in which optimization of resource utilization and service rate is of crucial importance. Consequently, by taking advantage of optimization, vital goals could be achieved, such as increase in patient satisfaction rate, productivity enhancement and increases in quality of offered health services. In this case, a discrete event simulation model based on RSM technique is implemented at this hospital to discover the optimum possible scenarios and utilize the available hospital resources as well as possible.

In this regard, the important model parameters should be defined. Model parameters in this research which should be calculated are entrance rate of patients to hospital, percentage of patients refereeing to emergency reception, first specialty reception, second specialty reception, intensive care ward reception, ophthalmology reception and maternity reception. Furthermore, determining service rate in emergency reception, first specialty reception, second specialty reception, intensive care ward reception, ophthalmology reception, maternity reception, neurosurgery, coronary surgery, orthopedics, ENT, internal, laboratory, general practitioner, pharmacy, labor room, radiology, sonography, morgue, physiotherapy and inpatient ward is required.

According to gathered data, after a patient enters a hospital, 6 different decisions could be made by him or her. In this case, the patient refers to the emergency ward with the probability of 30%, with the probability of 15% to first specialty ward, with probability of 15% to intensive health care ward, with the probability of 18% to second specialty ward, with the probability of 12% to ophthalmology ward and finally with the probability of 15% to maternity ward. The patient after referring to the general practitioner, with the probability of 25% is referred to the laboratory and again is referred back to the general practitioner and then with the probability of 10% (for each bed) he/

Table 1. Distribution Function of Input Variables

Wards	R	Entrance/Service Distribution
Entrance of patients	Random	4+ WEIB (12.1,0.69) (min)
Emergency reception	1 Person	3+LOGN (25.5,63.3) (min)
Specialty ward reception	1 Person	3+LOGN (426,2.72e+003) (min)
Intensive care reception	1 Person	3+LOGN (471,3.03e+003) (min)
Second specialty reception	1 Person	2+WEIB (99.2,0.834) (min)
Eye reception	1 Person	2+WEIB (45.3,0.843) (min)
Maternity reception	1 Person	7+1.23e+003×BETA (0.112,0.112) (min)
Internal reception	1 Person	Triangular (10,12,15) (min)
Neurosurgery	1 Person	Triangular (10,12,15) (min)
Cardiologist	1 Person	Triangular (10,14,18) (min)
Orthopedic	1 Person	Triangular (10,15,20) (min)
ENT	1 Person	Triangular (10,12,15) (min)
Optometrist	1 Person	Triangular (10,12,15) (min)
Ophthalmology	1 Person	Triangular (10,12,15) (min)
Maternity	1 Person	Triangular (10,15,20) (min)
Labour room	1 Person	Triangular (0.5,1,1.5) (hour)
Laboratory	1 Person	Triangular (10,12,25)
General practitioner	1 Person	Triangular (5,6,10)
ICU	1 Person	Triangular (1,3,5) (Day)
CCU	1 Person	Triangular(1,3,5) (Day)
Internal	1 Person	Triangular (1,3,7) (Day)
Sonography	1 Person	Triangular (10,15,20) (min)
Pharmacy	1 Person	Triangular (7,13,20) (min)
Beds 1, 2, 3	3 Beds	Triangular (5,10,30) (min)
Bed 4	1 Person	Triangular (5,10,20) (min)
Bed 5	1 Person	Triangular (10,15,30) (min)
Morgue	-	1 Day
Physiotherapy	1 (equipment)	Triangular (20,30,50) (min)
Radiology	1 (equipment)	Triangular (5,8,12) (min)
Pharmacy	1 Person	Triangular (7,13,20)
Sonography	1 (equipment)	Triangular (10,15,20)
Operating room	1 Person	Triangular (0.5,1,1.5) (hour)
Inpatient women	-	1 Day
Inpatients before departure	1 Person	1 Day

