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A Simulation Based Study for Managing Hospital Resources by Reducing Patient Waiting Time

JAWAD AHMAD[1], JAVAID IQBAL[2], (Member, IEEE), IMRAN AHMAD[3], ZUBAIR AHMAD KHAN[4], MOHSIN ISLAM TIWANA[2], (Member, IEEE), AND KHALID KHAN[5]

[1]Department of Energy Management and Sustainability, University of Engineering and Technology Peshawar, University Campus, Peshawar 25120, Pakistan
[2]Department of Mechatronics, National University of Science and Technology, Islamabad 24090, Pakistan
[3]Department of Industrial, University of Engineering and Technology Peshawar, University Campus, Peshawar 25120, Pakistan
[4]Department of Mechatronics, University of Engineering and Technology Peshawar, University Campus, Peshawar 25120, Pakistan
[5]Department of Renewable Energy, University of Engineering and Technology Peshawar, University Campus, Peshawar 25120, Pakistan

Corresponding author: Khalid Khan (engrkhaliduet@gmail.com)

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ABSTRACT In Pakistan most of the local hospitals have limited resources and budget deficits to address day-to-day routine activities. This is further intensified by inefficient management of hospital resources. Hence, it is essential to efficiently manage hospital resource as it will lead to health care costs reduction and increased patient's satisfaction. The focus of this research is to demonstrate the use of the tool in healthcare system, specifically in Pakistan, and balance the resources of a hospital, which will reduce the waiting time for the Outdoor Patients Departments. The resources at the Outdoor Patients Department including X-ray, Labs, Ultrasound and the ECG sections were included in the computer-based simulation model with the aim to find the bottleneck departments as they are the main cause of waiting time in the hospital. These bottlenecks are anticipated due to the lack of an optimized model, which has been addressed in this simulation. Based on the simulation study an optimized model is proposed to the hospital administration where the resources are readjusted resulting in the utilization of underutilized departments and decreasing the waiting time of the stations particularly the bottleneck stations. The motivation behind this research is to aid hospitals in better management of resources, which can ultimately improve customers (patients) satisfaction.

INDEX TERMS Discrete event simulation (DES), patient flow, utilization, split flow, utilization, medical record number (MRN), outpatient department (OPD), waiting time.

I. INTRODUCTION

Simulation is widely used tool in the healthcare industry and arguably one of the most principal tools of operational research. Simulation provides flexibility to the researchers to deal with variability and uncertainty [1]. In addition, the utilization of graphical user interface feature aids in decision making and makes the interpretation of results much easier. It is due to these features that simulation is one of the most popular methods used by healthcare professionals to study complex processes, organizational and human behavior among others [2].

A successful model development for the health systems lies in the proper representation of the system. Hence, all the characteristics need to be taken in account for the model, such as waiting time, number of incoming patients to emergency and outpatient departments with respect to time, etc. The modeling of a hospital processes with the help of simulation can be very useful in order to find the parameters such as, efficiency, utilization, service time and throughput of a hospital [3]. Simulation is a valuable tool in a hospital setting with complicated processes and numerous variations make analysis difficult. In some situations, simulation is the only tool with the help of which intricate interactions within processes can be determined. For instance, some factor like test results, acuity level, equipment availability, staff schedules,

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care giver skills, facilities and competition among patients for resources could impact parameters such as service time, utilization and throughput [4].

Vahdat used a Discrete Event Simulation (DES) model to find the frequency of movements in pediatric orthopedic outpatient clinic. The information was then used for mixed integer programming (MIP) model. Particle Swarm Optimization was used to solve MIP which is a metaheuristic approach enhanced with several heuristics. Finally, the optimization model outputs are evaluated with the help of simulation model which shows that patient experience can be improved by incorporating simulation optimization methods into the clinical design process [5].

Gul *et al.* presented a hybrid framework that uses artificial neural networks (ANNs) and DES to estimate the number of casualties and analyze the effect of surge in patient demand in emergency departments after an earthquake occurs. The simulation used a network of five EDs located in the region, which is estimated to have the highest injury rate after an earthquake occurs in the study. The result of the study contributed in the planning to deliver better health services to the patients during the earthquake [6].

Lehaney and Hlupic [7] have explored the area of Discrete Event Simulation (DES) just prior to the introduction of simple simulation software. Their research concludes potential of simulation as an operation research tool in the field of health industry. A review which covers some fields of operations research (OR) in health industry has been conducted by Flagle [8]. The vitality of simulation in making prompt responses in the time of emergencies in hospital has been thoroughly studied and reviewed by Gul *et al.* where proactive measures could mitigate the disastrous health situation by properly improving the policies [9].

