An Improvement in Master Surgical Scheduling Using Artificial Neural Network and Fuzzy Programming Approach

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Abstract. In this study, a new mathematical model is presented for the master surgical scheduling (MSS) problem at the tactical level. The capacity of the operating room for each specialty is determined in the previous level and used as an input for the tactical level. In MSS, elective surgeries are often performed in a cycle for a cycle. However, this problem considers both elective and emergency patients. The model of this problem is specifically designed to achieve this tactical plan to provide emergency care, as it provides the possibility of reserving some capacity for emergency patients. The current study, forecast emergency patients by applying an artificial neural network, and reserve capacity for them are based on the demand. Fuzzy chance-constraint programming is employed to handle the uncertainty in the model. The data of a private hospital in Iran is used to solve the problem using GAMS software. The results show that the performance of the proposed method against the solution in the hospital performed better.

Keywords: Master surgical scheduling, Fuzzy mathematical programming, Prediction, Neural network

1 Introduction

Due to an increase in society's ages and medical progress, the demand for health services worldwide is increasing [1, 2]. Besides, lower costs and a lack of human resources lead to increased pressure on hospital resources. Therefore, the importance of optimizing the use of scarce resources in hospitals is quite evident. The most valuable resource in most hospitals are in operating rooms (ORs). ORs are strongly linked to downstream resources, such as the post-anesthesia care unit (PACU), the intensive care unit (ICU), and the patients' general ward [3]. One of the major activities at a hospital is providing surgery to patients. Freeman et al. [4] stated that 60 to 70 percent of all hospitalized patients require surgery, and Hans [5] stated surgery costs account for approximately 40% of total hospital costs and operations generate about 67% of hospital revenues. Appropriate surgical planning methods are essential for the proper utilization of scarce hospital resources and the need to treat most patients.

Patients are usually divided into two groups: elective and emergency patients. Elective patients are not on medical emergencies, and their surgery can be pre-planned, depending on the availability of the surgeon and the patient. On the other hand, emergency patients may need surgery within a few hours or up to a few days. Surgery planning may be divided into three decision stages [6]. At the strategic level, the number of blocks assigned to the specialties. A master surgery schedule (MSS) is developed at the tactical level to schedule different specialties to the ORs through the week. Finally, at the operational level, the patients are scheduled to the ORs.

The primary purpose of this paper is to provide a tactical decision for the departments that provide surgery to both elective and emergency patients. More specifically, we consider both elective and emergency patients in the master surgery scheduling problem (MSSP). The schedule is typically made for one cyclic week, and this weekly schedule is generally applied for a period of six to twelve months [7]. The rest of this paper is organized as follows: Sections 2 and 3 present literature review and the problem; the artificial neural network and fuzzy methods are explained in sections 4 and 5, respectively. In sections 6, a case study and the numerical results are discussed, respectively. Finally, section 7 concludes the research and provides suggestions for future research.

2 Literature Review

The master surgical scheduling problem has been the object of several studies. Most authors considered only elective patients, arguing that the emergencies are taken care of by dedicated resources [8]. On the other hand, Adan et al. [9] considered the emergencies by estimating their arrivals based on simulation and Poisson process and reserve capacity for the patients based on this.

In addition to including the surgical specialties and the operating rooms, some authors include other resources, such as wards and intensive care units, as they may impose bottlenecks for efficient patient flow [10]. In contrast, others neglected wards in their model because they believed that access to beds does not impose a bottleneck on the efficient flow of patients [11]. Several authors include aspects of uncertainty when handling the MSSP. Ma and Demeulemeester [12] included probability distributions to account for uncertainty in the patient's length of stay (LOS) following surgery. Van Oostrum [13] dealt with the uncertainty of surgery duration by providing probability distributions. They calculate the distribution of patients resting in both the wards and the ICU resulting from a cyclical MSS. Most papers have used stochastic programming to deal with uncertainty in the MSS level [14]. Many predictive methods have been used in the literature to predict hospital demand. Batal et al. [15] estimated the demand for an emergency department by using a stepwise linear regression model. Jones et al. [16] used regression models, including climate variables, to estimate patient demand. Boutsioli [17] investigated the unpredictable hospital demand variations by using two types of forecast errors. The autoregressive integrated moving average (ARIMA), exponential smoothing (ES), and multiple linear regression (MLR) were found to be the most widely used techniques [18]. In this paper, we use a neural network to predict the emergency department admissions to achieve an efficient optimization model.

