

Demand and Capacity Modelling in Healthcare Using Discrete Event Simulation

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How to cite this paper: Singla, S. (2020) Demand and Capacity Modelling in Healthcare Using Discrete Event Simulation. *Open Journal of Modelling and Simulation*, 8, 88-107.

<https://doi.org/10.4236/ojmsi.2020.84007>

Received: July 28, 2020

Accepted: September 13, 2020

Published: September 16, 2020

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Abstract

The NHS is right now confronting huge pressures relating to demand and capacity in radiology. The purpose of this research has been to provide information about MRI usage, details of operational aspects of MRI services, and to ascertain the planning intentions of NHS radiology services to keep up and create MRI capacity. The report expands on using Discrete Event Simulation (DES) to inspect and plan the utilisation of NHS hospital resources for the radiology department to help a 24 hr service that is available to outpatients which will help with diminishing patient waiting time, better resource usage, understanding the capacity and demand. Consequently, this research examines to adjust staff and resources with the demand of the MRI. The research was investigated using DES in various scenarios to find which resources are inactive; patients are treated slowly. DES helped in discovering resource utilisation and outpatient throughout the system. It additionally helped in distinguishing the bottlenecks in patient flow. The DES simulation results demonstrated that time for the outpatient in the system is less and more outpatients have been treated too. There is a higher level of outpatient patients leaving the system under 120 minutes. The report uncovered an MRI report interpretation time. Reception room time and MRI waiting room time are decreased significantly. It additionally exhibited with an expanded outflow of outpatients, resources, for example, MRI capacity and radiographer utilisation expanded.

Keywords

Discrete Event Simulation (DES), MRI Services, Simulation, Radiology, Demand, Capacity

1. Introduction

The expanding utilisation of advanced imaging continues over the UK and all

through the world. Inside the NHS, MRI is for some time built up as the backbone of emergency and routine diagnostic cross-sectional imaging. The applications for MRI are across the board, both for critically sick and ambulant patients, with all body parts being assessed. The utilisation of MRI has expanded significantly over the previous decade, adding to medical expenses.

Be that as it may, there is recounted proof that in the UK, investment in MRI equipment is declining, which might be because of NHS funding limitations. There is a lot of strain to “sweat the assets”, operating services for longer hours and expanding throughput, to assist make with getting to diagnostic tests ever speedier. UK’s MRI capacity is extended compared to other countries. The UK has 6.1 MRI systems per million individuals, less than the nations including Estonia and Slovenia.

The NHS is as of now confronting noteworthy pressures relating to demand and capacity in radiology. Generally, out of hours radiology services during late evenings, nights and end of the week used to be an on-call model. The government has, again and again, ensured the public a 24/7 health service. The rise in demand for radiology services brought unevenness among demand and supply. At the present time, radiology 24/7 services are open to inpatient and emergency patients only. Supply of MRI resources is static and with the uncertain rise in demand over time can result in long waiting time for outpatients.

Here are a couple of issues in the radiology department as shown by [1] lop-sidedness makes Mondays busier when contrasted with different days of the week. In like way, [2] actualised Markov chains in planning different patients group coming at different arrival rate and confronted the problem of allocation of resources for the dynamic demand.

Another issue, at NHS Hospitals in the report [3] and [4], outpatient services, for example, radiology currently run day in and day out for inpatients and emergency; however, they are just accessible to outpatients between 9 am and 5 pm. [3] reports uncovered that around 8% of the outpatient missed their appointments and no show is an enormous issue. [5] clarifies that different patient groups such as inpatient, outpatient and the emergency patient are given different priority. The emergency patient is given more priority when contrasted with inpatient and outpatient. In like manner [6] states that disregarding random arrival of the patient can make the model off base.

At some of the time it is hard to incorporate all the aspects of the real problems in the simulation model. The issue which NHS is facing at the moment is an increase in patient waiting time and busier Mondays. This is due to the underutilization of the resources. This has further lead to randomness in-demand and mismatch between demand and capacity. According to [3] [7], in NHS £1 bn is being squandered every year by patients missing their appointments and no show. There are various implications in changing outpatient demand from 8 hours a day to 24 hours a day.

Various methodologies are proposed for better resource utilisation. Firstly, [8]

prescribes assigning exclusive blocks to the process with the anticipated demand and assign pool blocks to the process with less predictable demand. Also, [9] contends that a separate process for emergency patient helps in decreasing cancellation and overtime. Furthermore, [10] states that more patients booked at the start of the hour and less at the end of the hour to absorb delays. Two patients are booked at the beginning of morning and afternoon sessions and remaining patients are booked at equal interval to avoid delays.

According to [11] report expresses that consultants should be on a staggered rota throughout the weekend and public holidays from 9 am to 8 pm. The week-day evening rota should be 5 pm to 8 pm. The support staff should be available for extended hours. The radiographer and radiologist time should not be wasted on administrative tasks. This will help improve the utilisation of high worth equipment, for example, MRI. Moreover, [4] report proposes that staff rota for radiographer and consultant to be 3 days for one week and 4 days for the following week.

[12] DES helps with foreseeing future demand using historical patient arrival rates. Additionally, [13] states DES helps in assessing poor outpatient flow. It uncovers that scheduling and capacity planning in healthcare helps with improving efficiency. Moreover, [14] and [15] suggest using DES modelling in healthcare for improvement and enhancement. Also [10] states DES underpins in modelling, outpatient in scheduling system, number of appointments, physician time and patient flow.

[16] features that hospital expanded hours and opening on weekends encourages in improving access to hospital care. [17] diagrams that DES implemented hospitals in Sweden had improved the process quality. Moreover, [18] illustrates adjusting supply based on demand and time allocation for the activity assists in bringing balance. Likewise, [19] encourages to use DES for outpatient capacity planning, in healthcare. Similarly, [20] features DES to find the outpatient flow in healthcare. DES used for planning, testing and staff scheduling in a hospital facility with increased capacity.

[21] claims that DES is used in an outpatient clinic with batch arrivals to take care of the no shows problem. The other solution, to give same-day appointment in which the patient is less likely for no show. In like manner, [22] states that overbooking helps in utilising healthcare resources for the no shows. Likewise, [23] highlights that outpatient cancellation and no shows can be settled using overbooking of the appointments, to amplify the utilisation of radiology capacity.