Brennan *et al.* [10] proposed a classification of model structures in evaluating the economic effect of health technologies and, in so doing, identifies the role of DES in health economics. Furthermore, Jun *et al.* [11] classified different models with respect to the part of research's objectives. Fone *et al.* [12] reported that the majority of the models are discrete events as they are discrete parts of a health care, such as emergency rooms, clinics, and operation theatres.

DES is a widely used tool for modeling in the health care industry and a lot of research has been done by various researchers in this regard [13]. An extensive review is presented [13] where the classification of papers is done according to the area of application.

Aboueljinane *et al.* carried out research on French Medical Emergency service, which deals with assisting clients on a phone support and dispatching proper yet prompt response on emergency basis. After an emergency call is initiated, the time for the ambulance to arrive at the hospital is a key parameter in assessing the quality of the emergency services, since it is directly the patient's survival chances. In his research work a discrete simulation technique is deployed to model the performance of Val-de-Marne (France) department for investigating the various alternative configurations for any potential improvements. Various scenarios were developed and tested that included addition of more resources, relocating the existing teams and mitigating the processing time for any improvement in the response time. The study concluded that by implementing all the recommendations of the simulation study performed, the improvement in coverage area increases by 5.2% and reduces the regulation process time by 20% [14].

A similar work has been submitted by Aboueljinane *et al.* where the emergency response has increased by 15%, compared to the already employed system, by properly relocating the resources and relocation of dispatch teams based on the results of the simulation studies [15].

A case in point, Holm *et al.* [16] investigated the issue of minimizing overcrowding by assigning beds amongst hospital wards. The problem was addressed by presenting a generic discrete event simulation model for the movement of patients through hospital wards. Each ward has been assigned with a separate probability distribution of time of arrival and length of stay, which may be time dependent. Konrad *et al.* [17] used a split-flow process with a discrete-event simulation model to make improvements in a hospital's Emergency Department (ED). Paul and Lin [18] have addressed the issue of overcrowding in ED. They argue that overcrowding reduces ED care giving abilities. A generic model is given to inspect the reasons for overcrowding and different strategies has been identified to resolve them. These strategies are then implemented to the ED of a hospital participating in the study.

DES is used for modeling inpatient facilities which considers patient flows to hospital, ratio of occupation of beds and the amount of resources allocated. A compartmental modeling approach for bed possession is used by El-Darzi *et al.* [19]. The mathematical model developed by [19] is very useful in practical life. DES is extensively used in outpatient departments patient flow modeling. DES of outpatient and inpatient facilities have certain similarities, although their output parameters might be different(for example, much of the DES of outpatient departments focuses on Micro waiting time) [20].

Researchers have mainly explored the area of scheduling and capacity planning in the field of DES for outpatient departments, as is evident by the works of [21]–[23]. Although the OPDs are quite different in their operation as compared to the emergency department, they do bear certain similarities to the emergency departments. DES has been found useful in simulating the OPDs and tends to focus on the capacity planning and scheduling aspects of health care industry. Outpatient departments vary in different hospitals; however, some of the very common are eye, ENT, Skin, Paeds, Medical and Surgical, among others. The DES performed for outpatient departments is usually for a particular specialty, such as a simulation model for Ear Nose Throat (ENT) department performed by Harper and Gamlin [24].

Verma and Gupta Performed simulation study on a general hospital where hundreds of patients visited outpatient department every day for treatment. The current performance of the hospital was evaluated, and suggestions were given to improve the efficiency of outpatient department, using the same resources. He also got to a conclusion that it is basically a problem of maintaining discipline and scheduling of staff rather than lack of resources that leads to inefficiency and longer waiting times in outpatient departments [25].

Robielos conducted a study in a pediatric hospital in Manila, Philippines. The researchers used different statistical analysis to determine if there is any difference among different factors (gender and age) with queuing indicators (general pedia and specialized). After analyzing the data and finding a significance difference in the waiting and queuing times of general and specialized pediatrics, simulation was used to determine a model for peak and non-peak months and a complete scheduling system was proposed to the hospital to achieve a higher satisfaction rate of the patients that they treated [26].