Our main contribution to the present literature is the inclusion of emergency patients and the development of a mathematical model to simultaneously handle the uncertain demand of elective patients and emergency patients. Moreover, we provide an artificial neural network and a fuzzy method to cope with unknown parameters in the model.

3 Problem Definition

In this paper, the overall goal is to construct a cyclic schedule (MSS table) where each subspecialty is scheduled for surgery slots in one or several of the ORs to perform surgeries efficiently. By efficiently, we mean scheduling many elective patients for surgery and handling a fluctuating demand of emergency patients without having to cancel the elective surgeries. In developing MSS, the capacity for the non-elective operations shall be reserved. To avoid elective patients' cancellations in periods of high emergency demand for surgery, we want to devote surgery slots for emergency patients in the elective ORs. The resources considered in this problem are the ORs, the wards, the surgeons.

Determining the optimal mix of patients is referred to as the case-mix planning problem (CMPP). The target of case-mix planning is used to feed downstream issues such as MSS. We assume that the target throughput of elective patients to be scheduled within each patient category for the cycle is known, and we aim to schedule as many of these patients as possible. Also, we need to forecast the number of emergency patients entering the department each week and devote additional capacity for them. In this study, a mathematical model is developed to construct the MSS for elective surgeries while using the results obtained from solving CMPP as input. Moreover, based on the hospital requirements, a part of the OR's capacity is reserved for emergency surgeries.

Following is the new mathematical model presented in this paper.

Sets:

S	Surgical specialties
R	ORs
L	Block types
D	Working days (five days a week)
K	Surgery time for each specialty (1: short, 2: medium, 3: Long)

Parameters:

CL_{lrd}	block time for elective patients for OR r in day d in block l
AP_{sr}	1 if OR r is suitable for specialty s
DE_s	Demand of elective patients for surgery s
DM_{ks}	Demand of emergency patients for surgery s and index k
$d\tilde{u}r_{ks}$	Fuzzy surgery duration k for specialty s

T	Length of cycle

Variables:

X_{slrd}	1 if surgical specialty s is assigned to OR r in block l on day d; 0, otherwise
E_s	Total idle time of OR assigned to specialty s

$$\text{Min} \quad E_s \tag{1}$$

s.t.

$$\sum_{s} X_{slrd} \le 1 \qquad \forall l, r, d \tag{2}$$

$$X_{slrd} \le AP_{sr} \qquad \forall s, l, r, d \tag{3}$$

$$\sum_{s,r,l,d} X_{slrd} \times CL_{lrd} \le T - \sum_{k=1}^{3} \sum_{s} d\tilde{u}r_{ks} DM_{ks} \tag{4}$$

$$\sum_{r,l,d} X_{slrd} \times CL_{lrd} \le DE_s \times d\tilde{u}r_{ks} + E_s \qquad \forall s \tag{5}$$

$$X_{slrd} \in \{0,1\} \qquad \forall s, l, r, d \tag{6}$$

$$E_s \ge 0 \qquad \forall s \tag{7}$$

The objective function minimizes the underutilization of the operating room. Constraints (2) and (3) ensures the assignment of OR blocks to specialties. Constraint (4) determines that OR block time of elective patients assigned to each specialty should not exceed the total time of elective patients. Constraint (5) describes the amount of underutilization of the idle time related to specialties. Constraints (6) and (7) are the domain of the variables.

