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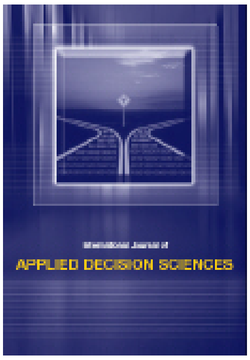

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A two phase approach based on multi-objective programming and simulation for physician scheduling in emergency rooms

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Abstract: Scheduling hospital staff is a complex problem because of the wide fluctuations in demand and staffing needs. Physician scheduling in an emergency room (ER) is the one that is most complex and crucial since it requires not only economic and patient perspectives but also the social needs of physicians. Thus, the working conditions and preferences of physicians should be considered in planning their schedules. This study aims to develop an approach for scheduling physicians in an ER to provide better conditions for physicians and, a qualified and reachable healthcare service to the patients. A multi-objective mathematical model is developed to ensure Pareto optimal solutions considering not only economic aspects but also social aspects including the physician preferences and balancing the workload. A Monte Carlo simulation is used to determine the best schedule among Pareto optimal solutions obtained from the mathematical model and deal with the fluctuations in demand. The approach is applied with real world data.

Keywords: physician scheduling; emergency rooms; multiple objective programming; Monte Carlo simulation; the augmented ε-constraint.

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1 Introduction

Hospitals play a vital role in helping people to continue their life comfortably providing a good quality of healthcare service. Performing a proper service is a tough and complex task because hospitals have many gruelling issues such as financial problems (Onder et al., 2022; Yuan et al., 2022), planning (Nico et al., 2022) and job satisfaction (Ishikawa, 2022; Lodh and Ghosh, 2022) issues.

In recent years, hospitals face an increase in expenditures and budget cuts for personnel (Erhard et al., 2018). They are forced by managers to reduce costs and increase the quality of the service to survive in the competitive environment (Stolletz and Brunner, 2012). These are objectives contradicting each other.

The number of patients in hospitals is uncertain and changes day to day, shift to shift (Brunner et al., 2010). The uncertainty in the patient demand may result in an understaffed service, which in turn, causes patients to wait a very long time to be treated and not receive the required treatment along with the exhausted staff or an overstaffed service ending up with idle hospital staff. In short, a planning problem occurs due to uncertainty in working hours, retaining physicians and inconsistent service requirements.

Besides patient related concerns, shift work, long working hours and stressful job environments already cause several disorders such as burnout which lead to depression, alcohol addiction, insomnia, and suicidal ideas, fatigue and anxiety (Wisetborisut et al., 2014). Excessive workload especially increases mental and physical disorders (Chamoux et al., 2018).

One of the main reasons for the above-mentioned problems is the lack of effective personnel scheduling, namely not assigning physicians to shifts in an appropriate way. Planning and applying efficient personnel scheduling is an important way of figuring out these problems (Gunawan and Lau, 2013). Making effective and optimum schedules by improving the assignment procedures becomes crucial more than ever for increasing satisfaction and efficiency of personnel, providing a good quality of service with optimal expenses.

Scheduling problems in the healthcare service are basically classified into two groups: nurse and physician scheduling. Nurse scheduling occupies most of the research in this field and most of these models cannot be applied to physician scheduling (Brunner and Edenharter, 2011). Because physician scheduling has a more complex nature originated from several characteristics. For instance, agreement rules such as individual contracts and vacation periods are different from the nurses. Providing job satisfaction is a very significant issue to retain physicians. Experiences and specialisations are crucial for assigning them to shifts or departments. So, the need and the rule for physicians vary, while for nurses are more standard.

Being a paramount issue regarding the entire hospital, physician scheduling in emergency rooms (ERs) is also one of the most complex scheduling problems for healthcare services (Al-Najjar and Ali, 2011). Because, ERs face problems at the highest level and provide service 365 days a year, 24 hours a day, 7 days a week. ERs are actually responsible for only urgent illnesses or injuries, but they are forced into treating all kinds of situations whether urgent or non-urgent (Cabrera et al., 2012). There is a very high level of fluctuations in demand that cause not treating the patients on time, long waiting and treatment times for patients, increasing the workload of physicians and not providing proper treatment to patients (Elalouf and Wachtel, 2016). These conditions negatively affect both physicians and patients. Stress and heavy workload can give rise to a lack of attention and contracting various disorders mentioned before. In ERs, these circumstances are intolerable for the physicians considering that a little mistake causes vital consequences for patients. Therefore, it is an obligation to provide appropriate conditions in ERs in terms of both giving proper service to the patients and the working conditions of physicians.

In this study, a two-phase approach is proposed for physician scheduling problem in ER to obtain an efficient schedule considering uncertainty for providing appropriate health services and improving the working conditions of the physicians. In the first stage, a multi-objective mathematical model is developed to obtain Pareto optimal solutions for physician schedules. Objectives of the model are:

1 minimisation of regular and outside physicians cost

2 balancing the workload of physicians

3 maximisation of physicians' preferences to enhance motivation and satisfaction.

There are several constraints some of which are satisfying all the patient demand, the legal working hours enforced by the government and labour unions, resting periods for physicians to regenerate themselves in terms of mental and physical health. A multi-objective optimisation method, the augmented ε-constraint (AUGMECON) (Mavrotas, 2009), is used to solve the mathematical model. The method produces several Pareto optimal solutions. In the second stage, a Monte Carlo simulation model is developed to select the best solution among Pareto optimal solutions without asking decision makers (DMs) to select the one among the existing schedules. Also, the simulation enables to consider the possible fluctuations in demand that help to deal with the uncertainty in the number of patients and the duration of the treatment. In the simulation model, the required total time to satisfy patient demand is determined using probability distributions obtained by historical data for each shift and day. The best efficient schedule is selected by evaluating Pareto optimal solutions for the required total time per shift in terms of several performance criteria such as physician overtime and idle time. The motivation of the paper is to provide a sustainable healthcare service by obtaining an efficient schedule. Sustainable healthcare is dealt with three aspects; economic, environmental and social (Buffoli et al., 2013). In the paper, only economic (Teherani et al., 2017) and social (Hamed et al., 2017) aspects are considered focusing on the management of costs, efficient use of resources, recovery rate and quality of service.

