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SIMULATION OPTIMISATION OF ULTRASONOGRAPHY RESOURCE SCHEDULING WITH MACHINE LEARNING

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Abstract
This study proposes a decision-support framework to optimize radiologist staffing in the ultrasonography department. Patient arrival rates were forecast using Light Gradient Boosting Machine (LightGBM) with feature expansion, achieving 99.99 % accuracy over one-month period. A discrete-event simulation model was subsequently used to determine the number of radiologists required to meet target waiting times. Based on the simulation results, hourly radiologist requirements were identified, and an optimized schedule was generated. By integrating machine learning, simulation, and scheduling, this framework supports data-driven planning and can be applied to other healthcare services and facilities facing demand uncertainty.
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Key Words: Machine Learning, Discrete-Event Simulation, Resource Scheduling, Healthcare Systems, Health System Resources

1. INTRODUCTION

Waiting time is critical in hospitals, especially for patients and families under stress. Reducing it, improves satisfaction and optimizes resources like ultrasonography (USG) devices, staff, and physicians. Unlike outpatient clinics, USG departments face unpredictable patient arrivals, causing planning challenges and queues [1]. As a widely used, safe, and non-invasive imaging tool, ultrasonography plays a vital role across many medical specialties.

In this study, patient flow in the USG department of a hospital was analysed. Machine Learning (ML) methods were employed to estimate the required patient arrival rates. Health is one of the fields, where ML can be useful. Chakraborty et al. [2] discussed how machine learning and deep learning can be useful for healthcare. Alghamdi et al. and Shahidian et al. [3, 4] discussed the possibility of applying ML models for the purpose of managing and organizing health records. Ensemble ML models were used to predict the future values of daily incidents and deaths [5]. ML also enables prediction and supports HR decisions [6].

The aim of this study is to demonstrate the use of ML to operations management in the healthcare sector. Patients arriving at the USG department first register and are admitted for consultation if the radiology physician is available. Due to variability in patient arrivals and service times, most simulation-based studies in healthcare have focused on emergency departments [7-9]. Corsini et al. [10] developed an agent-based simulation model designed for oncology departments working with external pharmacies to optimize patient flow and minimize wait times. Vázquez-Serrano et al. and Chen et al. [11, 12] developed a hybrid model based on the optimisation and discrete-event simulation (DES) by considering priority of patients, preparation times and resource-availability to reduce the waiting time.

There have been numerous studies focused on organizing patient appointment systems in the healthcare field, often in conjunction with emergency service simulation, to enhance patient satisfaction levels. Jlassi et al. [13] presented a mathematical model using integer programming to reduce the overall waiting time for patients. Olisemeke et al. [14] conducted a literature review summarizing patient waiting times in the radiology department, revealing the lack of studies that address waiting time reduction in the USG department, specifically. Shakoor [15] developed a simulation model to assess USG department performance under different appointment scheduling policies.

The novelty of this study lies in its use of ML to predict patient arrivals that will happen in a month's time even under unpredictable conditions, simulation technique to determine patient waiting times and decisions on the required number of radiologists by using mathematical modelling. While traditional simulation techniques rely on fitting patient arrivals to a specific statistical distribution [16], this study minimizes variability to a great extent by using machine learning methods to predict the number of incoming patients with a very high level of accuracy. Simulation technique is an effective and practical method, as its models require uncertain data and are straightforward and quick to apply. Beyond capacity estimation, queueing models and resource allocation studies offer key insights into optimal resource flexibility, specialization, and priority strategies in both healthcare and manufacturing contexts [17-19]. This study investigates how radiologist staffing in the USG department can be optimized by forecasting patient arrivals over a specific time period. The contributions of this study are as follows:

- We propose a model that integrates ML, simulation technique and optimisation model for systems where patient arrival numbers are unknown. For the USG department, we consider nonhomogeneous patient arrival rates, variations in human resource levels across different shifts, and stochastic processing times.
- The proposed model serves as a decision support system for effectively managing human resource allocation over different time periods.
- Although the machine learning approach has rarely been explored in the hospital operations planning literature, we show its effectiveness as a method for optimizing and simultaneously evaluating critical KPIs, enabling decision-makers to adopt a comprehensive perspective and make well-informed choices that are aligned with their priorities and preferences.

This study is useful for healthcare administrators, operations researchers, and hospital planning staff, offering a practical and scalable method for improving service under uncertainty.

