Abstract

The accident and emergency departments in UK hospitals have been the subject of great scrutiny due to a multitude of aspects which include negative patient experience and process inefficiency. This domain is very demanding as it requires a great emphasis on process efficiency and effectiveness. However, these performance factors are affected by a number of aspects. Overcrowding is one of the leading problems in this domain as it leads to poor overall performance since it increases overhead time, and specifically, patient waiting times. The main focus of this project is to simulate a one-week period in A&E across any NHS hospitals in the London Commissioning Region in order to examine this overcrowding problem which is measured by the number of people whose length of stay at the A&E exceeds the 4-hour mark. Interactions between staff and patients are simulated in the NetLogo environment from the point of entry to the A&E until the end of each patient’s journey. The simulation is an agent-based simulation which is capable of recreating results obtained through extensive statistical and literature research. This allows us to identify the effect of possible fixes on overcrowding reduction within the A&E leading to improved patient flow and process efficiency. The simulation built is considered repeatable and accurate. The bottleneck of the process is found out to be the doctors at the A&E. This is considered the main cause of overcrowding eventually whereby an incremental increase in this number of doctors massively decreasing overcrowding levels.

Acknowledgements

I would like to extend my gratitude to my advisor, Dr Simon Miles, who has been very supportive and understanding all throughout the course of this project. I would also like to again extend my gratitude to Dr Miles for his guidance and advice as well. Finally, I would like to thank my family and friends whose moral support and encouragement allowed me to complete this important chapter of my life.

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Nomenclature

A&E	Accident & Emergency
ABM	Agent-Based Model
DES	Discrete Event Simulation
ED	Emergency Department
FCFS	First Come, First Serve
HES	Hospital Episode Statistics
LoS	Length of Stay
NHS	National Health Service
P1	Priority / Triage 1
P2	Priority / Triage 2
P3	Priority / Triage 3
RCEM	Royal College of Emergency Medicine

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1 Introduction

1.1 Motivation and Problem Definition

More than 14 million patients are treated by the A&E units across Britain every year. The 95% target represents NHS's goal of achieving the 4-hour rule whereby the A&E unit sees the patient, treats him/her, makes a decision, and acts, all within 4 hours of the patient's arrival at the A&E. However, overcrowding is becoming an increasingly severe problem facing the A&E, leading to a multitude of other problems such as reduced care quality, increased patient mortality, and increased delays. In order to examine this problem, the causes must be identified and the different scenarios determined. A new rating system was introduced to assess the performance level of different A&E units across the UK. Out of the 176 A&E units examined, 57% were found to have been underperforming [1]. This is followed by a statement from the Royal College of Emergency Medicine declaring that A&E overcrowding leads to the unnecessary death of 500 patients yearly [1]. Due to excessive overcrowding at A&E units across the country, some units are being forced to turn away ambulances and close their doors. Such extreme cases occurred as many as 29 times during 2015 [2]. In some cases, due to the absence of enough beds in overcrowded situations, the treatment of patients is happening in corridors or on ambulance trolleys. This is referred to as "boarding" and is being considered a necessary measure in overcrowding cases, despite being deemed as inhumane. It is believed that thousands of yearly deaths are avoidable and merely due to overcrowding. This is attributed to a multitude of factors, one of which is that staff resources are being depleted and overwhelmed by the magnitude of work they have to accomplish. Boarding is currently being recommended as a solution for A&E overcrowding because it's considered better than leaving patients untreated in the waiting room. For the overcrowding problem to be solved, patient flow through the A&E should be improved. Methods like boarding only help minimize the harm caused by overcrowding, but do not provide a long-term solution [3]. Nursing staff ends up taking multiple duties (which don't fall within their assignment). Consequently, this reflects on the quality of care being given and the experiences of both the patients and the staff. Queuing has become increasingly time-consuming and many A&E units are falling short of meeting the 95% rule. One scenario was that of a 31-year-old woman who was turned away by the A&E unit twice despite coughing blood and suffering from a pulmonary embolism and a partially collapsed lung. The only reason she is still alive is that she was eventually seen by a consultant and then readmitted to hospital [2]. An additional cause of the problem is the 'Exit Block' condition. Exit Block is a self-spreading problem which poses an additional dilemma within the A&E and contributes to overcrowding while being a result of overcrowding as well. Exit blocks affect half a million of these patients yearly, resulting in more than a million patient hours wasted each year. Exit block is a condition which occurs when the A&E unit has finished seeing a patient, initially treated him/her, and decided to admit that patient into the hospital but there is no space in the hospital. This creates a chain of problems since new patients can't receive A&E treatment if the unit can't get old patients out, which leads to delays due to lengthy stays and could lead to inferior care. To better describe the magnitude of the problem in terms of spending and cost, 400 million pounds were allocated to alleviate pressure off A&E departments during the busy winter period in 2014, but 92 out of 144 NHS trusts failed to meet the 95% target. Furthermore, according to the RCEM, blocked A&E units lead to higher patient mortality [4]. Providing the necessary level of care is getting increasingly difficult for the staff due to A&E overcrowding. They end up feeling demoralized and frustrated due to the pressure they experience. The difficulty and load of the work they must do are not what is bringing down staff morals, but rather the unavailability of hope for a solution in the future whatsoever [4]. Furthermore, due to the harsh work environment caused by severe pressure imposed on staff, a large amount of staff is leaving the A&E department [5]. This increases the demand for hiring consultants to take over the jobs that need to be performed. The fact that 120 million pounds are spent on these locums a year shows that this can be quite expensive, soaking up the funding that should be used to improve and help solve the A&E overcrowding problem instead [5]. All of these facts and real-life scenarios serve to underline the inefficiency of the patient flow process through the A&E and its need for alterations. They also serve to highlight the urgency of solving the overcrowding problem in order to reduce patient mortality and improve the patient experience.

1.2 Desired Needs

The desired needs are to build an agent-based simulation capable of simulating a one-week period at any A&E within the London Commissioning Region during the 2016-2017 tax year which extends from April 2016 until March 2017. The simulation is expected to accurately model patient arrival during any day of any week of any month within the aforementioned period. The simulation is also expected to accurately simulate the flow of these patients through the A&E in order to highlight potential bottlenecks and examine the effect of different solutions in terms of reducing overcrowding and increasing efficiency.

1.3 Agent-Based Modelling

In order to simulate the A&E in this project, agent-based modelling (ABM) will be the type of simulation used. This method is concerned with the interaction between the environment and the individuals, called agents, and even the interactions of these agents with one another. By modelling such interactions, as small as they may be, the simulation will be able to provide a perspective on how such simple actions could affect the overall system. As mentioned, such simulations constitute the presence of agents who could be either individuals or entire collective entities. System attributes in an ABM are the following [6]:

- Agents' environment
- Agents' characteristics
- Agent's interaction with other agents

In the case of an A&E unit, individuals could be doctors, nurses, patients…etc. and collective entities could be a medical imaging room, for example. The role of agent-based simulation is to break down complex systems, whose performance or mode of operation we may know little about, into a set of simpler steps and simpler interactions between single or multiple agents in order to better understand the behaviour of the system as a whole. Each agent possesses a list of programmed rules and is capable of independently performing actions. This way, we need only know how one agent interacts within the system in order to build an initial model which then evolves over time. Thus, an agent-based model allows us to find the answer to questions concerning why a specific "system behaves the way that it does".

Agent-based modelling of such processes allows for the examination of the system down to individual interactions, thus providing a system-level prediction. By using such modelling techniques, the effect of changing different simple or individual aspects can be examined to determine whether or not it could positively influence process efficiency.

As we move away from the purpose of an agent-based simulation in general, it is crucial to highlight the goal of such simulation within the healthcare sector before we get to why it makes for an excellent way of modelling an A&E department. In healthcare, we are concerned more with the dynamic behaviour of a system which is then followed by dynamic analysis, while we are less concerned with static analysis. As such, agent-based modelling would allow us to assess multiple different scenarios and analyse such example questions concerning health care:

A somewhat simple scenario could be: *What if we add twenty beds in the trauma room?*

An increasingly complex scenario would be: *What if we increase the number of on-call medical staff between midnight and dawn on the weekends?*

These scenarios are typically possible improvements management could be willing to implement in order to improve one performance factor or another in this healthcare sector all the while being capable of predicting the influence and improvement level attached to one solution in contrast to another. This way, no required physical resource commitment or system interruption is necessary to examine possible improvement scenarios. ABM has seen a gigantic development in numerous regions in the course of recent years and recently in hospital and healthcare settings. ABMs in hospital settings focus on patient flow especially in the ED [6].