The major contribution of this paper is offering a new perspective to AUGMECON method. While only one is selected as the main objective among the defined objectives in the classical AUGMECON method, the proposed approach treats each objective as the main objective sequentially and solves the model for each main objective separately. Accordingly, a wider solution space has been searched and a more representative number of Pareto optimal solutions is obtained. Integrating the simulation also provides a new perspective in order to achieve a more objective way to select the most appropriate schedule. Real-world data used for the application of the study are collected from a public hospital.

The remainder of the paper is organised as follows. Literature review is presented in Section 2 and the proposed approach is given in Section 3. The application of the proposed approach using real-world data is presented in Section 4. Finally, in Section 5 concluding statements are mentioned.

2 Literature review

Physician scheduling is a sort of personnel scheduling which has become significant for service organisations such as call centres, education systems, and transportation systems (Gunawan and Lau, 2013). There has also been increased interest in healthcare services (Brunner et al., 2010). Erhard et al. (2018) classify physician scheduling problems as staffing, scheduling and re-planning problems. Besides, it groups the objectives as financial and non-financial goals. While financial goals are minimising wage costs and planned overtime costs, non-financial goals are minimising expected undercoverage of demand, maximising employee preferences, balancing the distribution of workload and satisfying the required level of experience. The constraints are considered to meet demand, satisfy assignment rules such as one shift at a time, minimum rest, specific shift limits, working time bounds, weekends off, preferred working stretch and night shifts. Also, shifts are defined as predefined and flexible. Flexible shifts vary in length and starting times. Many approaches and techniques including linear programming (LP), integer programming (IP), goal programming (GP), mixed integer programming (MIP), nonlinear programming (NLP), tabu search, genetic algorithm, and simulation models are proposed to handle the problem (Erhard et al., 2018; Van den Bergh et al., 2013).

Among papers that use monetary objective functions, Bard and Purnomo (2005) develop an IP model to cover patient demand through regular nurses, outside nurses and overtime. The objective of the model is to minimise the cost associated with regular working time, overtime, outside nurses, violated resting period and cost of nurses assigned to shift more than needed. Similarly, the flexible physician scheduling problem is modelled to minimise outside physician cost, regular cost and overtime cost to cover forecasted demand considering constraints which are the labour regulations, minimum and maximum shift length and minimum duration between consecutive shifts using MIP (Brunner et al., 2009). Outside physicians are hired when it comes to unmet demand. With similar constraints, a model is proposed to minimise regular and overtime cost using Branch&Price algorithm and a heuristic decomposition approach to divide the problem into sub problems (Brunner et al., 2010). Flexible shifts can be used to handle overcrowding in a particular time period. Several shift starting times and different shift lengths are determined to minimise total cost using column generation method to solve a MIP formulation for a long-term scheduling (Brunner and Edenharter, 2011). Besides the flexible shifts, the minimisation of the cost, the maximisation of fairness and hiring physician are considered using reduced set covering formulation.

Job satisfaction is a very significant issue in terms of increasing the quality of care and retaining physicians. The factors such as fairness between physicians and physician preferences can increase job satisfaction and motivation of physicians (Erhard et al., 2018). A MIP model is developed to balance assigning the number of shifts to the physicians and assigning workload in unpreferable shifts to the physicians (Bruni and Detti, 2014). The objectives of the model are weighted to be represented as one objective and the model is solved using Branch&Cut procedure. Gunawan and Lau (2013) propose a mathematical model with two objectives, which are minimising the number of unscheduled duties and maximising the ideal schedule of physicians, combined into one objective by weighted sum method. The model is solved using a heuristic algorithm. Physician preferences are maximised to make a schedule considering on-duty and off-duty shifts (Huang et al., 2016). Minimisation of total overtime is aimed to assign workload to the teams composed of six physicians and consider physicians' maximum workload and day-off times (Hidri and Labidi, 2016). Patient travel time from all locations to care and the penalty for unsatisfied patient's request is minimised considering the constraints, which are physician capacity and preferences using proposed column generation-based heuristic algorithm (Li et al., 2016). A monthly schedule is developed using genetic algorithm to satisfy hard constraints including the minimum number of physicians to assign to each shift, resting period and soft constraints including balance in workload sharing some types of shifts, assignment rules for permanent and temporary physicians (Puente et al., 2009). Maenhout and Vanhoucke (2011) introduce a meta-heuristic method to solve nurse scheduling problem considering service continuity (minimum level of care in terms of the number of nurses) and overtime, preferences, workload balance. A monthly schedule is constructed using goal programming model to minimise violations of resting periods and the permissible number of staff (Topaloglu, 2006). The objectives are weighted using analytical hierarchy process.

Simulation models are generally used to overcome randomness in demand and length of treatment time (Mustafee et al., 2010). The models also provide quality and robust solutions in terms of uncertainty (Erhard et al., 2018). Monte Carlo simulation, discrete-event simulation, system dynamics, and agent-based simulation can be used to model the systems (Mustafee et al., 2010). An agent-based simulation model is constructed to optimise the number of staff in the ER, which are the number of admission staff, triage nurses and physicians for handling the complexity of the problem (Cabrera et al., 2012). The model also minimises patient waiting time and maximises patient throughput rate. Oh et al. (2016) construct a discrete-event simulation model to maximise the throughput rate and minimise operational costs considering whole operations in the ER. In some studies, simulation and optimisation are combined to minimise patients' length of stay and construct an efficient shift schedule. In the paper of Sinreich and Jabali (2007), a linear model and iterative simulation-based algorithm are used for staffing and creating work shifts for all personnel. They consider different shifts' starting times to cover patient demand. Kuo (2014) proposes a simulation-optimisation approach to consider uncertainty in ER and to obtain a good solution for physician schedules. A simulated annealing algorithm is used in the study to minimise expectation of the patients waiting time in ER. Azcárate et al. (2008) introduce an approach that is a combination of simulation and multi-objective mathematical model solved by ε-constraint method to deal with healthcare management problems. The model considers cost, patient satisfaction and randomness in patient arrival pattern and service time. The output of the simulation is used in the mathematical model.

In Table 1, the objectives and methods used in the most relevant papers are provided.