she is confined to bed where after a while the patient is discharged. Furthermore, after being visited by general practitioner, he/she is referred to the pharmacy with the probability of 25% and then he/she leaves the hospital. In the specialty ward, the patient after reception, is referred to neurosurgery with the probability of 50% or referred to cardiologist with the probability of 50%. Then, he leaves the hospital with the probability of 10% or refers to the intensive care ward with the probability of 20% (in this ward, he/she refers to ICU or CCU or internal ward with probabilities of 30%, 30% and 40%, respectively) or refers to the pharmacy with the probability of 70% and then leaves the hospital. In the eye ward, after reception, he/she refers to optometrist and then refers to ophthalmologist and then refers to the pharmacy with the probability of 50% or leaves the hospital with the probability of 50%. In the maternity ward, after reception, she refers to obstetrician/gynecologist with the probability of 50% or refers to the labor room with to probability of 50%. After going into labor in the labor room, she is confined to bed and then leaves the hospital. After referring to obstetrician/gynecologist, she refers to the sonography and then refers back to obstetrician/gynecologist, or she leaves the hospital. After sampling and examining via Arena (version 14) by Input Analyzer, the distribution function associated with each ward is gathered in Table 1. Furthermore, the simulation model of the under investigation hospital is illustrated in Figure 2.

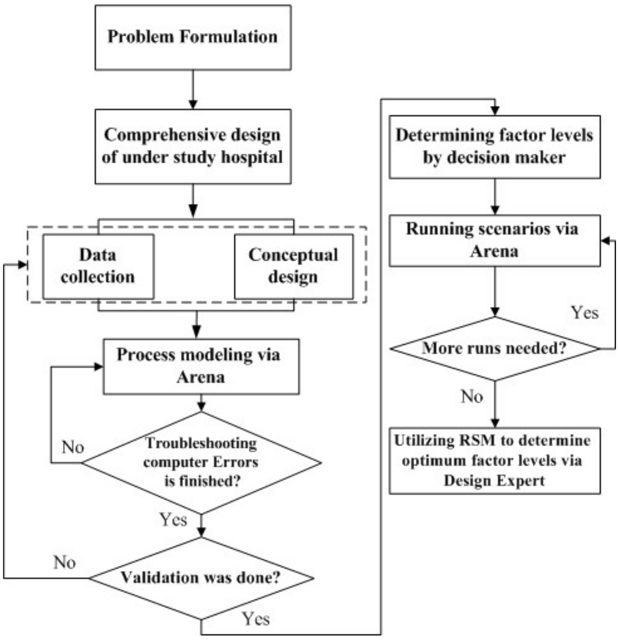

Figure 1. Research Conceptual Model.

According to the importance of this hospital besides the essential need for health services being provided there, round-the-clock medical care is offered by the hospital staff. Furthermore, due to different significance of different hospital wards, distinct weights are assigned to various wards based on the management decisions, to provide reasonable results as well as possible. Distinct assigned weights for various hospital wards are gathered in Table 2.

Results and Discussion

In this section, hospital simulation and associated results analysis achieved by running different scenarios, based on level of effective factors (variables) determined by decision maker, is taken into consideration. First, the existent hospital status is modeled according to available resources via ARENA based on distribution function for each hospital ward gathered in Table 1. Then, variables (resources of different hospital wards) which have constant values (or have slight variations) are eliminated, and variables having close natures have been integrated. In fact, this modification is done due to achievement of a reasonable result besides reduction of the effect of inessential variables on the studying system (hospital). Afterwards, for each factor (essential input variables) appropriate levels are determined for running different scenarios. Therefore, for the purpose of avoiding infeasible results, by taking advantage of decision makers opinion, appropriate levels for input factors have been determined and gathered in Table 3. Then, 4 objective functions, namely queue length minimization, patient waiting time minimization, departure rate maximization and productivity maximization are defined for the sake of investigating performance of different hospital wards. In this case, by

