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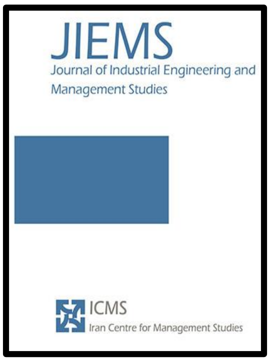

An innovative algorithm for planning a scheduling healthcare units with the aim of reducing the length of stay for patients (Case study: Cardiac SurgeryWard of Razavi Hospital of Mashhad)

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Abstract
One of the key applications of operational research in health systems management is to improve the mechanism of resource allocation and program planning in order to increase the system efficiency. This study seeks to offer an innovative method for the planning and scheduling of health service units with the aim of reducing the patients' Length of Stay (LOS) in the Cardiac Surgery Ward of Razavi Hospital of Mashhad. Also, to estimate the patients' LOS, two methods have been applied: multiple linear regression models and Bayesian networks. The introduced method takes into account all treatment processes of patients in an integrated system and by eliminating any undue waiting time, the length of stay can be reduced to a significant extent. Also, the system efficiency is considerably improved by resolving the current conflicts in the workflow of on-call physicians and optimum allocation of resources, gaining satisfaction of health sector officials and patients.

Keywords: Bayesian networks; Length of stay; Multiple linear regression; On-call physicians; An innovative algorithm.

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1. Introduction

The lack of efficiency and effectiveness of services not only reduces the level of life quality, but also prevents the productivity improvement in all other economic sectors and increases injustice and social inequality. Moreover, the health care system is one the most important service sectors, which serves as an indicator of development and social welfare (Abtahi and Kazemi 2005). Thus, the scientific and economic recognition of this sector is of paramount importance. As one of the primary organizations responsible for health service provision, hospitals play a pivotal role in the economy of health. Moreover, as the most expensive and critical element of the health system, hospitals are in need of special attention, so that in developing countries, more than a 70% share of healthcare resources is

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dedicated to hospital services (Sadaghiani 2005). It is obvious that due to the recent decrease in birth years, it is expected that in near future, countries will face with the issue of population ageing. As a requisite for proper management, the preparation of infrastructure, equipment and necessary resources, including hardware and software, are of special importance.

Now, considering the mounting cost of setting up a health center (hospital), a convenient and practical solution, from the perspective of health economics, to reduce the gap between supply and demand is to improve the planning and scheduling of these centers to realize the optimum use of the capacities. In this regard, the most fundamental issue that health sector managers have to cope with is scheduling, resource allocation and performance assessment of hospital to provide satisfactory service to patients. The scheduling and sequencing of operation is a decision making issue with a wide range of applications in manufacturing and service systems. In today's competitive atmosphere, an efficient scheduling and sequencing system is an essential and inevitable requirement for survival in the business environment (Pinedo 2012, Baker 1974). Scheduling and sequencing operations, as a decision making process, plays an integral role in most manufacturing and producing systems as well as most services environments. A survey of the relevant literature indicates that the issue of scheduling should be taken into account at different levels of decision making, whether short term, medium term and long term (Muchnik 1992; Hans and Nieberg 2007; Morton and Pentico 1993). Scheduling is especially important in the field of healthcare. The proper scheduling of health wards in a hospital can lead to the optimum use of resources and reduce the cost of staff, over times of surgeons, nurses, anesthesiologists and so forth.

Along with these achievements, the proper scheduling with the reduction of the waiting time of patients for the reception of services and accelerating the provision of services to emergency patients can upgrade the level of service provision. Scheduling in the health sector is a critical issue for at least two reasons:

1. The complexity of allocating resources (rooms, surgery, surgeons, etc.) to surgical operations and its sequencing.
2. The important uncertainty prevailing in most activities of health system.

The prevalence of various forms of uncertainties in the health sector, including uncertainty surrounding the duration of the surgery and the length of stay for patients, random admission of emergency patients, unpredicted inaccessibility of equipment, the untimely presence of the surgeon, patient and specialists for the surgery, has rendered this issue a critical challenge in health care planning. So far, a growing body of studies have been dedicated to this issue. Barkaoui et al. (2002) presented a model for the scheduling of operation rooms with the aim of reducing the waiting time of patients. In their model, they used discrete-event simulation method.