There are multiple reasons that make modelling patient arrival and flow through the A&E a complicated issue, ranging from the various possible pathways within the process to the mere differences in alternate paths. In more detail, the complexity of modelling such a system stems from the variable patient arrival rate across hours, days, and weeks. In addition, resource availability, different patient priority queues, and bed unavailability all add to the complexity of modelling.

Thus, as we move from more general healthcare simulation goals towards the purpose of agent-based simulations in accident and emergency departments in specific, we can see that these simulations can be integrated into a decision-making support system in order to identify the pros and cons of any given proposals before actual implementation. An example of this is the implementation of an A&E redesign which resulted in a 30% reduction in length of stay after the proposal was deemed to have significant potential by a simulation-supported decision system [7].

1.4 Report Structure

The report will begin by analysing and discussing the background through a careful literature review. After differentiation from this literature and all previous works is established, the next section will go over the design of our agent-based simulation by discussing requirement and specifications, after which the A&E process followed will be explained along with the different choice of agents and their respective rules. This design section will also explicitly show the statistical research done to acquire the data based on which the simulation runs. The next section will move to the implementation of this simulation in NetLogo. This simulation will then be evaluated and validated in the following section. The report will then conclude with final thoughts on possible future works and limitations assessment.

2 Background

2.1 Overview

This literature review examines past work pertaining to modelling and simulating A&E processes and patient flows in order to arrive at the differentiation between our simulation and the ones previously established. The section will be divided into two main sections. The first section is concerned with non-agent-based simulations and modelling done in the healthcare sector. The purpose of this is to examine different simulation approaches in order to arrive at that agent-based methods are more suitable for A&E modelling. Consequently, the second section of the literature review is concerned with agent-based simulations of A&E departments. This second section will start off with general agent-based A&E simulations and converge towards those done using NetLogo.

2.2 Non-Agent-Based Simulations

We will begin by examining the modelling done by Silvester et al. [8]. Silvester et al. explain that there is a strong correlation between A&E overcrowding and mortality and attempt to model this through modelling process flow and patient flow to gain a deeper understanding of the root causes and impacts of the A&E overcrowding problem. NHS A&E data was collected over a period of 3 years as a basis to build their model. Several delays influencing mortality were identified, with focus on four main delays: “mixed admissions and volume increase, process delays, unplanned hospital capacity adjustments, and long-term capacity restructuring downstream” [8]. Silvester also argues that finding a long-term solution for A&E overcrowding does not impose additional financial costs on trusts since the persistence of the problem could prove to be costlier. Thus, instead of investing in mitigating the effects of the problem, these resources could be allocated to finding a permanent solution. Similar to the purpose of my simulation, Silvester’s approach is aimed at studying system behaviour. The different research questions they hoped to examine were the following [8].

Does the occurrence of flow problems lead to increased death rates?

Is cost affected by poor flow?

What are the different consequences of improving the system and the management’s decision making?

The modelling method used by Silvester et al. is a process control approach as opposed to a multivariate regression tool in order to A&E system design and behaviour to examine how they cause problems. This is especially useful after knowing that there is a confirmed direct link between design and behaviour according to Berwick [9]. Moving to the matter of patient safety and how it correlates with A&E overcrowding, four key topics are found to be relevant. These include bed management and scheduling, central function support, staff workload, in addition to the different hospital procedures and policies [8]. This makes the increased delay in A&E waiting time, for example, a patient safety issue. That’s because overcrowding entails placing patients in inappropriate wards (boarding), admission delays, and reduced staffing which leads to poor infection control in the cases of overcrowding. In order to model the system, we must first obtain a detailed idea of the general flow of patients within the A&E department. It can then be possible to examine the stages at which delay minimization could be implemented especially that in order to minimize overall delays, there must be balanced flow across all stages of the journey [10]. Therefore, the first step of any simulation or modelling must be to decide on a detailed description of the patient flow within the A&E department to locate bottlenecks and root causes behind overcrowding. The UK A&E healthcare system journey can be described as follows. First, the patient arrives at the A&E unit directly, via ambulance, or after being referred by the family GP. If there is a shortage of beds, these patients have to wait in A&E. the patients are then triaged and assessed by staff. If a said patient requires admission to a specialist unit, he/she will be required to wait in A&E until there is an available bed. This is the first point where flow imbalance occurs, whereby the demand and availability for beds are mismatched. Further mismatching occurs when the required specialist ward is full, requiring the patients to be sent to an outlier ward. While most patients are eventually discharged and allowed to go home, some of them might need to remain in the hospitals while some others may also require nursing, therapy, or support from social services to get assistance in recovering at home. The elderly patients sometimes need to be placed into nursing homes, which is a complex process of its own, following their A&E trip. This process is reflected in the flowchart below [8].

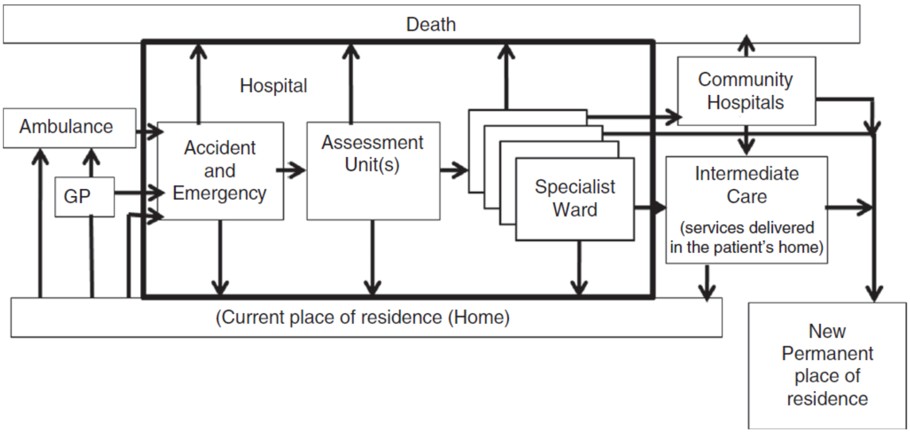

Figure 1: A&E Trip

We, now, come to the process of simulating and modelling the system as Silvester et al. attempt to do according to their paper. After deciding on the flow process of patients through the A&E journey, we reach the step of having to simulate or **model demand**. Demand is believed to have a stochastic variation according to Litvak [11]. It varies according to the different patient conditions, but does exhibit seasonality due to poorly controlled resources, especially during holiday periods. Aside from demand, it is also important to **model capacity**, which turns out to have a stochastic variation as well due to staff availability and skills. The data Silvester gathered pertained to flow (A&E attendance), hospital admissions, quality measures (deaths), and cost measures (salary and locum pay). Statistical process control is then used to generate control charts to get means and control limits concerning healthcare and its variability. Common cause variation is when performance variation occurs between the upper and lower control limits of the control charts. A p-chart is used to analyse death rate and an x-chart is used for routine data analysis. The findings are as follows. A&E breaches are displayed in the following chart where four breaches during April 2007 to June 2011 occur [8].

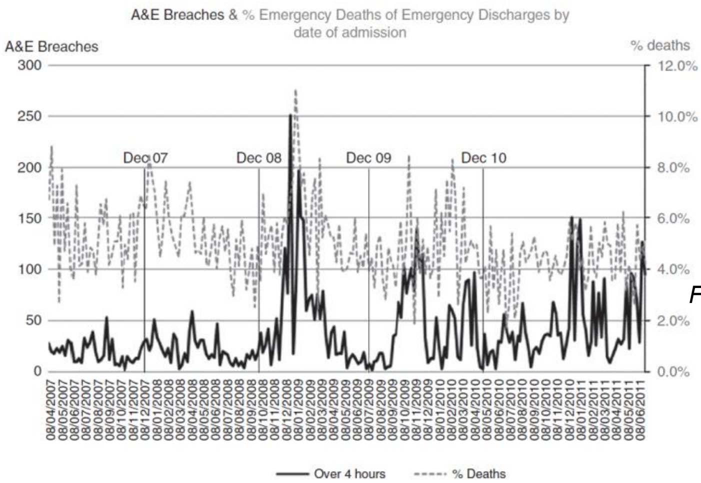

Figure 2: A&E Breaches

Overcrowding is further examined by studying the number of patients who spent more than 4 hours at the A&E in light of different contributing factors [8].