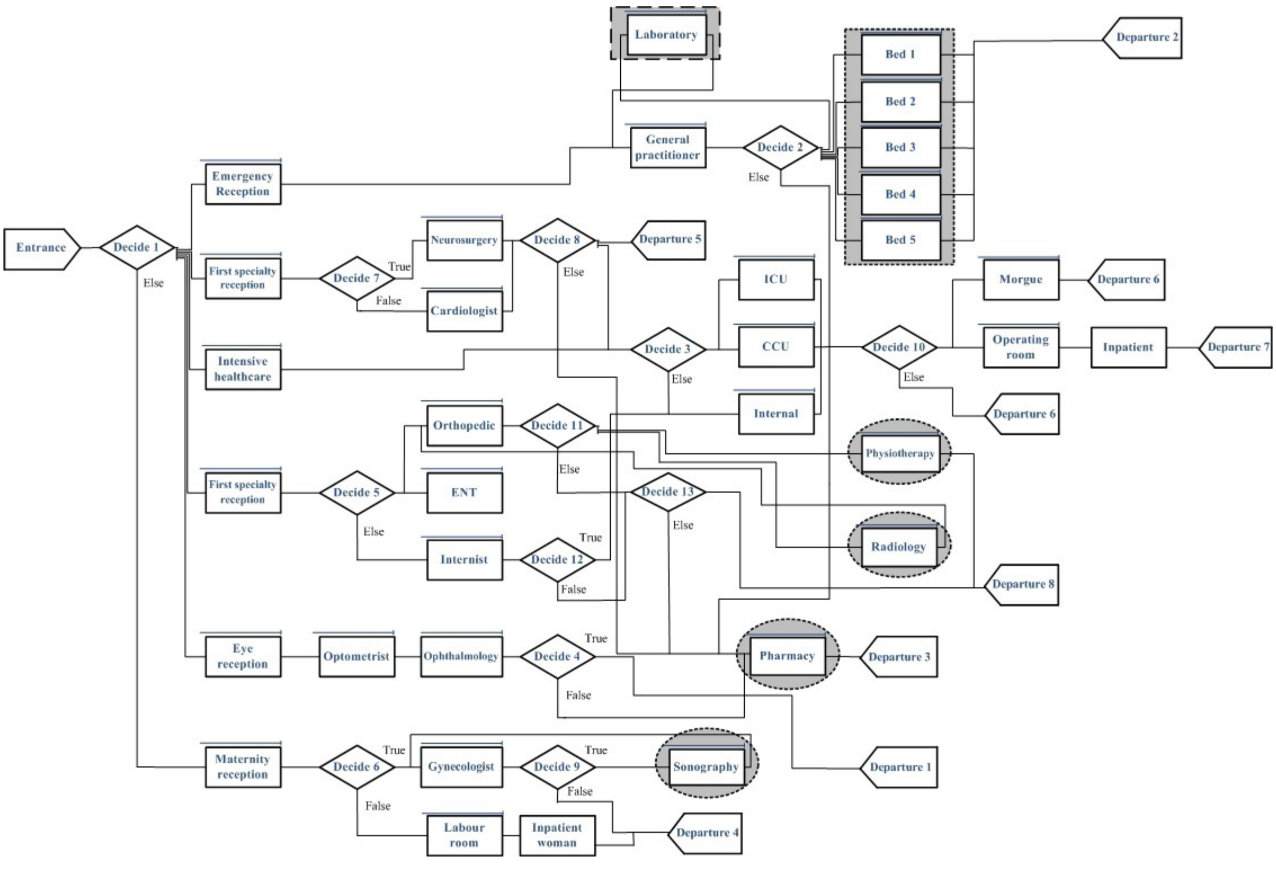

Figure 2. Simulation Model of Under Investigation Hospital.

Table 2. Importance Weight of Different Hospital Wards

Wards in which a queue has been developed	Weight
Laboratory	9
Emergency reception	10
General practitioner	8
Bed 1	10
Bed 2	10
Bed 3	10
Bed 4	10
Bed 5	10
First specialty reception	0.1
Neurologist	7
Intensive care reception	0.1
Operating room	10
Second specialty reception	0.1
Eye reception	1
Optometry	7
Ophthalmology	7
Maternity reception	0.1
ICU	10
CCU	10
Internal	7
Pharmacy	2
Internist	7
ENT	7
Gynaecologist	7
Cardiologist	7
Orthopedic	7
Radiology	9
Physiotherapy	3
Sonography	9
Labour room	10

taking advantage of Process Analyzer via ARENA, 40 distinct scenarios are created and the obtained results are gathered in Table 4.

