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Simulation of a Hospital Emergency Department in COVID-19 Conditions: A Case Study

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Abstract

Background: The COVID-19 virus has created many problems for human beings in the real world, particularly in the health sector. One of the issues is in emergency hospitals, which are vital pillars of the healthcare system in every country. Providing timely treatment and access to healthcare facilities is a major problem in developing countries.
Objectives: The aim of the study was to simulate a hospital emergency department under COVID-19 conditions.
Methods: This study simulates the operations of an emergency department in a hospital under COVID-19 conditions as a case study in Iran. This study considers several assumptions about hospital facilities, including doctors, nurses, and patients. The patients are divided into two categories: some require immediate examination, while others wait in line for appropriate services.
Results: A flow diagram for the department is provided and converted into a model, which is implemented using GPSS software. The model is then run multiple times, and the outputs are collected. The outputs of the simulation and their statistical distributions are analyzed, and the performance of various statistical tests is examined. Finally, recommendations for improving the performance of the emergency system are presented.
Conclusion: The findings of this study can be used as the first step in preparing this tool. Accordingly, this study was conducted to identify existing and valid tools for measuring hospital readiness against the COVID-19 virus, translate those tools, and compare them.
Keywords: Simulation, COVID-19, Emergency, Hospital, Modeling

1. Background

In December 2019, cases of severe respiratory infection were reported in Wuhan, China, caused by a new virus called COVID-19.[1] This disease quickly became a global pandemic and spread to different countries.[2] The disease has affected over 240 million people worldwide and has led to the deaths of more than 4.9 million people.[3] Although the direct impact of this disease on people's health is mostly seen in deaths due to the disease, the consequences on people's health extend beyond just the disease itself. Lack of protective equipment to provide services to others, reduction of capacity to provide services to other patients, lack of personal protective equipment, extreme fatigue of medical teams, hospital staff, and the like are common.[4-6] The consequences of the COVID-19 disease have extended beyond the health system and have had a negative impact on various economic and social dimensions of countries all over the world.[7-10] This has made COVID-19 a global concern, emphasizing the need to strengthen countries and their health systems to better handle similar crises.[11]

The COVID-19 virus has created many problems for human beings in the real world, particularly in the health sector. One of the challenges is in emergency hospitals, which are crucial components of the healthcare system in every country. Many public health officials are concerned about improving the performance of these facilities to ensure the satisfaction of patients.

People with COVID-19 infection, the flu, or the common cold typically experience respiratory symptoms such as fever, cough, and a runny nose. Although many symptoms are similar, they are caused by different viruses. Due to their resemblance, diagnosing the disease based solely on symptoms can be challenging. The World Health Organization recommends that individuals with coughs, fevers, and respiratory issues seek medical attention promptly. Patients should visit a healthcare provider if they have traveled within the past 14 days before symptom onset or have been in close contact with someone experiencing respiratory symptoms. To achieve this, it is essential to establish a COVID-19 disease management program in each hospital tailored to its strengths and weaknesses. Hospitals are diligently working to provide care for patients, their families, and their medical staff.

Iran has been one of the countries most severely affected by COVID-19. The first case of the disease was reported in February 2020, leading to widespread transmission and response efforts across many provinces. Currently, the healthcare system in various regions is critical and overwhelmed.[12]

Given the importance of promptly recognizing suspected COVID-19 cases and implementing effective health measures to limit the spread of the virus, it is essential to utilize all available health facilities and resources in emergency centers. Individuals suspecting, they may have COVID-19 can contact the pre-hospital emergency department or visit hospitals and community health centers 24/7.

It is necessary to evaluate the readiness of hospitals in the face of the COVID-19 disease. Conducting a hospital readiness assessment requires a comprehensive, complete, and valid tool for the assessment. Additionally, the tool should be localized according to the conditions of each area. A review of studies shows that there are tools available to measure the readiness of hospitals to deal with respiratory infectious diseases similar to COVID-19, such as SARS and MERS[13,14] as well as other infectious diseases like Ebola. Researchers have used these tools to evaluate and analyze the readiness of hospitals in dealing with pre-existing diseases.[15-17] In the case of COVID-19, tools have also been developed by some of the world's leading organizations. Therefore, due to the importance and locality of these tools, it is necessary to develop a specific tool to assess hospital readiness in Iran.

Given the need to conduct studies to assess the readiness of the country's hospitals, the necessity for standardized and localized tools is undeniable. One of the important tools is simulation. Saidani et al. (2021) used a discrete event simulation model applied on a university campus to determine optimal COVID-19 testing stations locally.[18] It helped identify specific bottlenecks and associated areas of improvement in the process to save human resources and time. The model was built and tested using actual data and processes implemented on campus at the University of Illinois at Urbana-Champaign, where an average of around 10,000 samples needed to be processed daily.

Simulation models and tools have played a crucial role in forecasting possible scenarios to provide decision support for COVID-19. One of the tools developed recently is COVIDSIM,[18,19] which is used for efficient control and management of the ongoing COVID-19 pandemic. Rashidi (2017) surveyed the taxonomies of discrete simulation software and presented six taxonomies for them.[20] The first taxonomy categorizes different approaches for worldviews, including event scheduling, activity scanning, three-phase, and process interaction. The second taxonomy is based on how the software handles entities, and the third one is whether the simulation software has programming capabilities. The fourth taxonomy is based on how discrete simulation software assists in constructing user applications. The fifth taxonomy is related to model execution, and the sixth one focuses on the level of autonomy used in simulation model elements. Subsequently, more than 60 simulation software programs are evaluated based on the provided taxonomies.

Hassanat et al. developed a simulation model to forecast the spread of the COVID-19 pandemic.[21] They utilized the model to analyze the evolution of the pandemic in two major cities in KSA, namely Riyadh (the capital city) and Jeddah (the second-largest city). The main advantage of this model is its ability to examine the parameters used to better understand and more accurately predict the shape of the infection curve, particularly in KSA. The results obtained highlighted the significance of several parameters in reducing the spread of the pandemic, including the infection rate, social distancing, and individuals' walking distance. Furthermore, they analyzed the current data of infected cases in KSA using a Gaussian curve fitting method. The results indicated that the expected pandemic curve is flattening, consistent with the real infection data. The experimental findings on KSA's updated cases demonstrated that the proposed model outperforms some previous prediction techniques, making it more effective in combating potential future pandemics.

Abdolrazaghnejad et al. conducted a study to assess the emergency preparedness of a hospital in Zahedan, Iran, to manage COVID-19 in 2020.[22] The study included 100 emergency personnel as participants, selected through a random sampling method. Two questionnaires were used to collect data: one assessing psychological readiness to deal with COVID-19 and the other focusing on epidemiological and clinical variables related to COVID-19. Data analysis was performed using SPSS software, and the Pearson test was utilized to examine the correlation between variables. The results indicated a significant positive correlation between the three psychological components (behavioral, cognitive, and emotional dimensions) of the cognitive readiness questionnaire for COVID-19 and the total score of the epidemiological and clinical variables questionnaire (COVID-19 Coping Rate). The study concluded that psychological components are significantly associated with the rate of COVID-19 coping among hospital emergency personnel. Additionally, the study revealed that the psychological readiness of the hospital's emergency treatment staff to deal with COVID-19 is at an acceptable level.

Hospitals play an important role in crisis management in society. Since the outbreak of COVID-19, the readiness of hospitals to continue medical care during the crisis has been under scrutiny.

