doi 10.54172/ijhr.2018.xx

IJHR

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Echocardiography Appointment Scheduling Through Better Utilization of Resources

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Abstract

Background and Objectives: Appointment scheduling systems are applied in a broad variety of healthcare environments to reduce costs, increase resource utilization, and facilitate patients' access to care. This study strives to present efficient scheduling models for the Echocardiography Department of Tehran Heart Center (THC). These models seek to optimize both patient and hospital utility by maximizing the weighted number of performed echos and minimizing overtime.

Methods: There are two major problems in developing such models: shift scheduling problem and capacity allocation problem. In this paper, two mixed integer linear programming (MILP) models are presented based on two different sets of assumptions. The first model is developed according to the current routines of the hospital. In this model, it is assumed that the assignment of specialists to echocardiography laboratories in different shifts is predetermined. Thus this model merely allocates the available capacity of specialists and labs to different types of patients. However, the second model is more comprehensive, as it schedules the shifts of the specialists and allocates the capacity to the patients simultaneously.

Findings: The efficiency of the proposed models is evaluated using the real data of the Echocardiography Department of THC. The results showed that both models increased the utility (12.35% and 19.14%, respectively) in comparison with the current status of the department. The first model improved the performance of the department significantly through better utilization of resources; however, the second model improved the performance much more than the first one through creating more capacity and utilizing the capacity efficiently.

Conclusions: Although both models showed significant improvements, the second model was found to be more efficient. The reason is that the first model assumes the specialists' shift assignment to be predetermined, while the second model finds the best shift assignment itself.

Keywords: Echocardiography, Appointment scheduling, Resource utilization, Shift scheduling, Capacity allocation, Optimization, Mathematical model

Background and Objectives

Echocardiography, often simply called "echo", is the second most common cardiac test after electrocardiography.[1] It uses sound waves to produce live images of the heart. Echocardiography, as one of the most powerful diagnostic and monitoring tools, provides specialists with vital information on how the heart and its valves are functioning.[2] It is frequently utilized for diagnosis, control, and follow-up of patients with any suspected or known heart diseases.[3] It also makes the consultation easier for the specialists.[4] Furthermore, it is ordered by non-cardiology physicians in many cases.[1] So, many parts of a patient's journey take advantage of it.[4] There are several types of echo, including transthoracic echo, stress echo, transesophageal echo, fetal echo, 3-dimensional echo, Doppler echo, and contrast echo. Echo is performed by cardiac sonographers or cardiac physiologists in echo laboratories equipped with required facilities such as ultrasound machines, probes, etc.

Long waiting time for a patient to receive healthcare services is probably associated with the delay in disease recognition, delay in the start of the treatment, disease progression,[5] psychological distress,[6] and patient dissatisfaction.[7] These delays can be due to imbalance between capacity and demand, or inefficient patient scheduling.[6, 8]

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The problem of patient scheduling, generally called appointment scheduling, is the joint consideration of patients' and healthcare providers' interests. From the patients' perspective, it is required to provide timely access to care[4] with paying attention to patients' preferences in choosing the appointment time/date and physicians. However, from the healthcare providers' perspective, resource utilization, capacity management[9] and cost management[10] should be considered.

This research focuses on appointment scheduling in echocardiography environments. A two-part weighted objective function is defined to incorporate the interests of both patients and hospitals. The first part is the maximization of the weighted number of performed echos, which is mainly patient-centered, since it strives to provide the highest possible level of access to care for patients. Also it can decrease patients' indirect waiting time (the average interval between requests for appointment by patients to the actual dates of appointment). Furthermore, it increases the hospitals' revenues and decreases resource underutilization. The second part of our objective function is the minimization of overtime. This part decreases both the hospitals' variable costs, and personnel dissatisfaction. In the rest of this paper, we call our objective function as maximization of utility, i.e. the utility of performed echos minus the disutility of overtime.

We have considered the case study of the Echocardiography Department of Tehran Heart Center (THC). With 460 inpatient beds, THC is one of the most advanced and best-equipped diagnostic and therapeutic cardiology centers in Iran and the Middle East. In the previous ten years, it has provided services for more than 1 133 162 outpatients and 179 312 inpatients. There have been 259 830 transthoracic, transesophageal, tissue Doppler, stress, and contrast echocardiography cases in its echocardiography department. In this department, laboratories are equipped with modern imaging facilities, and the specialists are amongst the best in their field.[11]

According to the authorities of THC, the Echo Department is the most crowded department of the hospital. Demands for different types of echo are from patients referred to this department from other clinics and hospitals all over the country, or inpatients of THC. Since an echo lab exists in the Emergency Department of THC, urgent patients do not refer to the echo department. The huge demand for echo has led to long indirect waiting time for outpatients, and prolonged length of stay for inpatients. This causes patient dissatisfaction and disrupts patient flow, especially in the hospitalization step.