Then, in order to calculate feasible optimum solutions according to input variables RSM is applied. The appropriate and efficient level of resources determined by decision maker is gathered in Table 3.

In the second phase of this research, and according to Table 3, for each scenario a desirability value has been calculated, by RSM via Expert Design. Afterwards, scenarios with desirability values above 0.65 were screened. The mentioned results are gathered in Table 5.

According to Table 5, it could be understood that scenarios 1 to 7 are the best and the values of input factors are at the optimum level, having a desirability value of 0.7. To clarify, these results are achieved by simultaneously optimizing four above mentioned objective functions and results are sorted according to their assigned desirability value, by applying RSM. By precisely investigating the obtained results it could be understood that ICU and CCU factors have been assigned values of 4 and 5, respectively. In other words, these two input factors are sensitive even to slight variations and by changing their assigned values their pertaining desirability decreases. Furthermore, the internal factor is sensitive and subject to change whenever high or low values are assigned to it. In addition, according to Table 5, 2 factors of operating room and labor room reveal an identical behavior and have been assigned relatively constant values, indicating sensitivity of these two input factors. Additionally, constant values have been assigned to two response variables of resource productivity and departure rate (21 and 348, respectively), indicating the fact that these two mentioned response variables are affected by two other response variables, namely queue length and waiting time in queue. In other words, it could be inferred that input factors of the designed experiment mainly affect response variables of queue length and waiting time in queue.

In this regard, Figure 3 illustrates a contour plot for desirability where X_1 is the operating room and X_2 is the Specialist. Contours are curves of constant response drawn

Table 3. Efficient Level of Input Factors (Variables) for Design of Experiments

Code	Experiment Factors	Levels of Factors (Variables)	Response Variables
A	Operating room	L_1=2,L_2=3,L_3=4	
B	Labour room	L_1=1,L_2=2,L_3=3	
C	Internal	[80,106]	R_1= Queue length
D	CCU	L_1=2,L_2=3,L_3=4	R_2=Departure rate
E	ICU	L_1=4,L_2=5	
F	Specialist	L_1=7,L_2=8,L_3=9, L_4=11, L_5=10, L_6=13, L_7=14	R_3=Resource productivity
G	General practitioner	L_1=2,L_2=3,L_3=4, L_4=5	R_4=Waiting time in queue
H	Physiotherapy	L_1=1,L_2=2	
J	Pharmacy	L_1=1,L_2=2,L_3=3	
K	Radiology	L_1=1,L_2=2	

Input factors are denoted with capital letters but the letter I is not assigned according to limitations associated with Expert Design software.

Table 4. Distinct Scenarios Created via ARENA as an Input for Design of Experiments