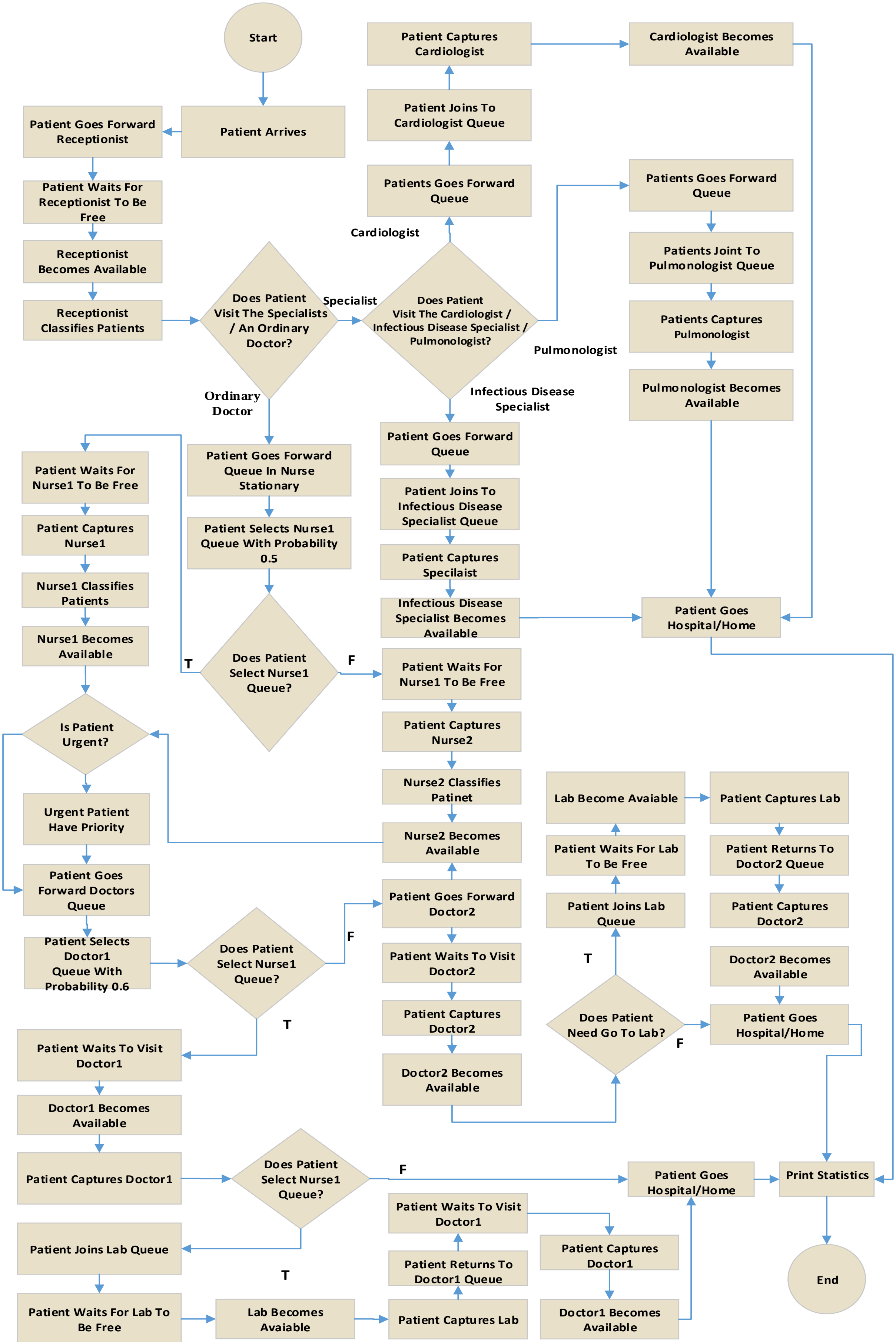

Figure 1. Flow Diagram of the Emergency Department

2. Objectives

The purpose of this research is to simulate the emergency department in a hospital and provide several recommendations to improve its efficiency in reducing patient waiting times and increasing patient satisfaction. The rest of this article is organized as follows: Section 2 presents the objectives; Section 3 presents the simulation model based on the assumptions; Section 4 provides an evaluation of the simulation model; Section 5 is dedicated to the discussion; and finally, Section 6 summarizes the conclusion.

3. Methods

In this section, the assumptions and simulation model of the emergency center in the hospital are described. The patients referred to the center are divided into two categories: outpatients and hospitalized patients. The hospital emergency department has two general doctors, three specialists (cardiologist, pulmonologist, and infectious disease specialist), and two nurse practitioners in the public sector. Some patients require immediate examination, while others can wait for service. To simulate the emergency department, we conducted a preliminary survey and gathered information. The results of this survey are summarized in the following assumptions:

Assumption 1: Patients arrive at the emergency department with an exponential distribution of 15 minutes mean and reach the reception after one minute. The reception classifies the patients, and the time for this classification is an exponential distribution with an average of 3 minutes.

Assumption 2: Patients go to one of the specialists with a probability of 30% and to a general practitioner with a probability of 70%. Fifty percent of patients who need to visit a specialist go to the pulmonologist, 30% to the infectious disease specialist, and 20% to the cardiologist. The patient arrives at the relevant line after one minute.

Assumption 3: The time a patient spends visiting the specialists follows an exponential distribution. On average, it takes 40, 30, and 20 minutes for the pulmonologist, cardiologist, and infectious disease specialist, respectively.

Assumption 4: Patients who visit a general practitioner join the queues at a nursing station. The patient arrives at the nursing station after one minute. The patient selects the queue for the first or second nurse with an equal probability of 50%.

Assumption 5: Nurses reclassify the patients, with 55% of the patients classified as Can Wait (CW) and the remaining 45% as Need Immediate Attention (NIA). The time taken by both nurses to attend to each patient is 15 minutes, following an exponential distribution. NIA patients have a higher priority for seeing a doctor than CW patients.

Assumption 6: Patients choose the queue for the first doctor with a 60% probability and the queue for the second doctor with a 40% probability.

Assumption 7: The NIA patient's visit with the first and second doctor takes an average of 30 and 35 minutes, respectively, with an exponential distribution.

Assumption 8: 65% of NIA patients are tested after visiting a doctor, while the remaining 35% complete their work. They may go home or to the hospital.

Assumption 9: Patients who need to be tested go to the laboratory queue. The average time each patient spends testing in the laboratory is 10 minutes following an exponential distribution. The laboratory work and Computed Tomography (CT) scanning, along with its preparation, take an average of 20 minutes following an exponential distribution. After obtaining the results, NIA patients should visit a doctor again. They should visit a doctor again in the first stage. The priority of patients who have to visit a doctor after the laboratory is lower than that of CW patients (patients who have not yet visited a doctor).

Assumption 10: Re-visiting NIA patients with the first doctor takes an average of 10 minutes with an exponential distribution, and with the second doctor, it takes an average of 15 minutes. The average operation time for CW patients with the first and second doctors is 20 and 25 minutes, respectively, with an exponential distribution.

Determining the existence and activities of a system for simulating a system are important factors. In a hospital emergency department, patients are entities of this system. Activities of the system consist of entering patients into the hospital emergency system and required operations for their treatment, and ultimately leaving the department. According to the assumptions, the procedure of activities in the emergency department is depicted in Figure 1.

4. Results

In this section, the GPSS program designed for the emergency system with its execution is presented. GPSS is a block-oriented software package, meaning it is programmed based on a set of blocks.[23] The software's commands are blocks of the program, and a set of blocks describes the movement of an entity from the time it is created to the time it exits the model. Additionally, multiple entities can be involved in one block, and not always one entity in one block. The program below is designed to run a 24-hour simulation.