The objectives focused on solving the problem using DES to simulate the demand for MRI services across different scenarios, each with different hours of operation, to decrease of waiting time, queue length and patient stay time in the system, streamlining of resources allocation on the basis of demand, formation of crisis and most extreme demand scenarios, identification of congestion bottlenecks, the examination of the effect of other no show on the existing system, and improvement of the current system operations and functions which can be

utilized to reconfigure the existing frameworks so as to improve system performance.

2. Performance Measures

Key performance metrics KPI are occupancy rate, clinic utilisation, staff utilisation (radiographer, clerk, nurse), patient throughout time, average waiting time, diagnostic procedure count. [24] approves using DES for demand and capacity model which will assist in identifying the key performance indicator. The other KPI can be resources average use, percentage of the patient leaving the system is under 120 min.

3. Input

Input parameters shown in **Figure 1** will be MRI service time, number of MRI, number of staff, patient process, patient arrival rate. As indicated by [25] key to classify the patient as each could have different processing time. Thus, the fitting of distribution for each group is very important. Understand the patient path and time to run the simulation for the model is significant. DES should be used to forecast capacity over time based on outpatient demand. Patient characteristics such as age, diagnosis, sex, the patient category should be taken into consideration. I have included patient inter-arrival time (dynamic random arrival), service time, servers. I have included a number of radiologists, radiographer, clerk. I have classified patient based on age, gender, type of patient. The fitting of the outpatient arrival data is done by Pearson V distribution.

4. Flowchart

[26] and **Figure 1** and **Figure 2(a)** clarify that the process chart is imperative to understand the problem, objectives, input, and output of the system. It is separate from the simulation model. Likewise, [27] notices to use activity-based the

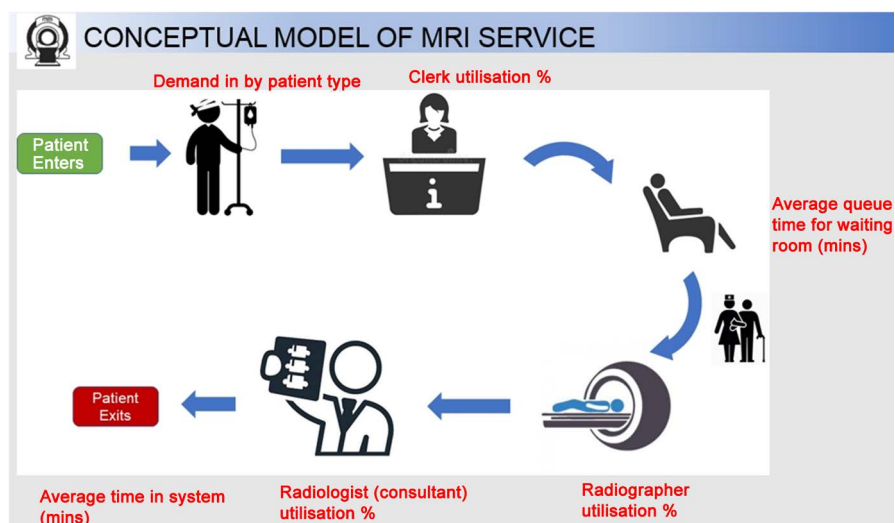
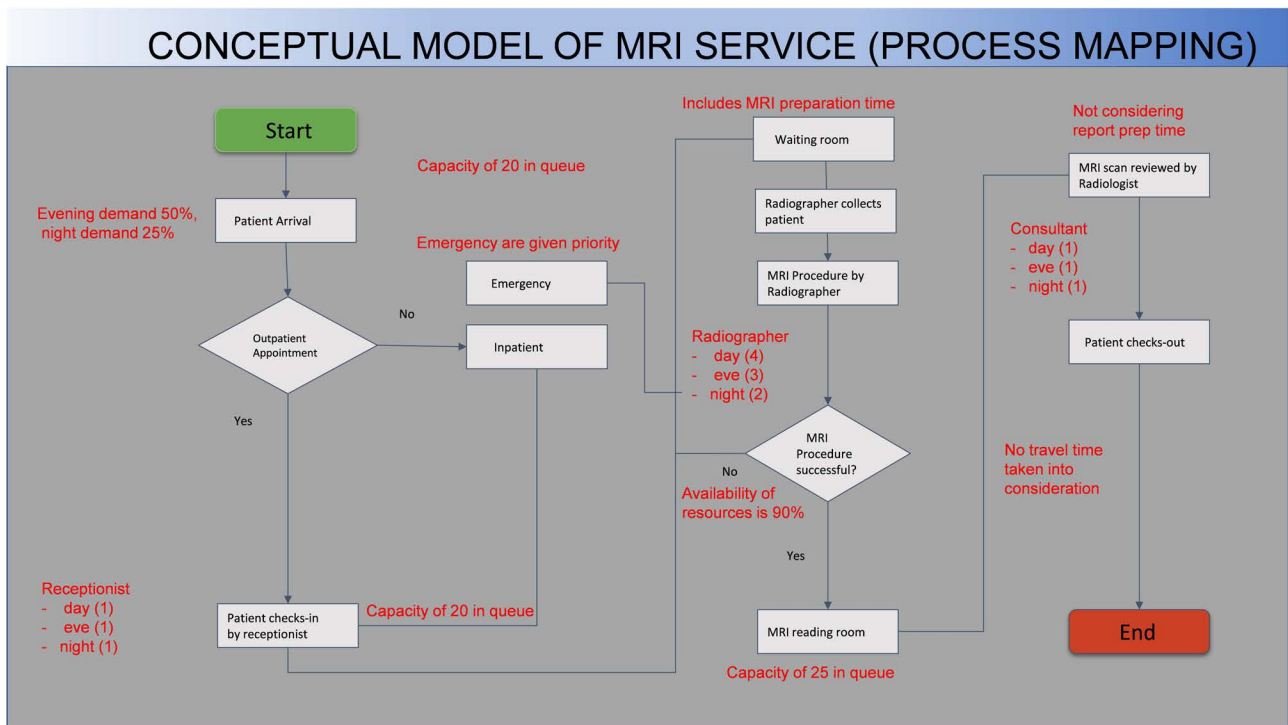
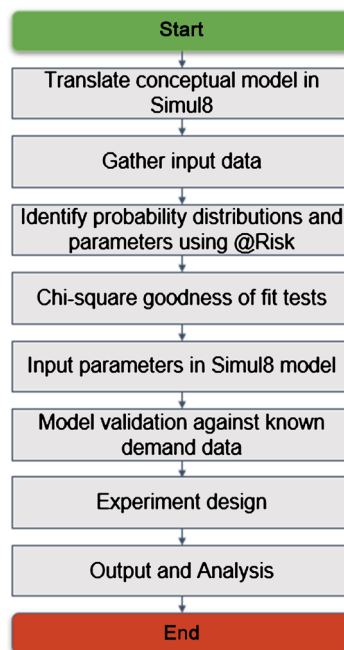


Figure 1. Illustration of conceptual model of MRI services.