Meegahapola *et al.* performed a study in Sri Lanka for longer waiting times in hospitals which caused several problems for doctors, patients and even administration staff. The research critically analyses and evaluates different queuing and scheduling rules to decrease waiting time [27]. The study proposed that about 60 % patient waiting time can be reduced if proper scheduling system is introduced.

Other models include [28] a simulation performed for (Adjuvant Breast Cancer-ABC Sim) trials of two alternative treatments to breast cancer, and [29] where a simulation for a dermatology clinic is performed for an appointment system. Several other simulations of outpatient clinic were performed for specific (hospitals and specialties) including [30]–[32], where the simulation model is comprised of the hospital layout, patient pathways and human resources. However, Kuljis *et al.* [33] designed a simulation model, which is not for a specific department rather for 20 clinics. This model was applied to the UK Department of Health observing the change in waiting time. In addition, Paul and Kuljis [34] implemented this simulation methodology in their study, which focuses on in-clinic waiting times.

All of the above studies highlight the use of simulation for performance improvement in healthcare system. However, developing countries, such as, Pakistan is not taking advantage of the tool for system analysis. This paper attempts to analyze an existing health care system in Pakistan using simulation techniques, identify areas for improvement and suggest alternative system.

II. GOALS AND OBJECTIVES

The goal of this paper is to analyze the hospital's resources based on indicators such as utilization and waiting time. In addition, providing recommendations based on the allocation of resources of the OPD. In this paper, simulation was taken under consideration for this purpose and a model was developed in SIMIO simulation software. The incoming patients were categorized based on the type of hospital care required. The main contributions of this paper are as follows.

- To develop a model for the patients' flow to mimic the real situation at hospital.
- To analyze all OPDs performance based on the utilization and patient waiting time.
- To reallocate the resources to reduce the waiting time and increase the utilization of underutilized departments.
- This paper also aims at answering the What-if scenario if the hospital wishes to expand the current facility.

Resource allocation has always been a challenging task in dynamic systems with stochastic input data. Hospitals, in this regard have always been subjected of interest as the healthcare service is considered as a significance factor in evaluating the performance of a hospital. This paper presents study of how the changes in resources can affect the performance of a hospital, specially the outpatient department. In order to carry out large number of replications, simulation was used to carry out experiment regarding how the outpatient department behaves in terms of utilization and waiting time. The stochastic nature of the number of patients coming to OPD (Outpatient Department) was also modeled as probability distribution and was used as input data in the simulation model.

It was found that by changing the number of doctors in the hospital there was a significance decrease in waiting time and increase in utilization of some of the OPD units. In the end a comparison was made between old and new resource allocation models and suggestion were presented.

This paper develops a model based on patient arrival probability distributions. The different days had different patient arrivals; hence, a probabilistic based methodology was developed to incorporate the variable arrival rate at each day. The model developed in SIMIO is able to handle infinite amount of entities theoretically and can further be utilized for monitoring the expansion of facility. The motivation behind this paper is to develop a better understanding of resource allocation so as to provide quick and better health care facility to the local people.

III. METHODOLOGY

The first step of the methodology involves defining the simulation problem. Outdoor Patient Department (OPD) is usually crowded and patients complain about improper service due to long waiting time for different resources including specialist doctors and diagnostics equipment. As a first step of simulation, process flow for a patient needs to be defined with identification of resources to be utilized.

The second step is about system definition, where all components are to be identified in the process flow for the OPD with definition of performance measures including waiting time, utilization of resources etc. The third steps will lead to formulation of the system modeling, which includes understanding the behavior of the actual system (OPD) to help in identifying basic requirements for the system simulation like identifying points (stations) and processes.