2. METHODOLOGY

The research question in this study involves an accurate forecasting of the patient arrivals ahead of time. The data collected in hospitals usually need immensive preprocessing due to many mistakes in records, such as missing details or some entries which cannot be possibly true. Therefore, first stage of the study involves data verification and analysis. The second stage of the study focuses on determining patient arrival rates on a daily and an hourly basis. After determining arrival rates, key performance indicators for different resource levels need to be identified, and for that purpose the third stage achieves this objective. Depending on the results of the first three stages, the application of the method requires another layer of calculations, namely optimal resource levels and shift schedules, and this is done in the fourth stage. Finally, resource requirements on daily and hourly bases need to be determined for the method to be applied. In the fifth and final stage, these calculations are made, and sensitivity analysis is applied to decide on the final assignments. These stages are illustrated in Fig. 1.

2.1 Data collection, analysis and cleaning

This study is a retrospective analysis of patient examinations conducted in the USG department of a private hospital in Istanbul between 1st January 2020 and 31st July 2023. Examinations in the USG department were carried out without prior appointments. Using the radiology information system, eight key examination parameters were extracted: patient arrival time, USG request time, USG registration time, examination code, description, start and completion times, and the referring department. Data entries suspected of being incorrect such as rows with an arrival time occurring after the exit time or a processing time of zero were removed from the dataset.

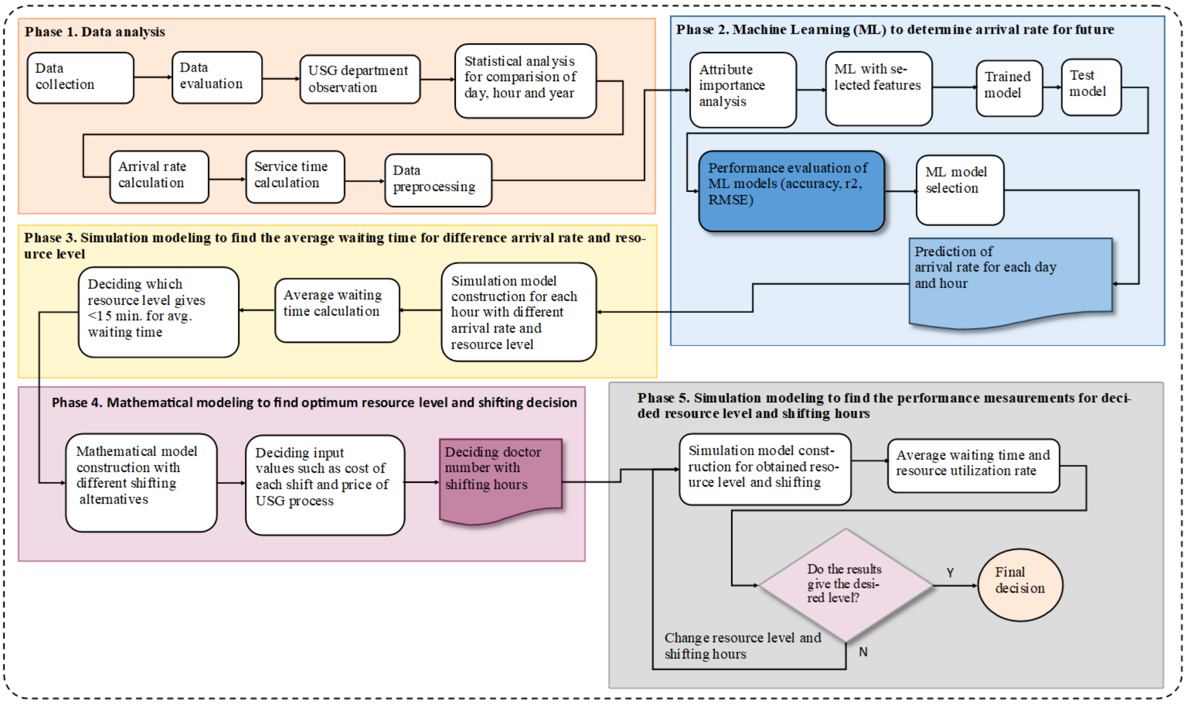

Figure 1: Schematic representation of proposed methodology.

2.2 Machine learning

ML is a subset of artificial intelligence that learns the pattern in data. The data may be in the form of a table or image. Owing to faster and less expensive computers with greater computational power, increasingly complex ML algorithms have been developed. Using advanced algorithms, it is possible to solve more complex problems that were once thought to be unsolvable. Owing to the nature of the problem of this work, regressors need to be used. To serve this purpose, eight algorithms are used. These include bagging, Adaptive Boosting (AdaBoost), random forest, decision tree, extra trees, Light Gradient Boosting Machines (LGBM), *k*-nearest neighbours (KNN) and logistic regressors.