The problem of patient scheduling is so challenging in an echocardiography environment because of (*i*) specialists with different specialty and quickness levels, (*ii*) non-identical echo labs equipped with different facilities, (*iii*) several echo types with different durations, required specialty levels and facilities, iv) possibility of overtime and many other complicating factors. A manual and empirical process to create a schedule for echo environment is very time-consuming. More importantly, using such a process does not guarantee an optimal solution, and we probably have to do with a feasible solution. Thus, it may cause long waiting time for patients, waste of capacity, and increase of overtime. In addition, it probably does not incorporate specialists' preferences.

Optimization is one of the broadly utilized methodologies in modeling and solving complicated healthcare problems.[12] This study addresses the research gap in developing applicable optimization techniques for appointment scheduling, which perfectly suit the characteristics of echocardiography environments. This being the case, the research question of this study is: "How to develop an optimal and practical appointment scheduling system for the Echo Department of THC such that the weighed number of performed echo is maximized and the overtime is minimized". Such a scheduling system is required to (*i*) indicate the assignment of specialists to different labs in each shift, (*ii*) allocate the available capacity to different groups of patients, (*iii*) predict the required overtime hours, and (*iv*) maximize utility via maximization of the weighed number of performed echos and minimization of overtime.

Decisions addressed in this paper are concerned with the assignment of specialists to shifts and labs, and the assignment of patients to shifts, labs, and specialists. So, it is required to handle the problems of shift scheduling and capacity allocation, considering the possibility of overtime.

The contributions of this paper are as follows:

- Developing 2 mixed integer linear programming (MILP) models in different levels of decision-making to optimize an objective function which incorporates patients and hospital utility. One of the models is based on the current procedure of the Echo Department and the other is based on a more comprehensive idea.

- Simultaneous shift scheduling and capacity allocation considering non-identical resources and preferences in the second model.

- Running the models for the real data of the Echo Department of THC resulting in considerable potential for improvement.

Related Works

Healthcare systems are the most challenging environments for appointment scheduling.[13] The reason lies in the fact that many conflicting goals and a variety of

constraints should be taken into account in these settings. Appointment scheduling in healthcare has been an attractive research area for more than half a century. From the earliest researches in this field, the work of Bailey can be mentioned.[14] Bailey has focused on the operational level of daily scheduling.

As mentioned, in order to develop an efficient scheduling system for echocardiography department, we should consider both shift scheduling and capacity allocation problems. To this end, first the most related papers on shift scheduling and capacity allocation have been reviewed.

As for shift scheduling, usually a large number of rules and requirements should be regarded. These rules/requirements are concerned with providing standard levels of patient care, educational opportunities,[15] hospital policies, labor laws, and preferences. Volland et al considered shift scheduling and task scheduling problems for a group of specialized nurses in charge of logistics tasks, called logistics assistants. They presented an MILP to determine the optimal number of required assistants, and also a column generation based approach to optimally solve the problem.[16] Hong et al presented a recursive algorithm in order to generate a set of pareto-dominant shift schedules for an emergency department.[15] Brunner et al addressed the shift scheduling problem of physicians considering a variety of legal and institutional constraints. They developed a mixed integer model to find an assignment that minimizes overtime.[17]

The next decision of this paper is the allocation of capacity to patient groups, which is a tactical decision. Generally, the main objectives of decisions at the tactical level are the maximization of productivity and the accessibility of high-quality care services.[13] Nguyen et al developed a network flow approach based on Branch and Cut algorithm to allocate capacity to different groups of patients in a re-entry system.[18] Choi and Wilhelm considered capacity allocation decisions in operating rooms (ORs). They proposed a non-linear model to allocate specialties to OR-days, aiming at minimizing the total expected costs of idleness and overtime.[19] LaGanga and Lawrence proposed a procedure to develop near-optimal overbooked appointment schedules to make a trade-off between visiting additional patients and the cost of patients' waiting time and providers' overtime.[20]