A model of discrete-event simulation for scheduling operating rooms was proposed by Denton et al. (2006). They intended to display how this model can inform the strategic and operational scheduling decisions of surgeries. Zhang et al. (2009) developed a mixed integer programming model for the allocation of operating rooms for various purposes under time constraints. Their major goal was to minimize the duration and waiting times of surgery. In their model, they took into account a variety of factors such as priorities of patients, including both emergency and non-emergency patients as well as resource constraints. Tànfani and Testi (2010) presented a zero-one linear programming model with an innovative method to solve the issue of scheduling surgeries. Their ultimate goal was to reduce patient waiting time. Niuet et al. (2011) proposed a discrete event simulation model for scheduling operating rooms. They intended to minimize waiting time and the patients' length of stay of in the hospital. They also provided some interesting evaluations regarding the efficacy of operations rooms and resource allocations thereof. Lee and Yih (2012) proposed a model for scheduling operating rooms.

The main assumption was concerned with the limitations in the post-anesthesia care unit and uncertainty during the operation. Their proclaimed goal was to reduce waiting time and their proposed model was solved by genetic algorithms. Lee and Yih (2014) presented an operating room scheduling problem to determine the start time of surgery. Again, the underlying assumption of their article was the uncertainty surrounding the length of operations, which the authors calculated by fuzzy sets. To solve their problem, they used a meta-heuristic method based on genetic algorithm.

Neyshabouri and Berg (2017) proposed a two-stage robust optimization model to address the existing uncertainty in surgery duration and length-of-stay in the surgical intensive care unit. Bruni et al. (2015) presented a comprehensive framework for modeling stochastic programming of operation rooms. One assumption adopted in their model was the uncertainty about the admission time of emergency patients and the operation time, for which an innovative method was considered.

Saremi et al. (2015) used a mathematical model to address the issue of scheduling patients with random service time and sequencing of heterogeneous services in a number of service centers. They also considered availability and compatibility of the work resources for providing services to various patients (scheduled and emergency). This paper presents a multi-objective searching method to solve the problem, with the aim of minimizing the patient waiting time and accomplishment of tasks. Deng et al. (2015) took up the scheduling problem of surgery operation with random surgery schedules and proposed a mixed integer programming model. To estimate the time of surgery, they used log-normal distribution. The objective of the problem was the allocation of operations and also specification of the schedule and sequence of their start time. Astaraky and Patrick (2015) developed a model based on Markov Decision Making Process for scheduling patients in a surgical ward with limited resources. The operation time in their model was probabilistic, which drew on lognormal distribution for computation.

Bai et al. (2016) studied a multiple-OR surgery scheduling problem. They designed a Discrete Event Dynamic System (DEDS) for this problem and proposed a sample-gradient-based algorithm for the sample average approximation of their formulation. The main objectives of this problem was minimizing the cost incurred from patient waiting time, OR idle time, OR blocking time and OR overtime. Maschler et al. (2017) used an Iterated Greedy (IG) algorithm to solve the Particle Therapy Patient Scheduling Problem (PTPSP). In this study they built upon this IG and exchanged two main components: the construction phase and the local search algorithm. Bam et al. (2017) presented a mixed-integer programming model for single-day in-patient elective surgery scheduling considering surgeons, operating rooms (ORs), and the post-anesthesia care unit (recovery). This model specifies the number of ORs to open for the day and surgeon-to-OR assignments in the first phase, and determine surgical case sequencing in the second phase. They evaluated schedules under uncertainty using a discrete-event simulation model too. Turhan et al. (2017) proposed a mixed integer programming based heuristics for the Patient Admission Scheduling (PAS) problem. This model uses patient decomposition considering patient length-of-Stay (LoS), room preference, admission date, specialism choice, and age, as well as time decomposition considering different optimization window sizes. The main goal of this study was to provide high quality solutions in shorter run times.

In a nutshell, the importance of scheduling operation rooms in healthcare units of hospitals cannot be ignored. However, it is worth noting that most studies have merely addressed the scheduling of operation rooms, while these rooms, as a part of a larger system, are influenced by a host of preceding and subsequent variables in this process. Therefore, the best scheduling and planning should also take into account other related hospital wards, beside operation rooms, in an integrated manner. In this paper, the procedure taken by patients in need of cardiac surgery is discussed.

For this purpose, first the length of stay in each of the health units is estimated, and then the allocation and scheduling is executed so that the overall patients' length of stay of is minimized. The results of this research were applied to the Department of Cardiac Surgery of Razavi Hospital in the city of Mashhad, Iran. Further analyses and discussions are provided at the end of the article.