Table 1 Objective and methods used in the literature

Article		*The objective function*	*Method*
Azcárate et al. (2008)	1	Minimising cost	Simulation and scatter search
	2	Minimising percentage of the patients turned away	
	3	Maximising the quality of physician service	
Maenhout and Vanhoucke (2011)	1	Minimising overstaffing and unplanned absences	Evolutionary algorithm
	2	Minimising preferences penalty cost	
	3	Balancing workload	

Table 1 Objective and methods used in the literature (continued)

Article	*The objective function*	*Method*
Topaloglu (2006)	Minimising deviations from restrictions about night shifts and weekend shifts	Goal programming
Brunner et al. (2009)	Minimising cost of paid out time, overtime and outside physicians	-
Brunner et al. (2010)	Minimising cost of paid out time, overtime and outside physicians	Branch and price
Brunner and Edenharter (2011)	Minimising cost of hiring physicians	Column generation algorithm
Bruni and Detti (2014)	Minimising maximum regular and inconvenient shifts of each physician group, and maximum preference unsatisfaction (weighted objective functions)	Branch and cut
Gunawan and Lau (2013)	1 Maximising number of ideal scheduled duties 2 Minimising number of unscheduled duties	Weighted sum and a heuristic algorithm
Huang et al. (2016)	Maximising physicians and residents preferences on on-duty and off-duty shifts	-
Oh et al. (2016)	Minimising patient's length of stay in the ER	Discrete event simulation
Sinreich and Jabali (2007)	Minimising overstaffed and understaffed hours to best cover demand.	Simulation and a heuristic algorithm
Kuo (2014)	Minimising average waiting time of patients	Simulation and simulated annealing
Puente et al. (2009)	Maximising overall weighted scores assigned to soft constraints	Genetic algorithm
Savage et al. (2015)	Minimising unmet patient demand	-
Cildoz et al. (2021)	Minimising difference between maximum and minimum working hours and number of assigned shifts of physicians	Greedy randomised adaptive search procedure and variable neighbourhood descent in combination with network flow optimisation
Wickert et al. (2021)	Minimising overall violations of weighted soft constraints such as minimum and maximum number of shifts, consecutive assignments, weekend shifts	Fix and optimise metaheuristic algorithm
Camiat et al. (2021)	Minimising over-covering and under-covering of emergency patient demand, deviations between shift types assigned to physicians, differences between wanted and assigned shifts of physicians and missing physicians to cover demand (weighted four objectives)	-

As a result of a detailed literature review regarding the scheduling problems, we want to emphasise the points that this paper contributes to the existing literature. Firstly, economic and social objectives which are cost, fairness, preferences are considered simultaneously to provide sustainable healthcare service. Different from the existing papers, we do not prefer to weight the objectives to simplify the model. Because collecting the weights from DMs results in a subjective evaluation due to the limited cognitive capacity of human and possible bias in the ideas. Besides, AUGMECON method used in the study guarantees to give only non-dominated solutions contrary to weighting and conventional ε-constrained which are the methods used for multi-objective problems (Yang et al., 2021). Secondly, the existing studies offer an expert opinion or a multi-criteria decision-making techniques such as fuzzy clustering method (Yang et al., 2021) and analytical hierarchy process (Majidian-Eidgahi et al., 2020) to select the final schedule among the Pareto optimal solutions obtained in AUGMECON. Since there are too many efficient solutions, it is not practical to make DMs assess the obtained schedules. Therefore, Monte Carlo simulation is proposed to select the best efficient solution among Pareto optimal solutions.

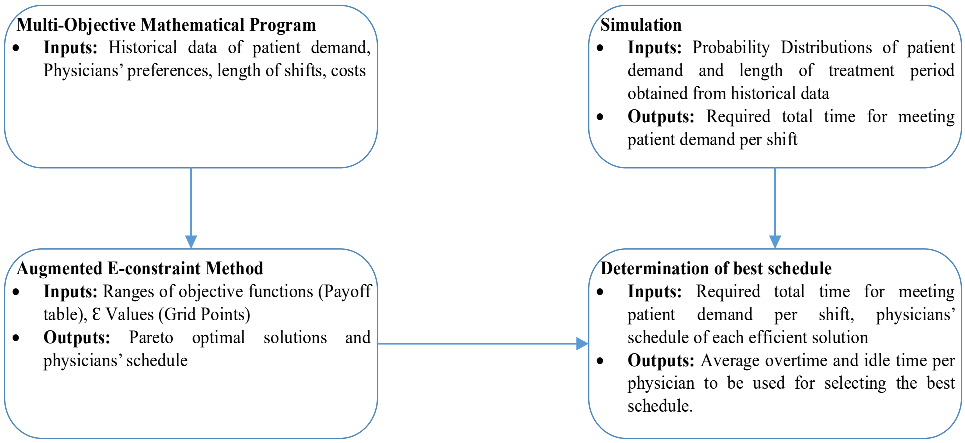
3 Proposed approach

The paper proposes a two-phase approach for physician scheduling in ERs to obtain several Pareto optimal solutions, then select the best solution among them to provide an appropriate schedule considering uncertainty. A multi-objective mathematical model is proposed in the first phase for scheduling the physicians in ER in order to maximise the physician preferences, balance the workload and minimise the cost simultaneously. The AUGMECON method is used to solve the model to guarantee Pareto optimal solutions, which are the non-dominated optimal solutions (Mavrotas, 2009). In the AUGMECON method, alternative solutions are generated that are subsequently assessed by the DMs to select the most preferred solutions (Aghaei et al., 2011). Since a human being has limited cognitive capacity (Glimcher, 2022; Sharp et al., 2022) under complex problems like the personnel scheduling problem, it is nearly impossible and unreliable for a DM to evaluate many alternative schedules and select the best one. Therefore, in this study, the DM in the selection of the best schedule is replaced by a simulation-based approach to ensure objectivity. By this way, the uncertainty in the demand and the treatment time in the ER services could also be considered. The best efficient solution among the Pareto optimals is the output of the two-phase approach. The general framework of the model is given in Figure 1.

3.1 Multi-objective mathematical programming model

The proposed multi-objective mathematical programming model is constructed to optimise three objectives set as minimising physician costs, balancing the workload of physicians and meeting the physician preferences subject to the constraints determined according to the hospital rules, international working agreements, and the aforementioned problems related to the application area. All variables, parameters, rules, assumptions and the model are described in this section.