Furthermore, due to the similarities between the scheduling of OR and the echo department, we can take advantage of the literature of appointment scheduling and resource utilization in OR. Aringhieri et al. considered OR planning and advanced scheduling problems simultaneously. They decided on the allocation of OR time blocks to specialties and the allocation of patients to time blocks. They applied a two-level metaheuristic to maximize the utility of both patients and hospitals.[21] Merchesi and Pacheco discussed the problem of allocating specialists to ORs over a one-week time horizon. They developed a genetic algorithm to minimize unmet demand and the difference between the allocated time of OR to each specialty and demand.[22] Fairley et al discussed sequencing OR procedures in order to minimize delays caused by unavailability of post-anesthesia care unit (PACU). In this paper, machine learning was applied to estimate the required PACU time. Two integer programming models were developed to schedule procedures in the ORs. Finally, discrete event simulation was used to show the efficiency of the proposed schedule.[23] Guido et al focused on maximizing the number of appointments in an outpatient setting. Answer Set Programming (ASP) was applied to solve the discussed problem. They developed a 3-phase solution approach based on patient's priority for the research problem.[24] M'Hallah and Al-Roomi proposed a stochastic model to schedule elective surgeries with the objective of maximizing the expected ORs throughput. This model considers the availability of both intensive care unit beds and post-surgery beds. Also a sample average approximation was applied to solve the problem.[25] Hamid et al focused on scheduling inpatient surgeries. In this paper, first the decision-making styles of the surgical team members were incorporated to improve the compatibility within the surgical teams. Then 2 metaheuristics based on genetic and particle swarms optimization were developed to find Pareto solutions.[26] Atighechian et al suggested a two-stage stochastic model for scheduling surgeries in teaching hospitals. The objective was to minimize idle-time and overtime. L-shaped algorithm was used to solve this model. The results showed the high efficiency of the proposed method over practical schedules.[27] Sadeghzadeh and Sadat discussed overbooking in OR scheduling to mitigate the negative effects of no-shows. First the feasibility of overbooking surgical procedures was shown using Monte-Carlo simulation. Then a model was developed to determine the surgeries for overbooking, aiming at maximization of profit. The results revealed significant improvements in comparison with the base case of no overbooking.[28] Holm et al applied discrete event simulation and soft systems methodology in a surgical unit to examine the effect of different factors on patient flow and resource utilization. They provided a lot of practical information and suggestions for the hospital management.[29] Durán et al focused on improving OR utilization. For this purpose, they developed 2 optimization models and 2 algorithms for scheduling interventions, incorporating patients' priorities. These 4

mathematical methods were compared under different scenarios. The findings showed that the proposed models could considerably improve OR utilization.[30] Najjarbashi and Lim presented a risk-based solution approach using the concept of conditional value-at-risk (CVaR) in order to reduce variability for the OR scheduling problem. They developed a stochastic MILP model with the objective of minimizing the CVaR of overtime and idle-time costs to solve the problem.[31]

From another standpoint, we reviewed the papers that discussed process improvements regarding echocardiography. Katsi et al proposed descriptive productivity measures of echocardiography studies of Greek National Healthcare System. It was concluded that the number of studies per physician per day is a good measure to evaluate productivity.[32] Bakshi focused on the workflows of different activities in a cardiology department. With the help of process reengineering methods, he studied the processes of the existing system and recommended necessary suggestions.[33] Geronimo attempted to improve access to stress echo in an emergency department via observations, time studies and Plan-Do-Study-Act process. In this work, by performing a root cause analysis and having team discussions, it was suggested to add a stress echo lab, purchase new stress testing equipment, and change the schedule of 2 registered nurses.[34] Gandhi discussed the appointment scheduling problem in an echo department, aiming at increasing the number of scans per day. For this purpose, 6 scenarios were presented and the effect of each scenario was evaluated using simulation. The scenario that eliminated the use of sonographer schedules was shown to be the best.[3]

In conclusion, many outstanding works have been conducted in the field of healthcare appointment scheduling or echocardiography workflow improvement. However, to the best of our knowledge, there is no research on appointment scheduling in echo departments using optimization techniques.

Methods

In this section, our developed models for making appointment scheduling decisions at the tactical level for echo departments are presented. As mentioned earlier, one of these models is based on the current decision-making process of our case study, and the other one is on the basis of a more comprehensive perspective.

Different patients requesting different echo types refer to an echo department. Each echo type requires specific facilities and specialty level to be performed. There are several echo labs in an echo department. Various kinds of facilities are located in each lab. Therefore, echo labs

are not exactly the same. Furthermore, there are several specialists with different specialty and quickness levels in an echo department. Each specialist is only capable of performing echos compatible with his/her specialty level. The echo duration for each patient depends on the requested echo type and the quickness of the specialist. Each echo type can be performed only in a lab with required facilities, and by a specialist with required specialty level. Since an echo needs a specialist and a lab to be performed, the problem discussed in this paper is a dual-resource appointment scheduling problem.