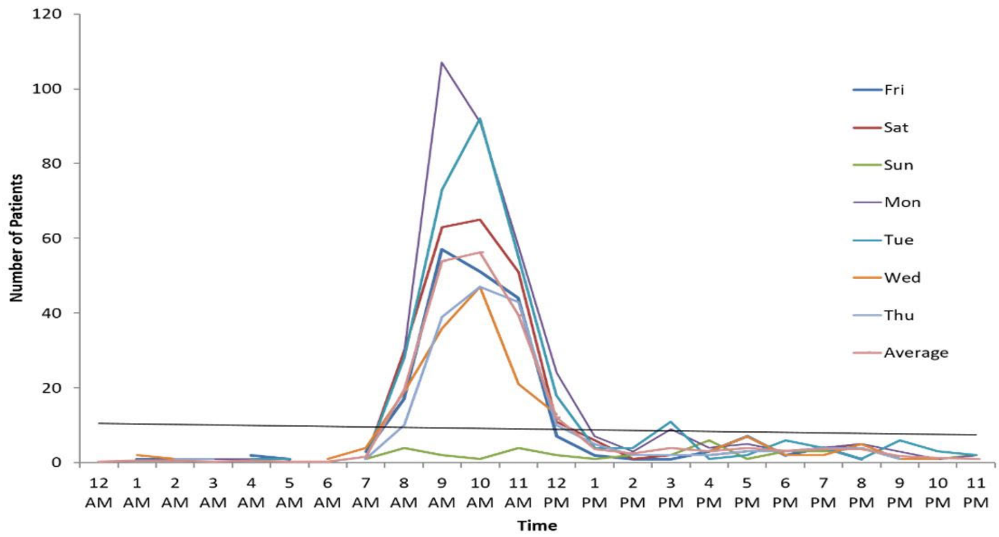

FIGURE 1. Routes of patients for different departments.

Input data needs to be collected for simulation model, which is followed by subsequent processing (obtaining distribution models) to be used as input to the simulation model. The fourth step is to translate the formulation into some logical programming through SIMIO simulation software, which is followed by verification and validation to check whether the model functions as intended, and results are meaningful. After verification and validation, the model is ready for experiments to do what-if analysis.

IV. DATA COLLECTION AND ANALYSIS

Approximately 1300 patients on the average were recorded over the four weeks. The hourly data of the Outdoor Patient Department (OPD) were recorded from 8 AM to 2 PM. Monday was found to be the day having maximum number of patients while minimum number of patients was observed on Sunday as shown in Figure 1. This collected data was deployed to determine the inter arrival time of the patients.

Figure 1 depicts the arrival of the average frequency of the patients for the entire week. The trend shows that the first two weekdays are the busiest days while Friday and Sunday are the days where the numbers of patients are lowest. The patient flow is highest at the peak hour, which is from 9:00am to 10:00am with Monday having the highest number of patients in the peak hour and also Tuesday having more patients. Patients at the peak hour on Sunday and Wednesday are the lowest at 2 patients and 24 patients, respectively. The total number of patients entering the reception area was divided into 35 different types of routes. The percentage of each type of routed patients was found to generate the entities accordingly. Figure 2 shows the different routes that the patients were following.

The data of patients gathered was further analyzed and the percentage of all the patients coming to OPD has been shown in Figure 3. This split of data helps in moving the patients to different departments for what-if analysis during simulation.

TABLE 1. Percentage of patient flow to different departments.

Departments	Percentage of Patients
XRAY	28.57%
LAB	48.57%
ECG	5.714%
ULTRASOUND	28.57%

Figure 3 shows that the largest numbers of patients were from the medical OPD (MED), which is 21.74%, while the least flow is to the dentistry (DENT) which is 4.42%. The patients flow to Gynecology (GNY) is 15.54%, while the patients flow to Eye and ENT OPD is almost the same as 13.95%.

Apart from the OPD, the patients also flow for diagnostics services which included X-Ray, Blood and Urine Testing Lab, ECG, Ultrasound. Of the total number of patients, that was following the above mentioned 35 routes, Table 1 shows the percentage of the patients for Lab, X-ray, ECG and Ultrasound.

V. MODEL DEVELOPMENT

The simulation model was developed using Simio simulation software. The exact layout of the hospital was considered which helped in development of simulation model. Patients flow analysis in the above section helped to simulate the patient flow through different departments.

Figure 4 depicts the layout of the hospital and the flow of patients between various departments. The blue line is showing the split flow pattern of patients throughout the hospital. The patients are then divided into 35 different routes as per percentage of each type of patients. Since the process is a split flow process, different OPDs have different percentages of patients flowing through them.