Logistic regression is a well-known statistical method for solving both classification and regression problems. It falls under the linear methods and is based on Bayesian inference [20]. KNN method is very simple in the sense that the distance between neighbours is measured, and their classes or values are stored in the memory, which makes the method memory dependent. If the class or value of a new sample is to be determined, the nearest *k* neighbours are retrieved from the memory for decision-making. The parameter *k* is the hyperparameter of the method and affects the accuracy of the classification or regression. Applying the decision tree method requires asking successive questions, thus forming branches stemming from a single root question and giving respective answers. Overall, it is a heuristic method. If a state is finally reached, where no further questions can be asked, branching stops and the last point is called a leaf node. This method is generally prone to overfitting since it learns through a specific path [21]. The random forest method is a type of ensemble learning. It exploits the predictions of multiple decision trees. The aim of a random forest model is to predict the required quantity more accurately than an individual tree that makes up the ensemble [22]. Extra trees method is also based on creating multiple trees during training as in the random forest method. However, nodes in decision trees are split randomly, thus eliminating bias [23]. AdaBoost method was proposed in [24]. It creates a stronger learning model using a weak machine learning algorithm [24]. It is less likely to overfit than many other models but sometimes may be sensitive to noise. Bagging regressors train base models on randomly selected data subsets with replacement, and the final prediction is obtained by averaging their results [25]. This model is less likely to overfit and be robust to noise. LGBM is another tree-based model. It is indeed a gradient boosting method and is optimized to handle large datasets [26].

2.3 Transform methods

In this study, eight different ML models were applied to predict the number of arriving patients. These algorithms or any other deep learning algorithms were found to be insufficient with the data under question. Therefore, a new method was sought. The new method proposed here employs feature expansion, which means augmenting data in such a way that ML is successful. The augmented data are not synthetic; rather, they were derived from the total number of USGs per hour. Therefore, there is no risk of introducing irrelevant data to the dataset. The applied transforms are phi, Gaussian and inverse Fisher transforms.

The phi transform [27] used in this study maps the given dataset into a new dataset that consists of the range of numbers $\emptyset: x \rightarrow [0, 1]$, where x is a discrete set that is mapped to a continuous set. The phi transform used here is slightly different than usual. In the usual case, x is also in [0, 1]. The Gaussian transform creates a normal distribution from a random distribution [28], which is defined by $N(x, \mu, \sigma) = \mathrm{e}^{-(x-\mu)^2/2\sigma^2}/\sqrt{2\pi\sigma^2}$, where μ is the mean of set x and where σ is the standard deviation. Therefore, the values of x are mapped into the range [0, 1], which means that the original values are scaled. The inverse Fisher transform (IFT) maps the given values into the closed interval [-1, 1] via $y = (e^{2x} - 1)/(e^{2x} + 1)$, where x is the input and y is the output of the transform [29].

2.4 Performance criteria

In ML experiments, the developed models are compared on the basis of accuracy, r^2 score, *RMSE* (root mean square error) and run time criteria. The accuracy of a regressor is calculated via Eq. (1):

$$accuracy = \left(1 - \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_i - \hat{x}_i}{x_i}\right|\right) \cdot 100 \tag{1}$$

where x_i is the i^{th} true value, $\hat{x}_i$ is the i^{th} prediction and N is the total number of samples. Another metric for calculating how good a regressor is, the coefficient of determination, namely r^2 = model variance / true variance. The result should be between 0 and 1 under normal conditions, where 1 indicates a perfect result. The *RMSE* is a positive number that is equal to the average of the distances between the true and predicted values of the data and is given by Eq. (2):

$$RMSE = \sqrt{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2/N} \tag{2}$$

where x_i is the i^{th} true value, $\hat{x}_i$ is the i^{th} prediction and N is the total number of samples. The root mean square error does not have an upper bound and it may increase as the number of samples, N, increases. The run time is also calculated to compare the models.

2.5 Discrete-event simulation modelling

DES is a simulation modelling technique used to represent systems where changes occur at distinct points in time due to specific events. It enables the analysis of complex processes by simulating the sequence and timing of events, allowing performance evaluation under various conditions. A model is constructed to associate patient waiting times with uncertain factors, such as arrival and service times, and with a controllable factor, such as the number of servers.