In each working day, usually, 2 shifts are defined for specialists: morning shift and evening shift. Therefore, the planning horizon of our developed schedule is made up of date-shift combinations. For simplicity, in the rest of this paper, combinations of date-shift are just referred to as shifts. Furthermore, it is possible for specialists to work beyond their regular shift time as overtime.

The First Mixed Integer Linear Programming Model

According to our conducted interviews and observations in the Echo Department of THC, first, a weekly timetable is provided empirically by the chief of the department. This timetable determines the assignment of the specialists to the labs in different shifts. The next step is to determine the number of echos of each type that should be performed in each shift and by each specialist to maximize utility. Currently, the decision of this step is made by specialists based on their experience. We developed our first MILP to make this decision more efficiently. The proposed model gets the predetermined assignment of specialists to shift-lab combinations as the input, and finds the optimal assignment of patients to the resources. In summary, our first model specifies the number of patients of each type that could be assigned to each combination of specialist-shift-lab and also the expected required overtime for each specialist in each shift. A brief review of the assumptions and the research question of the first MILP is provided in Table 1.

According to the assumptions and the research question, the first MILP contains the following objective function and constraints. Details of the parameters and the decision variables of this model are provided in Supplementary file 1.

The objective function, as presented in Eq. (1), is to maximize the utility. The first part incorporates the weighted number of performed echoes, while the second part accounts for disutility of overtime.

$$\max \sum_{i\in I, t\in T, l\in L} W_i \times X_{itl} - CO \times \sum_{t\in T, j\in J} OH_{tj} \quad (1)$$

Table 1. The Assumptions and the Research Question of the first MILP

Assumptions
− There are several echo labs with different facilities.
− There are several specialists with different specialty and quickness levels.
− Each type of echo can be performed only in a lab with required facilities, and by a specialist with required specialty level.
− The echo duration depends on the echo type and the quickness of the specialist.
− At any time and in each echo lab, at most one specialist can perform echo, and at most one patient can be visited.
− Overtime is allowed.
− A regular available time and a maximum possible overtime are defined for each lab in each shift.
− Total allowable overtime for each specialist in the planning horizon is limited.
− Total demand of each echo type in the planning horizon is known based on historical data.
− To keep a certain service level for each echo type, a predefined minimum number of echos of each type should necessarily be performed within the planning horizon.
− The utility of performing each echo type and the disutility of the overtime (per hour) is given.
− A timetable, which determines the assignment of specialists to labs in different shifts, is available (created manually by the chief of the department).

Research Question
− How to allocate the available capacity to different groups of patients, i.e. how many echos of each type should be performed in each shift and each lab (considering the overtime possibility)?

Constraint set (2) ensures that the total required time of all echos assigned to any lab-shift combination is less than or equal to the sum of regular shift's length and overtime of the specialist assigned to that lab in that shift.

$$\sum_{i \in I}(X_{itl} \times \sum_{j \in J}(A_{jtl} \times P_{ij})) \leq WH_{lt} + \sum_{j \in J}(A_{jtl} \times OH_{tj}) \quad \forall t \in T, l \in L \quad (1)$$

Constraint sets (3) and (4) determine the overtime of specialist *j* in shift *t*. Constraint set (3) ensures that the total overtime of specialist *j* in the planning horizon does not exceed the total allowable overtime for that specialist. Constraint set (4) guarantees that if specialist *j* does not work in shift *t,* then his/her overtime in shift *t* should be zero. It also assures that if specialist *j* is assigned to lab *l* in shift *t*, the corresponding overtime should not exceed the maximum allowable overtime of lab *l* in shift *t*.

$$\sum_{t \in T} OH_{tj} \leq MO_j \qquad \forall j \in J \qquad (3)$$

$$OH_{tj} \leq \sum_{l \in L}(TO_{lt} \times A_{jtl}) \quad \forall t \in T, j \in J \qquad (4)$$

Constraint set (5) is incorporated into the model to keep a certain service level for each echo type. It makes sure that the total number of scheduled patients of each echo type in the planning horizon satisfies at least a predefined minimum level. Constraint set (6) ensures that the total number of scheduled echos of each type is equal to or less than the total demand of that echo type.

$$\sum_{t \in T, l \in L} X_{itl} \geq K_i \qquad \forall i \in I \qquad (5)$$

$$\sum_{t \in T, l \in L} X_{itl} \leq D_i \qquad \forall i \in I \qquad (6)$$

Constraint set (7) supports the fact that the assignment of patients of echo type *i* to specialist *j* is possible, if and

only if specialist *j* has the required specialty level.