Figure 1 The general framework of the model (see online version for colours)



The mathematical model is constructed based on the following assignment rules:

- The total working time per month per physician should not be exceeded as in compliance with the working agreements.
- Physicians should not exceed the total working time per month determined by working agreements.
- In order to prevent overtime (and also its undesirable effects), the unmet demand is met through hiring outside physicians.
- Two types of shifts are applied in the hospitals (8-hours and 24-hours).
- There is a predetermined number of 24-hours shifts per physician that should not be exceeded.
- There is a predetermined number of weekend shifts to be assigned in order to balance the physicians' social and physical circumstances.
- If a physician works in a 24-hours shift, she/he must rest for two consecutive days to provide mental and physical rehabilitation of physicians.
- Each physician can be assigned to only one shift in a day.
- Wage and hourly fees are assumed to be the same for all physicians.

The notations used in the model are as follows:

Indices

i index for physicians (regular physicians having permanent contract) ($i = 1, \ldots, I$)

k index for outside physicians ($k = 1, \ldots, K$)

j index for shift type ($j = 1, \ldots, J$)

g index for days ($g = 1, \ldots, G$)

$hs(g)$ sub-index for days of weekends.

Parameters

D_{jg} the required number of physicians on day g shift j

L_j the length of the shift j

Pr_{ijg} preferences rate of the physician i for day g and shift j (0–10 scale)

WA wage for a month per physician

HC hourly fee for the regular shift per physician

OC_j hourly fee for shift j per outside physician

WT^{Max} the maximum total working time per physician for a month period

OT^{Max} the maximum total working time per outside physician for a month period

NS^{Max} the maximum number of 24-hours shift to be assigned per physician for a month period

WS^{Max} the maximum number of weekend shift to be assigned per physician for a month period

WS^{Min} the minimum number of weekend shift to be assigned per physician for a month period.

Decision variables

$P_{ijg}=1$ if physician i is assigned on day g and shift j 1, o/w $P_{ijg} = 0$

y_{ig} control variable which takes binary values ({0, 1}) to be used for physicians assigned to 24-hours shift

$A_{kjg} = 1$ if outside physician k is assigned on day g and shift j 1, o/w $A_{kjg}=0$

$S_i=1$ if physician i works for that month, o/w $S_i=0$

WT_i total working time of physician i

OT_{kj} total working time of outside physician k for shift j

WT^{Ave} average total working time of physicians

d_i^+ positive deviation of the difference between average working time and working time of physician i

d_i^- negative deviation of the difference between average working time and working time of physician i.

The model can be stated as follows:

$$\text{Minimise } f_1 = \sum_i S_i \times WA + \sum_i WT_i \times HC + \sum_i \sum_j OC_j \times OT_{ij} \tag{1}$$

$$\text{Minimise } f_2 = \sum_i^I \left(d_i^+ + d_i^-\right) \tag{2}$$

$$\text{Minimise } f_3 = \sum_i \sum_j \sum_g P_{ijg} \times Pr_{ijg} \tag{3}$$

$$\sum_{i}^{I} P_{ijg} + \sum_{k}^{K} A_{kjg} \geq D_{jg} \qquad \forall j, g \qquad (4)$$

$$\sum_{j}^{J} \sum_{g}^{G} P_{ijg} L_j = WT_i \qquad \forall i \qquad (5)$$

$$WT_i \leq WT^{Max} \qquad \forall i \qquad (6)$$

$$\sum_{j}^{J} \sum_{g}^{G} P_{ijg} \leq M * S_i \qquad \forall i \qquad (7)$$

$$WT^{Ave} = \sum_{i}^{I} WT_i / \# Physicians \qquad (8)$$

$$d_i^+ - d_i^- = \left(WT^{Ave} - WT_i\right) \qquad \forall i \qquad (9)$$

$$\sum_{g}^{G} A_{kjg} L_j = OT_{kj} \qquad \forall k, j \qquad (10)$$

$$\sum_{j}^{J} OT_{kj} \leq OT^{Max} \qquad \forall k \qquad (11)$$

$$\sum_{j}^{J} P_{ijg} \leq 1 \qquad \forall i, g \qquad (12)$$

$$\sum_{j}^{J} A_{kjg} \leq 1 \qquad \forall k, g \qquad (13)$$

$$\sum_{g}^{G} P_{i2g} \leq MS^{Max} \qquad \forall i \qquad (14)$$

$$WS^{Min} \leq \sum_{hs(g)} P_{i2g} \qquad \forall i \qquad (15)$$

$$\sum_{hs(g)} P_{i2g} WS^{Max} \qquad \forall i \qquad (16)$$

$$P_{i2g} \leq M * \left(1 - y_{ig}\right) \qquad \forall i, g \qquad (17)$$

$$\sum_{j}^{J} P_{ij(g+1)} + P_{ij(g+2)} \leq M * y_{ig} \qquad \forall i, g \qquad (18)$$

$$P_{ijg}, A_{ijg}, S_i, y_{jg} \in \{0, 1\} \qquad \forall i, j, g \qquad (19)$$