In this study, the number of patients expected to visit the USG department in the coming days and hours was predicted using ML methods. The average service times of patients were determined via the simulation method. To build an efficient system, this study aims to minimize patient waiting times by deciding optimal resource level and shift scheduling. The study seeks to determine radiologist scheduling within 24-hour periods. A statistically significant difference between the hours was observed via analysis of variance (ANOVA) with a 95 % confidence level ($p < 0.001$), using Minitab (version 2021). Due to the statistically significant differences observed between the hours, the simulation model was designed on an hourly basis. The simulation model was validated by comparing its outcomes with actual system performance metrics derived from historical data. Recent studies support the effectiveness of our simulation-based approach in improving radiology scheduling and reducing delays. Rezaei et al. [30] demonstrated that integrating simulation with optimization methods can significantly reduce ultrasound and radiology waiting times, achieving reductions of approximately 42–43 %. Sensitivity analysis was conducted on key parameters such as arrival rates and number of radiologists to evaluate the robustness of the proposed scheduling strategies under uncertainty.

3. NUMERICAL EXAMPLE

3.1 Data analysis

Historical patient arrival data has been statistically analysed to identify patterns. The original data file contains 63,996 rows and 22 columns of data. The names of the columns and their properties are shown in Fig. 2 (left). The data contains many unnecessary columns, such as the Protocol number, Protocol year, Request date and Request time. The data in the original form was not useful for predicting the number of patients' arrival; therefore, it was rearranged. The data range captures both normal operating conditions and the impact of the Covid-19 pandemic. The USG examinations significantly declined during the Covid-19 pandemic. This fact adds diversity to the training data, thus making the model generalizable.

A new file was generated from the original dataset, consisting of 32,016 rows and 4 columns, which are summarized in Fig. 2 (right) and are suitable for predicting the number of patient arrivals within a given hourly interval. The size of the new file is much smaller than that of the original file since the focus of this study was to predict the total number of arrivals in a given hour. The original file contains a detailed account of patients, which is redundant as far as the research question is involved.

	column	dtype	nunique	null	duplicates
0	nr	int64	63996	0	0
1	Protocol nr	int64	54276	0	9720
2	Protocol year	int64	4	0	63992
3	Radiologist name	object	59	0	63937
4	Arrival date	object	1310	0	62686
5	Arrival time	object	1416	0	62597
6	Request date	object	1310	0	62686
7	Request time	object	1399	0	62592
8	USG date	object	1310	0	62686
9	USG time	object	1404	0	62601
10	Date	object	1310	0	62686
11	Time	object	1395	0	62601
12	End date	object	1310	0	62686
13	End time	object	1397	0	62599
14	Service name	object	32	0	63964
15	Age	int64	102	0	63894
16	Gender	object	2	0	63994
17	Branch	object	33	0	63963
18	Arrival type	object	5	0	63991
19	Quarter	int64	4	0	63992
20	USG duration	object	1110	0	62886
21	USG waiting time	object	4621	0	59375

	column	dtype	nunique	null	duplicates
0	nr	int64	32016	0	0
1	USG date	object	1334	0	30682
2	USG time slot	int64	24	0	31992
3	Total nr of USGs/hour	int64	20	0	31996

Figure 2: Columns of the original data file (left), columns of new data file (right).

3.2 Arrival rate prediction with machine learning

In the experiments, 32 different models were formed and tested in terms of accuracy, r^2 score, *RMSE* and run time. The models were tested without any feature expansion; hence, there was no transform, and then phi, Gauss, and inverse Fisher transforms were used. The models were formed by bagging, AdaBoost, random forest, decision tree, extra trees, LGBM, KNN and logistic regressors. The results show that without feature expansion, it was not possible to predict the arrivals with the given dataset. Among all the models developed, the LGBM in combination with the IFT had the best performance results. This is due to both the LGBM's strength, and the richness of the data introduced by expanding the features via the inverse Fisher transform. Feature expansion transforms greatly increased the performance of all algorithms except for KNN and logistic regressors, as shown in Table I which was formed by the ensemble averages of the performances. Historical data were used for training, and the last month's data, namely, the last 744 rows of the new data file were called the planning horizon. Fig. 3 shows the histogram of patient arrival rates obtained from all ML algorithms.

Table I: Feature transforms increase the performance of all the algorithms.