4.1. The Output of the Simulation Program and Results of the First Run

Table 1 shows the output of the simulation model execution. In this table, the column BLOCK refers to the specific block in the simulation model. According to the program above, there are 106 blocks - the third column of the program. Each block in GPSS represents a particular process within the system, such as a queue, server, or decision

```
GPSS/H Release 3.60 (EP108)     26 Feb 2021   12:56:45
File: C:\Documents and Settings\Administrator\Desktop\s1.txt
Line# Stmt#  If Do  Block#  *Loc        Operation A,B,C,D,E,F,G       Comments

1     1       ********************************************************************************
2         2 * Program to simulate a hospital emergency room with 2 nurses,2 doctors and
3     3       * 3 specialists, persons first go to the receptionist to be classified
4     4       * then go to the nurse to be classified again.
5     5       * patients arrival: 15 minutes
6     6       * termination condition: 24 hours
7     7       * base time unit: 1 minute
8     8        ********************************************************************************
9     9        * Exponential function:
10    10       ********************************************************************************
11    11       EXPO function RN2,C24
12    12       .0000,.000/.1000,.104/.2000,.222/.3000,.355/.4000,.509/.5000,.690/
13    13       .6000,.915/.7000,1.20/.7500,1.38/.8000,1.60/.8400,1.83/.8800,2.12/
14    14       .9000,2.30/.9200,2.52/.9400,2.81/.9500,2.99/.9600,3.20/.9700,3.50/
15    15       .980,3.90/.9900,4.60/.9950,5.30/.9980,6.20/.9990,7.00/.9997,8.00/
16    16       ********************************************************************************
17    17       *  model segment 1 (classification by receptionist)
18    18       ********************************************************************************
19    19       *
20    20               SIMULATE
21    21    1          GENERATE 15,FN$EXPO         patient arrives
22    22    2          PRIORITY 10                 initial priority
23    23    3          ADVANCE  1                  patient drives to the receptionist
24    24    4          QUEUE    RECEP              patient waits for the receptionist
25    25    5          SEIZE    RECEP              patient reaches the receptionist
26    26    6          DEPART   RECEP              remove patient from waiting line
27    27    7          ADVANCE  3,FN$EXPO          classification time
28    28    8          RELEASE  RECEP              patient departs
29    29       *
30    30    9          TRANSFER .7,SPECIAL,ORD     70% of patients choose ORD doctor
31    31       ********************************************************************************
32    32       * model segment 2 (patients who want to see specialists)
33    33       ********************************************************************************
34    34   10   SPECIAL ADVANCE    1               patient drives to the specialists
35    35   11           TRANSFER  .5,PLINE,OTHER   patient selects PULMGIST or other
36    36   12   PLINE   QUEUE     PULMGIST         patient waits for PULMGIST
37    37   13           SEIZE     PULMGIST         patient reaches the PULMGIST
38    38   14           DEPART    PULMGIST         remove patient from waiting line
39    39   15           ADVANCE   40,FN$EXPO       visiting time
40    40   16           RELEASE   PULMGIST         patient departs; goes home or the hospital
41    41   17           TERMINATE 0
42    42   18   OTHER   TRANSFER  .3,CLINE,ILINE   patient selects Cardiologist or Infectious Disease specialist line
43    43   19   CLINE   QUEUE     CARDGIST         patient waits for Cardiologist
44    44   20           SEIZE     CARDGIST         patient reaches Cardiologist
45    45   21           DEPART    CARDGIST         remove patient from waiting line
46    46   22           ADVANCE   30,FN$EXPO       visiting time
47    47   23           RELEASE   CARDGIST         patient departs; goes home or the hospital
48    48   24           TERMINATE 0
49    49   25   ILINE   QUEUE     INFDISPE         patient waits for Infectious Disease specialist
50    50   26           SEIZE     INFDISPE         patient reaches Infectious Disease specialist
51    51   27           DEPART    INFDISPE         remove patient from waiting line
52    52   28           ADVANCE   20,FN$EXPO       visiting time
53    53   29           RELEASE   INFDISPE         patient departs; goes home or the hospital
54    54   30           TERMINATE 0
55    55       ********************************************************************************
56    56       * model segment 3 (patients who want to see ordinary doctor)
57    57       *******************************************************************************
58    58    31   ORD     ADVANCE    1                patient drives to the ordinary doctor
59    59    32           TRANSFER  .5,NURSE1,NURSE2  patient selects nurse1 or nurse2
60    60    33   NURSE1  QUEUE     NURSE1            patient waits for nurse1
61    61    34           SEIZE     NURSE1            patient reaches nurse1
62    62    35           DEPART    NURSE1            remove patient from waiting line
63    63    36           ADVANCE   15,FN$EXPO        classification time
64    64    37           RELEASE   NURSE1            patient departs; goes home or the hospital
65    65    38           TRANSFER  .55,NIA,CANWAIT   45% of patients are not urgent
66    66    39   NURSE2  QUEUE     NURSE2            patient waits for nurse2
67    67    40           SEIZE     NURSE2            patient reaches nurse2
68    68    41           DEPART    NURSE2            remove patient from waiting line
69    69    42           ADVANCE   15,FN$EXPO        classification time
70    70    43           RELEASE   NURSE2            patient departs
71    71    44           TRANSFER .55,NIA,CANWAIT    45% of cases are not urgent
72    72        ********************************************************************************
73    73        * model segment 4 (Patients who need immediate attention)
74    74        ********************************************************************************
75    75        *
76    76    45   NIA     PRIORITY  15                nia-patients have priority to see doctor
77    77        *
78    78    46           TRANSFER  .4,FIRST,SECOND   patient selects doctor1 or doctor2
79    79    47   FIRST   QUEUE     DOCTOR1           patient waits for doctor1
80    80    48           SEIZE     DOCTOR1           patient reaches doctor1
81    81    49           DEPART    DOCTOR1           remove patient from waiting line
82    82    50           ADVANCE   30,FN$EXPO        visiting time
83    83    51           RELEASE   DOCTOR1           patient departs; goes home or the hospital
84    84    52           TERMINATE 0
85    85    53           TRANSFER .35,LAB1,NIAH1     65% of NIA patients should go to laboratory
86    86    54   LAB1    QUEUE        LAB            patient waits for laboratory
87    87    55           SEIZE        LAB            patient reaches laboratory
88    88    56           DEPART       LAB            remove patient from waiting line
89    89    57           ADVANCE   10,FN$EXPO        time need for test
90    90    58           RELEASE      LAB            patient departs; goes home or the hospital
91    91    59           PRIORITY      5             drop priority for next stage
92    92    60           ADVANCE   20,FN$EXPO        time need to get results
93    93    61           QUEUE     DOCTOR1           patient waits for doctor1 again
94    94    62           SEIZE     DOCTOR1           patient reaches doctor1
95    95    63           DEPART    DOCTOR1           remove patient from waiting line
96    96    64           ADVANCE   10,FN$EXPO        visiting time
97    97    65           RELEASE   DOCTOR1           patient departs; goes home or the hospital
98    98    66   NIAH1   TERMINATE 0
99    99    67   SECOND  QUEUE     DOCTOR2           patient waits for doctor2
100   100   68           SEIZE     DOCTOR2           patient reaches doctor2
101   101   69           DEPART    DOCTOR2           remove patient from waiting line
102   102   70           ADVANCE   35,FN$EXPO        visiting time
```

```
71            RELEASE   DOCTOR2           patient departs; goes home or the hospital
72            TERMINATE 0
73            TRANSFER .35,LAB2,NIAH2     65% of NIA patients should go to laboratory
74   LAB2     QUEUE        LAB            patient waits for laboratory
75            SEIZE        LAB            patient reaches laboratory
76            DEPART       LAB            remove patient from waiting line
77            ADVANCE     10,FN$EXPO      time need for test
78            RELEASE      LAB            patient departs
79            PRIORITY      5             drop priority for next station
80            ADVANCE   20,FN$EXPO        time need to get results
81            QUEUE     DOCTOR2           patient waits for doctor2 again
82            SEIZE     DOCTOR2           patient reaches doctor2
83            DEPART    DOCTOR2           remove patient from waiting line
84            ADVANCE   15,FN$EXPO        visiting time
85            RELEASE   DOCTOR2           patient departs; goes home or the hospital
86   NIAH2    TERMINATE 0
    ********************************************************************************
    * model segment 5 (Patients who CAN WAIT)
    ********************************************************************************
    *
87   CANWAIT QUEUE     CWLINE1
88            SEIZE     CWLINE1
89            DEPART    CWLINE1
90            ADVANCE   1,FN$EXPO
91            RELEASE   CWLINE1
92            TRANSFER  .4,FIRST2,SECOND2 60% of CW patients choose line doctor2
93   FIRST2   QUEUE     DOCTOR1           patient waits for doctor1
94            SEIZE     DOCTOR1           patient reaches doctor1
95            DEPART    DOCTOR1           remove patient from waiting line
96            ADVANCE   20,FN$EXPO        visiting time
97            RELEASE   DOCTOR1
98            TERMINATE 0
99   SECOND2  QUEUE     DOCTOR2           patient waits for doctor2
100           SEIZE     DOCTOR2           patient reaches doctor2
101           DEPART    DOCTOR2           remove patient from waiting line
102           ADVANCE   25,FN$EXPO        visiting time
103           RELEASE   DOCTOR2           patient departs; goes home or the hospital
104           TERMINATE 0
    ********************************************************************************
    * model segment 6 (RUN-CONTROL Xact)
    ********************************************************************************
    *
105            GENERATE   1440
106            TERMINATE  1
    ********************************************************************************
    * RUN-CONTROL Statements
    ********************************************************************************
              START      1
              END
```