$$WT_i, OT_{ij}, WT^{Ave} \geq 0 \ \forall i, j \qquad (20)$$

$$d_i^+, d_i^- \geq 0 \ \forall i \qquad (21)$$

The objective function [equation (1)] minimises total financial cost including wages, hourly fees for regular physicians, and hourly fees for outside physicians. The goal is to assign and staff physicians with minimum cost. The second objective function [equation (2)] prevents the model from assigning total workload to particular physicians. Using this function allows the model to balance the workload of physicians based on monthly workload. This objective is important to ensure fairness among physicians and their motivation. The purpose of the objective function [equation (3)] is to maximise physician preferences. The maximisation of preferences is considered to retain physicians increasing commitment and job satisfaction. The constraint in equation (4) satisfies the required number of physicians per day and shift based on patient demand. When the physicians are not enough to meet the demand, outside physicians are hired. The constraint in equation (5) calculates monthly working time per physician. The equation [equation (6)] is the monthly working capacity. In other words, the monthly working time of each physician cannot exceed this capacity. The monthly working time is determined due to the international agreement to provide humanistic conditions. Equation (7) is used to if a physician is assigned to a shift, then the physician has worked for that month. The average monthly workload is calculated using equation (8). Deviation from the average monthly workload for each physician is calculated by equation (9). Equation (10) calculates the monthly working time per outside physician for each shift while equation (11) represents the monthly working time capacity. Each physician can be assigned to at most one shift in a day [equation (12)]. Each outside physician can be assigned to at most one shift in a day [equation (13)]. The 24-hours shift capacity constraint [equation (14)] satisfies that a physician cannot be assigned to 24-hours shift in a way that exceeding the predetermined number (Note: the index number 2 corresponds to the 24-hours shift). Each physician cannot be assigned to a weekend shift for more or less than the predetermined number of days. Assignment to weekend shifts is limited from the left and right sides using equation (15) and equation (16), because of providing balance among physicians and, ensuring their mental and physical rehabilitation. If a physician is assigned to a 24-hours shift, she/he has to rest for the two consecutive days, which are held by equation (17) and equation (18). The resting period is determined regarding the health of physicians. The last three constraints [equations (19)–(21)] are non-negativity and binary variable constraints.

3.1.1 Formulating the problem using the AUGMECON method

The solution approach of the mathematical model is based on an improved and novel version of the ε-constraint method proposed by Mavrotas (2009). The augmented ε-constraint method is selected because it generates only efficient solutions evenly distributed on Pareto optimal curve. Augmented ε-constraint method accelerates the whole process by avoiding redundant iterations and the method has flexibility in terms of selection of Pareto optimal solutions.

Different from Mavrotas's method, a Monte Carlo simulation-based selection procedure is used in this study to choose the best solution among the Pareto optimal solutions. In Mavrotas's method, the best solution is selected by the DMs. However, in this particular problem, it is very difficult and inefficient for a human being to assess all the different Pareto optimal schedules and make a decision. The proposed simulation model not only makes it possible to consider the uncertainties but also establishes performance criteria while selecting the best schedule.

Steps of augmented ε -constraint method are given as follows:

a Constructing the model: One of the objective functions is selected as a main objective function and, the remaining objective functions are written as constraints. Slack and surplus values are added to the main and other objective functions to be maximised. The example including three objectives is given below:

$$Max\ f_1 + \varepsilon \times (s_2/r_2 + s_3/r_3) \tag{22}$$

$$f_2 - s_2 = e_2 \tag{23}$$

$$f_3 - s_3 = e_3 \tag{24}$$

where f_1, f_2, and f_3 are the objective functions, f_1 is selected as the main objective. To generate only efficient solutions, slack or surplus values up to the type of the objectives (min or max), s_i, are used. The term s_i / r_i is used to overcome scaling problems between objective functions, where r_i is the range of the i^{th} objective function. The e_i is the right hand side restriction varying from the minimum value of the objective function i to the maximum value. The ε is a small number taken with the value usually 10^{-3} or 10^{-6}.

b Generating payoff table: The range of each objective function must be determined to apply the method properly. To calculate the ranges, the payoff table is constructed using Lexicographic optimisation. First, the first objective function is optimised under the determined constraints. Then, this optimum value is used as a right hand side value of a new constraint included into the model to optimise the second objective function. Finally, to find the optimum value of the third objective function, both the first and second objectives are included into the model as constraints. The outputs of this process construct the first row of the payoff table. For the second row, the second objective function triggers the explained process, and so on.

c Determination of the value of *e* (grid point): Ranges of the objective functions are divided into several equal intervals to obtain Pareto optimal solution set on Pareto front. For example, if there are nine equal intervals, there will be ten grid points as the value of *e*.

e_k (k = 2, 3), is calculated for objective function k as follows:

$$e_k = lb_k + (i_k \times r_k)/g_k \tag{25}$$

where i represents the order of grid point, lb_k is the lower bound for objective k, r_k is the range of the objective function k obtained from the payoff table and g_k is the number of grid points. For example, if there are nine grid points from eight equal intervals, there will be 81 (i.e., 92) solutions to be obtained by the three objective functions model. Several efficient solutions obtained from the model are determined to construct physician scheduling.

In this paper, different from Mavrotas's method, all objective functions are selected as a main objective function one by one. If there are eight grid points, you have 64 solutions for one main objective and if there are three objective functions, 192 solutions are obtained in total. Repetitive or infeasible solutions might be obtained. Yet, all feasible solutions are Pareto optimal. When the first objective function is selected as the main objective function, the proposed model is formulated as follows:

$$Max - f_1 + 10^{-3} \times (s_2/r_2 + s_3/r_3) \tag{25}$$

$$f_2 + s_2 = e_2 \tag{26}$$

$$f_3 - s_3 = e_3 \tag{27}$$

Constraints (5) to (21) (28)

3.2 Monte Carlo simulation model

The simulation model is proposed to take into account uncertainties originated from randomness in demand. The model is also used to determine the best solution replacing the subjective assessments of the DMs as it is in Mavrotas (2009).