Regressor	**Transform function**	**Test accuracy**		**Test r^2 score**		**Test *RMSE***		**Run time** (s)	
		Mean	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**
Logistic	No transform	0	0	-0.48	0	9.28	0	4.19	0.08
	Gauss	0	0	-0.48	0	9.28	0	4.66	0.05
	Phi	0	0	-0.48	0	9.28	0	4.83	0.02
	Inv Fisher	0	0	-0.48	0	9.28	0	4.84	0.03
KNN	No transform	9.12	0	-0.39	0	8.76	0	0.03	0
	Gauss	9.12	0	-0.39	0	8.76	0	0.04	0
	Phi	9.12	0	-0.39	0	8.76	0	0.04	0
	Inv Fisher	9.12	0	-0.39	0	8.76	0	0.04	0
AdaBoost	No transform	25.50	2.04	0.35	0.02	4.11	0.12	0.69	0.01
	Gauss	95.44	0.19	0.94	0	0.38	0.03	0.30	0
	Phi	94.20	3.09	0.94	0	0.39	0.03	0.30	0
	Inv Fisher	94.04	0.17	0.97	0	0.16	0.03	0.31	0
Bagging	No transform	23.51	3.51	-0.25	0.06	7.84	0.37	0.87	0.01
	Gauss	95.76	0.37	0.94	0.01	0.38	0.06	0.28	0.01
	Phi	95.84	0.26	0.94	0.01	0.38	0.05	0.29	0.01
	Inv Fisher	99.10	0.10	0.99	0	0.08	0.02	0.24	0.01
Decision tree	No transform	11.98	2.15	-0.39	0.02	8.74	0.10	0.15	0.01
	Gauss	93.72	0.18	0.86	0.01	0.90	0.03	0.04	0
	Phi	93.76	0.04	0.86	0	0.90	0.02	0.05	0
	Inv Fisher	98.72	0.13	0.97	0.01	0.18	0.04	0.04	0
Random forest	No transform	24.05	0.71	-0.24	0.01	7.78	0.06	8.91	0.1
	Gauss	95.92	0.12	0.95	0	0.33	0.02	2.66	0.06
	Phi	95.99	0.14	0.95	0	0.32	0.01	2.75	0.02
	Inv Fisher	99.10	0.03	0.99	0	0.08	0	2.29	0.02
Extra trees	No transform	26.25	0.37	0.07	0.01	5.82	0.05	4.11	0.03
	Gauss	96.06	0.05	0.94	0	0.36	0	1.04	0.03
	Phi	96.10	0.05	0.94	0	0.35	0	1.09	0.02
	Inv Fisher	99.39	0.03	0.99	0	0.04	0	0.71	0.01
LGBM	No transform	28.72	0	-0.11	0	6.97	0	0.49	0.04
	Gauss	98.40	0	0.99	0	0.07	0	0.43	0.05
	Phi	99.95	0	1	0	0	0	0.45	0.05
	Inv Fisher	**99.99**	**0**	**1**	**0**	**0**	**0**	**0.47**	**0.05**

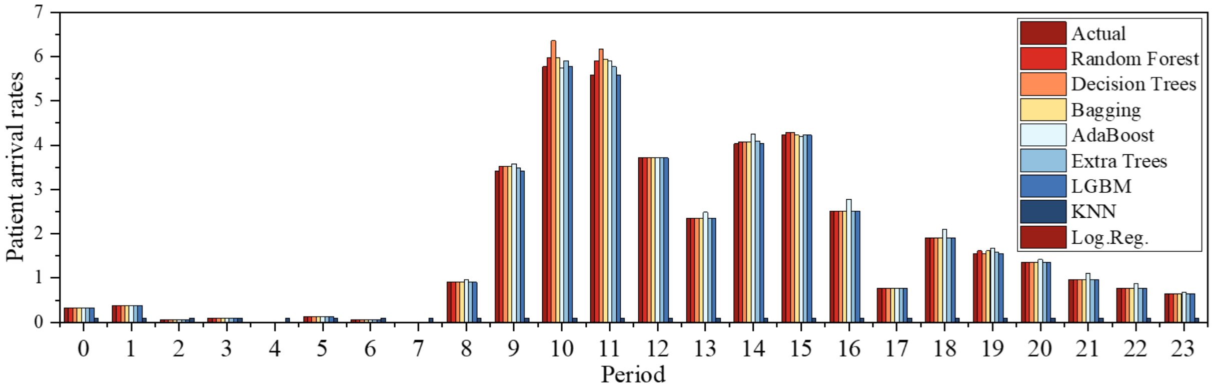

Figure 3: Histogram for all machine learning algorithms results.

3.3 Simulation modelling to determine resource requirements

Using ML, patient arrival rates for the next month of 31 days were predicted with 99.99 % accuracy on an hourly basis. To determine the radiologist requirements for the upcoming one-month period, the expected number of patients for each hourly time slot is analysed. The average number of patients expected during weekdays and weekend hourly time slots is presented in Fig. 4. Actual data from the USG department showed an average weekly patient waiting time of 32.72 minutes, while the simulation model produced a similar result of 33.56 minutes with a half-width of 4.58. A *t*-test at the 95 % confidence level yielded a *p*-value of 0.18, confirming that the simulation model accurately represents the real system.