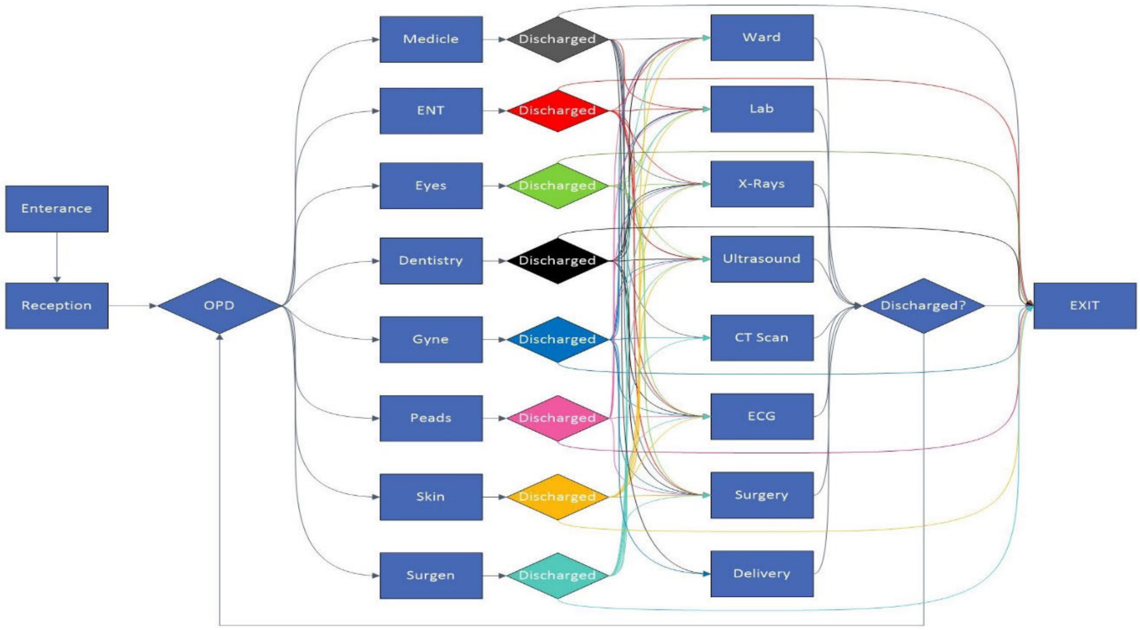

FIGURE 2. Routes of patients for different departments.

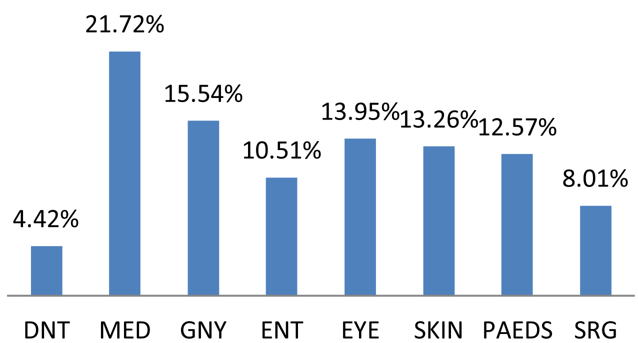

FIGURE 3. Percentage of Patients to each department.

Several assumptions were made to make the model simple and exempt the model from various non-significant constraints.

- The arrival of each entity represents only the patient and not the people (family and friends) coming with the patient.
- All the paths are bidirectional as shown by blue lines (Figure 4).
- The output buffer capacity of each department was considered as having infinite capacity

The departments which are ignored during the simulation have no patient connecting flow line. However, the OPDs and other departments such as, the Labs, Ultrasound, ECG and X-ray are all considered in the simulation model, connected through the patient flow lines.

The stochastic nature of the data requires it to be modeled as probability distribution models, which was then used as input to the simulation software. The historical data was collected from the existing Management Information System (MIS) system of the hospital, which resulted in normal distribution for different resources. The model formulation was translated into simulation model using Simio Software. The snapshot of the model is given in Figure 5 below.

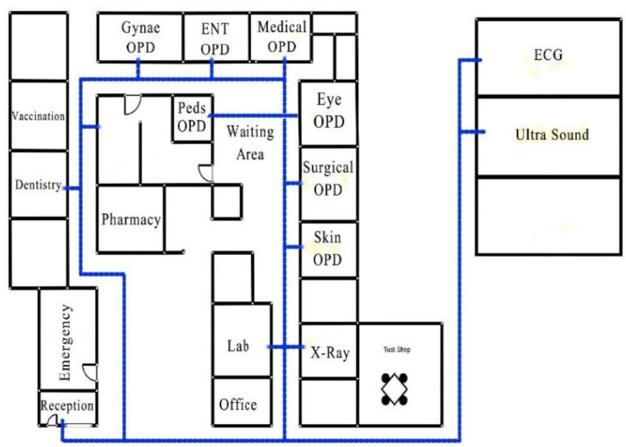

FIGURE 4. Layout of the hospital for formulation of simulation model.