Decision Variables										Objective Function Values			
A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**
4	2	86	4	4	13	6	1	2	2	89.6	331	15.27	32464
4	2	96	3	3	14	4	2	2	2	330.5	377	24.5	62620.5
2	1	80	1	1	10	4	2	2	1	416.2	404	27.78	84565.4
4	1	85	3	5	11	2	1	2	2	110.9	392	19.1	23943.9
2	1	120	4	5	7	2	1	2	1	112	335	16.45	21595.83
2	1	83	1	2	7	2	2	1	1	399.6	367	29.94	91601.54
4	3	101	3	5	7	6	2	2	2	164.4	363	23.78	65332
2	3	108	4	5	7	6	1	3	2	62.6	339	20.15	23591.69
2	3	90	4	4	11	5	1	1	1	128.1	356	17.28	17645
4	3	86	4	5	13	5	2	3	1	59.6	396	16.04	22857.63
2	1	80	1	1	9	2	1	1	2	122.6	313	22.95	72538.2
2	1	103	4	4	10	4	2	1	1	57.1	328	12.01	16478.67
4	2	86	3	3	11	4	1	3	1	145.2	349	17.53	41368.66
4	2	80	3	3	10	2	1	1	1	303.5	341	27.55	72783.25
4	2	100	3	3	14	4	2	2	1	330.5	377	24.31	62620.5
4	2	87	3	3	8	3	2	1	1	41.7	328	16.38	25991.6
4	3	98	4	5	7	3	1	1	1	85.9	314	19.13	22232.82
4	2	101	3	5	7	3	2	2	2	100.4	360	19.49	26810.34
2	1	80	1	1	7	2	1	1	1	101.5	340	25.55	67764.3
2	2	81	4	5	7	5	2	1	2	101	341	20.83	21391.8
4	3	100	4	3	11	4	2	2	1	49.1	338	16.1	26815.7
2	1	100	1	1	10	2	2	1	1	455.7	391	28.52	61155.5
2	2	100	4	2	10	4	1	2	1	274	403	23.83	66120.15
4	3	100	3	3	11	2	1	2	1	69.8	340	21.44	31032.67
4	2	100	3	3	10	5	2	1	2	44.4	358	19.83	34051.08
4	2	100	3	3	14	4	2	2	2	330.5	377	24.31	62620.5
4	2	100	3	3	9	2	2	2	2	187.1	362	26.55	63765.1
4	2	100	3	3	10	2	1	1	2	161.7	337	14.52	23562.1
4	2	116	4	5	10	6	1	1	2	186.3	331	20.6	29595.3
4	2	80	1	2	7	2	1	1	2	127.8	302	24.11	53812.8
4	2	117	2	5	9	6	1	2	2	180.9	325	23.23	59599.5
4	2	93	4	5	11	2	2	3	2	106	325	18.1	23800.78
5	3	105	1	5	7	3	2	2	2	112	347	17.05	28550
5	3	120	3	5	7	6	2	2	2	220.6	359	25.6	87105.6
5	3	80	1	1	7	3	2	2	1	556.2	355	26.87	74876.6
5	3	120	4	5	7	4	1	2	2	107.9	345	20.77	26576.9
2	1	120	4	5	10	3	2	1	2	82.8	341	22.39	32274.9
2	1	80	1	1	7	2	2	1	2	101.5	340	25.43	67764.3
5	2	105	3	2	9	6	2	2	2	254	308	20.3	59562
2	1	111	3	5	12	5	2	3	2	96	319	18.8	40899.3

A, Operating room; B, Labour room; C, Internal; D, CCU; E, ICU; F, Specialist; G, General practitioner; H, Physiotherapy; I, Pharmacy; J, Sonography; K, Que length; L, Number of departures; M, Resource productivity; N, Waiting time in queue.

in the X_i, X_j plane keeping all other variables fixed. Each contour corresponds to a particular height of the response surface, as shown in Figure 3. According to Figure 3 it is evident that by simultaneously decreasing the value of operating room and labor room desirability increases and in its best status reaches to 0.7. Furthermore, by having a precise look at the contour plot lines and their pertaining slope it could be understood that although both factors have a reverse impact on increasing desirability but the factor of specialist has a higher impact on desirability.

In this regard, Figure 4 illustrates a contour plot for desirability where X_1 is the operating room and X_2 is the Internal ward. Contours are curves of constant response drawn in the X_i, X_j plane keeping all other variables fixed. Each contour corresponds to a particular height of the response surface, as shown in Figure 4. According to Figure 4 it is evident that by simultaneously decreasing the value of operating room and Internal ward