To apply the simulation model, it is essential to have information about patient arrival rates and examination durations. During the planning period, it was realised that a maximum of 14 patients will arrive per hour. As shown in Fig. 4, the busiest times were between 10:00 A.M. and 12:00 P.M. The USG department works 24 hours a day and 7 days a week, whereas outpatient appointments in other clinics start at 8:00 A.M. and finish at 5:00 P.M. Following the initial physician consultation, patients who need ultrasonography examinations are referred to the USG department. Between 12:00 P.M. and 2:00 P.M., patient density decreases due to lunch breaks, but it increases again at 2:00 P.M. After 3:00 P.M., the number of patients decreases to an average of less than two per hour. The number of patients during different time intervals is grouped by weekdays, Saturdays, and Sundays. Outpatient clinics operate until noon on Saturdays and are closed on Sundays. Owing to differing working hours, the number of patients visiting the USG department was analysed separately for weekdays, Saturdays and Sundays. However, on Saturdays, the number of patients arriving during the 11 o'clock time slot differs from those arriving during other time slots. This finding statistically demonstrates that differences between days and time slots should be considered when scheduling radiology physicians, highlighting the need for careful planning.

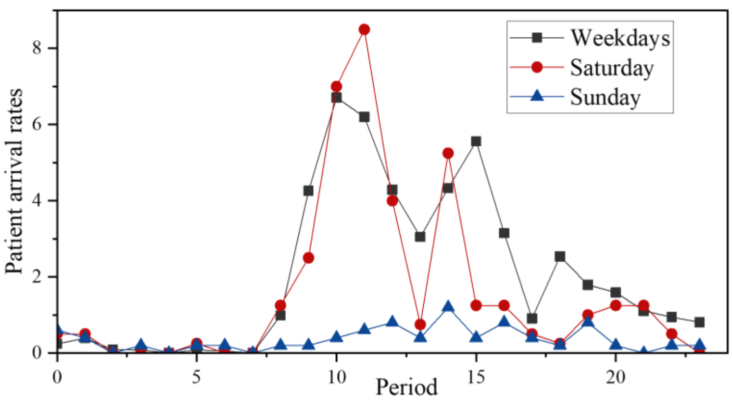

Figure 4: Predicted arrival rates across days.

Using historical data, input analysis was done using Arena Simulation software, and the examination time was expected to be exponentially distributed with $5.5 + \text{Exp}\,(7.2)$ minutes. A simulation model was run for each radiologist level to determine the average waiting time for a patient. The maximum arrival rate in a month was predicted to be 14 arrivals by using ML, and then a simulation model was run for every arrival rate with the criteria of 1 to 4 radiologist resources. With ML technique, we know the exact arrival rate in an hour, but we don't know specific time at which patients arrive within each hour. Thus, the expected waiting times were calculated based on the number of radiologists and the rate of arrivals with 100 replications. The goal of this study was to determine the necessary human resources to ensure that patients wait an average of 15 minutes or less. In line with these targeted values, the number of radiologists that should be present in the USG department at that hour corresponding to the patient arrival numbers were determined. According to the simulation model analysis, if the waiting time was less than 15 minutes and the number of incoming patients was 2 or less, 1 radiologist was assigned; if it is less than 8, 2 radiologists were assigned; if it is less than 13, 3 radiologists were assigned; and for more incoming patients, 4 radiologists were assigned. The number of radiologists required corresponding to the estimated number of patient arrivals is provided in Table II. The analysis results have been shown for a one-week period.

Table II: Resource requirements to achieve the target waiting time.

Hours	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
08:00-09:00	1	2	1	1	1	1	1
09:00-10:00	2	3	1	2	2	1	1
10:00-11:00	1	3	1	2	3	2	1
11:00-12:00	3	2	3	2	2	4	1
12:00-13:00	2	2	1	1	2	2	1
13:00-14:00	2	2	2	2	1	1	1
14:00-15:00	2	2	2	2	2	3	1
15:00-16:00	2	2	2	2	1	1	1
16:00-17:00	2	2	2	2	2	1	1
17:00-18:00	1	1	1	1	1	1	1

Currently, three radiologists work in the department on weekdays from 9:00 A.M. to 6:00 P.M., and one radiologist works on weekdays from 9:00 A.M. to 1:00 P.M. On Saturdays, these four physicians work until noon. In the evenings, at night and on Sundays, on-call physician is available to provide services. After determining the required number of radiologists in the USG department, a mathematical model was developed to evaluate the working hours of the resources and to find the number of radiologists needed in the designated shifts.