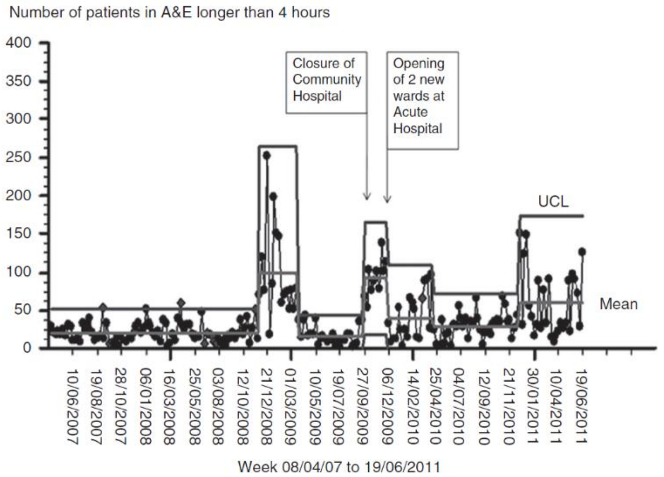

Figure 3: Patients spending more than 4 hours

The findings of Silvester's study include the following three ways in which balance in the flow process is compromised. Firstly, the absence of financial incentives for providers to raise capacity is a major problem when dealing with extra demand. Secondly, there exists a huge amount of pressure on elderly care services which makes the process less efficient. Finally, transitioning a patient to continued care is an uncoordinated process which generates delays throughout the entire A&E healthcare system [8].

Moving away from this modelling method, Brailsford et al. attempt to model the emergency healthcare in a large complex system. The chosen system to model is Nottingham Emergency Healthcare. The different research questions posed are the following [12].

What is the current healthcare system configuration, and what are the supporting processes?

What demand characteristics can we obtain from analysing retrospective patient flow data?

How should health policy and demand influence the development of the emergency care system?

A discrete-event simulation is used to model large populations, which makes it suitable for Brailsford's application. However, the modelling approach used was system dynamics. The state of data they are dealt with was a population size of more than 600,000 and they were concerned with the flow of patients through the NHS front doors. Staffing levels were ruled out from being the main drive behind the A&E problems, but rather the immense volume and resulting pressure on A&E resources. Thus, the STELLA software was used to generate a quantitative model of the system proposed below by Brailsford [12].

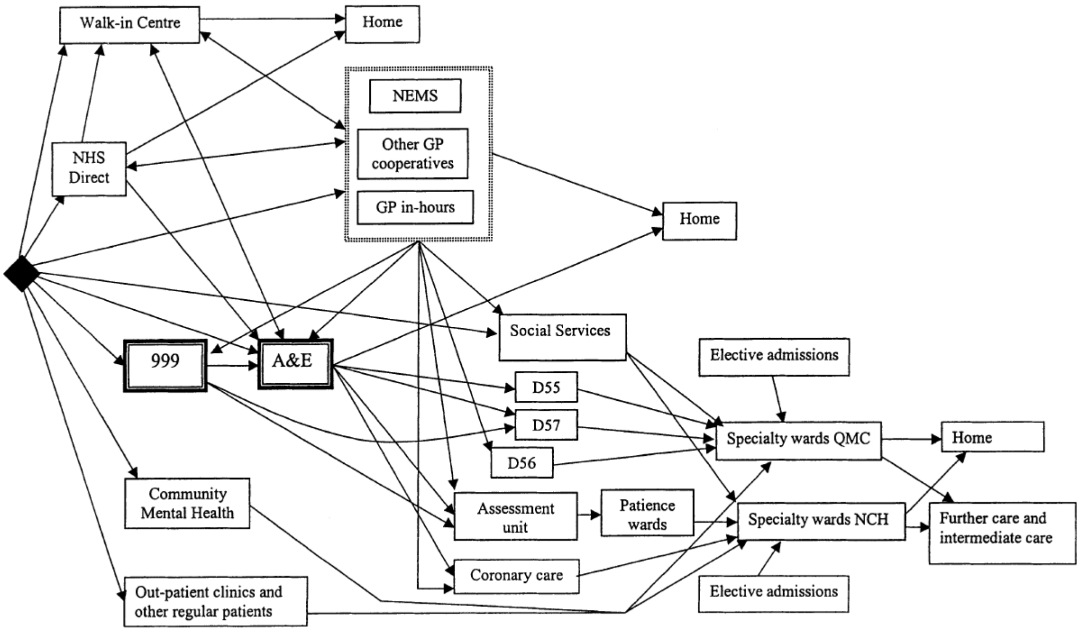

Figure 4: A&E Process

This software was fed year-long data concerning patient arrivals and their taxonomy by the hour, day, sex, age, arrival source, and destination. This data was obtained from the different providers in Nottingham and also included the hospital stay length. Below is the NHS Direct submodel of the STELLA model [12].

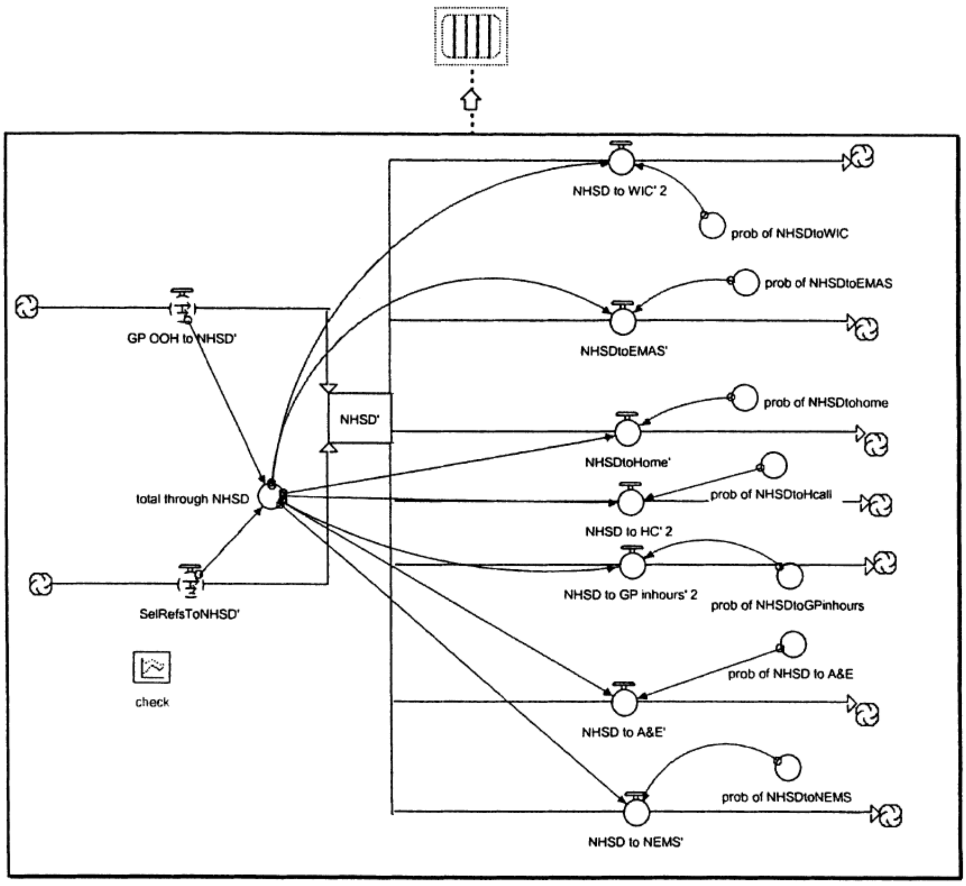

Figure 5: STELLA Model

Brailsford concluded that the STELLA model was helpful for two main things. First, it allowed him and his colleagues to investigate certain scenarios pertaining to bottlenecks and patient flow. Second, the model served as a suitable device in order to provoke discussion. The scenarios examined by the STELLA model included examining the effects and implications of an array of things including a 3% increase in GP referrals yearly, minimized emergency admissions for certain groups of people such as allowing elderly patients to be handled through other community services, and early discharges into nursing homes for elderly people [12].

As for researchers who actually did use the aforementioned Discrete-event Simulation, we find the likes of Maull et al. who were concerned with preparing and modelling different stages of the patient flow process through the A&E unit [13]. For this reason, they examine the arrival pattern of patients, the time needed for triage, the time needed at reception, the time needed to treat, and the percentage of patients discharged in proportion to those admitted. The process flow chart proposed is the following [13].