$$\sum_{t \in T, l \in L}(A_{jtl} \times X_{itl}) \leq D_i \times S_{ij} \quad \forall i \in I, j \in J \qquad (7)$$

Constraint set (8) guarantees that the assignment of patients of echo type *i* to lab *l* is possible, if and only if lab *l* has the required facilities**.**

$$\sum_{t \in T} X_{itl} \leq D_i \times E_{il} \quad \forall i \in I, b \in B, l \in L \qquad (8)$$

Finally, Constraint set (9) represents the integer and continuous variables.

$$X_{itl} \geq 0, int \quad \forall i \in I, t \in T, l \in L \qquad (9)$$

$$OH_{tj} \geq 0 \quad \forall t \in T, j \in J$$

The SECOND Mixed Integer Linear Programming Model

After developing the first model, we decided to extend the model to cover the decision of the specialists' assignment as well, with the hope of obtaining more improvement. Also providing a timetable to determine specialists' assignment manually is very time-consuming since it requires to consider many factors. Furthermore, this timetable might fail to incorporate some preferences or limitations. Consequently, it may not be the best possible assignment. This being the case, we developed our second model. The output of this model consists of 2 parts. The first part assigns the specialists to the shift-lab combinations. The second part specifies the number of patients of each type that could be assigned to each specialist-shift-lab combination. It also determines the required overtime. A brief review of the assumptions and the research questions of the second MILP is provided in Table 2.

According to the assumptions and the research

Table 2. The Assumptions and the Research Questions of the Second MILP

Assumptions
– All the assumptions of the first MILP are hold except the existence of a timetable for specialists' assignment (the last assumption).
– Sum of regular hours that each specialist works should be in the range of allowable hours to work for that specialist in the planning horizon.
– Specialists might have different preferences on their assigned shifts. Some specialists are strictly unwilling to work in some shifts.

Research Questions
– How to assign specialists to labs in each shift?
– How to allocate the available capacity to different groups of patients, i.e. how many echos of each type should be performed in each shift and each lab (considering the overtime possibility)?

questions, the second MILP is developed as follows. In this model, other than the constraints considered in the first model, some other limitations or preferences related to specialists' assignment should be regarded. Details on the parameters and the decision variables of this model are provided in Supplementary file 1.

The objective function, as presented in Eq. (10), is defined to maximize the utility i.e. the utility of performed echos minus the disutility of overtime.

$$\max \sum_{i \in I, t \in T, l \in L} W_i \times X_{itl} - CO \times \sum_{t \in T, j \in J} OH_{tj} \quad (10)$$

Constraint set (11) ensures that in each shift, at most one specialist should be assigned to each lab. Constraint set (12) makes sure that if a specialist is unwilling to work in a specific shift, no lab should be assigned to him/her in that shift. Otherwise, at most one lab is assigned to him/her in that shift.

$$\sum_{j \in J} Y_{jlt} \leq 1 \qquad \forall t \in T, l \in L \quad (11)$$

$$\sum_{l \in L} Y_{jlt} \leq F_{jt} \qquad \forall t \in T, j \in J \quad (12)$$

Constraint sets (13) and (14) guarantee that the sum of regular hours that specialist *j* works is in the range of allowable hours t for that specialist in the planning horizon.

$$\sum_{t \in T, l \in L} (WH_{lt} \times Y_{jlt}) \leq ZU_j \quad \forall j \in J \quad (13)$$

$$\sum_{t \in T, l \in L} (WH_{lt} \times Y_{jlt}) \geq ZL_j \quad \forall j \in J \quad (14)$$

Constraint sets (15)-(21) are similar to Constraint sets (2)-(8) of the first model. However, for some of them, the formulation has been changed to keep the model linear (data not shown).

$$\sum_{\forall t \in T, j \in J \ l \in L} (X_{itl} \times P_{ij}) \leq WH_{lt} + OH_{tj} + (1 - Y_{jlt}) \times M \quad (15)$$

$$\sum_{t \in T} OH_{tj} \leq MO_j \quad \forall j \in J \quad (16)$$

$$OH_{tj} \leq \sum_{l \in L} (TO_{lt} \times Y_{jlt}) \quad \forall t \in T, j \in J \quad (17)$$

$$\sum_{t \in T, l \in L} X_{itl} \leq D_i \quad \forall i \in I \quad (18)$$

$$\sum_{t \in T, l \in L} X_{itl} \geq K_i \quad \forall i \in I \quad (19)$$

$$X_{itl} \leq D_i \times \sum_{j \in J} (S_{ij} \times Y_{jlt}) \quad \forall i \in I, l \in L, t \in T \quad (20)$$

$$\sum_{t \in T} X_{itl} \leq D_i \times E_{il} \quad \forall i \in I, l \in L \quad (21)$$