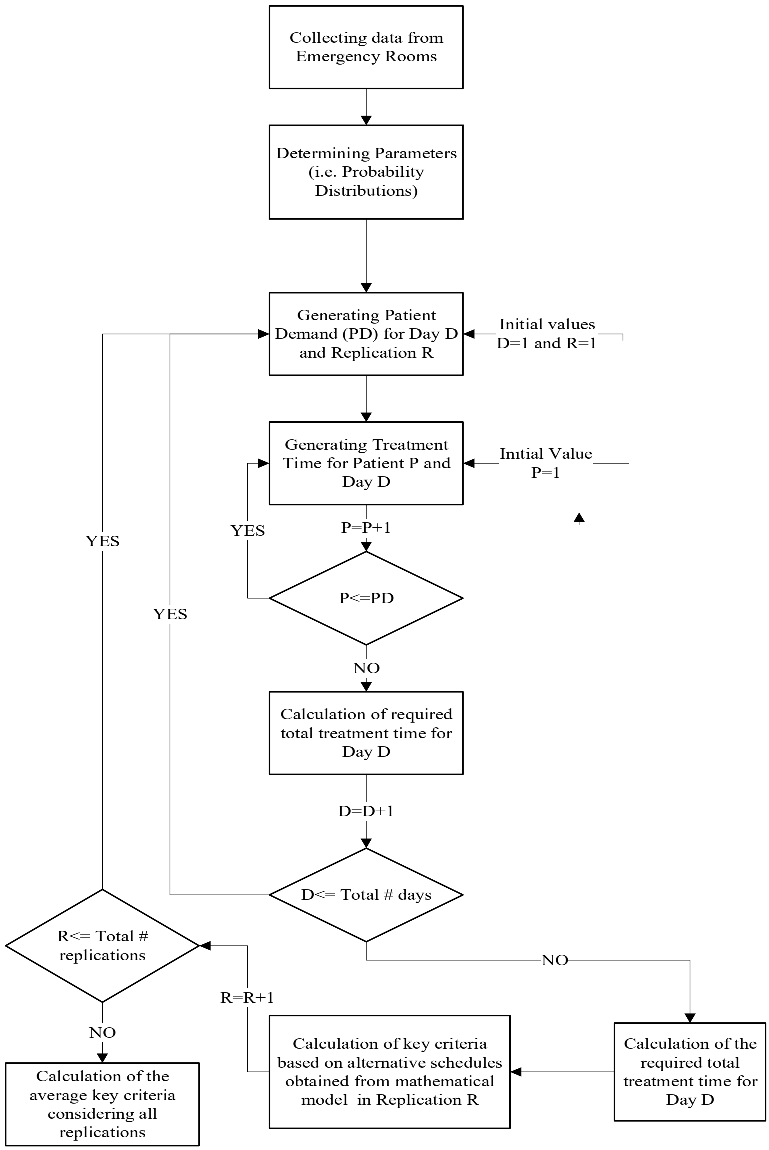
ERs have high variability in terms of patient demand and length of the treatment period. The number of patients applies to ER per shift and the severity of diseases are uncertain. Many of the problems in the ERs are originated from this variability and also the uncertainty in the system. When the number of physicians to be assigned to the shifts is determined assuming the patient demand is constant, it can result in under or overstaffed service.

Since ERs are of great importance in patient survival and emergency medical intervention, it is vital to overcome variability. Using a mathematical model alone is not enough to solve these problems because of the stochastic nature of the problem. Simulation is an effective and proper method for modelling complex stochastic systems. Therefore, a simulation model is proposed to determine the best solution among efficient solutions obtained from the mathematical model, which minimises the effects of variability on the functioning of ERs. It is aimed to select the best schedule for physicians that is robust against uncertainties. The schedules of efficient solutions are compared by using the simulation model where the patient demand and length of treatment time are randomly generated based on the historical data. The comparison is made according to the physicians idle time and overtime of the efficient solutions. The flowchart of the simulation is given in Figure 2.

In the simulation model, first, data related to the shift types and days, the number of physicians in the ER, the number of patients to apply ERs, and the treatment time of patients are obtained from historical data. Probability distributions of the patient demand and the length of treatment time based on the severity of the disease are obtained by analysing the data. Patients are classified according to the severity of the disease. Treatment time is analysed based on these classes. Then, patient demand per shift varying day by day is randomly generated based on the probability distribution for a month period. The severity of the disease and treatment period for each patient is determined using the related probability distribution. Finally, the total treatment time per shift is calculated and several replications are performed for a month period.

Schedules obtained from the mathematical model show the number of physicians assigned to a particular shift. The total working times of the physicians per shift are calculated according to the number of physicians. Then, these total working times are compared with the total treatment time per shift obtained from the simulation. Outside physicians are not taken into account in the calculation of the total working time of physicians, because outside physicians are hired to satisfy patient demand and they are assigned to the shifts based on deterministic data. Since probability distributions of demand and treatment time are considered in the simulation, calculations and comparisons are made according to physicians working in the hospital with a permanent contract. So if overtime occurs, the hospital management can decide whether they use outside physicians or not considering the workload and amount of overtime.

Figure 2 The flowchart of the simulation



The comparison can be made based on cost, total or average overtime and idle time, average waiting times of patients, throughput rate for determined time interval and utilisation of physicians. If the goal is to give healthcare service to all patients, the performance measure becomes throughput rate or, if giving healthcare service on time is the goal, then the performance measure becomes average waiting times of patients. Average idle time and overtime per physician are used as performance criteria. Finally, the best solution in terms of the selected performance criteria is determined as an efficient schedule to be used in the ER.

4 Application of the proposed approach

The proposed model is applied to the ER of a public hospital in a metropolitan city of Turkey. The ER provides 7 days 24-hours service. Therefore, in addition to regular 8-hours shift (type 1), the hospital assigns physicians to 24-hours shift (type 2) to maintain uninterrupted healthcare service.

On workdays, both shifts are active while on the weekends and public holidays, physicians are only assigned to 24-hours shifts. Currently, schedules are constructed manually in the hospital. 22 physicians work in the ER department. According to the triage method, patients are classified into three groups: urgent, less urgent, and non-urgent. The treatment period of patients varies for these groups. The scheduling period is determined as a month, which consists of 30 days and the first day of the month is assumed to be Monday. Contracted physicians have a constant wage and for the working hours in polyclinics, they receive an additional fee. On the other hand, the outside physicians are paid depending only on the total working hours.

4.1 Multi-objective mathematical model

The model parameters are obtained through observations, historical data and interviews. The required number of physicians is determined based on the historical data on patient demand for each day and shift of the month. First, average demand is calculated for each day and each shift. Then, patients are classified according to the triage method. As a result of the interviews made with hospital employees, 80% of patients are assumed to be non-urgent, while 15% are less urgent and 5% are urgent. Treatment periods of the patients are determined by the help of healthcare employees to provide qualified healthcare services to patients. The treatment period for non-urgent, less urgent and urgent patients are taken as between 5 and 10 minutes, between 10 and 40 minutes and between 40 and 120 minutes, respectively. These treatment periods do not correspond to the actual times for examining a patient properly, but they are as close as possible to the required times. For the deterministic model, these durations are determined as an average 7.5, 25 and 80 minutes. Model parameters are given in Table 2, but the parameters about cost and preferences cannot be provided due to the confidentiality agreement.