Table 5. Running Scenarios and Calculation of Response Variables

Efficient Factors in Experiment										Response Variables				Desirability
A	B	C	D	E	F	G	H	I	J	K	L	M	N	
2	2	91	4	5	12	2	2	2	2	14	348	21	16308	0.7
2	2	84	4	5	8	2	2	1	1	15	348	21	14102	0.7
3	3	82	4	5	13	4	1	2	2	15	348	21	12684	0.7
2	2	82	4	5	7	2	2	2	1	11	348	21	16432	0.7
3	3	91	4	5	9	3	2	1	2	11	348	21	14036	0.7
2	2	92	4	5	7	2	1	1	1	15	348	21	13987	0.7
2	2	96	4	5	9	2	1	2	2	5	348	21	15075	0.7
2	3	106	4	5	8	4	1	1	2	17	348	21	16478	0.699
2	2	80	4	5	11	2	1	2	1	22	348	21	11049	0.698
2	1	84	4	5	7	2	2	2	1	8	348	21	17887	0.696
2	2	101	4	5	8	2	2	2	2	28	348	21	16480	0.696
2	2	94	4	5	9	2	2	3	1	28	348	21	16214	0.696
2	3	87	4	5	7	3	2	2	1	33	348	21	16832	0.693
2	2	80	3	5	8	3	1	1	1	16	348	21	19368	0.693
2	3	88	4	5	14	5	1	1	2	52	348	21	16945	0.686
2	1	80	4	4	13	2	1	1	1	58	348	21	13512	0.686
4	3	93	4	5	12	2	2	3	2	59	348	21	17675	0.682
4	3	80	2	5	13	2	1	1	2	66	348	21	20938	0.672
3	1	80	4	5	13	5	2	3	2	45	348	21	28736	0.66

A, Operating room; B, Labour room; C, Internal; D, CCU; E, ICU; F, Specialist; G, General practitioner; H, Physiotherapy; I, Pharmacy; J, Sonography; K, Que length; L, Number of departures; M, Resource productivity; N, Waiting time in queue.

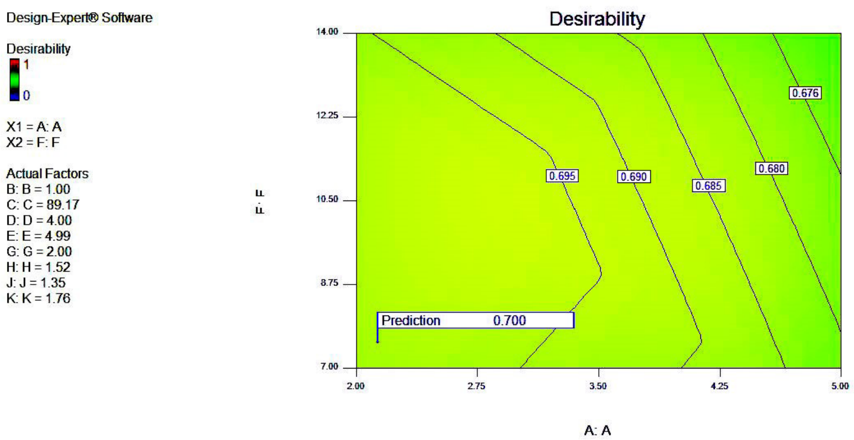

Figure 3. Contour plot for desirability where X_1 is the operating room and X_2 is the specialist.

desirability increases and in its best status reaches to 0.7. Furthermore, by having a precise look at the contour plot lines and their pertaining slope it could be understood that although both factors have a reverse impact on increasing desirability but the factor of operating room has a higher impact on desirability.

Figure 5 illustrates a contour plot for desirability where X_1 is the operating room and X_2 is the ICU. Contours are curves of constant response drawn in the X_i, X_j plane keeping all other variables fixed. Each contour corresponds to a particular height of the response surface, as shown in Figure 5. According to Figure 5 it is evident that by decreasing the value of operating room and increasing the value of ICU desirability of the scenario increases and in its best status reaches to 0.7. Furthermore, by having a precise look at the contour plot lines and their pertaining slope it could be understood that although the factor of operating room has a reverse impact on increasing desirability and the ICU factor has a straight relation with desirability, but the factor of operating room has a higher impact on desirability.

Figure 6 illustrates a contour plot for desirability where X_1 is the internal ward and X_2 is the Specialist. Contours are curves of constant response drawn in the X_i, X_j plane keeping all other variables fixed. Each contour corresponds to a particular height of the response surface,

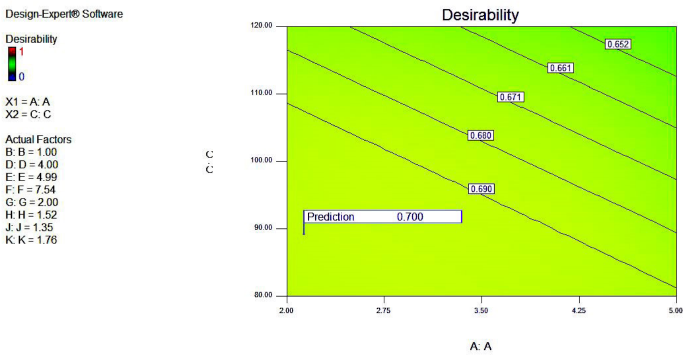

Figure 4. Contour plot for desirability where X_1 is the operating room and X_2 is the internal ward.