Finally, Constraint set (22) represents the binary, integer, and continuous variables.

$$Y_{jlt} = 0 \, or \, 1 \ \forall t \in T, j \in J, l \in L$$

$$X_{itl} \geq 0, int \ \forall i \in I, t \in T, l \in L \quad (22)$$

$$OH_{tj} \geq 0 \ \forall t \in T, j \in J$$

Figure 1 shows the decision area of the first and second MILP models. Also Figure 2 illustrates the inputs and outputs of each model.

For our schedule, the planning horizon of one week seems to be suitable. Many hospitals keep their schedule with minor alterations until a substantial change takes place.[24] Since the weekly demand does not vary significantly among different weeks within a month, the efficient schedule obtained by our proposed methods for one week can be repeated for several weeks until the demand rate or any other important parameter of the system changes.

Results and Discussion

In this section, we evaluate the performance of our developed models using the real data provided by the Echo Department of THC. We compare the results of the proposed models with the current performance of THC and

Decision 1: Specialists' assignment to the labs in each shift

Decision 2: Determination of the number of patients of each echo type that should be assigned to each specialist in each shift plus determination of the required overtime
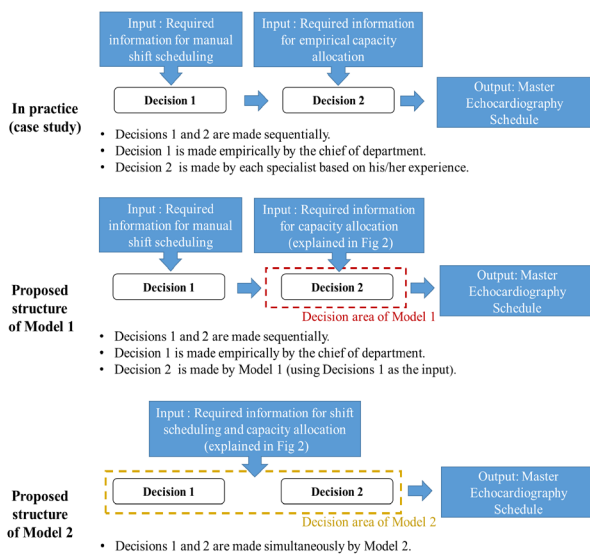

Figure 1.Decision Area of the First and Second MILP Models.

Figure 2. Inputs and Outputs of the First and Second MILP Models.

show how practical capacity utilization can be increased. The models are coded in CPLEX 12.8 (an optimization software package) and the experiments are conducted on a computer with Intel(R) Core i5-4300U CPU @ 1.90 GHz and 4 GB of RAM.

In the Echo Department of THC, there are 5 major types of echo: Transthoracic echo, Doppler echo, Contrast echo, Stress echo, and Transesophageal echo. This department is equipped with 14 echo labs with different facilities. A group of 17 echocardiologists, fellows, residents and heart specialists with different specialty and quickness levels work in this department. We consider one week as the planning horizon; each week consists of 4 days with 2 shifts (morning and evening) and one day with one shift (morning). Typically, the labs are available for about 4.5 hours in the morning shifts, and about 3 hours in the evening shifts. Since an echo lab exists in the Emergency Department of THC, urgent cases are not referred to the Echo Department. Therefore, these cases are not included in our experiments.