4 Forecasting Emergency Demand

Among various intelligent methods, artificial neural networks (ANNs) are suitable instruments to solve complicated problems. In this study, 24 months of data were used, and the data were extracted from a private hospital in Tehran. The data were divided into two: the training and test sets.

4.1 Data and Variable Selection

The daily number of patients visiting the ED was employed as a dependent variable, whereas information including the month, day of the week, a quarter of the year, holidays, seasons, weather, rate of insurance and number of accidents per area were employed as independent variables [19-21].

4.2 Artificial Neural Network

The most conventional ANN model is the multilayer perceptron (MLP). It has one or several layers between the input layer and the output layer. In this research, we predict the demand for emergency patients, then, we determine the capacity of ORs for emergency patients. To implement the ANN depending on the purpose, different types of neural networks can be used. In this study, MLP is used. Every MLP neural network has three parts, including the input layer, the hidden layer(s), and the output layer. Mean arctangent absolute percentage error (MAAPE) is an indicator to assess a neural network structure. The equation of this criteria is given below. In this equation, N indicates the number of samples, F_t shows the predicted value of the model for sample t, and A_t represents the real demand for sample t.

$$MAAPE = \frac{100}{N}\sum_{t=1}^{N}\arctan\left(\left|\frac{A_t - F_t}{A_t}\right|\right)$$

Based on a trial and error method, several neural network structures are evaluated to find an appropriate configuration for MLP (see Table 1). According to column MAAPE, the best configuration is MLP 9 that is highlighted. The output of the designed model is the number of emergency patients refer to the hospital that is 374 in the mentioned hospital.

Table 1. Parameters of the neural network

Structure Code	MLP						Transfer Function in Output Layer	MAAPE
	Learning Function	Number of Hidden Layers	First Hidden Layer		Second Layer	Hidden		
			Transfer Function	Number of Neurons	Transfer Function	Number of Neurons		
MLP 1	GDX	2	Tansig	6	--	--	Purelin	4
MLP 2	BFG	2	Logsig	11	Tansig	13	Purelin	5
MLP 3	GDX	1	Tansig	10	Logsig	15	Purelin	5
MLP 4	LM	2	Tansig	4	--	--	Purelin	3
MLP 5	GDA	1	Logsig	9	Tansig	10	Purelin	3
MLP 6	OSS	2	Tansig	18	--	--	Purelin	4
MLP 7	LM	2	Logsig	7	--	--	Purelin	5
MLP 8	BFG	1	Logsig	15	Tansig	23	Purelin	3
MLP 9	GDA	1	Tansig	8	Logsig	4	Purelin	2
MLP10	OSS	2	Logsig	26	Tansig	19	Purelin	4

5 Fuzzy Method

Different approaches can be found in the field of uncertainty to cope with uncertain values based on the analyzed data. According to experts' judgments, fuzzy mathematical programming is a practical approach to this type of uncertainty. In this paper, we use a fuzzy method by Jiménez et al. [22], which is a strong mathematical concept, such as the expected interval and the expected value of fuzzy numbers. Consider the following model in which the parameters are defined as fuzzy triangular numbers. According to Jiménez et al. [22], the equivalent crisp model can be are as follows:

$$x \in N(\tilde{A},\tilde{b}) = \left\{ x \in R \mid \tilde{a}_i x \geq \tilde{b}_i, \tilde{a}_i x \leq \tilde{b}_i, i = 1,...,m, x \geq 0 \right\}$$
$$[(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]x \geq \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i}$$
$$[(1-\alpha)E_1^{a_i} + \alpha E_2^{a_i}]x \leq \alpha E_1^{b_i} + (1-\alpha)E_2^{b_i}$$
$$i = 1,...,m \; ; \; x \geq 0 \; ; \; \alpha \in [0,1]$$