2. Method

In this article, the issue of the scheduling cardiac surgery ward has been treated as a flexible job shop problem. That is, first patients are admitted to the cardiac surgery ward, and then depending on their conditions, a hospital bed is allocated to them. Afterward, they are scheduled for the operating room so that the necessary surgery can be performed. In the next step, these patients, for the purpose of recovery and recuperation, are transferred to the intensive care unit (ICU) and stay there for a certain period of time. Ultimately, these patients are transferred from the intensive care unit to the department of cardiac surgery and once again a bed is allocated to them until they are discharged. Of course, this procedure may vary in specific cases. For example, it is possible that a patient, due to a series of unpredicted problems, needs another surgery after being transferred to the ICU, which means a scheduling of the operation room for the second time. However, given the rare occurrence of these situations, they have not been considered in this study. Another point that should be noted is that the patients are brought to the cardiac surgery department from three different places, including:

- Home
- Cath-lab (a group of echocardiography, angiography, CCU and other similar units in the hospital)
- EMS (Emergency Medical Services)

Patients who are brought to the cardiac surgery ward from their home fall in the category of elective operations, which are not treated as urgency. However, patients transferred from the Emergency Unit to the cardiac surgery ward are treated as emergency, and should receive care and treatment immediately. Moreover, patients brought from the Cath-lab unit to the surgical ward could fall in either of the above categories (emergency and non-emergency). Nonetheless, it should be noted that these patients take higher priority compared to patients brought from home, because they have been already hospitalized in the department and if their operation is postponed, the length of their stay in the hospital may be prolonged.

The present article, assumes that there are h healthcare units which are supposed to accommodate n patients until the course of their treatment is completed. It is also assumed that each of these wards can take as many as m_h beds. Additionally, patients can be allocated to a specific ward more than once. For instance, patients are assigned to one of the beds in the cardiac surgery department at the time of admission and after leaving the ICU. The goal of this problem is to determine the exact date of the surgery and hospitalization of patients in each ward with the aim of reducing the length of stay for patients, which can contribute to the enhanced satisfaction of patients and hospital officials and the increased efficiency of healthcare units.

Obviously, any problem is underlined by a series of assumptions and limitations. Now, the closer these assumptions are to reality, the possibility of their application in the real world is increased. Therefore, in this problem, attempts have been made to employ assumptions that correspond to real conditions and current situations of hospitals in Iran. The assumptions and constraints employed are:

- Lengths of treatments (surgery, ICU, inpatient care and so forth) are not fixed and vary from case to case.
- At any moment, only one patient can use a bed.
- For every patient in need of surgery, only a surgeon assumes the responsibility of the operation.
- The planning horizon for scheduling of patients is on a daily basis.
- Each day, physicians should be on-call for emergency operation.
- The time horizon for the allocation of on-call physicians is on a monthly basis.
- Emergency patients and children are given priority.
- The capacity of operation rooms, ICU units and inpatient beds is limited.
- Patients with similar first or family names, due to the possibility of human error in the process of performing surgery, should be operated in the same day.
- For emergency patients in the operating room, a separate bed should be allocated.
- One of the ICU beds must be remained vacant over 24 hours to provide services to emergency patients.
- The doctors on the on-call list are not allowed to choose their preferred surgery.
- To perform a preferred surgery, a doctor is assigned a specific time interval. These periods, however, are distributed in different days.
- Since the time of transferring patients between wards is negligible, it has not been considered in our planning.
- A time period should be considered between any two surgeries for the preparation of the operating room.
- It is not possible to assign more than one period of time in a day to a doctor.

Now, to solve the problem, first the length of stay for patients in each ward of cardiac surgery department (inpatient wards, operating rooms and intensive care unit) is estimated accurately and then an efficient algorithm is employed for the scheduling of doctors and patients.

Figure 1 demonstrates the flow chart of the method applied for the LOS estimation.