(a)



(b)

Figure 2. (a) Illustration of conceptual model of MRI services (process mapping); (b) Methodology.

diagram in healthcare for service delivery processes. Also, [28] proposes changing hospital process flowchart into the DES model which assists in analysing how much resources of the hospital are being utilised. Additionally, [29] features simulation assists in incorporating different customer arrival rates and service time for modelling without affecting the real system of the radiology depart-

ment. The process includes such as patient scheduling by the clerk, scanning by a radiographer and report interpretation by a radiologist. **Figure 2(b)** shows the methodology adopted for simulation.

5. Assumptions

- No travel time for any resources taken into consideration;
- Preparation time is included in the waiting area time;
- Patients are always coming in time;
- Outpatient is coming with an appointment;
- Emergency patient care given priority;
- The lateness of staff is zero;
- The capacity of 20 in the reception and waiting room queue;
- The capacity of 25 in the MRI reading room queue;
- Radiographer takes the patient from the waiting room;
- Availability of resources (staff and machines)—90% of the time;
- 3 shifts morning 9 am to 5 pm, evening 5 pm to 1 am and night 1 am to 9 am;
- **Figure 3** shows Radiographer morning 4 nos, evening 3 nos, night 2 nos;
- **Figure 3** Clerk morning, evening, night 1 no for each shift;
- **Figure 3** Consultant morning, evening, night 1 no for each shift;
- We are not taking into consideration MRI report preparation time but considering consultant MRI report interpretation time;
- Evening demand calculated from 50% of the total outpatient demand and Night demand calculated from 25% of the total outpatient demand;
- Constraints are morning, evening, and night shifts.

Activity\Resource	Radiographer	Clerk	Senior C
Inpatient			
Outpatient			
MRI R Room			1
Emergency			
Reception MRI		1	
Waiting Room MRI	1		
MRI 1	1		
MRI 3	1		
MRI 4	1		
MRI 2	1		

Figure 3. Resource assignment matrix.

6. Pros Cons of Different Modelling Techniques

[30] uncovered that DES results are better for nonlinear systems as compared with system dynamics and agent-based modelling (ABM). DES takes into consideration patient arrival rate, staff scheduling and resource constraints. In like manner, [31] clarifies that DES is used for operational and strategic purposes. It is likewise called a dark grey box, where clients can link different processes in the model easily. DES is the best solution to this problem. System Dynamics (SD) is good to see the holistic view and for this problem, a detailed view is essential consequently, DES is applied.

7. Key Data

7.1. Sources

[32] DES is in high demand in healthcare for resource planning, capacity estimation and evaluating alternatives. Key resources in healthcare are nurses, consultants, and physicians. Data for the simulation can be collected through primary sources such as survey and current records of the hospital. The other means of collecting data is secondary source such as a literature review.

Different service time is recommended for MRI. Moreover, [33] states that service time for MRI is 33.2 minutes with a minimum of 10 minutes and a maximum 120 minutes. Also, [34] states that around 55% patient goes to the preparation area and for the contrast, preparation time is a triangular distribution (3, 4, 5) and patient preparation in the MRI room is 6 minutes. MRI process time for changing room is Gamma (3.41, 0.86), setting patient and MRI machine is Gamma (2.08, 2.01), MRI scanning is Gamma (7.86, 2.67), after scan activities Gamma (1.66, 1.81). Furthermore, [35] states that MRI total process time is normal distribution (26.46, 20.47). Additionally, [1] states that service time for the critical patient is more as compared to the normal patient. As well, [36] states that an old patient scan takes more time as compared to the young patient as young are very responsive. In addition, [37] states service time using lognormal (4.15, 0.335) distribution.

The input parameters are listed in **Table 1**.

- 8% of the total outpatient is no show;
- 57% outpatient, 43% inpatient & emergency;

Table 1. Input parameters.

Input Parameters	
Description	Description
No-show	8%
Emergency patient	Priority
57% outpatient, 43% inpatient & emergency	
56% inpatient, 44% emergency	

- 56% inpatient, 44% emergency;
- **Figure 4** shows age distribution of 0 to 19 ages 12%, 20 to 39 ages 35%, 40 to 59 ages 25%, 60 to 79 ages 21%, above 80 ages 7%;
- **Figure 5** shows gender distribution of 42% men, 58% women;
- Patient inter arrival time follows Pearson V distribution;
- MRI waiting room & patient preparation time follows triangular distribution (4, 5, 6);
- MRI reading room time follows a uniform distribution 6 min to 12 min;
- MRI service time follows a normal distribution;
- Reception service time follows exponent distribution 8 min.

7.2. Assumptions

- Increased the standard deviation of MRI processing times for inpatient of 5 min and emergency patient of 10 min;
- Warmup period of 4320 minutes (1/10 of the total run period);
- Simulation run 1 month;
- No of runs 20;
- **Figure 6** shows the precision with 20 runs;
- Random Sampling 17.