Table 2 Model parameters

Parameters	*Values*
L_j	$L_1 = 8$, $L_2 = 24$
WT^{Max}	160
OT^{Max}	20
NS^{Max}	6
WS^{Max}	2
WS^{Min}	1

Table 3 and Table 4 show the required treatment time for a shift and how to calculate the required number of physicians for a shift on a hypothetical example in detail.

Table 3 Determination of total treatment time per shift

Patient group		*# Patients*	*Treatment time (TT) (min)*	*Total TT (min)*
1	Non-urgent	160	7.5	1,200
2	Less urgent	30	25	750
3	Urgent	10	80	800
Total		200	-	2,750

Table 4 Calculation of required number of physicians per shift

Shift type	*Required TT*	*Required # physician*
1 (8-hour)	2750	5.73 (6 physicians)
2 (24-hour)	2750	1.91 (2 physicians)

4.1.1 Constructing payoff table

The proposed mathematical model transformed to the required structure to solve it by augmented ε-constraint is mentioned before, so the first step of the augmented ε-constraint method is given in Section 3. The second step is constructing a payoff table using lexicographic optimisation of objective functions. Initially, for the first objective function, the following MIP is solved.

$$f_1^* = \min f_1$$

subject to equations (4) to (20).

The optimal solution of this model is f_1^* = 351,920. Subsequently, the best possible values of the other objectives are found by the following MIPs (for i = 2, 3) adding f_1 = 351,920 as a constraint.

$$f_{i1} = \min f_i$$

subject to equations (4) to (20).

$$f_1 = 351,920$$

First, f_2 is optimised after adding optimum f_1 as a constraint, and we find that f_{21} = 88. Lastly, f_3 is optimised adding f_2 = 88 and f_1 = 351,920 as constraints. We find f_{31} = 916. A similar procedure is applied to the other objective functions selected as the main function and the results are given in Table 5.

Table 5 Payoff table

Payoff table	f_1	f_2	f_3
min f_1	351,920	88	916
min f_2	352,720	0	825
max $f3$	380,560	0	1,498
Range	28,640	88	673

Using the payoff table, the range of each objective function is obtained, and then these ranges are divided into seven equal intervals to distribute evenly on the Pareto optimal curve. Eight grid points, given in Table 6, are determined as the value of ε.

Table 6 Grid points

Objective function/grid points	*0*	*1*	*2*	*3*
f_1	380,560.00	376,468.57	372,377.14	368,285.71
f_2	88.00	75.43	62.86	50.29
f_3	825.00	921.14	1,017.29	1,113.43
Objective function/grid points	*4*	*5*	*6*	*7*
f_1	364,194.29	360,102.86	356,011.43	351,920
f_2	37.71	25.14	12.57	0
f_3	1,209.57	1,305.71	1,401.86	1,498

Initially, the first objective function is optimised where the second and the third objective functions are selected as constraints and 64 solutions are obtained. Subsequently, the second objective function is selected as the main objective function and optimised, where the others are considered as constraints. Finally, a similar procedure is applied to the third objective function. As a result, 192 solutions, containing 34 unique feasible solutions which are not the same, are obtained to compare using Monte Carlo simulation. To give the idea, 10 of 63 solutions are given in Table 7. The mathematical models are performed on computer system i7-6700 CPU and 2.60 GHz using GAMS software. Obtaining 192 solutions takes approximately 250 minutes long in total.

Table 7 Selected Pareto optimal solutions

Pareto optimal solutions			
	Cost (TL)	*Balance workload (hours)*	*Preferences*
1	354,320	29.09	1,012
2	368,959	15.27	1,218
3	351,920	82.27	916
4	376,400	0	1,444
5	352,560	29.09	835
6	364,399	30.54	1,211
7	372,079	0	1,368
8	360,080	15.27	1,128
9	359,120	0	1,119
10	374,719	15.27	1,405

4.2 Simulation model

After Pareto optimal solutions and physician schedules are obtained, the simulation model is run. In the proposed simulation model, parameters are generated randomly based on the real data collected from the hospital. Thirty replications are run and each simulation model is developed for 30 days.

The assumptions related to model parameters are made based on interviews with the hospital personnel, observations, and historical data, and given below:

- The number of patients applied to the ER is supposed to be distributed normally for each day of the month. For example; for Monday, the mean and the variance are 460 and 4,847, respectively (i.e., N(460, 4847)).
- 80% of patients applied to ER is non-urgent patients, 15% are less urgent and 5% are urgent based on the historical data.
- The probability distribution of the treatment time for urgent, less urgent, and non-urgent patients is triangular distribution with the parameters TRI (40, 80, 120), TRI (10, 25, 40), and TRI (5, 7.5, 10), respectively.

For each day and shift for a month, patient demand is generated randomly using the probability distribution function mentioned in the assumptions. Then, these patients are classified based on the severity of the disease randomly. A random number for determining the severity of the disease is generated from uniformly distributed [0–1] interval. If the random number is less than 0.80 then the patient is non-urgent, if it is between 0.80 and 0.95 then the patient is less urgent, and finally for values greater than 0.95 the patient is urgent. Treatment time for each patient is generated using the probability distribution function with the parameters.

An illustrative example for the generation of treatment time and classification of patients due to the severity of the disease is given in Table 8. In the example, initially, the number of patients is generated randomly from N(460, 4847) as 429. Then, the severity of the disease for each patient is generated. The treatment time is found based on the type of severity of the disease for each patient. Finally, the total required treatment time to meet patient demand per shift for a month period is calculated by summing patients' treatment time up.