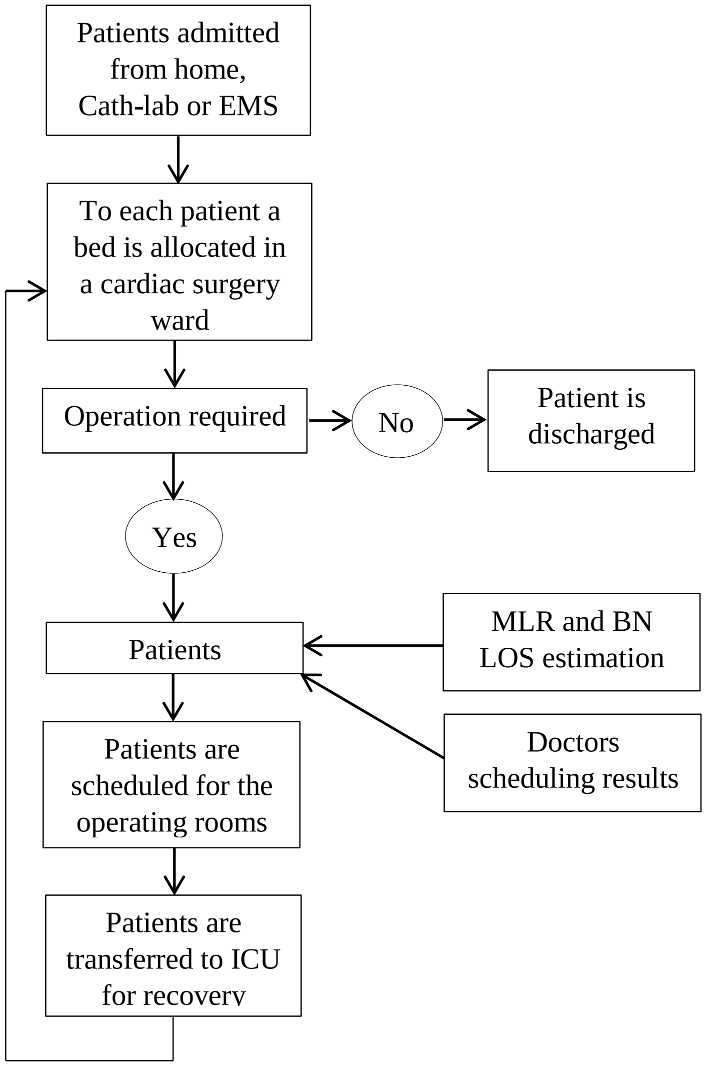


Figure 1. Process flow for the patients' length of stay estimation

2.1. LOS estimation

In this paper, the multiple linear regression (MLR) method and Bayesian networks (BNs) have been used to estimate the times under study.

2.1.1. Multiple Linear Regression

Multiple linear regression attempts to model the relationship between two or more explanatory variables (x_i, i=1, 2,…,p, p>1) and a response variable (y) by fitting a linear equation to the observed data (Freedman 2009). Every value of the independent variable is associated with a value of the dependent variable. Formally, the model for multiple linear regression, given *n* observations, is:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i, \qquad i = 1,2,\dots,n$$

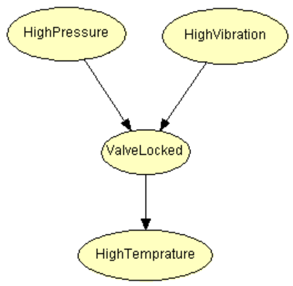
To evaluate the efficiency of the regression models, R^2 is applied. R^2 is the fraction of variance in observed data that is explained by a model. It ranges from 0 to 1, where higher values correspond to better predictions.

2.1.2. Bayesian networks

A BN, B = (G,θ_G), consists of two parts. The first is related to the directed acyclic graph (DAG) and the second indicates the parameters of the network. These parameters provide the conditional probabilities between variables. In $G = (X, E_G)$, nodes of network is collected in X and E_G denotes the set of directed edges which represents dependency relationships between variables. For a directed edge $Pa(X_i) \rightarrow X_i$, X_i is a child and $Pa(X_i)$ is the parent set of X_i (Lauritzen 2004).

In order to construct a Bayesian network, two parts should be determined: a DAG which specifies the structure of the Bayesian network and the probability distributions. In this paper, where we have no prior knowledge about the dependencies between variables, the PC algorithm (Spirtes 1993) is used for the structure learning step. Once the structure of the Bayesian network is learnt, the parameters for this specified DAG are calculated using maximum likelihood estimation (MLE) methods.

A simple Bayesian network that can be applied in the field of system failure prediction is shown in Figure 2. This Bayesian network indicate that 20 percent of the time system suffers from the high pressure (P(HP=True)=0.2) and once the system has a high pressure and high vibration the valve will be locked with probability 0.9 (P(VL=True| HP=True, HV=True)=0.9) leading to a high temperature in the system in 80% of the time (P(HT=True| VL=True)=0.8).



HighPressure (HP)	T	F
	0.2	0.8

HighVibration(HV)	T	F
	0.3	0.7

ValveLocked (VL)		P(VL|HP, HV)	
HP	HV	T	F
F	F	0.1	0.9
T	F	0.4	0.6
F	T	0.6	0.4
T	T	0.9	0.1

HighTemprature (HT)	P(HT|VL)	
VL	T	F
T	0.8	0.2
F	0.1	0.9

Figure 2. A simple example of a Bayesian network with conditional probability tables

2.1.3. Performance evaluation

To evaluate the performance of each model and compare the efficiency of multiple regression models with that of the Bayesian networks, data set are divided into train set (85% of the data set) and test set. Regression models as well as the Bayesian networks are fitted to the train set and the models' predictive efficiencies are evaluated using Mean Absolute Percentage Error (MAPE) calculated from test sets.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Predicted\ value_i - Actual\ value_i}{Actual\ value_i}\right|$$

Smaller values of MAPE indicate a better fitting model.