VI. MODEL VALIDATION AND VERIFICATION

The Medical Record Number (MRN) generated through the MIS system of the hospital was used to compare the actual throughput at each OPD and the main exit. Both the results agreed with a deviation of 11 to 14 patients between the actual and the simulation model made, as shown in Figure 6. This deviation was due to the probability distribution used for generating the entities (patient). The number of replications was kept at fifteen to average out the results for comparison.

All the error messages that were produced during the simulation of the models by the software were eliminated

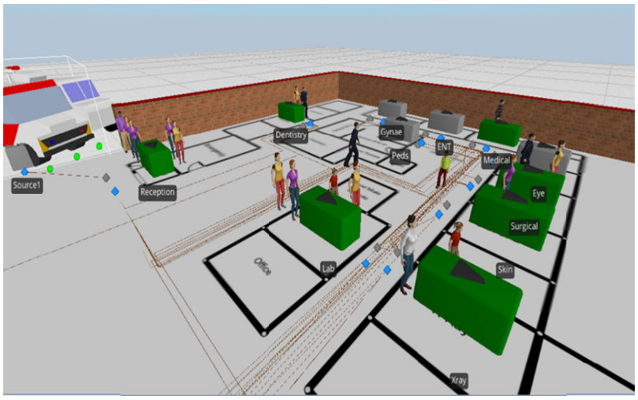

FIGURE 5. Snapshot of 3D model developed in Simio.

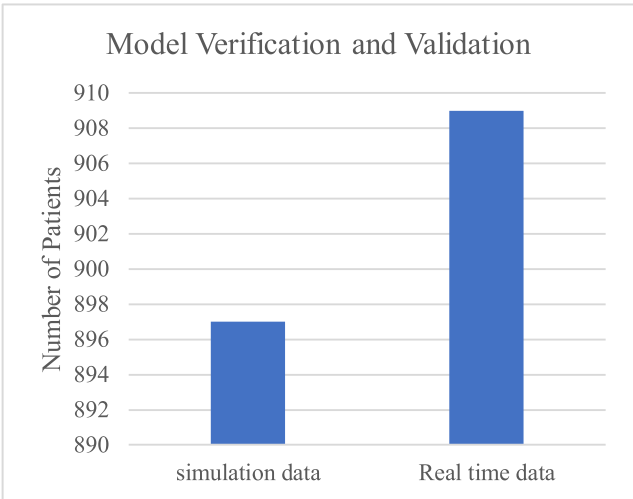

FIGURE 6. Comparison of real and simulation results.

from the model. The model results were discussed in detail with the hospital administration and staff and it is concluded that the results were logical and represents the actual system.

The proposed model results were implemented on a test basis for a period of two weeks and it was concluded that improvements made actually facilitates the patient care. A patient survey of about 800 patients in the test period showed that patient satisfaction has increased.

VII. RESULTS AND DISCUSSIONS

Along with the hospital administration an exhaustive observation of the system was carried out, based on the observation and collection of patient's data and hospital's resources, a detailed simulation study was conducted. The results were then discussed with the hospital administration and it was found that the results mimic the actual system. Those results gave a clear and concise view of the hospital system.

A model with some changes, as shown in Table 2 in the capacity and schedules was then proposed to the hospital administration.

Table 2 provides the changes that were made to the current hospital administrative system and the effects of the proposed changes. A comparison of the results of simulation of both

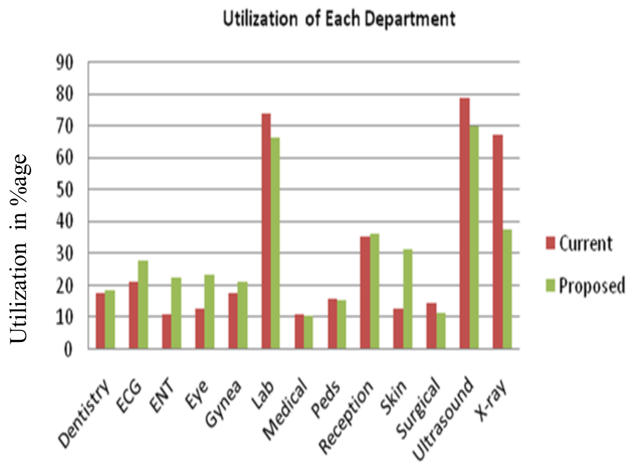

FIGURE 7. Utilization of current and proposed model for various departments.

previous system and the proposed system indicate that the performance of the hospital can be significantly improved in terms of patients care and satisfaction if the identified resources for diagnostic services are managed as proposed.