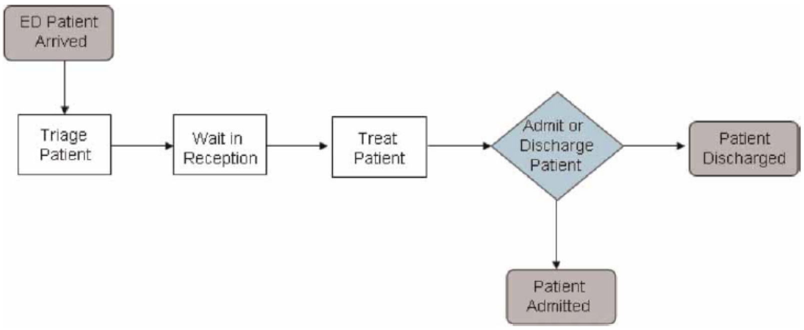

Figure 6: Process Flow Chart

Finally, HealthIQ is a UK-based company that provides solutions for healthcare related topics and problems. They also make use of Discrete-event simulations in order to model an A&E path simulation where they stress on examining staff availability from receptionists, to triage nurses, assessment nurses, nurse practitioners, doctors, and locums. Each of the patients is given a status and the overall statuses are examined. These statuses include waiting for the receptionist, registered by the receptionist, waiting for triage, triaged, waiting for nurse assessment, assessed by a nurse, waiting for doctor treatment, treated by a doctor, waiting for nurse treatment, and treated by a nurse. This helps make the simulation more representative of the events that are occurring throughout the day. The following figure shows the interface of this discrete-event simulation prepared by HealthIQ.

The advantage of discrete-event simulations is that it breaks up a process into steps (discrete events) so that we could get a dynamic model which incorporates the key importance of the time variable. This makes it easier to assess indicative factors such as efficiency and throughput in the purpose of fine tuning the overall process or examine system responses to change. It also helps identify bottlenecks and resource utilization. However, contrary to the simulation approaches mentioned in this section, my simulation will differ. I will be using agent-based modelling to simulate the A&E unit and the different factors which lead up to the problem of overcrowding within the department. Rather than focusing on specific events, my simulation is differentiated from the literature in the sense that it focuses on the relationship between agents to examine how that affects the overall system and patient flow. This facilitates understanding the different patterns of behaviour within the A&E department.

2.3 Agent-Based Simulations

While examining different strategies that could reduce waiting times in a hospital ED, Kaushal et. al attempt to use discrete event simulation (DES) and agent-based modelling (ABM) to simulate an ED [14]. Amongst their strategies for such improvement, they discuss floor plan modification of the ED, adjustment of human resources, adjustment of staff roles, process improvements, and fast track treatment. All of these methods, if carefully and correctly executed, could result in an improved ED process, thus reducing patient waiting times. The method aims to combine the two simulation approaches and recreate the following process in a simulation environment [14].

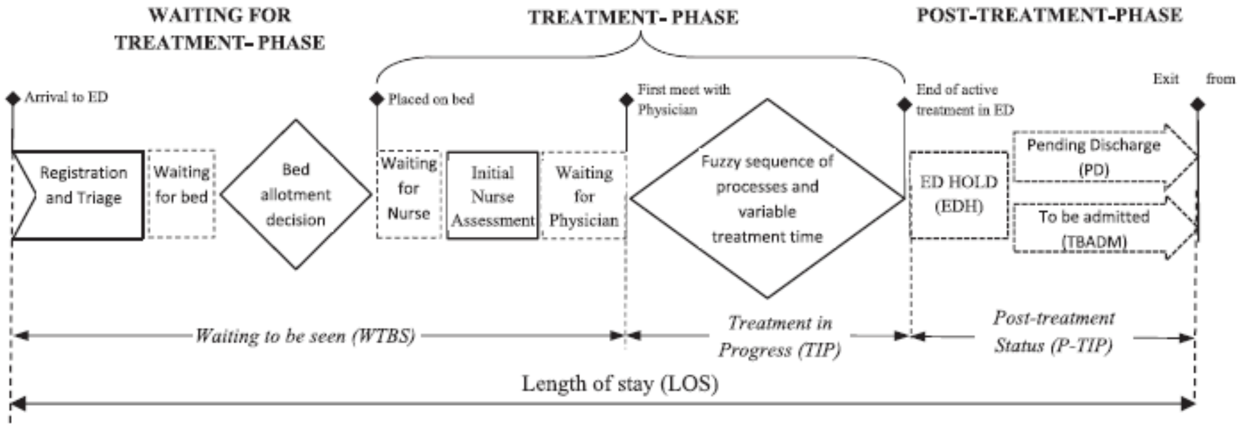

Figure 7: Proposed Process

The following is a screenshot of the suggested floor plan.

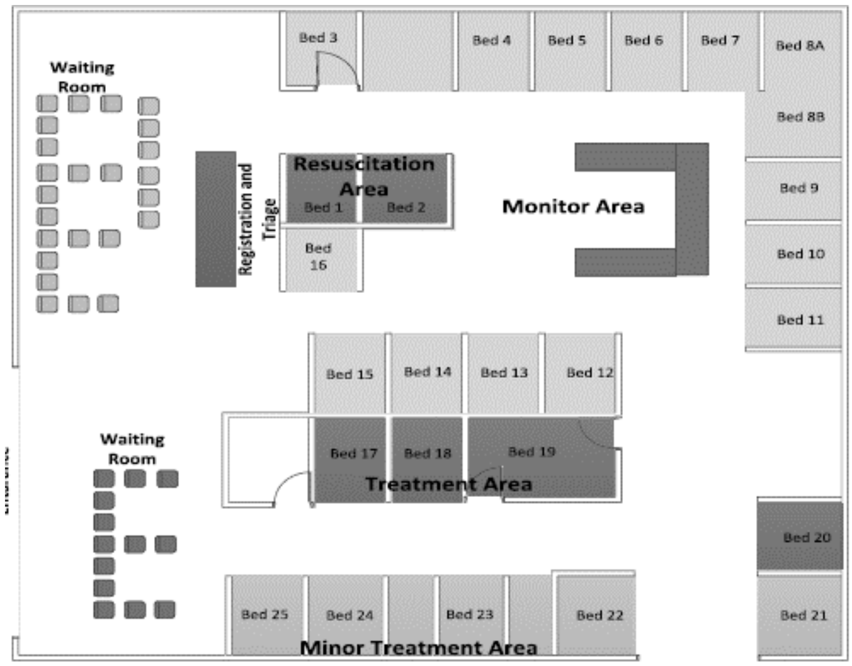

Figure 8: Suggested Floor Plan

These authors concluded that through triage improvement and lab-testing-time reduction, it is possible to optimize the ED process. The result was an improved throughput by about 26% [14].

Liu et al worked on building a simulation in order to quantitatively analyse and predict emergency department (ED) behaviour [15]. Their simulation is based upon the Spanish emergency department organization, process, and standards. The process describing flow within the ED adopted by Liu is shown in the following process flow chart. The agents are the patients, care boxes, triage nurse, doctors, medical imaging rooms, and laboratory testing room [15].

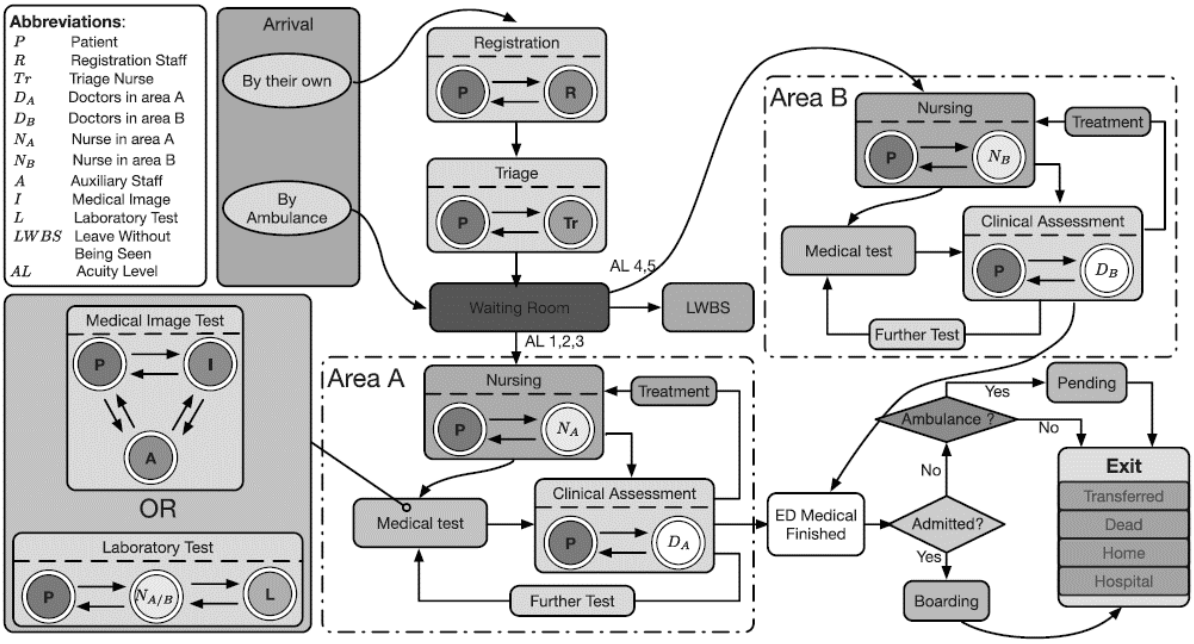

Figure 9: Elaborate Process

It is worth noting that two arrival methods are taken into consideration: self or ambulance. The exit paths are either discharge, referral, admission, or death. Modelling bed availability was also a part of their simulation as it is considered a crucial part which could act as a bottle neck in the process throughout the ED [15]. This is considered essential because patients who are to be admitted into the hospital usually occupy a bed until their admission which prevents the use of this bed by other patients who should start treatment. This can cause overcrowding. Patient arrival is modelled as follows. Since arrival rate varies throughout the day, it is also a crucial part of the simulation if the result were to be accurate. In this paper, the arrival process is modelled as a non-homogeneous Poisson process with the following probability density function [15].