2.2. Scheduling algorithm

After estimating the length of stay for patients in each ward, we have to address the scheduling algorithm. This algorithm consists of two parts dedicated to scheduling of on-call doctors (doctors taking care of emergency patients) and scheduling of patients. To schedule on-call doctors, this algorithm follows specific steps described below. The goal of this algorithm is to allocate days of a month to on-call doctors so that first the length of their stay in hospitals remain relatively equal and the scheduling is based on days during which a doctor has the highest free time. To better understand the algorithm, parameters, sets and variables are defined as follows:

Parameters	
The maximum difference between days dedicated to on-call doctors	d
The maximum times of estimating the difference between days dedicated to doctors	n
Sets	
The number of on-call doctors for whom the planning is made	$r = 1, \dots, R$
Days of a month	$k = 1, \dots, K$, $K = 30$ or 31
The sum of hours that r^{th} doctor on k^{th} day of the next month cannot attend the hospital	u_{rk}
Variables	
The index of r^{th} doctor selected for k^{th} day of the next month	p_{rk}

Step 1) doctors register the schedule of their attendance in a table similar to Table 1:

Table 1: the schedule for the absence of doctors in the next month

Days of a month	1	2	3	......	K
1st Doctor	u_{11}	u_{12}	u_{13}	......	u_{1K}
2nd Doctor	u_{21}	u_{22}	u_{23}	......	u_{2K}
......					......
*r*th Doctor	u_{R1}	u_{R2}	u_{R3}	......	u_{RK}

Step 2) A table made of two rows and *k* columns where the first row represents the days of the following month and second row shows P_{rk} (see Table 2).

Table 2: The on-call list of the next month

1	2	3	4	5	6	7	..	K
p_{r1}	p_{r2}	p_{r3}	p_{r4}	p_{r5}	p_{r6}	p_{r7}	..	p_{rK}

Step 3): To the values of p_{rk}, a set of sequential number (1,2,..., R) is allocated. For example, if there are three doctors, the second row of Table 2 is completed as - 3-2-1-3-2 ……… 1 3-2-1. This step gives a relatively good dispersion to the final results, reducing the need for correction in later stages.

Step 4): At this stage, doctors randomly selected in the previous step are taken into account. In other words, for a given day *k*, if the total hours of absence for a given doctor is equal to $\min_k\{u_{rk}\}$, he/she would remain unchanged in that cell; otherwise, he/she is allocated to a cell with the value of $\min_k\{u_{rk}\}$**.** In case of equality of states, one will be chosen randomly.

Step 5): In this stage, the adjacent cells in Table 2 (k and k + 1) are compared with each other. If the same doctor is allocated to each one, the k + 1 cell is chosen and allocated to a doctor with greater value of u_{rk}. Otherwise, none of the two cells would change.

This process continues until it is ensured that no doctor is put on the on-call list for two consecutive days.

Step 7): In this step, the total number of days assigned to each doctor must be calculated for the following month. If the difference between the total numbers of days allocated to doctors *i* and *j* is less than or equal to d, the on-call planning is accepted; otherwise, the number of days greater than d is assigned to a doctor with fewer allocated days, and then the constraints regarding the non-repetition of adjacent cells is checked. This process is repeated until the difference between the number of cells assigned to doctors is less than or equal to d. Of course, in exceptional cases (such as when a doctor has a long business trip and obliged to take leave), to avoid any problem for the termination of the algorithm, the n repetition limit is also applied, meaning that if the calculation times of the total difference between cells allocated to doctors is equal to the number n, the algorithm is halted.

Step 8): At this stage, the program is compared to the surgery plans selected by physicians and in case of any interference, this problem would be solved by a substitution; otherwise the final answer is saved as the final on-call schedule. For the purpose of substitution, the doctor with the interference in his/her schedule is substituted by a doctor without any scheduled surgery on that day, who is also qualified to be included in the on-call list.

The second part of the scheduling algorithm is about the scheduling of patients. The purpose of this algorithm is to reduce the length of stay in the cardiac surgery ward of the hospital and therefore raise the level of patients' satisfaction. For this purpose, first the required parameters are given values as follows, and then steps of algorithm are described.

It should be noted that each working day is divided into two working shifts (morning and afternoon), with each being assigned to a doctor. It is impossible to allocate two working shifts to a doctor in a day.