From simulation of the current system, it was observed that the bottleneck stations were Lab, Ultrasound and X-ray. All of these departments were running at a high utilization and their waiting time was significantly high as compared to other departments. In order to reduce the waiting time, extra resources were added to these departments which effect can be observed in Table 2, Table 3 and Figure 7.

Table 2 depicts that the utilization of the underutilized departments of Eye, ENT and Skin has been increased by decreasing the number of doctors by one in each of these OPD's while increasing the Lab, Ultrasound and the X-ray by one. The readjustment of these resources has the opposite effect on waiting time as the waiting time of Lab, X-ray and Ultrasound decreases significantly, whereas there is a slight increase in the waiting time of Eye, ENT and skin Departments.

A comparison of average waiting time for the current and proposed systems shows that by increasing the capacity of x-ray the waiting time decreases from 30.5 minutes to 3.8 minutes. Similarly, the waiting time of ultrasound decreases from 72.166 to 41.26 minutes by increasing the capacity by 50 %. The Lab also showed a decreased in waiting time from 51.7 minutes to 29.7 minutes with the change of capacity by 25%.

The change in capacity also effected the utilization of each department. Figure 7 shows the comparison of old and new utilization.

Figure 7 represents the utilization of the current system and the model which was proposed to the hospital administration departments. The figure shows that the utilization of the bottleneck stations (Lab, X-ray and Ultrasound) has decreased from (74.16, 78.8 and 67.5) to (66.6, 70.2 and 37.8) percent

TABLE 2. Comparison of Simulation models results.

Model	Department	Resource state	Effect	
			Utilization	Average waiting time (minutes)
Current to Proposed changes	Lab	Increased by 25%	Decreased by 7.55%	Decreased by 22.2
	x-ray	Increased by 50%	Decreased by 8.6%	Decreased by 30.90
	Ultrasound	Increased by 50%	Decreased by 29.7%	Decreased by 26.68
	ENT	Decreased by 50%	Increased by 10.6%	Increased by .985
	Eye	Decreased by 50%	Increased by 11.48%	Increased by 1.981
	Skin	Decreased by 50%	Increased by 18.8%	Increased by 1.30

TABLE 3. Comparison of average waiting time in minutes for the current and proposed models.

Departments	Average Waiting time (min) per each department	
	Current System	Proposed System
Dentistry	0.188057	0.181814
ECG	0.230629	0.630171
ENT	0.096357	1.215171
Eye	0.109	2.092457
Gynae	0.249929	0.299957
Lab	51.77687	29.57144
Medical	0.032914	0.115729
Paeds	0.1006	0.098457
Reception	1.520886	1.329086
Skin	0.120643	1.429571
Surgical	0.151671	0.059283
Ultrasound	72.16614	41.26109
X-ray	30.5536	3.872571

respectively and the utilization of the underutilized departments (Eye, ENT and Skin) increases from (12.9, 11.02 and 12.8) to (23.5, 22.7 and 31.6) percent respectively.

It was concluded that the utilization of different departments increases by decreasing the resources such as Eye, ENT and Skin departments. But these resources were allocated to the stations where bottlenecks were being created, namely the lab, x-ray and ultrasound. The effect of this allocation is evident in the substantial decrease in waiting time for patients hence improving patient care.

It can be seen that of all the eight OPDs, the combined percentage of all the OPDs in which there is increase in waiting time accounts for 40.3% while the combined percentage of OPDs in which the waiting time decreases is 42.3%. Further analysis showed that the X-ray and Lab accounts for 77% of all the 35 different routes followed by the patients, which applies a large number of patients get a decrease in waiting time in their routes than those who experience increase in waiting time. Also, the Skin, ENT and Gynae experienced increase in waiting time which is less critical than surgical, Lab, Ultrasound and Pediatrics.

It can be observed that the departments with decreased capacity showed a remarkable increase in utilization with insignificant change in the waiting time. This increase in utilization is due to the overall change in patient flow rates as the patient flow rates increases by reducing waiting time. The hospital data showed that most of the patients entering the hospital were recommended for tests of blood, urine, X-Rays or the Ultrasound for a proper diagnosis. This in turn leads to a very high patient flow to these department, hence creating bottlenecks. These bottlenecked departments are proposed with the additional resources to eliminate the bottleneck effects.