In the following evaluations, utility (utility of performed echos minus the disutility of overtime) is considered as the key performance measure of the system. Thus, utility analysis has been carried out to assess the performance of developed models and scenarios. The appropriate values for the utility of performing an echo of each type, and the disutility of overtime are defined such that they incorporate both monetary and non-monetary factors (e.g., priorities of different echo types or dissatisfaction due to overtime).
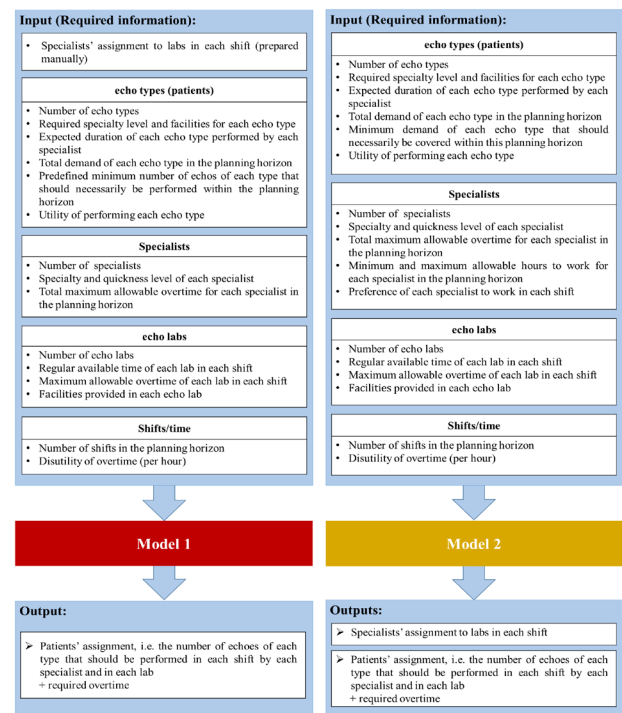
We collected the data of 12 weeks and ran the 2 proposed models for each week. The first part of Table 3 demonstrates the average results of 2 models as well as the average performance of the Echo Department for these 12 weeks. The table shows that the first MILP model can improve the performance of the Echo Department by 12.35% on average through better utilization of the resources. Also the second MILP model improves the performance even more by about 19.14% on average since it creates more capacity and utilizes the resources efficiently. Moreover, the covered level of demand has increased from 66% (current performance of THC) to 77% and 81% using the first and second models, respectively. Figure 3 depicts the schedule for the Echo Department of THC provided by the second MILP model.

We also ran the 2 models on several random practical-sized test problems. The results are provided in the second part of Table 3. The findings show that the second model outperforms the first model by about 6.23%. Also, the second model increased the covered level of demand by about 4% in comparison with the first model. These results confirm the superiority of the second model over the first model. As mentioned, the reason of this superiority lies in the fact that the second model creates the optimal assignment of specialists to shift-lab combinations, instead of using an empirically predetermined assignment.

In the implementation phase, when a new request arrives, the scheduler can easily book it in the most appropriate specialist-shift-lab combination regarding the

Table 3. Performance of the Proposed Models

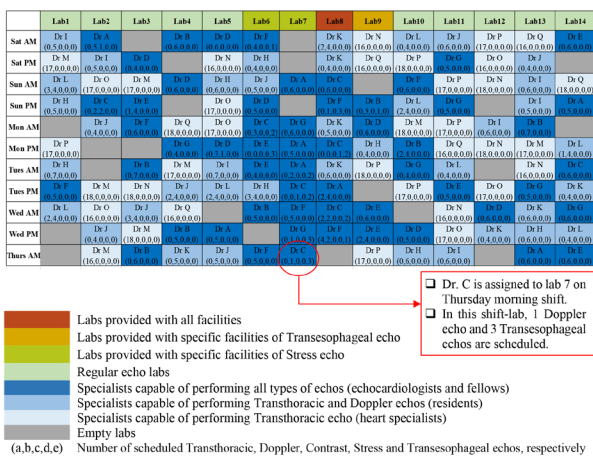|		Number of Performed Echos	Required Overtime (min)	Utility	Covered Level of Demand	Utility improvement Compared to THC	Utility Improvement Model 2 vs. Model 1	Computational Time (s)	Optimality Gap
Real data of THC	THC	911	127	8269.6	66%				
	Model 1	1061	275.69	9291.16	77%	12.35%		2.39	0.00%
	Model 2	1112	148. 32	9852.4	81%	19.14%	6.04%	60*	2.95%
Practical-sized random data	1 Model 1	773	99	7017.2	72%			6.42	0.00%
	1 Model 2	824	63.54	7467.75	76%		6.42%	60	2.14%
	2 Model 1	953	105.75	8511.1	81%			3.05	0.00%
	2 Model 2	1003	63.04	9064.35	85%		6.50%	60	1.57%
	3 Model 1	1130	109.5	10040.6	82%			9.53	0.00%
	3 Model 2	1174	51.33	10640.4	86%		5.97%	60	1.74%
Average						6.23%			

Figure 3. The Schedule for the Echo Department of THC Provided by the Second MILP Model.

available capacity and the patient's preference. Patient's preference might be having his/her echo done by a specific specialist in a specific date/time or just as soon as possible.

*To have a tradeoff between computational time and quality of solution, a computational time limit of 60 seconds is defined for the second MILP model.