Table 1. Output of the Simulation Model Execution

BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL	BLOCK	CURRENT	TOTAL
1		98	37		32	72		18
2		98	38		32	73		0
3		98	NURSE2		38	LAB2		0
4	1	98	40		38	75		0
5		97	41		38	76		0
6		97	42	1	38	77		0
7	1	97	43		37	78		0
8		96	44		37	79		0
9		96	NIA		33	80		0
SPECIAL		25	46		33	81		0
11		25	FIRST		15	82		0
PLINE		17	48		15	83		0
13		17	49		15	84		0
14		17	50	1	15	85		0
15		17	51		14	NIAH2		0
16		17	52		14	CANWAIT		36
17		17	53		0	88		36
OTHER		8	LAB1		0	89		36
CLINE		6	55		0	90		36
20		6	56		0	91		36
21		6	57		0	92		36
22		6	58		0	FIRST2	1	21
23		6	59		0	94		20
24		6	60		0	95		20
ILINE		2	61		0	96		20
26		2	62		0	97		20
27		2	63		0	98		20
28		2	64		0	SECOND2		15
29		2	65		0	100		15
30		2	NIAH1		0	101		15
ORD	1	71	SECOND		18	102	1	15
32		70	68		18	103		14
NURSE1		32	69		18	104		14
34		32	70		18	105		1
35		32	71		18	106		1
36		32						

Table 2. Average Utilization of the Facilities

Facility	Total Time	Entries	Average Time/Xact	Current Status	Seizing Xact
RECEP	0.217	97	3.221	AVAIL	98
PULMGIST	0.424	17	35.912	AVAIL	
CARDGIST	0.053	6	12.671	AVAIL	
INFDISPE	0.037	2	26.464	AVAIL	
DOCTOR1	0.682	35	28.041	AVAIL	93
DOCTOR2	0.777	33	33.913	AVAIL	96
CWLINE1	0.025	36	1.010	AVAIL	
NURSE1	0.327	32	14.737	AVAIL	
NURSE2	0.302	38	11.452	AVAIL	95

Table 3. Information on the Queues Formed in the Running Model

Queue	Maximum Contents	Average Contents	Total Entries	Zero Entries	Percent Zeros	Average Time/Unit	$Average Time/Unit	Current Contents
RECEP	2	0.053	98	74	75.5	0.778	3.175	1
PULMGIST	4	0.576	17	10	58.8	48.806	118.529	0
CARDGIST	1	0.000	6	6	100.0	0.000	0.000	0
INFDISPE	1	0.000	2	2	100.0	0.000	0.000	0
DOCTOR1	6	1.425	36	11	30.6	56.999	82.079	1
DOCTOR2	13	4.946	33	6	18.2	215.816	263.776	0
CWLINE1	1	0.000	36	35	97.2	0.008	0.301	0
NURSE1	3	0.150	32	25	78.1	6.770	30.947	0
NURSE2	3	0.077	38	28	73.7	2.921	11.101	0

point. The column CURRENT indicates the current state or count of entities within the specified block at the time of reporting. For example, BLOCK 4 shows one entity currently waiting in that queue. The column TOTAL represents the total number of entities that have passed through or interacted with the block since the beginning of the simulation. This number accumulates over time, providing insight into the overall activity and throughput of that block. For example, BLOCK 1 shows 98 patients passing through each block.

According to the assumptions and procedure depicted in Figure 1, there are nine facilities in the department: 1) Reception; 2) First Nurse; 3) Second Nurse; 4) Pulmonologist (PULMGIST); 5) Cardiologist (CARDGIST); 6) Infectious Disease Specialist (INFDISPE); 7) First Doctor; 8) Second Doctor; and 9) Laboratory. Additionally, there are ten queues: 1) Reception; 2) First Nurse; 3) Second Nurse; 4) PULMGIST; 5) CARDGIST; 6) INFDISPE; 7) First Doctor; 8) Second Doctor; 9) Laboratory; and 10) CW patients (patients who can wait). The information obtained from running the model for the facilities and queues are included in Table 2 and Table 3.

Table 2 shows the average utilization of the facilities in the model. The columns of this table are described below:

Total Time: This metric indicates the total amount of time that the facility has been in operation during the simulation. It reflects the cumulative time that the facility has been busy serving entities or processing transactions.

Entries: This represents the total number of entities that have entered the facility throughout the simulation. It gives insight into how many transactions or jobs have utilized the facility, helping to assess demand.

Average Time/Xact: This metric calculates the average time an entity spends in the facility. It is derived by dividing the Facility Total Time by the number of Entries. This metric helps in understanding the efficiency of the facility and the service time for each entity.

Current Status: This indicates the current operational state of the facility. It may specify whether the facility is busy, idle, or in another state (like waiting for resources). This information is crucial for real-time analysis of the system's performance.

Seizing Xact: This refers to the current transaction or entity that is seizing or occupying the facility. It may include details such as the ID of the entity or its status. Monitoring the seizing transaction helps in understanding which entities are currently being processed and can aid in troubleshooting or performance analysis.

Table 3 shows the information on queues formed during the model's operation. The columns of this table are described below:

Queue: This indicates the specific queue block being reported. Each queue block in GPSS is designated to hold entities waiting for a resource or service.

Maximum Contents: This metric indicates the maximum number of entities that have been in the queue at any given time during the simulation. It helps identify peak load conditions and potential bottlenecks in the system.

Average Contents: This represents the average number of entities present in the queue over the entire simulation period. It is calculated by averaging the number of entities in the queue at various points in time, providing insight into typical queue lengths.

Total Entries: This indicates the total number of entities that have entered the queue since the start of the simulation. It helps assess the demand for the resource or service associated with the queue.

Zero Entries: This metric shows the number of times the queue had zero entries, meaning it was empty at certain points during the simulation. This can indicate periods of low demand or inefficiency in the system.

Percent Zeros: This is calculated as the percentage of time the queue was empty compared to the total simulation time. It provides insight into how often the queue is not being utilized, which can be useful for identifying inefficiencies.

Average Time/Unit: This metric represents the average time an entity spends in the queue. It is calculated by dividing the total time all entities spent in the queue by the total number of entries. This helps assess the waiting time for entities.

$Average Time/Unit: This metric is similar to the previous metric, except that it excludes entities that were served without waiting from the calculations. It is calculated by dividing the total time spent in the queue by the total number of entries (minus entities with zero waiting time for service). This helps to assess the waiting time for entities.

Current Contents: This indicates the current number of entities present in the queue at the time of reporting. It provides a snapshot of the queue's status, which is critical for real-time monitoring and decision-making.

As we can see in Table 1, 98 patients came to the emergency department, 91 of whom were treated (see the BLOCKs 4,7,31, 42, 50, 93, and 102 of the table). They went home or to the hospital. From running the model for the first time, we obtained the following observations:

Observation 1: The percentage of use of the hospital reception unit was 21.7%. In fact, this unit was busy 21.7% of the time, and 97 patients arrived at this unit. The rate of use of this unit for each patient was about 3 units of time.