Parameters

No. of wards	h
No. of beds per ward	m_h
No. of patients	n
No. of medical operations for patients	O_n
The maximum interference between a surgery and its following time intervals	t

Step 1): In the first step, patients are sorted out in terms of their medical priority. These priorities are defined as follows:

- priority (1): emergency patients
- priority (2): patients admitted to Cath-lab, whose surgery type is elective and are aged under 20
- priority (3): patients admitted to Cath-lab, whose surgery type is elective and are aged over 20
- priority (4): patients not admitted to Cath-lab, whose surgery type is elective and are aged under 20
- priority (5): patients not admitted to Cath-lab, whose surgery type is elective and are aged over 20

Step 2): in this stage, the patients belonging to one of the above groups are assigned with a priority. In this algorithm, the priority is given based on the lowest processing time.

Step 3): in this stage, based on previous steps and all the assumptions underlying the flexible job shop scheduling, the insignificance of the displacement time of patients and time of preparing an operating room after each surgery, the scheduling is performed. In fact, given the type of surgery and the time intervals dedicated to that surgeon, the patient is scheduled in the operating room time and the start and end times of his surgery are determined. Afterwards, the steps before and after surgery (admission to the surgical ward or ICU) are implemented in case the wards are vacant. In case a ward is occupied, the operation is postponed until it is no longer occupied.

Step 4): in this step, the target function of the problem that determines the length of stay is calculated for all patients as follows:

$$LOS_k = C_k - S_k \qquad k = 1, \dots, n \tag{6}$$

Where LOS_k represents the length of stay for k^{th} patient, C_k is the discharge time of k^{th} patient and S_k is the admission time of k^{th} patient.

Step 5): in this step, the algorithm is reverted to step 4 with some changes in tasks of equal priority to compute the target function. If the new answer is better than the previous one, it takes the place of the previous one; otherwise, the same answer remains unchanged. This process is repeated until after n implementation of this algorithm, no further improvement is made in the answer of the problem. Finally, the proposed algorithm specifies the date and time of discharge from each ward and calculates the length of stay for patients. It is clear that this is not a global optimal answer, but considering the priorities that should be determined at the outset(compulsory or health priorities), the number of possible answers may be reduced and it will be more likely for the algorithm to provide a satisfactory answer. In the next section, attempts have been made to evaluate the performance of the algorithm by solving a practical and real-life example.

3. Date Description and Numerical Results

In this research to estimate the patients' LOS we need to study the patient's length of stay in the surgery ward before the operation, the time spent for the surgery, length of stay in the ICU and finally the length of stay in the surgery ward, after being discharged from the ICU. Hence four response variables should be estimated. Times spent in each ward are independent of each other, so separate models are fitted for each response variable.
Table 3 describes the data collected from the Cardiac Surgery Ward of Razavi Hospital of Mashhad concerning 200 patients (August, 2015).

Table 3. Variable description of data records coming from the Cardiac Surgery Ward of Razavi Hospital of Mashhad.

Variable		**Type**	**Description**
Predictor variables	Age	Discrete	Patients ages are discritisized into 10 categories: 0-10, 10-20, …, >80
	Gender	Discrete	Male and Female
	SurType	Discrete	There are 10 surgery types: Coronary Artery Bypass Grafting (CABG), Aortic Valve Replacement (AVR), Mitral Valve Replacement (MVR), Tricuspid Valve Replacement (TVR), Atrial Septal Defect (ASD), Ventricular Septal Defect (VSD), Bentall, CABG+MVR, MVR+TVR, MVR+TVR+AVR
	Surgeon	Discrete	8 surgeons operate the surgeries.
	TransPlace	Discrete	The place from which the patient was transferred to the surgery ward: Home, Cath-lab, EMS
Response variables	SurTime	Continuous	Duration of the operation.
	LOS_ICU	Continuous	Length of stay in the ICU.
	LOS_pos	Continuous	Length of stay in the surgery ward, after being discharged from the ICU.
	LOS_pre	Continuous	Length of stay in the surgery ward before the operation.

To estimate each response variable, a multiple regression model and a Bayesian network is fitted to the response variable along with the five predictor variables. The regression model obtained for the 'Duration of the operation' is:

$$SurTime = 1.46 - 0.217\, SurType_2 - 0.227\, SurType_3 - 0.050\, SurType_4 - 0.471\, SurType_5 - 0.442\, SurType_6 + 0.117\, SurType_7 + 0.212\, SurType_8 + 0.104\, SurType_9 + 0.096\, SurType_{10}$$

Indicating that the only factor affecting the *SurTime* is the *SurType* (p-value<0.05), with R^2= 0.796. *SurType* and *Age* are two factors identified as the variables affecting the *LOS_ICU*, with R^2=0.965. *Surgeon* and *SurType* are the two most important factors in predicting *LOS_pos* (R^2= 0.955) and *LOS_pre* is mostly affected by *TransPlace*.