Based on the above method, Constraints (4) and (5) are converted by:

$$\sum_{s,r,l,d} X_{slrd} \times CL_{lrd} \leq T - \sum_{k=1}^{3} \sum_{s} [(1-\alpha)E_2^{dur_{ks}} + \alpha E_1^{dur_{ks}}] \times DM_{ks}$$

$$\sum_{r,l,d} X_{slrd} \times CL_{lrd} \leq DE_s \times \sum_{k=1}^{3} \sum_{s} [(1-\alpha)E_2^{dur_{ks}} + \alpha E_1^{dur_{ks}}] + E_s$$

6 Case Study and Results

The results presented in this section are obtained based on the data collected from a private hospital in Tehran. The hospital consists of five specialties, five ORs, two wards, 65 beds. All the ORs are not capable of undergoing any surgery, so some specialties must be executed in a particular operating room. ORs are open eight hours a day, and working days are five in a week from Saturday to Wednesday (Thursday and Friday are holiday in Iran). To perform the surgeries, the department has access to four elective and one emergency ORs. The case hospital has faced some issues in the scheduling MSS table. In this section, we apply our approach to this case. The aim is to provide an MSS that enables the department to handle fluctuating emergency patient demand and at the same time provide a sufficient throughput of elective patients. First, the amount of capacity is reserved for emergency patients. Secondly, the new MSS is introduced, and finally we apply the fuzzy method to obtain a more reliable solution. Table 2 presents the parameters of the model. The model is solved in GAMS software using CPLEX solver. For example, the optimal schedule at the first week of planning horizon is shown in Table 3. It is deduced that the optimum MSS meets all the time blocks assigned to specialties in strategic level.

Table 2. Parameters of surgical specialties

Surgical Specialties	DE_s	dur_{sk}
Orology	(200,250,300)	(30,90,180)
Orthopedic	(90,130,170)	(45,120,250)
General	(280,340,400)	(30,150,300)
Vascular	(350,400,450)	(40,100,150)
Cardiology	(550,650,750)	(60,200,360)

Table 3. Optimum MSS

		OR1	OR2	OR3	OR4	OR5
Sat	Block 1	Orthopedic	Orthopedic	General	General	General
	Block 2	Orthopedic	Orthopedic	General	General	General
Sun	Block 1	Orology	Orology	Cardiology	Vascular	Vascular
	Block 2	Orology	Orology	Cardiology	Vascular	Vascular
Mon	Block 1	Cardiology	Cardiology	Orthopedic	General	General
	Block 2	Cardiology	Cardiology	Orthopedic	General	General
Tue	Block 1	Vascular	Vascular	Vascular	Orology	Cardiology
	Block 2	Vascular	Vascular	Vascular	Orology	Cardiology
Wed	Block 1	Orology	Orthopedic	General	Cardiology	Orthopedic
	Block 2	Orology	Orthopedic	General	Cardiology	Orthopedic

7 Conclusion

In this paper, we have developed a mathematical model for the master surgical scheduling (MSS) problem and to provide tactical decision support for managers in a department with both elective and emergency patients. To deal with daily emergency patients, we used neural**-** network algorithm to predict the demand for emergency patients. Due to current uncertainty in the problem, surgery duration was considered uncertain. Therefore, a fuzzy approach was applied to convert to a crisp model. The proposed model was solved using GAMS software. The results revealed that the model is improved in an uncertain environment. For future studies, it is suggested to consider the cancellation of elective patients, and it might be interesting to investigate the effect of different policies to improve hospital performance.

References

1. Hamid, M., M. Hamid, M. Musavi and A. Azadeh (2019). "Scheduling elective patients based on sequence-dependent setup times in an open-heart surgical department using an optimization and simulation approach." Simulation **95**(12): 1141-1164.
2. Hay, J. W. (2003). "Hospital cost drivers: an evaluation of 1998–2001 state-level data." Am J. Management Care **9**(spec No 1): SP13-SP24.
3. Hamid, M., M. M. Nasiri, F. Werner, F. Sheikhahmadi and M. Zhalechian (2019). "Operating room scheduling by considering the decision-making styles of surgical team members: a comprehensive approach." Computers & Operations Res. **108**: 166-181.
4. Freeman, N., M. Zhao and S. Melouk (2018). "An iterative approach for case mix planning under uncertainty." Omega **76**: 160-173.
5. Hans, E. W., M. Van Houdenhoven and P. J. Hulshof (2012). A framework for healthcare planning and control. Handbook of Healthcare System Scheduling, Springer**:** 303-320.