Observation 2: The percentage of pulmonologist (PULMGIST) use for patients was about 42.4%, and 17 patients arrived at this specialist and received the service.

Observation 3: The rate of pulmonologist (PULMGIST) use per patient was about 36 units of time.

Observation 4: The percentage of patients using the services of the Cardiologist (CARDGIST), Infectious Disease Specialist (INFDISPE), General Practitioner 1, General Practitioner 2, Nurse 1, Nurse 2, and CW queue is approximately 5.3%, 3.7%, 68.2%, 77.7%, 32.7%, 30.2%, and 2.5%, respectively.

Observation 5: The number of patients who have crossed their blocks and received services from the Cardiologist (CARDGIST), Infectious Disease Specialist (INFDISPE), Doctor1, Doctor2, CWLINE, Nurse 1, and Nurse 2 are 2, 6, 35, 33, 36, 32, and 38, respectively.

Observation 6: Throughout the simulation, all specialists, both nurses, and both doctors were available.

Observation 7: Patients in the laboratory receive service upon arrival, so no queue forms for the laboratory. The maximum queue length at the reception unit is 2, with an average queue length of 0.053.

Observation 8: Out of a total of 98 patients entering the queue, 74 patients (75.5%) were classified without any waiting time, meaning they were in the queue for zero time units.

Observation 9: The average waiting time for a patient in the admission queue is 0.778 time units, increasing to 3.175 units for patients with zero time units in the queue.

Observation 10: The last column indicates that there are no patients in the queue at the end of the simulation.

Observation 11: The maximum length of the queue for the Pulmonologist (PULMGIST) is 4 and the average length of this queue is 57.6.

Observation 12: A total of 17 patients entered the queue, out of which 10 (58.8%) received the service without waiting.

Observation 13: Comparing the queues of the first and second doctors, we see that the maximum length of the first doctor's queue is 6, while the maximum length of the second doctor's queue is 13.

Observation 14: The last column shows that at the end of the simulation period, there is one patient left in the reception queue and the first doctor.

Observation 15: The queue for the second doctor is longer than the other queues because the number of patients referred to both doctors is almost the same, while the speed of the second doctor is slower than that of the first doctor, so his queue is longer.

Observation 16: According to the CW queue, it can be seen that 36 patients have entered this queue, 35 of whom did not have any waiting time for processing.

Observation 17: After 24 hours (the end of the simulation period), the queues related to the hospital reception and the second doctor still had patients, and their work was not finished.

4.2. The Output of the Simulation Program for Different Runs

We ran the simulation model 15 times. Table 4 shows the output of the simulation model at each execution time. The information in the table is described below:

- **R (Run):** Indicates the run number of the simulation.
- **MC (Maximum Contents):** The maximum number of items or patients processed during that run. The maximum contents ranged from one to five across different medical professionals, indicating variability in their maximum patient or item capacity per run.
- **AC (Average Contents):** The average number of patients processed during that run, ranged from zero to 0.954. The average contents were generally lower than the maximum contents, suggesting that while some peaks exist, the daily averages reflect a moderate patient volume.
- **TC (Total Entries):** The total number of entries or

Table 4. Output of the Simulation Model for 15 Runs

	Reception						Cardiologist						Infectious Disease Specialist					
R	MC	AC	TC	ZE	ATU	$ATU	MC	AC	TC	ZE	ATU	$ATU	MC	AC	TC	ZE	ATU	$ATU
1	2	0.022	84	72	0.371	2.6	1	0.077	8	7	13.882	1	0	3	3	0	0	1
2	4	0.062	85	68	1.049	5.243	1	0.011	9	7	1.828	1	0	7	7	0	0	1
3	2	0.043	83	66	0.737	3.601	1	0	10	10	0	1	0	4	4	0	0	1
4	2	0.041	103	78	0.57	2.348	2	0.186	15	9	17.811	1	0	3	3	0	0	1
5	3	0.062	92	67	0.972	3.576	1	0	10	10	0	1	0	4	4	0	0	1
6	4	0.093	106	78	1.262	4.778	2	0.176	16	11	15.865	1	0.042	6	5	10.171	61.027	1
7	2	0.057	96	75	0.856	3.912	1	0.021	8	6	3.721	1	0.039	5	4	11.266	56.328	1
8	2	0.03	93	78	0.462	2.864	1	0.018	9	7	2.853	1	0	4	4	0	0	1
9	1	0.014	79	74	0.261	4.118	2	0.134	12	9	16.091	1	0	1	1	0	0	1
10	2	0.045	96	75	0.676	3.092	1	0.003	11	10	0.456	1	0	3	3	0	0	1
11	3	0.064	92	69	0.999	3.998	1	0.019	13	12	2.093	1	0	1	1	0	0	1
12	2	0.046	89	70	0.741	3.47	1	0.085	17	12	7.237	1	0	2	2	0	0	1
13	3	0.074	101	74	1.055	3.948	1	0.007	13	11	0.816	1	0	2	2	0	0	1
14	2	0.045	101	84	0.64	3.805	1	0.052	11	8	6.756	1	0.033	7	5	6.703	23.462	1
15	3	0.089	110	78	1.172	4.027	3	0.274	15	10	26.302	1	0	1	1	0	0	1

	Pulmonologist						Doctor1						Doctor2					
R	MC	AC	TC	ZE	ATU	$ATU	MC	AC	TC	ZE	ATU	$ATU	MC	AC	TC	ZE	ATU	$ATU
1	3	0.393	20	9	28.32	51.491	3	0.248	31	16	11.528	23.825	4	0.289	22	15	18.946	59.544
2	3	0.223	15	8	21.401	45.859	4	1.007	33	12	43.935	69.041	3	0.297	21	13	20.35	53.419
3	1	0.047	7	5	71.4	33.696	5	1.211	37	10	47.135	64.592	2	0.115	23	16	7.172	23.564
4	4	0.954	19	6	72.269	105.625	5	0.679	37	14	26.441	42.536	3	0.404	29	16	20.072	44.777
5	1	0.031	10	7	4.478	14.928	16	4.661	40	8	167.809	209.761	4	0.853	26	9	47.228	72.231
6	1	0.008	13	11	0.909	5.909	5	0.804	41	13	28.254	41.371	5	0.584	28	17	30.02	76.414
7	3	0.525	16	8	47.25	94.501	6	0.787	36	14	31.492	51.532	4	1.011	28	9	52.01	76.647
8	5	0.552	14	4	56.804	79.525	6	1.372	41	10	48.196	63.743	3	0.192	24	15	11.53	30.747
9	3	0.29	10	5	41.763	83.527	5	0.935	33	16	40.782	79.165	3	0.255	23	14	15.99	40.864
10	3	0.561	18	6	44.91	67.365	4	0.491	33	13	21.407	35.322	4	0.859	28	13	44.163	82.438
11	1	0.131	13	9	14.526	47.21	6	0.609	35	14	25.062	41.769	9	2.166	30	10	103.963	155.945
12	1	0.064	13	11	7.036	45.736	4	0.289	36	18	11.556	23.111	2	0.122	19	9	9.217	17.511
13	3	0.16	15	8	15.329	32.848	3	0.641	36	15	25.62	43.92	2	0.195	30	17	9.366	21.615
14	4	0.937	20	7	67.435	103.746	5	0.643	33	14	28.077	48.765	3	0.736	25	7	42.378	58.858
15	2	0.071	16	12	6.376	25.506	14	4.76	52	6	131.817	149.011	3	0.588	26	8	32.563	47.035