Figure 3(a) also illustrates the Bayesian network for the *SurTime* as the child node of the predictor variables. Unlike the regression models, the structure of the Bayesian networks are the same for the four response variables but the strength of the relationships, shown in the form of probability tables (Figure 3(b-c)), varies in the obtained Bayesian networks. In the Bayesian network models, response variables are directly affected by *SurType*, *Surgeon* and *TransPlace*. On the other hand, *SurType* is the child of *Gender* and *Age*. It means that they are the direct cause of surgery type and once we know the type of surgery, gender and age of the patient have no effect on the response variable.
Table 4 shows the MAPE values for the Multiple Linear Regression models and Bayesian network models considering four response variables. All four numbers are lower for the Bayesian network models compared to the Multiple Linear Regression models. Therefore, Bayesian networks seem to provide the better fit.

Table 4. MAPE values for the Multiple Linear Regression models and Bayesian network models considering four response variables

	Response variable			
Model	**Sur.time**	**LOS_ICU**	**LOS_pos**	**LOS_pre**
MLR	0.0937	0.0535	0.0428	0.0478
BN	0.0572	0.0514	0.0334	0.0396

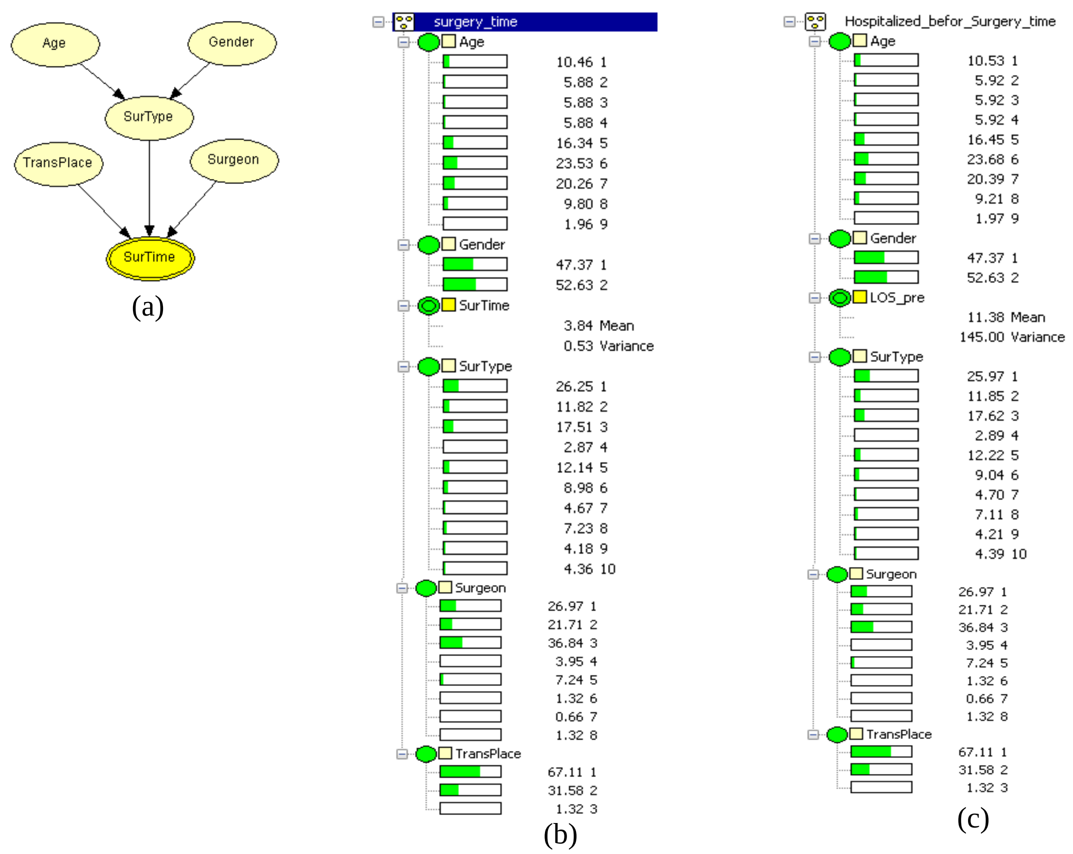


Figure 3. (a) Structure of the Bayesian network for *SurTime* and 5 predictor variables (b-c) Probability tables of the Bayesian networks for *SurTime* and *LOS_pre* respectively.