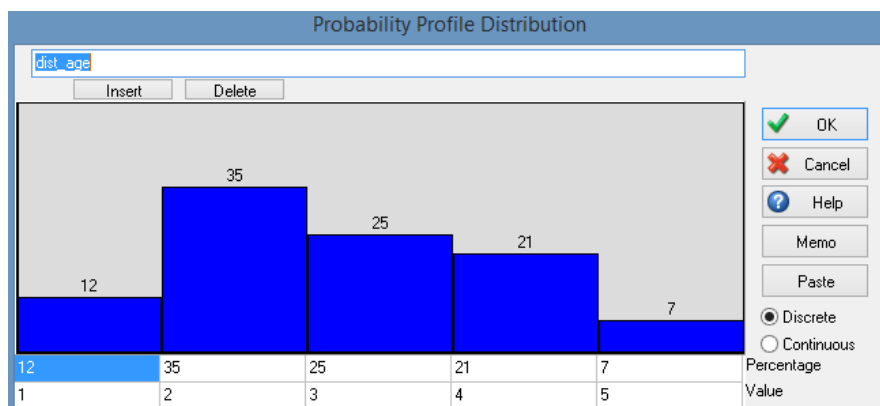


Figure 4. Patient age distribution.

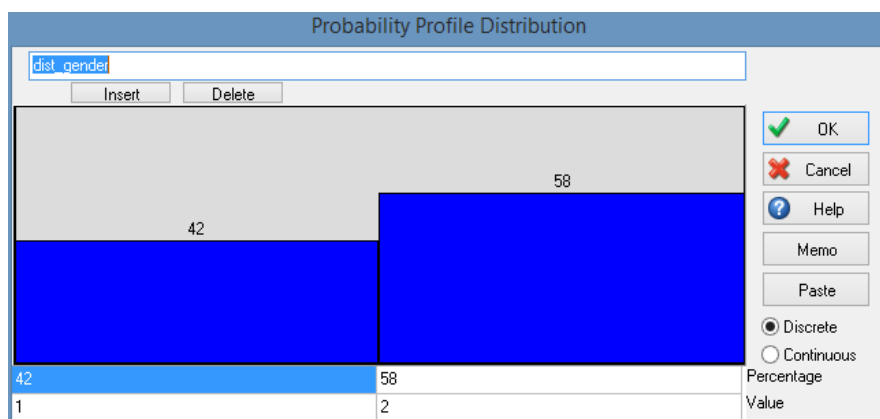


Figure 5. Gender distribution.

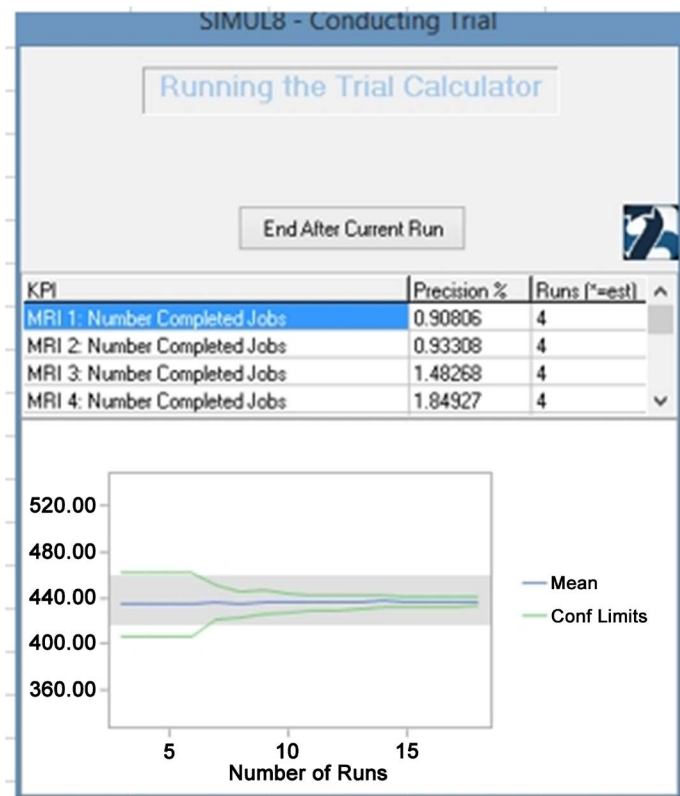


Figure 6. No. of run for precision.

7.3. Fitted Distribution

Different statistical distributions can be applied using Lognormal, Normal, Exponent, Gamma, Pearson V and Weibull. The input parameters are estimated and fitted using chi-square goodness of fit. Fitted distributions help the model incorporate the stochastic nature of the hospital system. In case, seasonal data is not available [37] suggests using Poisson distribution means static distribution for patient arrival. I had only daily data, so I divided it by 24 hrs and then by 60 min—get interarrival times in minutes. I have used Pearson V distribution for patient arrival time and the patient arrival during the morning, evening, night. [38] highlights in the radiology department Pearson distribution is used. The input parameter fitted distributions type and value is given in Table 2.

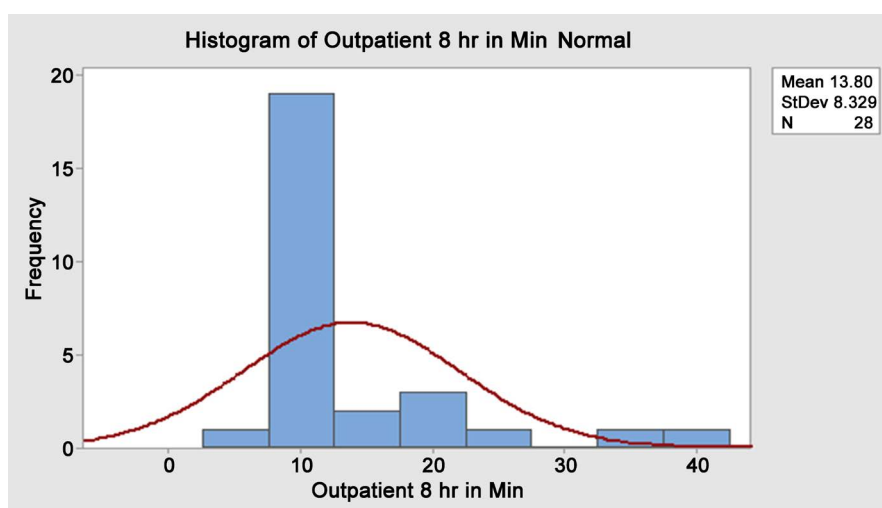
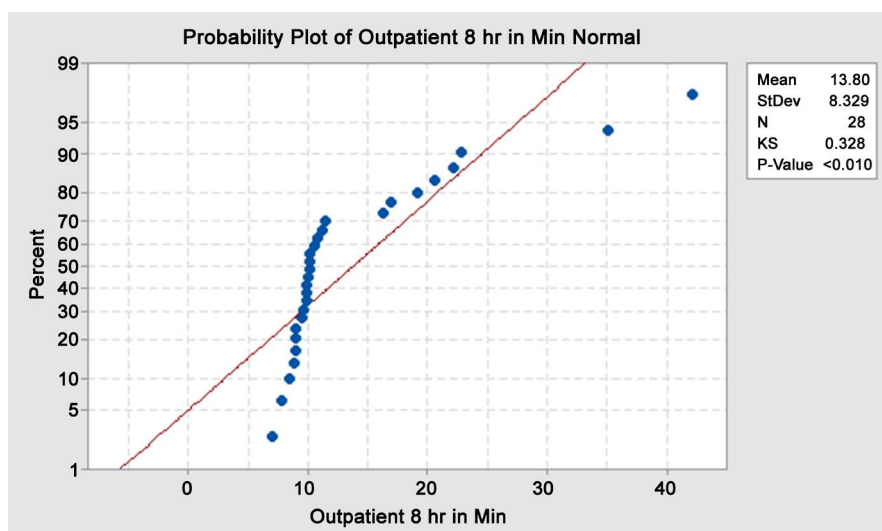
Figure 7 and Figure 8 show the histogram and Q-Q plot demonstrated patient arrival data is not normally distributed. I have also used a Chi-Square test to check the normality of the patient arrival data and found P value less than 0.05 which means poor fit. I have tried to fit data using Chi-square goodness of fit and found P value greater than 0.05 which means each category has the same proportion.