3.4 Integer linear programming model formulation for radiologist scheduling problem

The predicted patient arrivals for different hours, as obtained in Section 3.2, were used in a mathematical model. In this section, an Integer Linear Programming (ILP) mathematical model was developed to solve the resource allocation and workload distribution planning for the next one-week period. Assumptions of the model are defined as follows:

- Radiologists working regularly were required to complete 45 hours per week.
- Part-time radiologists were considered in different shift alternatives.
- It was not considered for radiologists to work overtime.
- The periods covered by external on-call radiologists – weekday nights, after 2:00 P.M. on Saturdays, and all day on Sundays – were excluded when determining the number of full-time radiologists employed by the hospital.

Different work shifts were considered as follows:

Shifts	Weekday working hours (5 days)	Saturday working hours
Shift 1:	8:00 A.M. to 5:00 P.M.	8:00 A.M. to 1:00 P.M.
Shift 2:	9:00 A.M. to 6:00 P.M.	9:00 A.M. to 2:00 P.M.
Shift 3:	10:00 A.M. to 6:00 P.M.	10:00 A.M. to 3:00 P.M.
Shift 4:	9:00 A.M. to 1:00 P.M.	10:00 A.M. to 6:00 P.M.
Shift 5:	10:00 A.M. to 2:00 P.M.	10:00 A.M. to 4:00 P.M.
Shift 6:	11:00 A.M. to 3:00 P.M.	1:00 P.M. to 6:00 P.M.

The components of the developed optimization model are listed in Table III.

Table III: Notations of the mathematical model.

	Notation	Description
Sets and indices	M	Number of days, $i = 1, \ldots, M$.
	T	Number of hours, $t = 1, \ldots, T$.
	N	Number of shifts, $j = 1, \ldots, N$.
Parameters	c_j	Weekly salary for shift j.
	$p_{i,t}$	Number of patients arrival in a day i and hour t.
	$r_{i,t}$	The number of radiologists required in a day i and hour t.
	$y_{i,j,t}$	1 if shift hours are active for a given day and hour; 0 otherwise.
	z	Revenue obtained from ultrasonography process.
Decision variables	x_j	Number of radiologists to be assigned to the shift j.

Objective function: $$Maximize\ Z = \sum_{i=1}^{M} \sum_{t=1}^{T} p_{i,t} z - \sum_{j=1}^{N} c_j x_j \tag{3}$$

Subject to: $$\sum_j y_{i,t,j} \cdot x_j \geq r_{i,t}\ ,\ \ \forall i, \forall t \tag{4}$$

$$x_j \geq 0, \text{an integer} \tag{5}$$

It was considered that the weekly salary, c_j, of a radiologist who works a regular 45 hours was \$650.00, and in the case of part-time work, they would be paid according to the hours worked. On the average, the fee for an ultrasonography service is \$75.00. The objective function, shown by Eq. (3), maximizes the total weekly profit, which was calculated by subtracting the total radiologist cost, based on the number of radiologists assigned to shifts and their associated shift costs, from the total revenue, estimated using the expected number of weekly ultrasonography procedures and the average procedure fee. The constraint, Eq. (4), ensures that the number of radiologists assigned each day, and hour is not less than the required number of radiologists. The second constraint, Eq. (5), ensures that the number of radiologists is an integer.

As a result of the model's operation, the total expected weekly profit would be \$16,548.33, and it was determined that one radiologist should work in the 1st shift, one radiologist in the 2nd shift, one radiologist in the 4th shift, and two radiologists in the 5th shift. Thus, two radiologists need to work full-time, and three radiologists need to work part-time. Based on the number of radiologists found and their shift durations, the simulation model was re-run for an entire week, and the system performance was evaluated again.

3.5 Simulation study with obtained resource scheduling

In the simulation study, daily patient arrivals ($p_{i,t}$) were modelled as an hourly-based arrival schedule. The optimal number of radiologists and their working durations during USG procedures were defined separately by the mathematical model. The simulation was executed for each day, and the average patient waiting times were tested and summarized in Table IV. This table compares the proposed model to the current state in terms of the expected average waiting time with 95 % confidence intervals (C.I.), and percentage change. The proposed scheduling method reduces the average patient waiting time from 33.56 to 13.57 minutes.

Despite only a 1.18 % reduction in radiologist costs and a 0.17 % decrease in profit, the approach yields a 59.56 % improvement in waiting times.

Table IV: The comparison results of current case and proposed model results.