Table 8 Generation patient groups and treatment time

Patient	*Random number*	*Severity of disease*	*Random number*	*Treatment time*
1	0.65	Non-urgent	0.62	8
2	0.96	Urgent	0.06	43
3	0.20	Non-urgent	0.48	7
4	0.27	Non-urgent	0.68	8
5	0.41	Non-urgent	0.80	8
6	0.75	Non-urgent	0.13	6
7	0.61	Non-urgent	0.41	7
8	0.70	Non-urgent	0.26	7
9	0.16	Non-urgent	0.90	9
10	0.85	Less urgent	0.94	33
..	..	..	..	..
..	..	..	..	..
429	0.88	Less urgent	0.31	15
Total required treatment time				2,689

After calculating the total treatment time, the performance criteria, which are overtime and idle time, for the given shift are calculated by comparing the schedules of the efficient solutions obtained from the mathematical model. Total idle time and total overtime are calculated by subtracting the total physician available time for each shift from the total required treatment time and taking the average of all replications. These calculations are given in Table 9 as an illustrative example. In the example, after the simulation run, the total treatment time for a particular shift is obtained as 2,689 minutes. Five physicians are assigned to the shift based on the mathematical model solution. The length of a regular shift is 480 minutes. Therefore, the total available time for treatment becomes 2,400 (480*5) minutes. As given in Table 9 the 1st replication, since the total treatment time is greater than the total available time, there will be 289 minutes of unmet demand. For instance, in the second replication, the total available time is greater than the total treatment time. Therefore, there will be idle time.

Table 9 Calculations of overtime and idle time

Replication no.	*Shift type*	*Total treatment time from simulation (min)*	*# Phys for a shift from the mathematical model*	*Length of shift (min)*	*Total available time for treatment (min)*	*Unmet demand (min)*	*Idle time (min)*
1	Regular shift	2,689	5	480	2,400	289	-
	24-hour shift	5,880	4	1,440	5,760	120	-
2	Regular shift	2,200	5	480	2,400	-	100
	24-hour shift	5,660	4	1,440	5,760	-	200

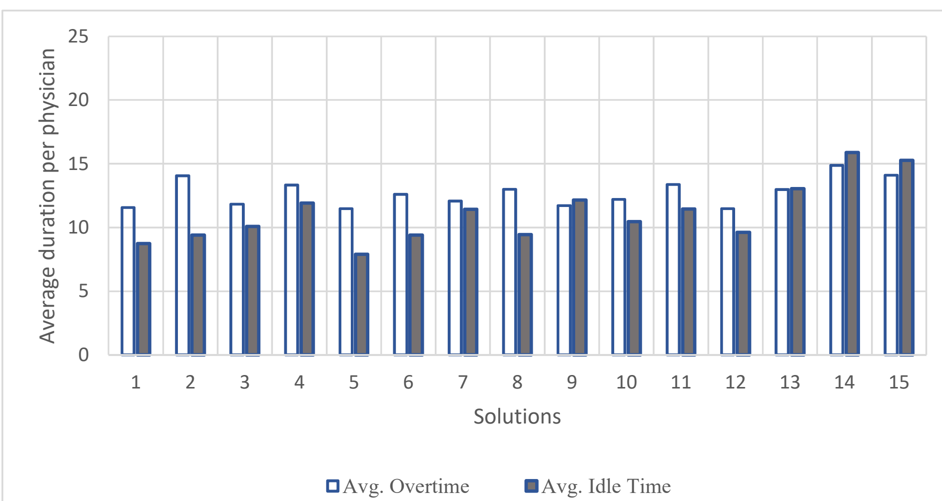
A similar procedure is applied for 30 replications and each Pareto optimal solution. Table 10 and Figure 3 show the average overtime and idle time per physician for Pareto optimal solutions.

Physicians should not work more than the determined working hours in terms of physicians' and patients' health. But, physicians are forced to work overtime because of excessive and uncertain demand. They need some rest in such an intensive work environment like the ER. Thus, it is expected that average overtime should be minimum, average overtime and idle time should be balanced. Also, total working time is stabilised in this way. For this, a solution with low overtime and a small difference between overtime and idle time is selected as the best schedule. According to the results given in Table 10 and Figure 3, solution 12 is selected as the best schedule. The solution provides minimum cost for satisfying demand even if hospital management decides to use outside physicians or overtime. The physicians do not have to work more than the required time, since the overtime and idle time are balanced or outside physicians work. For both situations, objectives like meeting patient demand providing qualified healthcare service, decreasing stressful and intensive work environments led to several disorders of physicians relatively are satisfied.

Table 10 Average overtime and idle time

Pareto optimal sol.	*Overtime per doctor monthly*		*Idle time per doctor monthly*	
	Average (hour)	*Standard dev. (hour)*	*Average (hour)*	*Standard dev. (hour)*
1	11.57	1.79	8.73	1.18
2	14.05	1.90	9.40	1.05
3	11.83	1.78	10.08	1.08
4	13.32	1.69	11.92	1.22
5	11.47	1.91	7.90	1.16
6	12.59	1.83	9.39	1.15
7	12.08	1.62	11.42	1.19
8	13.00	1.73	9.44	1.46
9	11.71	1.72	12.15	1.19
10	12.20	1.69	10.45	1.24
11	13.37	1.75	11.45	1.14
12	11.47	1.78	9.62	1.16
13	12.98	1.88	13.05	1.28
14	14.88	1.80	15.89	1.21
15	14.09	1.86	15.26	1.21

Figure 3 Average overtime and idle of each solution (see online version for colours)



5 Conclusions and further suggestions

In this study, a two-phase approach consisting of a multi-objective mathematical model and a simulation model is proposed to solve the scheduling problem of physicians in the

ER considering the uncertain nature of the hospitals. AUGMECON method is used to obtain Pareto optimal solutions selecting each objective function as the main objective. The significant contribution is using the simulation to select the best Pareto optimal solution which is affected the least by the uncertain nature of the problem.

The proposed approach is applied to a real-world problem to show its applicability. As a result of the proposed approach, an efficient schedule is obtained in accordance with the purpose of the study by solving the mathematical model with three objectives and using Monte Carlo simulation. The approach can be used for staffing problems and other personnel scheduling problems with simple modifications.

The proposed approach satisfies objectivity in selecting the final schedule among Pareto optimal solutions by using simulation unlike the approaches using directly DMs' choices (Aghaei et al., 2011) or applying MCDM methods (Majidian-Eidgahi et al., 2020; Yang et al., 2021). Some approaches (Bruni and Detti, 2014; Camiat et al., 2021; Barafkandeh et al., 2022) determine the weight or importance of objectives, but in the proposed approach there is no need for such an empirical judgement that may result in a biased solution.

In further research, waiting times of patients can be considered as a new performance criterion in the simulation model. Patient demand can be determined using forecasting methods like regression and neural networks. In addition, flexible shift starting times and flexible shift lengths can be performed to decrease the effects of variability in demand and treatment time.

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