	CW						Nurse1						Nurse2					
R	MC	AC	TC	ZE	ATU	$ATU	MC	AC	TC	ZE	ATU	$ATU	MC	AC	TC	ZE	ATU	$ATU
1	1	0	29	26	0.023	0.225	1	0.024	22	18	1.572	8.643	2	0.192	31	20	8.936	25.182
2	1	0.001	27	26	0.033	0.895	1	0.018	23	21	1.112	12.791	2	0.134	31	20	6.237	17.576
3	1	0	28	27	0.02	0.554	4	0.517	34	12	21.909	33.859	3	0.092	28	21	4.712	18.849
4	1	0	39	39	0	0	2	0.11	29	17	5.445	13.159	3	0.237	37	23	9.224	24.377
5	1	0.001	38	37	0.052	1.974	7	0.675	32	17	30.365	64.779	1	0.03	35	28	1.242	6.212
6	1	0.001	38	37	0.02	0.746	3	0.141	37	23	5.501	14.539	5	0.668	34	17	28.3	56.601
7	1	0.001	37	34	0.044	0.537	3	0.138	34	22	5.862	16.61	3	0.224	33	23	9.758	32.202
8	2	0.003	40	37	0.106	1.416	3	0.317	31	21	14.727	45.653	3	0.226	35	21	9.301	23.251
9	1	0	27	27	0	0	4	0.184	26	17	10.191	29.44	3	0.156	30	21	7.48	24.934
10	1	0	40	39	0.006	0.25	2	0.034	34	28	1.452	8.226	3	0.228	30	21	10.935	36.449
11	1	0	37	37	0	0	3	0.105	38	22	3.981	9.454	2	0.041	27	20	2.168	8.364
12	1	0	36	36	0	0	2	0.134	30	18	6.411	16.027	2	0.073	27	18	3.889	11.668
13	1	0	40	38	0.004	0.089	3	0.102	37	24	3.976	11.318	1	0.047	34	26	2.011	8.545
14	1	0	28	28	0	0	5	0.388	34	21	16.435	42.984	3	0.131	29	18	6.512	17.169
15	1	0	42	42	0	0	2	0.178	38	18	6.74	12.806	3	0.169	40	26	6.082	17.379

patients processed. Total entries ranged from one to 110 across runs and professions, demonstrating significant differences in workload and patient throughput in different scenarios.

- **ZE (Zero Entries):** The number of entries that had zero content or no patients. The zero entries indicate that some runs had instances where no patients were processed. This occurred at least once in each professional grouping, reflecting variability in activity or resource allocation.
- **ATU (Average Time/Unit):** The average time taken per unit (could be per patient or per procedure). ATU values varied across runs, with some runs showing very efficient averages (e.g., as low as 0.001 minutes for some professionals) while others exhibited higher averages (e.g., up to 4.661 minutes). This variability suggests potential differences in case complexity or operational efficiency between the runs.
- **$ATU (Average Time/Unit):** This metric is similar to the previous metric, except that it excludes entities that were served without waiting from the calculations. It is calculated by dividing the total time spent in the queue by the total number of entries (minus entities with zero waiting time for service). This helps to assess the waiting time for entities.

From the information in Table 4, we can draw the following observations:

Observation 18: The ATU values exhibit a substantial range as well, indicating that some patient entries or units may be significantly more costly in terms of time and resources than others.

Observation 19: The variation in ATU and $ATU suggests that certain runs or medical professionals are significantly more efficient than others.

Observation 20: Capacity Utilization: Maximum contents indicate potential capacity limits that certain professionals might hit, which could affect patient care if consistently reached.

Observation 21: Clinical Demand Fluctuations: The presence of zero entries highlights the fluctuation in demand and resource utilization across different periods of the simulation.

The results of these runs are illustrated in Figures 2-7. Figure 2 shows the maximum number of patients in the queues. Figure 3 shows the average waiting time of the patients in the queues. Figure 4 shows the total number of patients that captured the facilities. Figure 5 shows the number of patients who received service without being in the queues. Figure 6 shows the average time taken by a patient in the queues. Figure 7 shows the average duration time of all patients in the queues, excluding the patients who passed through each queue in zero simulated time.

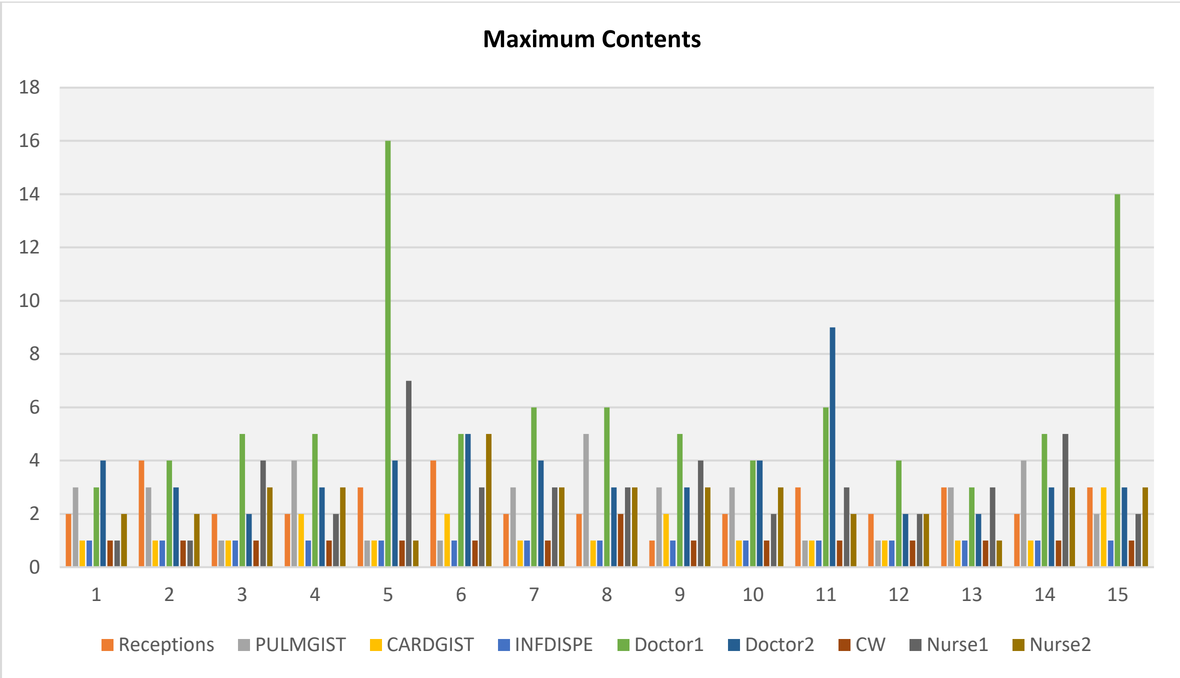

Figure 2. The Maximum Number of Patients in the Queues.

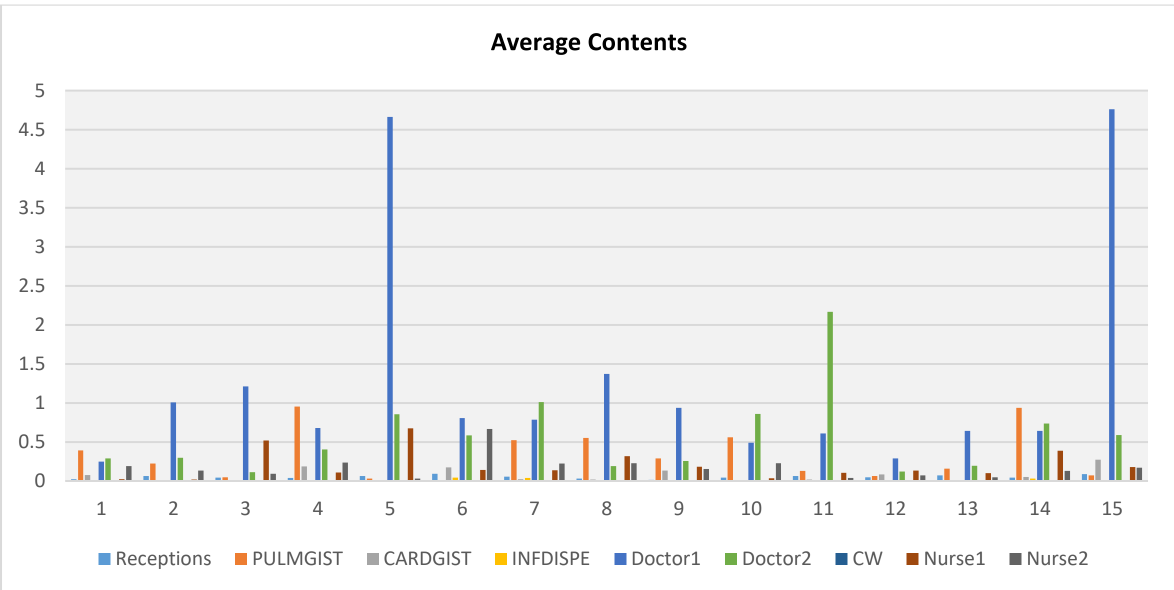

Figure 3. The Average Waiting Time of Patients in the Queues.