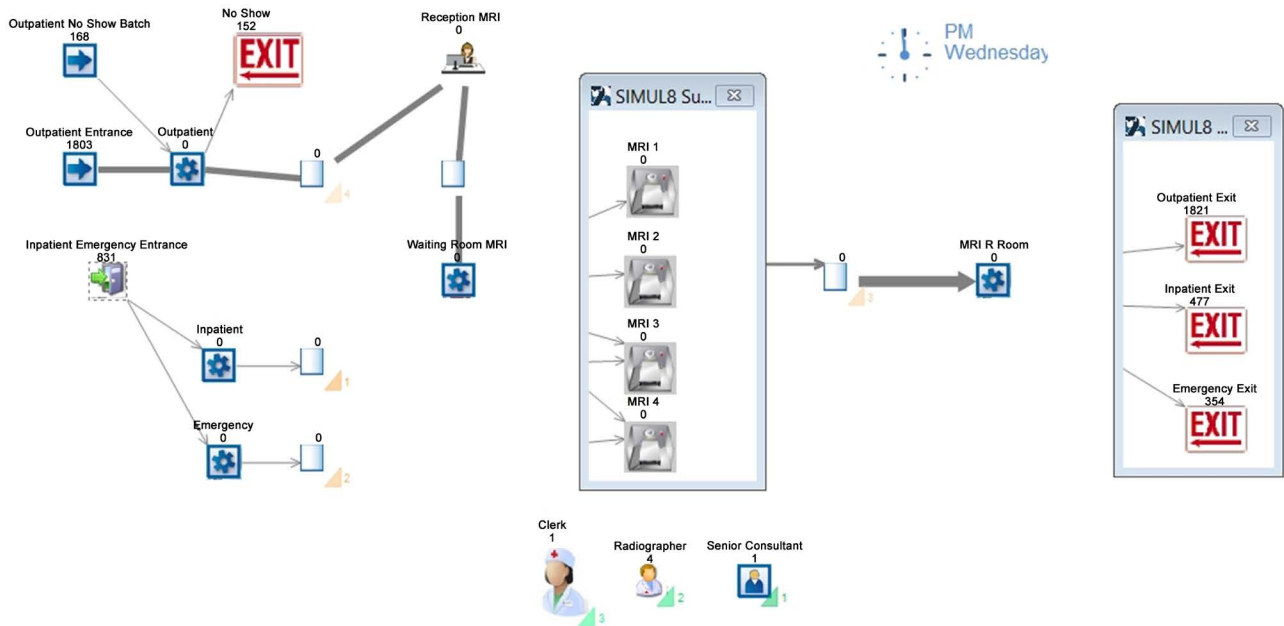
8. Simul8

I have used Simul8 for the creation of the model. Figure 9(a) demonstrates the final model snapshot in which outpatient is given exclusive blocks and inpatient

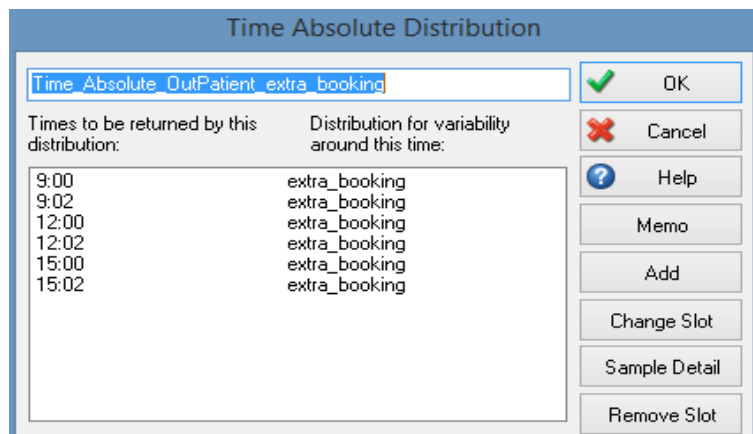
Table 2. Input parameter fitted distributions.