$$f(k;\lambda) = \frac{\lambda^k e^{-\lambda}}{k!} \; (k \geq 0) \qquad \text{with} \qquad \lambda = \frac{60}{N_{ar}[week] \times R_{ar}[hour, day]} \tag{1}$$

where e is Euler’s number, k is inter-arrival time between two subsequent patients, and lambda is the average minutely arrival rate. N_{ar}[week] is the number of arrivals per given week, and R_{ar}[hour, day] is the rate of arrival within a given hour of a given day [15].

The agent rules set up in this paper are structured in an IF/THEN format since the action of each agent is dependent on the received signal. The following tables summarize the different set of rules implemented in this agent-based simulation. The tables below specify these rules for the patient agents, triage nurse agents, and doctor agents respectively [15].

IF	THEN
Notified by *IS* (before entering treatment area).	Go to the corresponding place in the notification.
No requests from *IS* (before entering treatment area).	Stay in waiting room.
No interaction requested by healthcare staff (nurse, doctor or auxiliary).	Remain in carebox (for patients in area A).
No requests from *IS* or healthcare staff.	Stay in waiting room (for patients in area B).
Notified by *IS* (in area B).	Go to diagnosis room or medical image test-room as indicated in the notification.
Needs additional help.	Ask nurse through *IS*.

IF	THEN
Time to work.	Interact with doctor in previous shift, take over patients from them.
No task assigned by *IS* (task queue is empty).	Stay in their office (IDLE).
IS notifies a new patients in carebox *i* (in area A)/A new patient comes into office (in area B).	Move to carebox *i* (in area A), perform first-interaction, make treatment plan.
IS notifies: the test report for one of the patients in set D_i^P is ready to review.	Review medical test report, walk to the carebox (in area A) if necessary, and make follow-up treatment plan (do more test, drug therapy, discharge or admit to hospital).
Scheduled drug therapy time of any patient in set D_i^P is up.	Walk to the carebox (in area A), check effect of drug therapy, and make follow-up treatment plan.
Shifting of duty time is up.	Accomplish work at hand, interact with doctors in following shift, hand over all the patients in D_i^P.

IF	THEN
Time to work (start shift).	Interact with colleague in previous shift, take over materials from them.
No patient in front of the desk/window.	Keep waiting for patient (IDLE).
One patient is waiting in front of the desk.	Interact with patient for registration/triage.
Shifting of duty time is up (end shift).	Accomplish work at hand, interact with colleague in following shift, hand over requested material.

Table 1: Sets of Rules

Length of stay was determined as the sum of every activity the patients were involved in from the entrance to the ED and until departure. This includes all the time spent waiting for drugs to take effect, waiting for doctors, and waiting for resource availability. Triage at the hospital under examination in this paper sorts patients according to five acuity levels as per the Spanish standards. The data was gathered from a one-year actual data collection from the Hospital Tauli de Sabadell. The two graphs below show patient arrival time by an hour on each of the weekdays (left), while the second graph shows this arrival as a distribution amongst the acuity levels [15].

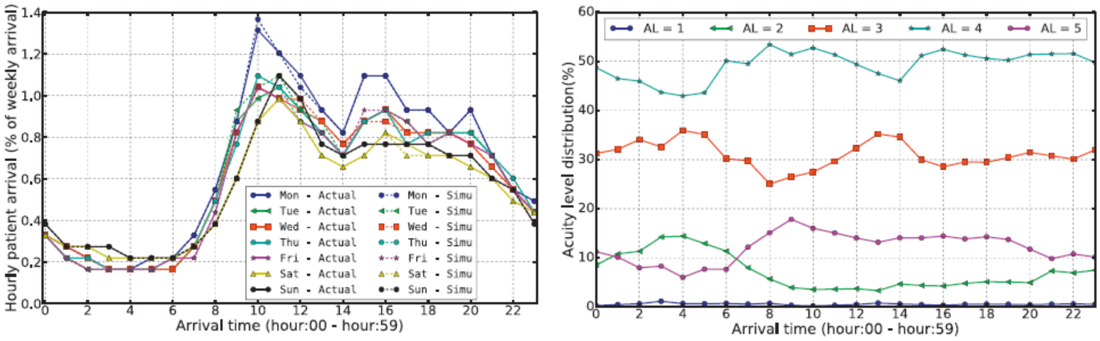

Figure 10: Arrival Times by Hour and Acuity

Finally, the simulation was built in the NetLogo environment and then placed into the following decision framework [15].

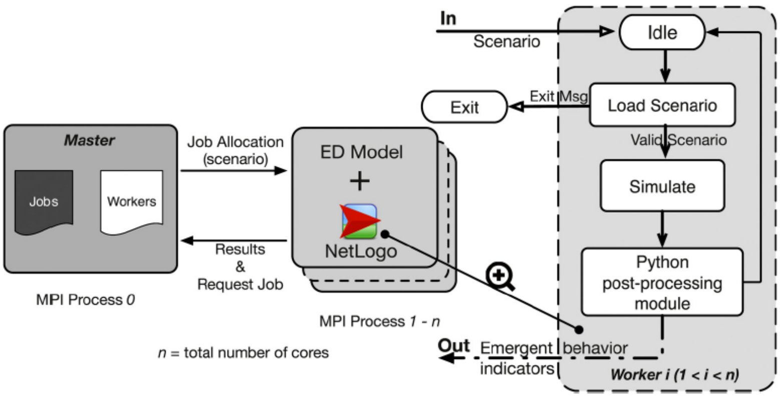

Figure 11: Framework

Liu et. al discuss the development of a generalized ABM which aims to simulate Spanish EDs [16]. In their paper, the bottom up approach is explicitly described beginning with the agents all the way up to Quality of Service. This allows the simulation to effectively assess the Quality of Service at the ED by analysing the simulation output results [16]. This is shown in the figure on the left below.

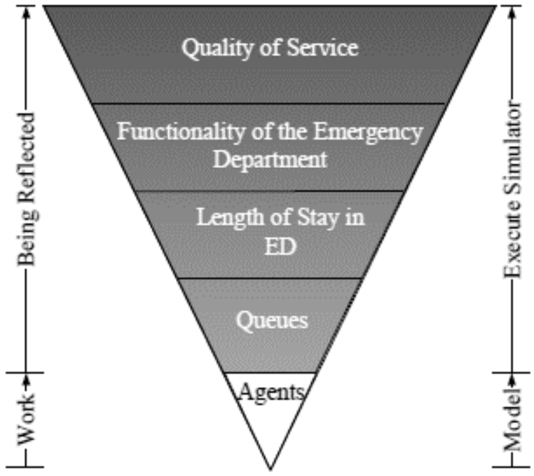

Figure 12: Bottom-up Approach

Agent	Behavior
Patient	Waiting for service. Accepting service. Waiting for treatment takes effect.
Admission Staff	Provide admission service for patient. Waiting for next patient.
Triage Nurse	Provide triage service for patient. Waiting for next patient.
Doctor	Look over test result. Provide diagnostic service. Arrange test for patient. Arrange treatment plan. Waiting for task.
Auxiliary Staff	Moving patient to the specific place. Waiting for task.
Nurse	Take and send samples for laboratory test. Provide treatment service. Waiting for task.
Laboratory Test	Accept sample from nurse. Analyze samples of patient. Send analyzing result to the corresponding doctor. Waiting for samples.
Internal Test	Provide test service. Send analyzing result to the corresponding doctor. Waiting for next patient.
External Test	Provide test service. Send analyzing result to the corresponding doctor.
Ambulance	Providing service to patients. Waiting for task.
Carebox	Providing treatment place to patient. Waiting for next patient.