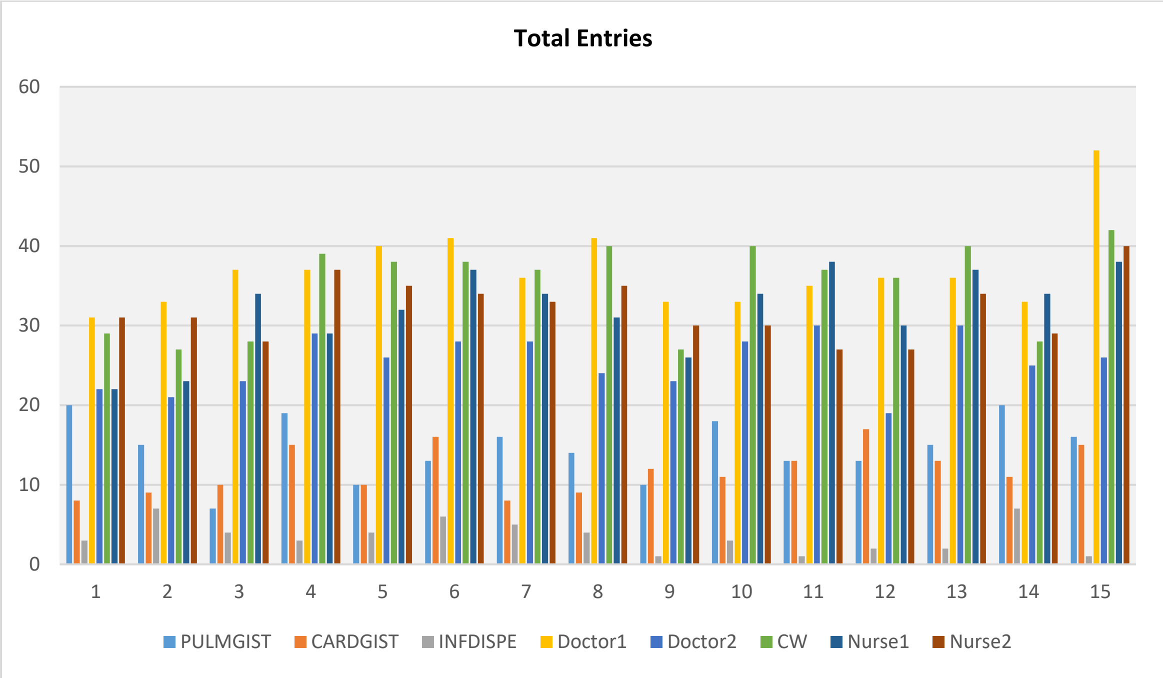

Figure 4. The Total Number of Patients That Capture the Facilities.

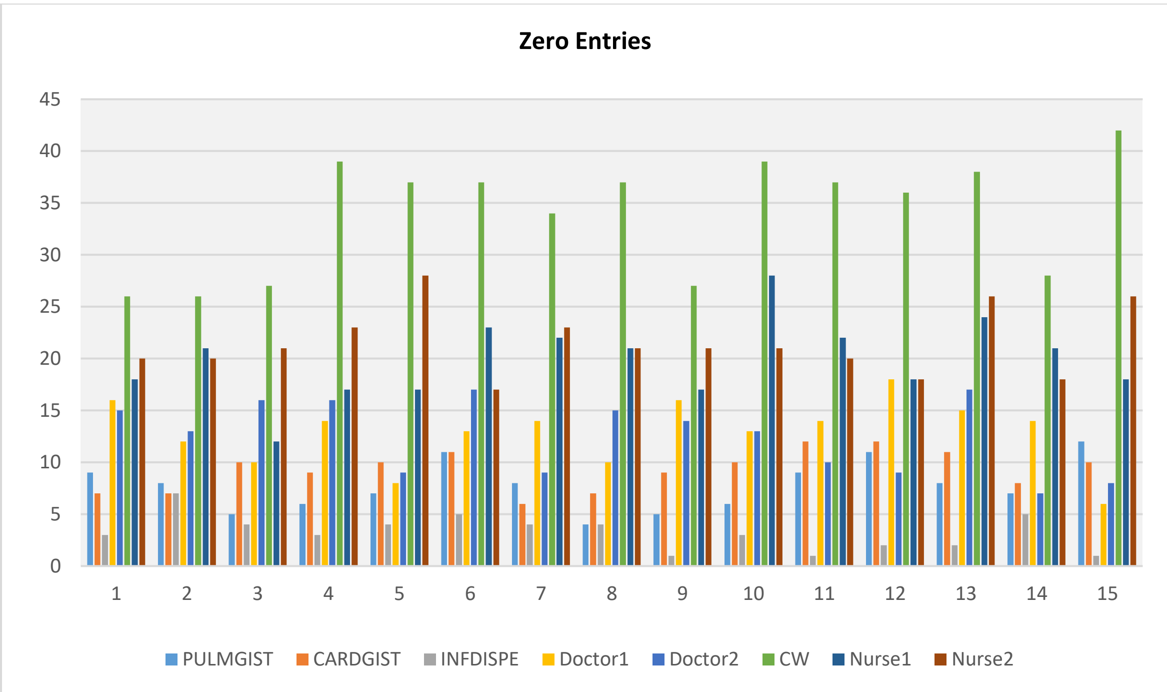

Figure 5. The Number of Patients Who Received Service without Waiting in the Queue.

From these figures (2-7), we obtained the following observations:

Observation 22: According to Figure 2, the maximum number of patients that formed for 'Doctor1' is greater than those of other queues in most runs.

Observation 23: As shown in Figure 3, the average waiting time of patients in the 'Doctor1' queue is longer than that of other queues in most runs.

Observation 24: Based on Figure 4, the total number of patients that capture the INFDSPE is less than in other facilities.

Observation-25: According to Figure 5, the total number of patients that could wait (CW) is greater than in other queues.