Input Parameter Fitted Distributions	
Description	Distribution
MRI Waiting Room & MRI preparation Time	Triangular (4, 5, 6)
MRI Report Interpretation Time	Uniform (6, 12)
Patient Arrival-Demand	Pearson V
MRI Service Time (Standard deviation more with Emergency)	Normal (26.46, 30.47)
MRI Service Time (Standard deviation more with Inpatient)	Normal (26.46, 25.47)
MRI Service Time (Outpatient)	Normal (26.46, 20.47)
Reception Processing Time	Exponential (8)

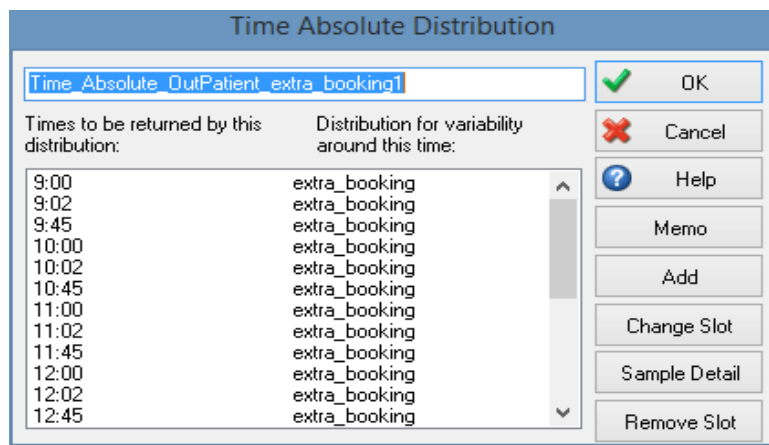
**Figure 7.** Histogram of patient arrival data.**Figure 8.** QQ plot of patient arrival data.



(a)



(b)



(c)

Figure 9. (a) Discrete event simulation incorporated in Simul 8; (b) Time bounded distribution for noshow; (c) Time Absolute distribution for noshow.

& emergency patient is given a different route to access the MRI services. In this, a separate queue is given for inpatient & emergency. No-show problem of outpatient is resolved by overbooking shown in **Figure 9(b)** and **Figure 9(c)**. Outpatient gave access for the reception and further going to the waiting room for MRI.

9. Experimentation & Output Analysis

9.1. Experiments

Table 3 exhibits in scenarios 1, 2, 3 outpatient arrival rates changed with a change in time. In scenarios 4, 5, 6 different distributions were experimented for the MRI service time. In scenario 7, to resolve the problem of no show, overbooking was implemented during normal hours. In scenario 8, no show was further fixed using overbooking at the start and end of the hour and this resulted in long queues. In scenario 9, exclusive resources were allocated to the emergency patient. In scenario 10, exclusive resources were allocated to inpatient & emergency patient. In scenario 11, staff changes were conducted according to the demand.

9.1.1. Simulation Type

Implement non-terminating simulation to evaluate the system behaviour in the long run which is called steady state. It starts with the warmup period which is one-tenth (4320 min) of the simulation run period. I have not used the warmup period data. I have done statistical analysis on steady-state data to find the system behaviour.

Table 3. Different scenarios input parameters.

Different Scenarios		
Scenarios	Description 1	Description 2
Scenario 1	Outpatient 8 Hours	Pearson V (8.15, 89.228)
Scenario 2	Outpatient 16 Hours	Pearson V (8.15, 178.46)
Scenario 3	Outpatient 24 Hours	Pearson V (8.15, 354.84)
Scenario 4	MRI Service Time	Triangular (10, 33.2, 120)
Scenario 5	MRI Service Time	Log Normal (4.15, 0.335)
Scenario 6	MRI Service Time	Triangular (20, 45, 120)
Scenario 7	No Show—Overbooking (2 patient at the begin of morning, afternoon, evening)	
Scenario 8	No Show—Overbooking (More patient at start & less at end of hour)	
Scenario 9	Exclusive resources for Emergency	
Scenario 10	Exclusive resources for Emergency & Inpatient & Outpatient given exclusive block	
Scenario 11	Staff changes (Radiographer)	Mor-5, Eve-4, Night-3

9.1.2. Run Length and Replication

To get precise and narrower confidence interval, I have run the simulation for one month with 46 replications for each scenario. I have used Simul8 to find the precision of 46 runs.

9.2. Output

Validation of the Model

- The total demand in February 2018 for MRI scans was 2089 (historical data).
- Our model simulates a demand of approximately 1828 to 1930 scans, so is between 85% and 90% accurate in terms of demand.
- **Figure 10** display that outpatient flow of 8 hr, 16 hr, 24 hr was validated in Simul8 and there is an upward trend from 9 am to 5 pm for 8 hr. There is a rising trend from 9 am to 1 am for 16 hr and uphill trend for 24 hr.

9.3. Output Analysis

After running different scenarios, **Figure 11** and **Figure 12** and **Table 4** show scenarios 9, 10, 11 gives the best result, throughout time for the patient in the system is less. More outpatients have been treated as well. There are a higher percentage of patients leaving the system in less than 120 minutes. Furthermore, in scenarios 9, 10, 11 approximate 1900 outpatient are treated with reasonable average time in the system.

Figure 11 shows that scenario 8, more overbooking as compared to scenario 7, resultant to increase in average time in the system for inpatient and outpatient.

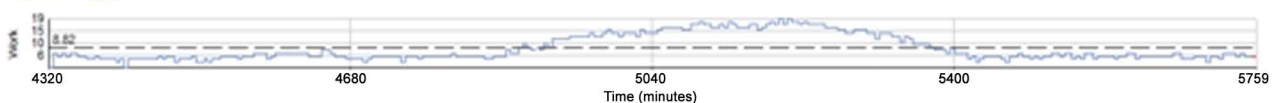
Figure 12 shows that there is a trend to be seen with an increase in average time in the system for the outpatient results to a smaller number of outpatient being treated.

Figure 12 shows that scenarios 4, 6 outpatient average times in the system dramatically shoots up due to slow processing at the MRI machine.

In **Figure 13** elaborates that in scenarios 9, 10, 11 outpatient, inpatient &

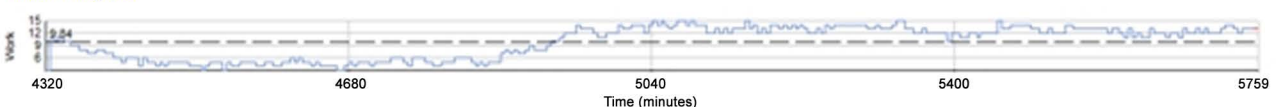
8-Hour Shift

Work In Progress



16-Hour Shift

Work In Progress



24-Hour Shift

Work In Progress

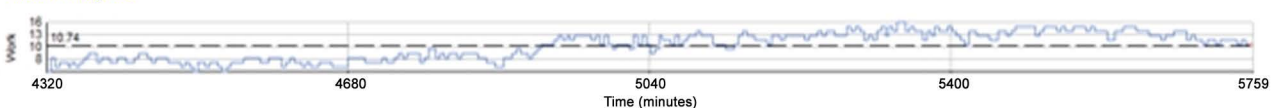


Figure 10. Outpatient inflow trend in Simul8.