To assess the performance of the scheduling algorithm of on-call doctors, the absence hours of on-call doctors in the February were collected. Then, based on these hours and planning of the elective surgeries, the proposed algorithm scheduled on-call doctors for the next month. It is worth noting that elective surgeries were not performed on holidays (Fridays in Persian calendar), and in working days, they were scheduled for two morning and afternoon shifts. Only three doctors were selected for on-call schedule. The parameters of this algorithm for the problem under study were defined as d = 3, n = 100. Table 5 shows the results of this section.

Table 5. Results of on-call doctor scheduling algorithm

	Proposed algorithm	Under real conditions
Sum of days allocated to doctor A in February	12	10
Sum of days allocated to doctor B in February	10	10
Sum of days allocated to doctor C in February	8	1
No. of interferences with the elective surgery schedules	0	12

As shown in Table 5, there is much interference between the planning made for the on-call doctors under real conditions and their preferred surgical schedules, while the planning generated by the proposed algorithm does not cause any interference. In addition, the planning made under real conditions has failed to account for the absence hours of on-call doctors and the cells are merely planned sequentially and randomly. Results clearly demonstrate the efficiency of the proposed algorithm for allocating and scheduling on-call doctors.

To measure the efficiency of the scheduling algorithm of patients, 30 samples included in the test set of the LOS estimation were used. It is worth mentioning that since the goal of this research is a comparison of the results with real-life conditions, the studied parameters must be based on reality. Accordingly, the surgeries in the morning shift started at 7.30 am and continued until 3 pm. The surgeries in the afternoon shift also started from 3:30 pm and lasted until 9:30 pm. In addition, no patient was discharged between midnight and 8 am. Moreover, a 30-min time interval was considered between surgeries for the preparation of the operation room. To increase the flexibility of the scheduling, a period of 2 hours was considered for the interference between each surgery and its subsequent time interval (t = 2). In this study, the number of health units is h=30, the number of beds in each ward is $m_3 = 2m_1 = 15\ , m_2 = 10\ ,$ the number of patients is n=30 and the number of therapeutic operations of patients is O_n= 4. The estimated LOS value for the proposed algorithm is 147.93 hour while the LOS under real conditions is 178.33 hour. It can be concluded that the proposed algorithm leads to the production of superior answers with respect to real conditions and can reduce the length of stay for patients, which further indicates the high efficiency of this algorithm. The proposed algorithm can compute the admission and discharge times of patients in each ward separately, and determine the efficiency and the extent of resources appropriation, including beds, operation rooms and ICUs.

4. Conclusions

A review of articles related to scheduling of the operation rooms suggests that most studies in this field have addressed the issue of scheduling operating rooms separately. Only a few studies have examined the operating rooms along with ICUs and recovery units (Cardoen et al. 2010; Demeulemeester et al. 2013). Moreover, the literature review in the introduction section of this article reveals that articles that have explored the scheduling of the operating rooms under uncertainty at the time of treatment as one of their assumptions, have not employed the multiple linear regression method nor the Bayesian networks for the patients' LOS estimation (Lee and Yih 2014; Demeulemeester et al. 2013). The two above mentioned can be the strength points of this research.

On the other hand, assumptions which have been used in this study, such as the inclusion of the first and family name of patients in scheduling, giving priority to children, and reserving

and allocating vacant beds to emergency patients are also among assumptions not mentioned in previous studies (Cardoen et al. 2010; Demeulemeester et al. 2013), though these matters are of utmost significance in the reality and can hugely affect the planning.
In this study, an algorithm for planning and scheduling patients with the aim of reducing the length of stay for patients was presented. This paper estimated the length of treatment for patients in all hospital wards applying two estimation methods: multiple linear regression method and Bayesian networks. Then efficient algorithms were used to schedule patients and make appointments for their examination and surgical operations. Also, based on the presence or absence times of doctors in the hospital, a monthly planning for on-call doctors was specified. This planning had the minimum interferences with elective surgery schedules and led to a high decrease in patients' LOS. Furthermore, lack of interference in surgeons schedules and their appropriate dispersion during each month, can be one another of the strength points of proposed algorithms. Additionally, for better and more accurate allocation of surgeries, in this research a specific time period was allocated to each surgeon during the week. That is, the surgeon can only have the surgery of their choice in the specified time periods. To increase the flexibility of these periods, a time window (the maximum interference with the following surgery) was assumed.
Another contribution of this study is the consideration of all the therapeutic processes of patients, which can significantly, increases the accuracy of the data and results. Obviously, excluding any of the hospital wards can lessen the accuracy of calculations and increase the chance of errors. Furthermore, giving priorities to children, eliminating similarities of names in surgeries and allocating separate beds to emergency patients in hospital wards and ICUs are the other outstanding contributions of this research.

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