Average waiting time	**Current case**		**Proposed schedule**		**Deviation**
	Average (min)	**95 % C.I.**	**Average** (min)	**95 % C.I.**	
Monday	35.95	(31.76; 40.14)	14.45	(12.67; 16.22)	-59.81 %
Tuesday	33.33	(29.60; 37.04)	15.93	(14.20; 17.66)	-52.19 %
Wednesday	28.01	(23.25; 32.77)	13.55	(11.79; 15.30)	-51.62 %
Thursday	31.82	(27.34; 36.30)	9.93	(8.46; 11.40)	-68.79 %
Friday	33.94	(29.15; 38.73)	10.44	(8.811; 12.05)	-69.25 %
Saturday	38.30	(32.74; 43.84)	17.13	(14.39; 19.85)	-55.28 %
Average (min)	**33.56**	**(28.97; 38.14)**	**13.57**	**(11.72; 15.41)**	**-59.56 %**
Staff cost ($)	2,455.56		2,426.67		-1.18 %
Profit ($)	16,519.44		16,548.33		0.17 %

Accordingly, we conducted a sensitivity analysis to assess the model's variability in response to changes in the number of radiologists and patients' arrival, with Fig. 5 illustrating the resulting variations in profit, waiting times, and utilization rates across all parameter values.

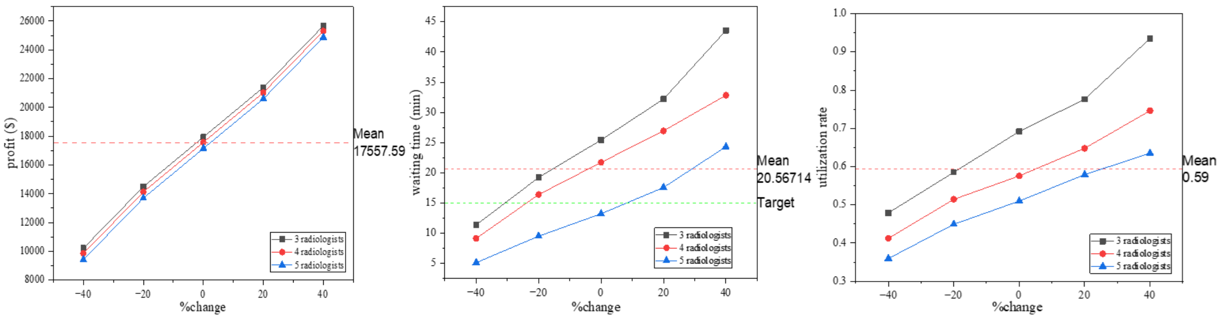

Figure 5: Effect of patient load variation on key performance metrics by radiologist's count.

This represents a multi-criteria decision analysis to identify the most suitable planning strategy for hospital managers. As profit increases, waiting time also increases, reflecting a trade-off between efficiency and service quality. As shown in Fig. 5, with 3 radiologists, profit and utilization increase; however, utilization exceeds 95 % in certain hours, and average waiting times surpass the 15 minute target. With 4 radiologists, the system handles moderate patient increases better, yet waiting times still exceed the threshold. In contrast, employing 5 radiologists enables the department to manage higher patient volumes while maintaining near-target waiting times and improving profitability.

4. CONCLUSIONS

The time spent by a patient waiting to be served by a radiologist for an ultrasonography scan is wasted, causes frustration and adds no value to the healthcare system. The primary driver of the increased USG waiting time is the imbalance between the demand for services and the supply of physical space and/or human resources needed to provide these services. To optimize the efficiency of USG visits, machine learning, simulation techniques and mathematical models were integrated and evaluated for decision making. This study used arriving patients' data and predicted the number of possibly arriving patients in a one-month planning horizon. The proposed method, which combines feature expansion via IFT and LGBM, achieves a 99.99 % accuracy and perfect r^2 and *RMSE* scores. The limitation of this study is the length of the run time of the proposed model in comparison to AdaBoost, bagging and decision trees. In the future, this disadvantage will be overcome via optimisation.

Simulation modelling estimates the minimum staffing needed to meet service targets by predicting patient arrivals and evaluating system performance across resource levels. This study eliminates the event arrival variability, one of the limitations of queueing theory, by predicting it with the highest accuracy via machine learning. Our data shows that arrival rates at the USG department follow a random distribution but can be predicted via a combination of the IFT and LGBM.

This study empowers the administration of a busy private hospital in the sense that human resource planning can be performed efficiently. The method developed here is generalizable since it can also be applied to other departments of medical institutions and any facilities that need similar resource planning, which may target resources such as humans or equipment. It may serve as a valuable tool in planning human and medical facility resources.

For future research, multi-objective optimisation can be modelled to investigate the relationships among costs, services, human resources and KPIs. In multi-objective optimisation, weighting methods can be used to decide the importance levels of the factors influencing the decisions of health system managers.

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