Table 2: Agent Behaviour

This simulation is developed using NetLogo, where the table above summarizes the agents of the simulation and their respective rules. Similar to some of the other simulations we have examined so far, the authors in this paper implement the presence of two separate waiting areas A and B for low priority and high priority patients respectively [16]. This simulation assumes three exit paths for the patients in the ED, which are hospital wards, discharge, and death. Each of these paths is given a certain probability. The path flow chart for the ED process assumed by the simulation is described in the figure below [16].

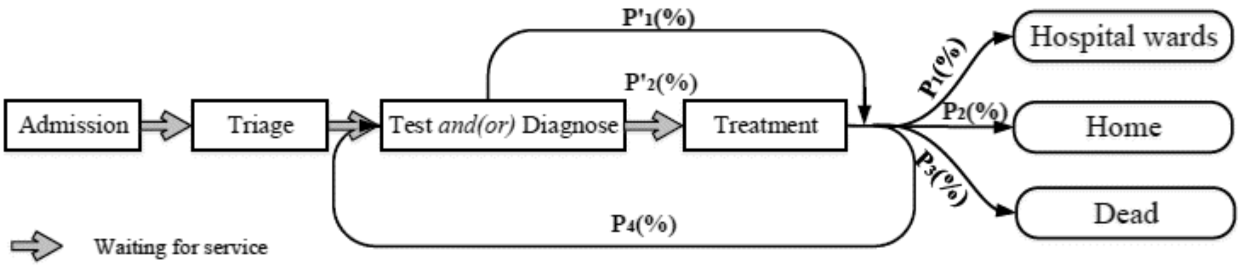

Figure 13: Process Flow

The results of this simulation are not confirmed yet as no validation process has been followed.

Friesen and McLeod present the model of an agent-based simulated A&E in their paper. The environment is the A&E's floor plan. The agents are the patients and staff. NetLogo was used in order to build this simulation. A screenshot of the simulation is shown below [6].

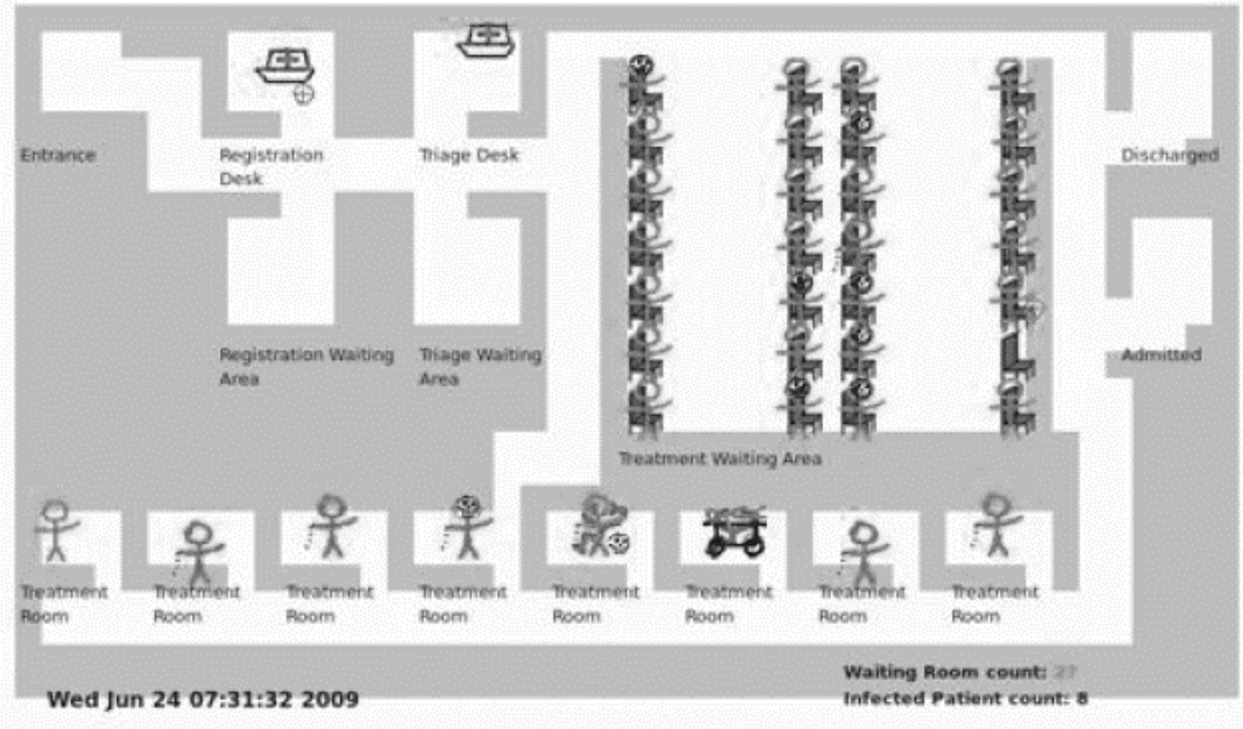

Figure 14: Simulation Screenshot

As can be seen, the simulation is made up of several units of registration desks, waiting rooms, triage rooms, and waiting rooms. The exit paths in this simulation are only via discharge or via admission [6].

Jones and Evans discuss a different agent-based model in their paper which was built in order to analyse the effect of multiple different staff resources on patients' length of stay at the ED [17]. All patients must be checked out by the ED physicians, who are often the main reason for constricting patient flow. Therefore, in order to improve the quality of the ED services, the "Door-to Doc" times must be reduced. Picking the ideal staffing arrangement for an ED is made difficult by the unpredictable patient arrivals. However, reliable daily and weekly patterns rise allow significant decreases in patients' length of stay if staffing fittingly takes these patterns into consideration [17].

After covering the literature, reviewers concluded that queuing theory, linear programming and simulation are the most suitable methods to solve the doctor scheduling problem. Each approach is legitimate; however, in this paper, the use of agent based modelling was investigated [17].

The aim was to build a tool that would be helpful and utilized in more than one ED; therefore, Jones and Evans came up with a single simple process flow describing all the events that are to occur at an ED. The simulation was developed in the NetLogo environment [17]. Moreover, the model included 5 classes of agents: patients, doctors, registration units, triage units and beds. The model concentrates on the delays during the early stages of the patient's visit to the ED and not the delays related to the diagnosis and treatment of the patient's condition. The following flowchart describes the process followed in this simulation [17].

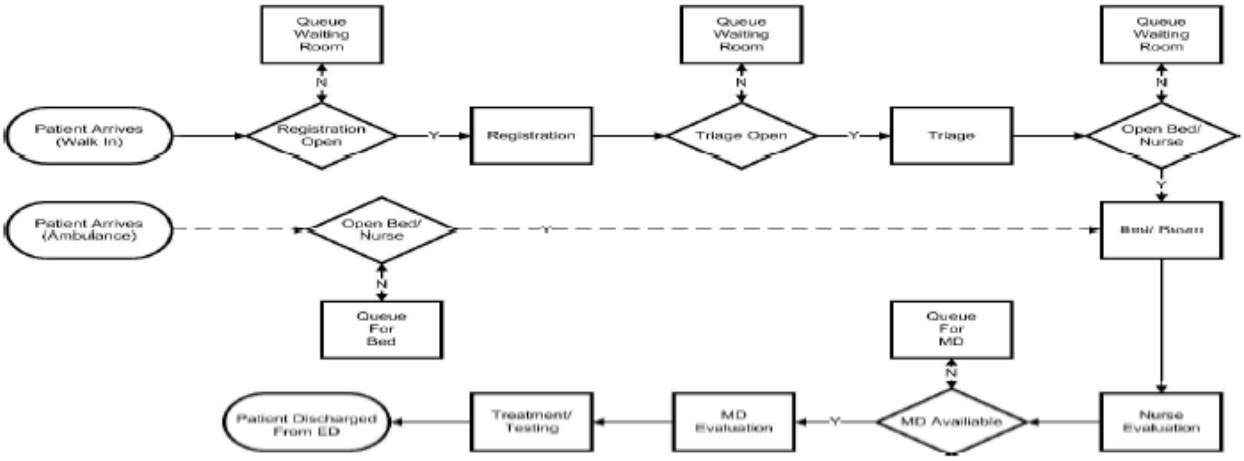

Figure 15: Process Flow Chart

Patient rules are concerned with the queueing of these patient agents in the respective registration, triage, and treatment queues. As for the physicians, their rules entail that they should provide an initial evaluation of a patient. After that, the physician would be "busy" providing treatment, putting orders, consulting with other healthcare professionals, checking on test results or following up with other patients. This process is repeated until the physician finishes his shift and thus leaves the system [17].