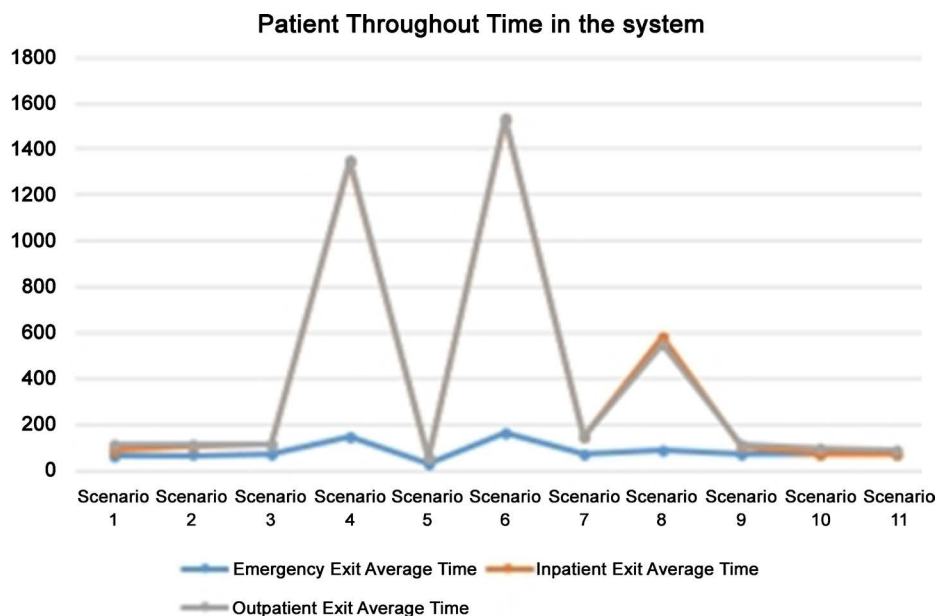


Figure 11. Patient throughout time in the system.

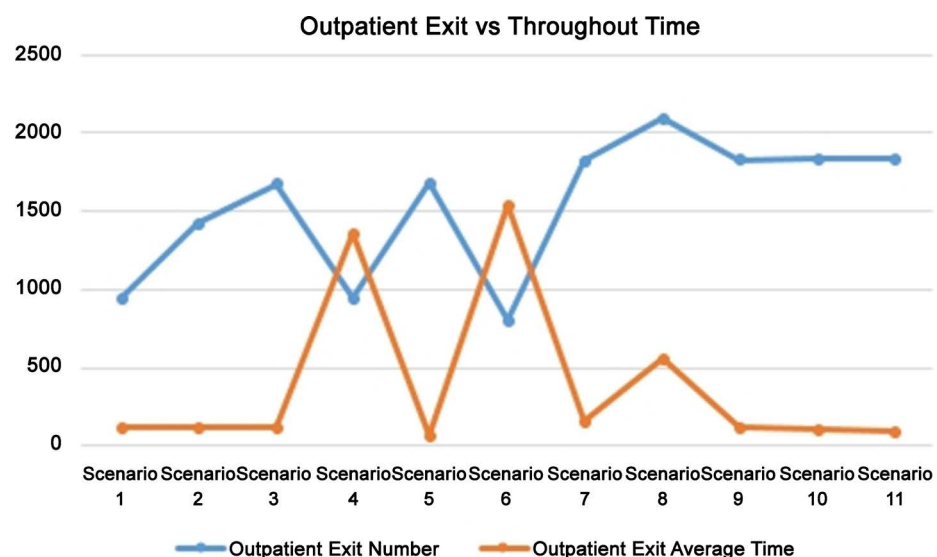


Figure 12. Outpatients exit number and average time in the system. X axis is scenarios (experiments) and Y axis is No. of Outpatients/Time (in minutes).

emergency exit numbers are steady. The results are better as compared with scenarios 1, 2, 3, 4, 5, 6. The exit numbers of scenario 8 are more but adversely affecting the other KPIs. Therefore, scenario 8 was ignored. Additionally, more outpatients are treated in the system. Furthermore, in scenario 11, there is an upward slope which states the percentage of patients leaving the system has increased for the outpatients, steady for the emergency and inpatient.

Table 5 shows statistical significance using one-way Anova and Tukey test to find the variation between different scenarios.

Figure 14 shows that Report reading, Reception and MRI waiting room queue time is reduced dramatically.

Table 4. Output analysis of different scenarios.