6. Hulshof, P. J., N. Kortbeek, R. J. Boucherie, E. W. Hans and P. J. Bakker (2012). "Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS." Health Systems **1**(2): 129-175.
7. van Essen, J. T., E. W. Hans, J. L. Hurink and A. Oversberg (2012). "Minimizing the waiting time for emergency surgery." Operations Research for Health Care **1**(2-3): 34-44.
8. Cardoen, B., E. Demeulemeester and J. Van der Hoeven (2010). "On the use of planning models in the operating theatre: results of a survey in Flanders." The Int. J. of Health Planning and Management **25**(4): 400-414.
9. Adan, I., J. Bekkers, N. Dellaert, J. Jeunet and J. Vissers (2011). "Improving operational effectiveness of tactical master plans for emergency and elective patients under stochastic demand and capacitated resources." Eur. J. of Operational Res. **213**(1): 290-308.
10. Testi, A., E. Tanfani and G. Torre (2007). "A three-phase approach for operating theatre schedules." Health Care Management Sci. **10**(2): 163-172.
11. Li, X., N. Rafaliya, M. F. Baki and B. A. Chaouch (2017). "Scheduling elective surgeries: the tradeoff among bed capacity, waiting patients and operating room utilization using goal programming." Health Care Management Sci. **20**(1): 33-54.
12. Ma, G. and E. Demeulemeester (2013). "A multilevel integrative approach to hospital case mix and capacity planning." Computers & Operations Res. **40**(9): 2198-2207.
13. van Oostrum, J. M., M. Van Houdenhoven, J. L. Hurink, E. W. Hans, G. Wullink and G. Kazemier (2008). "A master surgical scheduling approach for cyclic scheduling in operating room departments." OR Spectrum **30**(2): 355-374.
14. Fügener, A., E. W. Hans, R. Kolisch, N. Kortbeek and P. T. Vanberkel (2014). "Master surgery scheduling with consideration of multiple downstream units." European Journal of Operational Res. **239**(1): 227-236.
15. Batal, H., J. Tench, S. McMillan, J. Adams and P. S. Mehler (2001). "Predicting patient visits to an urgent care clinic using calendar variables." Academic Emergency Medicine **8**(1): 48-53.
16. Jones, S. S., A. Thomas, R. S. Evans, S. J. Welch, P. J. Haug and G. L. Snow (2008). "Forecasting daily patient volumes in the emergency department." Academic Emergency Medicine **15**(2): 159-170.
17. Boutsioli, Z. (2010). "Forecasting the stochastic demand for inpatient care: The case of the Greek national health system." Health Services Management Res. **23**(3): 116-120.
18. Ordu, M., E. Demir and C. Tofallis (2019). "A decision support system for demand and capacity modelling of an accident and emergency department." Health Systems: 1-26.
19. Kam, H. J., J. O. Sung and R. W. Park (2010). "Prediction of daily patient numbers for a regional emergency medical center using time series analysis." Healthcare Informatics Res. **16**(3): 158-165.
20. Yazdanparast, R., M. Hamid, A. Azadeh and A. Keramati (2018). "An intelligent algorithm for optimization of resource allocation problem by considering human error in an emergency." J. of Industrial and Systems Engineering **11**(1): 287-309.
21. Amalnick, M. S., N. Habibifar, M. Hamid and M. Bastan (2019). "An intelligent algorithm for final product demand forecasting in pharmaceutical units." Int. J. of System Assurance Engineering and Management: 1-13.
22. Jiménez, M., M. Arenas, A. Bilbao and M. V. Rodrı (2007). "Linear programming with fuzzy parameters: an interactive method resolution." Eur. J. of Operational Res. **177**(3): 1599-1609.