A huge number of variables required setting by the user of the simulation before executing it. These included the number of beds, average weekly patient arrivals, average registration time, average triage time, average service time, in addition to the percentages assigned to ambulance arrivals, admission rates, and referral rates. This tool was employed in a 32-bed ED that treats approximately 40,000 patients yearly and is staffed by 16 practice physicians and a group of emergency medicine residents [17].

The simulated data and the summary statistics confirm the tool's capability of providing a reasonably accurate representation of patient waiting times at this ED as can be seen in the figure below. The limitations surrounding this tool are the fact that it is specific for a single ED and employs rigid queueing rules [17].

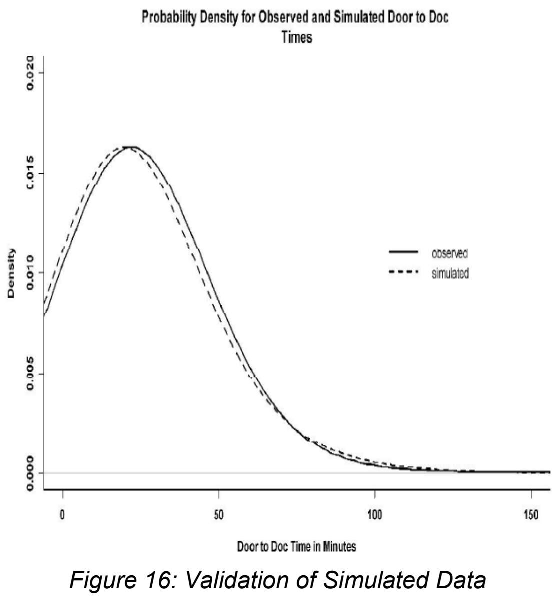

Figure 16: Validation of Simulated Data

Taboada et. al discuss the use of an agent-based model for the purpose of predicting patients' derivation policies' effects within EDs. The goal of this simulation is to predict the effect of providing ambulatory care services to the portion of ED attendances who do not require more extensive treatment [18]. This portion of attendances is estimated by the authors of this paper to be at around 50%. This simulation uses data gathered from the Hospital of Sabadell in Spain. Contrary to other papers examined within this literature survey, the authors have those to identify two classes of agents: active (patients, staff…etc.), and passive (labs, IT…etc.). The figure below describes the general elements included within this model [18].

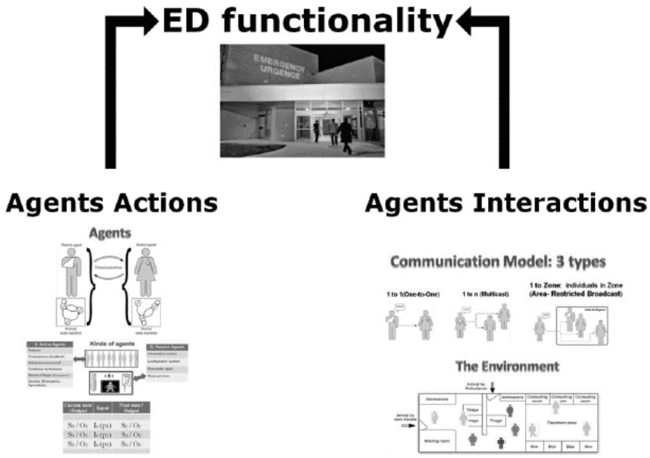

Figure 17: General Model Elements

This model explores three different communication types between agents. These are one-to-one, which occurs between two agents, one-to-n, which signifies one agent communicating with a group, and one-to-place, which indicates the communication between an agent and all those residing within a specific area of location. This is the first author who goes into detail surrounding communication protocols in agent-based simulations, whereas the rest assumed one-to-one communication all throughout their simulations [18]. As for how similar this simulation is to the aforementioned ones, it is also developed using NetLogo. The following is a screenshot of the simulation interface.

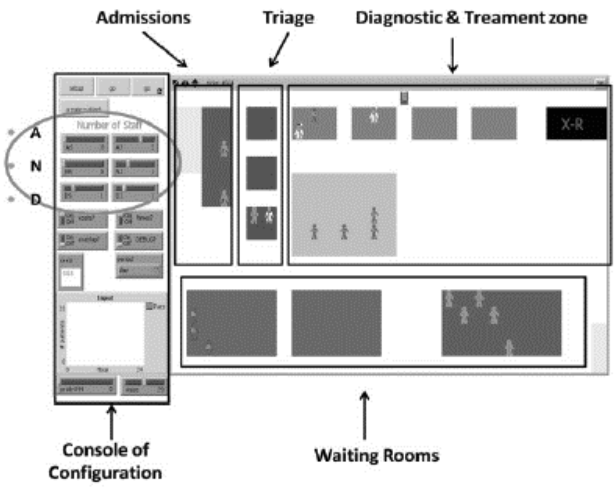

Figure 18: Simulation Screenshot

After executing this simulation and gathering the data, the results confirmed the authors' hypothesis surrounding the fact that dealing with low priority patients separately has a positive influence on the average waiting time of patients by reducing their length of stay at the ED [18].

Now that the literature review has been concluded, it is important to compare and contrast the previous works and simulations and my simulation in this paper. The similarities between my simulation and those discussed in the second section of this literature review are the fact that the simulation method employed is agent-based modelling. The second similarity is the use of the NetLogo tool to build this simulation. However, contrary to all of the examined simulations, the one I built is concerned with being compatible with a large number of hospitals rather than representing a generic A&E unit somewhere in the world. My simulation deals and is capable of modelling 32 hospital A&E units located within the London Commissioning Region. Each of their arrival models is implemented and the varying percentages of admission within each unit are taken into consideration in my simulation. Furthermore, my simulation is more concerned with suggesting fixes for the overcrowding problem in A&E, which is going to be quantified by the number of patients who wait for more than 4 hours, thus having the A&E violate its 95% rule. While the process adopted by my simulation may resemble those discussed in the literature, this aspect is beyond control as the A&E process is mostly generic for most hospitals. There are minor differences in the routes and exit paths, as will be discussed in the design section of this paper. Finally, none of the previous simulations discussed in the literature takes into consideration the triage portion of the process by segregating those in the waiting area into the three main queues (priority/triage 1, priority/triage 2, priority/triage 3). As a result, the simulation I have built can be considered more complete than any of the aforementioned ones in this section as it takes into consideration arrival models (self/ambulance), triage models, and exit models across hours on any given day within the period of the 2016-2017 tax year of any hospital within the London Commissioning Region.

3 Design

3.1 Overview

This section will cover the solution methodology followed in order to reach a suitable design for the agent-based simulation. It will then move to a brief explanation of the different requirements and specifications integrated into the simulation. After that, the A&E process will be explicitly discussed as it will represent the overall view of what is happening in the simulation. This will be followed by a discussion of the different agents employed in the simulation along with their characteristics and set of rules. Finally, the data upon which the simulation has been built will be derived and examined.

3.2 Solution Methodology

The overall goal of the simulation is to simulate a one-week period of A&E activities. This can be simulated at any of the hospitals within the London Commissioning Region. After setting certain variables and selecting the desired A&E unit before executing the simulation, the simulation is expected to run for an equivalent of one-week's worth of activities, yielding the total number of people whose length of stay (LoS) exceeded 4 hours during the week, along with the maximum LoS recorded. This is because, in this paper, we aim to quantify overcrowding as the volume of A&E attendances whose LoS exceeded 4 hours.

In order to correctly build the simulation, several steps have to be carried out in order. The first step of this methodology is to lay out a list of requirements for the simulation in addition to each of these requirements' specifications. This will help in having a clear idea of the basic functions of the simulation to serve as a checklist at the end of the project and as an indicator of success or failure of the simulation.

The second step is to use the literature survey performed in the previous sections to come up with a suitable and general process design to model the A&E process at all of those hospitals. For this reason, the process has to be somewhat more general than specific in order to ensure applicability and representation of each of these hospitals' A&E units.

After this is completed, thorough consideration of possible agents for the simulation has to be completed. There needs to be a list of such agents along with their characteristics (or attributes). Following that, each agent must then have a set of rules which govern its actions and interactions with other agents. While the agents are autonomous and do act independently, they should adhere to this set of rules.

Finally, to ensure that the simulation resembles reality, the data used to build it must be derived from approved NHS or HES statistics. Each set of data should be described and their use within the simulation defined and explained. After the completion of all these steps, the simulation is ready for implementation. The following chart summarizes this methodology.