	Scenario 1	Scenario 2	Scenario 3	Scenario 9	Scenario 10	Scenario 11
Clerk Average Use	0.37764	0.4722	0.52238	0.55177	0.46339	0.46333
Radiographer Average Use	1.8712	2.30694	2.52527	2.30232	1.93109	2.06466
Consultant Average Use	0.3922	0.49953	0.55479	0.58616	0.58253	0.58221
Clerk Utilisation in %	37.76409	47.21967	52.23802	55.17714	46.33918	46.3329
Radiographer Utilisation in %	62.3733	76.8981	84.17554	76.74403	64.36968	51.61644
Consultant Utilisation in %	39.21988	49.95343	55.47938	58.61572	58.25313	58.22078
Emergency Exit Number	360.28261	360.23913	360.17391	354.17391	346.82609	345.78261
Emergency Exit% in System Less than Time	94.35535	92.28045	91.47295	90.66555	90.83936	90.38067
Emergency Exit Average Time	68.14455	71.68905	74.97567	73.4164	72.64874	72.79855
In Patient Exit Number	450.86957	451.02174	450.41304	441.84783	432.32609	431.63043
Inpatient Exit% in System Less than Time	79.57232	68.16426	62.19634	65.42124	91.94291	91.18735
Inpatient Exit Average Time	92.03049	108.51371	115.77779	110.54778	73.90358	74.60519
Out Patient Exit Number	947.34783	1428.73913	1675.97826	1831.02174	1831.78261	1831.80435
Outpatient Exit% in System Less than Time	60.06564	58.66865	59.41306	59.42708	73.37698	78.4367
Outpatient Exit Average Time	116.27903	119.90133	118.7711	117.0021	100.30613	95.41869
No Show Exit Number	82.69565	122.95652	144.23913	157.3913	157.3913	157.3913
Inpatient Entrance	811.23913	811.23913	811.23913	811.23913	811.23913	811.23913
Outpatient Entrance	1030.04348	1551.04348	1820.6087	1820.6087	1820.6087	1820.6087
MRI 1 Job Completed	438.1087	557.45652	620.30435	615.78261	547.28261	543.6087
MRI 2 Job Completed	441.21739	562.43478	622.30435	615.91304	544.06522	541.54348
MRI 3 Job Completed	441.1087	559.78261	620.93478	615.54348	784.08696	787.3913
MRI 4 Job Completed	438	560.21739	623.08696	779.82609	735.36957	736.30435
MRI Reading Room Job Completed	1758.43478	2240.15217	2486.56522	2627.23913	2610.86957	2609.19565
Reception Job Completed	1398.30435	1879.30435	2127.30435	2273.36957	1831.5	1831.47826
MRI R Room Average Queuing Time	4.29639	4.33675	4.2407	6.03234	7.2554	8.25991
Reception MRI Average Queuing Time	10.20958	8.74832	8.08661	12.39665	7.92818	7.96882
Waiting Room MRI Average Queuing Time	17.47638	27.46382	29.9532	24.61126	11.73228	5.00171

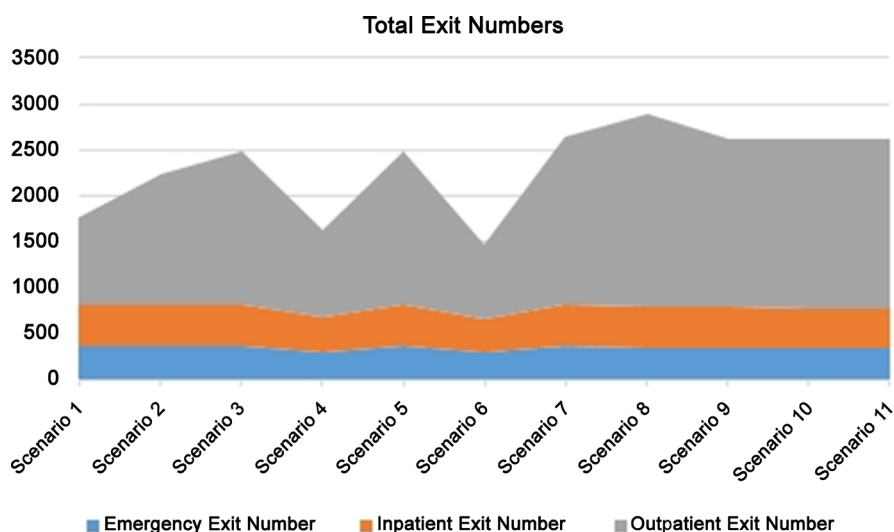


Figure 13. Outpatients exit number.

Table 5. One-way Anova for variation check in different scenario.

One Way Anova Table	Sum of Squares	Degrees of Freedom	Mean Squares	F-Ratio	p-Value
Between Variation	3.490914	10	0.349091	3233.222121	<0.0001
Within Variation	0.053445	495	0.000108		
Total Variation	3.544359	505			

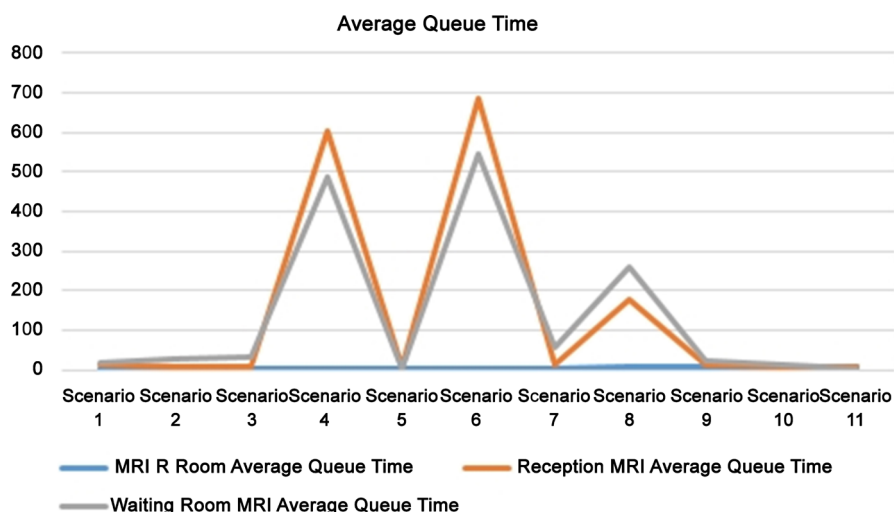


Figure 14. Average queue time.

10. Conclusions

10.1. Learn

The things I learnt in the model is that the scenarios in which resources are idle, patients are treated slowly. This model really helped in finding out resource utilisation patient throughout. It also helped in identifying the bottlenecks in patient flow. It also demonstrates with the increased outflow of outpatients, re-

sources such as MRI and radiographer utilisation increased. Waiting Room MRI Average queue time dropped from 17 min to 5 min. Outpatient exit average time in the system is reduced by 20 minutes in scenario 11. Also, I learnt to match demand with capacity in different hours.

10.2. Recommendations

We can also take into consideration that the cost as the KPI and agent-based modelling can be implemented for it, in which patient, radiographer, clerk, radiologist as a separate agent can be classified, and it takes a little bit more time to build. The hybrid model which is the combination of DES and agent-based modelling can also be applied for the planning and finding cost in healthcare.

10.3. Difficult to Model

- Gather more evidence for demand at night through a survey of family and friends.
- DES is difficult to model interactions between the large diversity of staff.

10.4. Model Limitations

- Restriction only to MRIs, rather than the whole Radiology service.
- Using resources that are presumably shared with other scans or services.
- Only limited data from NHS, and lots of data taken from literature or assumed.
- Demand at night which has been assumed and needs more evidence to support it.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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