The hospital management and staff were thoroughly involved during the whole process. Their insights and daily practices proved to be valuable during the simulation of the hospital. The hospital's administration was able to see the day to day processes graphically due to the interactiveness and graphical displays of the Simio simulation software and were able to point out the discrepancies in the model during the model development stages and were able to see the results of the proposed model graphically thus getting a clear image and understanding of their hospitals system. This in turn helped them in decision making whether to implement the proposed changes or not.

VIII. CONCLUSION

While simulation is used extensively in the health care industry in the developed world, the concept of using simulation in the underdeveloped countries is relatively new. After a detailed literature review and observing the advantages of simulation applied elsewhere in the world, a successful simulation study was carried out for a hospital in Pakistan. The study effectively and efficiently identified the areas of bottleneck which helped in better management of hospital resources and improving customer care. The simulation model proved to be a useful tool for the hospital administration in decision making in terms of management of hospital resources.

The readjustment of hospital resources by the Hospital Administration with the help of simulation model helped to increase the utilization of resources (for example, eye by 11.5%, skin by 21%) and the waiting time at bottleneck station reduced like reception by 21%, and Med by 21%, among others). This resulted in improving customer care due better management of resources with help of simulation modeling of the system. About 75% patients who were suffering from long queue are now benefiting from the quick service in terms of reduced waiting time.

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JAWAD AHMAD was born in Peshawar, Pakistan, in 1992. He received the bachelor's degree in industrial engineering from the University of Engineering and Technology Peshawar, in 2014, and the master's degree in energy management and sustainability from the U.S. Pakistan Center for Advanced Studies in Energy, University of Engineering and Technology Peshawar, in 2019. He worked as a Project Engineer with the UNIDO project, implementing the Energy management system (ISO 50001). He is currently working as an Energy Auditor in the Higher Education Funded Research project under the fund of TDF (Technology Development Fund). His research interests include industrial process simulation, ergonomics, human factors, energy management and sustainability, and solar and wind power mapping.

JAVAID IQBAL (Member, IEEE) received the bachelor's and master's degrees in mechanical engineering from the College of Electrical and Mechanical Engineering (CE & ME), National University of Science and Technology (NUST), Islamabad, and the Ph.D. degree from the University of New South Wales, Australia. He is currently performing his duties as the Dean of the Faculty of Engineering CE & ME, NUST. His research interests include industrial simulation, machine learning, mechanical systems, and mobile robots among others.

IMRAN AHMAD received the bachelor's degree in mechanical engineering and the master's degree in industrial engineering from the University of Engineering and Technology Peshawar, and the Ph.D. degree in industrial systems simulation, human factor simulation from Hanyang University, South Korea. He is currently an Assistant Professor with the Department of Industrial Engineering, University of Engineering and Technology Peshawar. His research interests include industrial system simulation, human factors simulation, and ergonomics.

ZUBAIR AHMAD KHAN received the bachelor's degree in mechatronics engineering from the National University of Science and Technology, Peshawar, Pakistan, and the master's degree in mechanical from the University of Engineering and Technology Peshawar, Pakistan, in 2012, where he is currently pursuing the Ph.D. degree in manufacturing automation. He is currently a Lecturer with the Department of Mechatronics Engineering, University of Engineering and Technology Peshawar. His research interests include manufacturing automation, robotics, and intelligent control systems.

MOHSIN ISLAM TIWANA (Member, IEEE) received the B.E. degree in mechatronics engineering from the National University of Sciences and Technology (NUST), Pakistan, in 2007, and the Ph.D. degree in biomedical engineering from the University of New South Wales (UNSW), Sydney, Australia. He received a Rectors Gold Medal for his B.E. degree. For his pioneering work on artificial limb design, he was given the Presidential Award. He received a Global Innovation Award for his Ph.D. degree in 2012. In 2013, he was awarded the prestigious Technology Transformer of the Year Award by CRDF Global, USA.

KHALID KHAN received the bachelor's degree in mechanical engineering from the University of Engineering and Technology Peshawar, Pakistan, in March 2015, and the master's degree in 2018. He joined the U.S. Pakistan Center for Advances Studies in Energy in 2016; did his research work in Fuel Cell from Arizona State University, Tempe, AZ, USA, in 2017. He is currently working as a Mechanical Team Lead in a joint research project of University of Engineering and Technology in collaboration with TDF and Pakistan Airforce (Technology Development Fund), funded by the Higher Education Commission of Pakistan. His research interests include renewable energy, fuel cell, industrial simulation, ergonomics, robotics, artificial intelligence, renewable energy, and biomaterials and manufacturing.