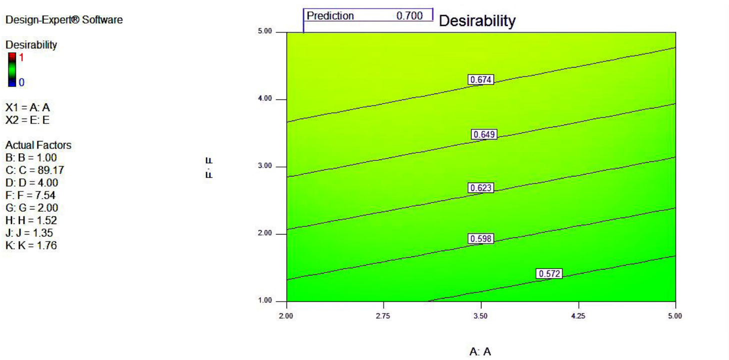

Figure 5. Contour plot for desirability where X_1 is the operating room and X_2 is the ICU.

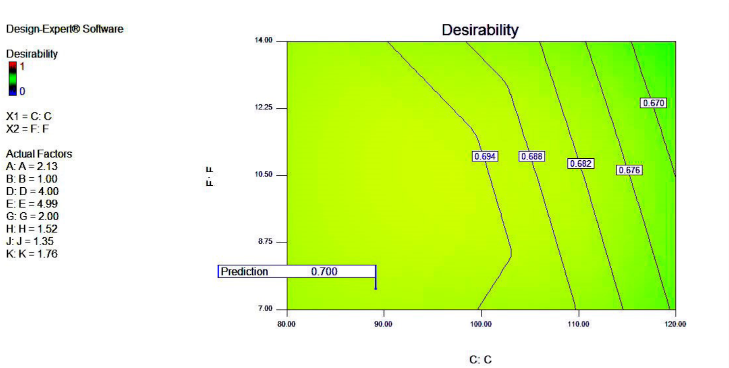

Figure 6. Contour plot for desirability where X_1 is the internal ward and X_2 is the specialist.

as shown in Figure 6. According to Figure 6 it is evident that by simultaneously decreasing the value of internal ward and specialist desirability increases and in its best status reaches to 0.7. Furthermore, by having a precise look at the contour plot lines and their pertaining slope it could be understood that although both factors have a reverse impact on increasing desirability, but the factor of specialist has a higher impact on desirability.

Conclusions

The purpose of this study is integrating a computer simulation model with RSM (as a design of experiments technique) to examine and optimize hospital processes, thereby increasing the satisfaction rate of patients and decreasing hospital costs. In fact, in this study discrete event simulation is utilized and simulation outputs are considered as RSM inputs, providing the possibility to consider all hospital wards simultaneously despite previous researches which examined hospital wards individually. The presented approach has the advantage of pausing the system or even changing the system layout. According to this study, ten main wards are defined as input factors for RSM, namely operating room, labor room, ICU, CCU, specialist, general practitioner, physiotherapy, pharmacy, radiology and sonography. In this regard, desirability is considered as the response surface for RSM. After running the model by Expert Design results indicated that the best possible desirability was 0.7 associated with 7 different scenarios. Although, this research is aiming at determining optimum levels of input factors in a real system, but some data related to some unpredictable events (such as human errors while gathering data) were eliminated. In conclusion, future works may encompass other industrial cases besides applying more precise and developed DOE techniques, to mitigate the risks and limitations encountered in this study.

Competing interests

The authors have no conflict of interest about this research.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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