Observation 26: Figure 6 indicates that the average time taken by a patient in the Doctor1 queue is greater

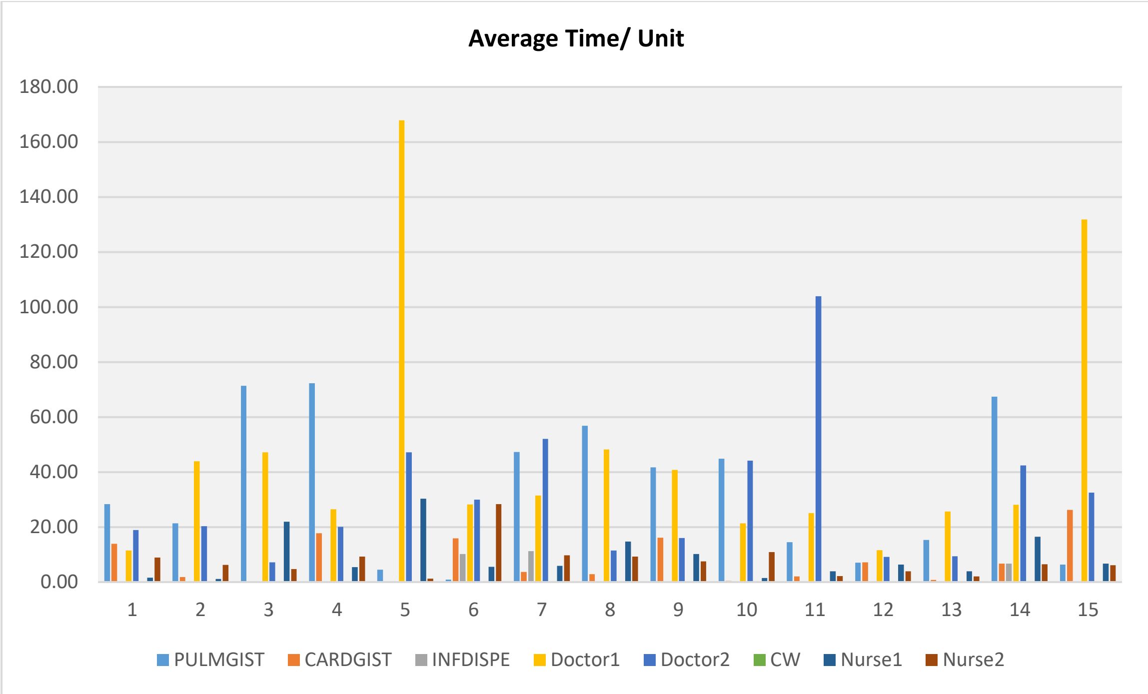

Figure 6. The Average Time Taken by a Patient in the Queues.

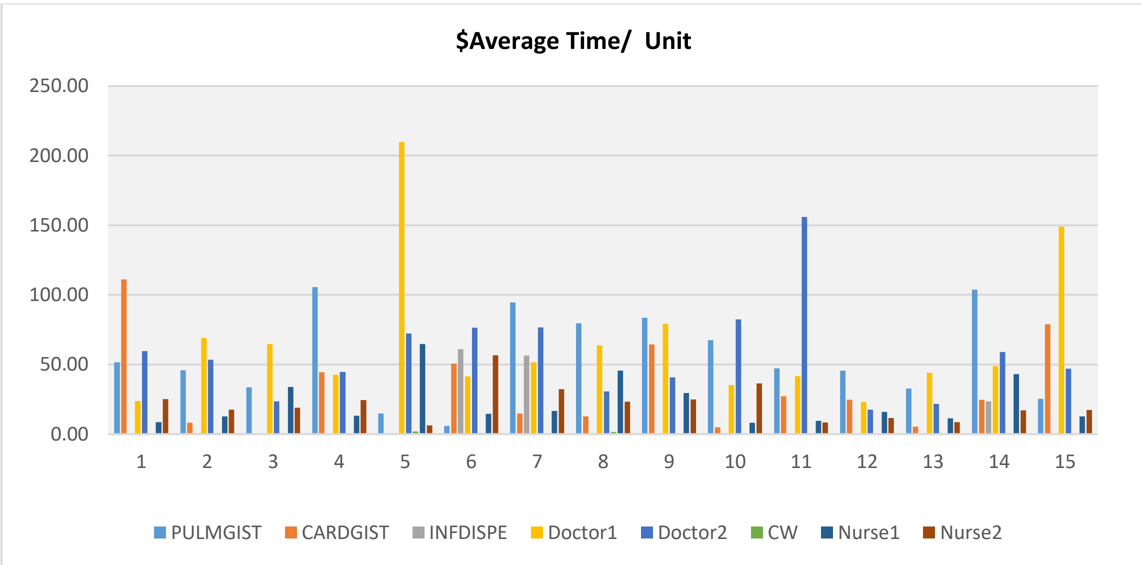

Figure 7. The Average Duration Time of All Patients in the Queues, Excluding the Patients Passing through each Queue in Zero Simulated Time.

than in other queues.

Observation-27: Figure 7 shows that the average duration time of all patients in the queues, excluding those who passed through each queue in zero simulated time, for Doctor1, is greater than in other queues.

5. Discussion

To determine the distribution parameters in the emergency simulation program, we conducted a non-parametric Kolmogorov-Smirnov test. This test evaluated the parameters of the maximum queue length and the total number of services received without waiting for each of the queues to determine if they follow a normal, poisson, uniform, or exponential distribution. Considering a significance level of $\alpha = 0.05$ and using the P-value of the distribution of these parameters, the results indicate that:

- For the reception unit, the variables "Total Number of Patients" and "receive service without waiting" are also distributed normally. The maximum queue length distribution is uniform.
- For the infectious disease specialist, the maximum queue length and "receive service without waiting" also follow the poisson distribution. The "Total Number of Patients" distribution is normal.

- For the pulmonologist, the variables "Total Number of Patients", "receive service without waiting", and the maximum queue length also follow the poisson distribution.
- For the cardiologist, the variables "Total Number of Patients" and "receive service without waiting" are also distributed normally. However, the maximum queue length distribution is not uniform.
- For Doctor1, Doctor 2, Nurse1, and Nurse2, the variables "Total Number of Patients", "receive service without waiting" and the maximum queue length distribution are not normally distributed.
- For the patients who can wait, the variables "Total Number of Patients", "receive service without waiting" and the maximum queue length distribution are not normally distributed.
- The variable "receive service without waiting" for the emergency reception queue and the "Total Number of Patients" for Second-line Nurses, among other variables, have a poisson distribution.
- The distribution of patients who have received services without waiting is normal, while the distribution of "Total Number of Patients" is uniform.

6. Conclusion

In this study, we developed a simulation model for the operations of an emergency department in a hospital under COVID-19 conditions and applied the model to a case study in Iran. We considered several assumptions about hospital resources, including doctors, nurses, and patients. Upon arrival at the system, patients were categorized into two groups: those needing immediate examination and those waiting in line for appropriate services. We created a flow diagram for the department and translated it into a simulation model using GPSS software. The model was executed fifteen times, and the resulting outputs were analyzed. Statistical distributions of the outputs were examined, and various statistical tests were performed to evaluate system performance. Based on the test results and variable distributions, we offered suggestions for improving system performance.

- Patients who were referred to the laboratory immediately received service, so a queue never formed. Therefore, it seems that the queue definition for the laboratory should be eliminated.
- Many times, the queue for the second doctor is busy. The reason is that more patients select the second doctor. If the nurses guide them to select the queue for the pulmonologist, the queue for the second doctor will be diminished.
- It is necessary to create a coordinated network using all capacities. To control cases optimally, according to local facilities and after making local agreements between the head of the network, the head of the university emergency department, and the approval of the university health and vice-chancellors, several steps should be taken depending on different cases.

The findings of this study can be used as the first step in preparing this tool. According to national and international health organizations, the virus seems to persist for a long time and will not be eradicated soon. Therefore, the introduction of these tools, while helping to provide a suitable tool for Iran, can help hospitals identify their weaknesses in the fight against this virus and plan to eliminate and improve their preparedness.

The limitation of the current research is that it is a case study of a hospital emergency department during the COVID-19 pandemic, conducted under its specific conditions and assumptions. Naturally, these assumptions must be adapted for application to other hospitals.

Research Highlights

What Is Already Known?

- There is no significant simulation model for hospital management, particularly a computer software-based simulation model for COVID-19, in Iran.

What Does This Study Add?

- This study simulates the operations of an emergency department in a hospital under COVID-19 conditions.
- Patients who were referred to the laboratory immediately received service, so a queue never formed.
- If the nurses guide patients to select the queue for the doctor, the waiting line for a doctor's visit will be reduced.

Author Contributions

Authors contributed equally to this work.

Conflict of Interest Disclosures

All authors declared that they have no conflict of interest.

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