For the next step, we defined some scenarios to improve the performance of the Echo Department of THC as our case study. These scenarios are: adding a heart specialist, adding a resident, adding an echocardiologist or fellow, adding facilities for Transesophageal echo, adding facilities for Stress echo, adding an ordinary lab, and adding a fully-equipped lab. Table 4 presents the effects of the proposed scenarios on the current performance of the Echo Department. All the results are provided by the second MILP model. As can be seen, adding a specialist (heart specialist, resident, fellow or echocardiologist) has the most effect on the department's performance.

The managerial applications of the developed models for planning and scheduling of echo departments are as follows:

- These models help managers to make challenging decisions on shift scheduling of specialists and capacity allocation to different groups of patients. The models take all the parameters, constraints and preferences into account, and consider an objective function which is mainly patient-centered, but incorporates hospitals' interests as well.

- While a manual process to develop the appointment scheduling system is time-consuming and does not guarantee good solutions, the proposed models provide high quality solutions in short computational times. In fact, they are capable of providing the best possible solutions to optimize the performance of the system.

- By optimizing the utility (through maximization of the weighted number of performed echoes and minimization of overtime), these models can potentially increase resource utilization, facilitate patient access to care, streamline patient flow within departments related to the echo department, increase patient and personnel satisfaction, and finally, increase hospital's revenue.

Conclusions

In this study, we approached the appointment scheduling problem in the Echo Department of THC, aiming at maximization of the utility. Different types of patients requiring various types of echo refer to this department. There are several specialists with different specialty and quickness levels, and echo labs with various available facilities. Each type of echo can be performed only in a lab with required facilities and only by a specialist with

Table 4. The effects of **scenarios for improvement on the performance of system**

Scenarios	Number of Performed Echos	Required Overtime (min)	Utility	Covered level of Demand	Utility Improvement
Current resources of THC	**1112**	148.32	9852.04	**0.81**	-
Adding a heart specialist	**1143**	34.71	10318.33	**0.83**	4.73%
Adding a resident	**1150**	51.43	10400.28	**0.84**	5.56%
Adding an echocardiologist/fellow	**1152**	53.49	10405.68	**0.84**	5.62%
Adding facilities for Transesophageal echo	**1116**	173.27	9856.07	**0.81**	0.04%
Adding facilities for Stress echo	**1115**	166.97	9855.62	**0.81**	0.04%
Adding an ordinary lab	**1114**	157.09	9857.48	**0.81**	0.06%
Adding a fully-equipped lab	**1118**	163.36	9881.96	**0.81**	0.30%

required specialty level. In the Echo Department of THC, first, a weekly timetable is provided empirically by the chief of the department, which specifies the assignment of the specialists to the labs in different shifts. Next, the number of echos of each type that should be assigned to each shift and each specialist is determined based on the specialists' experience. According to this practical routine, 2 MILP models for different levels of decision-making were developed in this paper. The first model gets the predetermined specialists' assignment as the input, and finds the optimal assignment of patients to the resources. However, the second model does both of these assignments simultaneously. The results of applying the proposed models for the real data of the Echo Department of THC showed that both models could improve the performance of the system (12.35% and 19.14% on average, respectively). Moreover, the covered level of demand increased from 66% (current performance of THC) to 77% and 81% using the first and second models, respectively. Furthermore, we ran the 2 models on several random practical-sized test problems. In all the test problems, the second model outperformed the first model both in increasing the covered level of demand and increasing utility. The second model presented better results because it is capable of finding the optimal assignment of specialists to shift-lab combinations, instead of using an empirically predetermined assignment. Furthermore, several scenarios for improvement of performance were proposed, and the utility of implementing each one was compared to the base case of current performance. According to the results, adding a specialist was found to be the most effective one among all the other scenarios. The development and evaluation of the proposed models suggest several applicable areas for future works. First, the operational decisions involving the exact time and the sequence of patients in the appointment dates can be discussed. Second, other objective functions, such as minimization of patients' waiting time and specialists'

idle-time can be considered. Third, stochastic approaches can be developed for the environments with stochastic demand or duration of echo. Finally, the performance of the proposed models can be evaluated for several hospitals working together and requiring a large number of specialists and labs to be considered.

Competing Interests
The authors declare that there are no conflicts of interest.

Authors' Contributions
SHZ and HA contributed to study design. DC contributed to developing the solution method and models, analyzing the data, drafting and revising the manuscript. SHZ contributed to developing the models, preparing and revising the manuscript. HA contributed to data collection and analysis. All authors read and approved the final manuscript.

Supplementary Materials
Supplementary file 1 contains 2 MILP models.

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