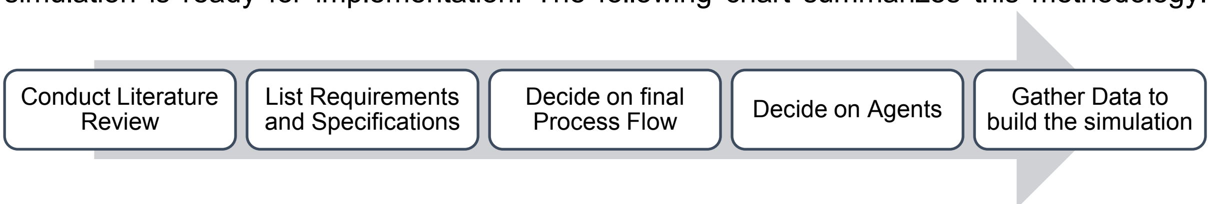

Figure 19: Methodology

3.3 Requirements and Specifications

3.3.1 Requirements

1. The simulation must be able to accurately model patient arrival, which includes arrival via entrance and via ambulance.
2. The simulation must be able to correctly place patients in suitable queues according to their position in the A&E process.
3. The simulation must be able to correctly estimate each of these patients' waiting-time starting from their arrival at the A&E.
4. The simulation must be able to accurately model the patient's exit path.
5. The simulation must be valid for all A&E units within the London Region.
6. The simulation must be valid for each of the days within the period under examination (2016-2017 tax year).

3.3.2 Specifications

1. For requirement 1:

Table 3: Specifications 1

Function	• Model patient arrival down to the hours of each day within the period of the 2016-2017 tax year.
Source	• Patient attendance statistics by month. • Patient attendance statistics by week. • The probability distribution of patient arrival by weekday, knowing the volume of patient attendances in a given week. • The probability distribution of patient arrival by the hour, knowing the volume of patient attendances in a given day.
Obtained from	• NHS A&E monthly attendances statistics for 2016-2017. • HES A&E statistics for 2014-2015.
Output	• Patient arrival model at A&E by hours of the day on any given day of the 2016-2017 tax year.

2. For requirement 2:

Table 4: Specifications 2

Function	• Place the patients in correct queues according to each of their individual journeys through the A&E process.
Source	• For the triage queues: Probabilities of being priority 1, priority 2, or priority 3. • For all other queues: First come, first serve.
Output	• Registration queue. • Waiting-for-triage queue. • Three triage queues (waiting for treatment).

3. For requirement 3:

Table 5: Specifications 3

Function	• Estimate the patient's waiting time in real time.
Source	• Waiting-time agent variable given to each patient.
Output	• All patient waiting times at any given point in the simulation.

4. For requirement 4:

Table 6: Specifications 4

Function	• Model patient end of journey path.
Source	• Admission rate via A&E rate by the hospital by month. • A&E mortality rate by the hospital by month.
Obtained from	• NHS A&E monthly attendances statistics for 2016-2017. • HES A&E statistics for 2014-2015.
Output	• Proper patient exit paths used to measure the volume of patients being discharged, admitted, or dead.

5. For requirements 5 and 6:

Table 7: Specifications 5

Function	• Simulation validity for all hospitals within London Commissioning Region for all days of the year under examination.
Source	• Attendances for all A&E units within this region for all the days in question.
Obtained from	• NHS A&E monthly attendances statistics for 2016-2017. • HES A&E statistics for 2014-2015.

3.4 Process

After comparing all the process flows gathered from the literature, the following process seems to be the most suitable, especially in regard to being as representative as possible of all the A&Es that are part of the simulation.

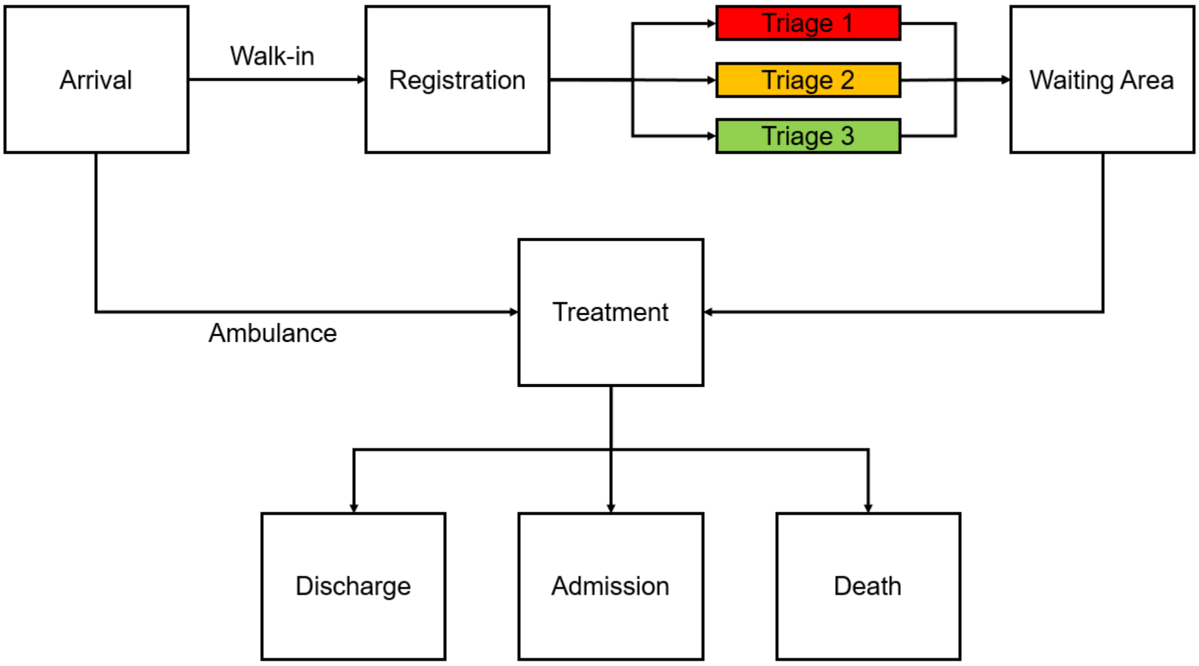

Figure 20: A&E Process Flow Chart

The A&E journey begins by arrival to the A&E. This can occur by either walking in or arrival by ambulance. Beginning with those who walk into an A&E, the first part of their journey is the registration. These attendances are placed into a first come first serve (FCFS) registration queue. After registering, these patients, then, either directly go into a triage unit to be assessed by a triage nurse or wait in the waiting area until they are called for triage by these nurses. During triage, the triage nurses perform an initial assessment of the patient and may or may not be taking note of their vitals. Patients are then placed into three queues according to the acuity of their condition. These queues are “Priority 1 (P1)” denoted by the colour red, “Priority 2 (P2)” denoted by the colour orange, and “Priority 3 (P3)” denoted by the colour green. These priority queues are ordered by decreased level of acuity, P1 being the most severe. After triage, the patients head back to the waiting area in order to wait for treatment. A patient does not receive treatment until everyone in the higher queues has been treated (the queues of higher acuity levels are empty), and everyone ahead of them in their respective queue has also been treated (they are the head of their queue).

As for those who arrive via ambulance, they have a priority higher than even those in P1. These patients skip registration and triage. If an ambulance patient is waiting and a bed becomes available, he/she directly takes the bed regardless of any of people in the three triage queues. After a patient is called on to be seen by the doctor or physician, the treatment part of the process begins and goes on until they are either discharged, admitted to the hospital, or pronounced dead. This concludes the process flow in A&E.

3.5 Agents

3.5.1 Patients

Patients are the key agents in this simulation as their LoS is the primary characteristic under examination. Each of the patients has a set of attributes and a set of rules which will be discussed below.

Characteristics of agent:
- Arrival method: walk-in vs ambulance.
- Location: registration, waiting room, a triage room, treatment room.
- Triage: this attribute is regarding whether the patient is in P1, P2, or P3.
- Length of stay (LoS): the patient's total wait time from entrance to exit.

The agent rules are given in the following table.

If	**Then**
Not yet registered.	Go to registration queue.
Registered (waiting to be triaged).	Go to the waiting room and wait for the triage nurse.
Called upon by triage nurse.	Follow triage nurse to triage unit.
Triaged (waiting to be treated).	Go to the waiting room and wait for the doctor.
Called upon by doctor.	Follow doctor to the treatment room.
Treated.	Exit A&E via appropriate exit route.

Table 8: Patient Rules

3.5.2 Registration Staff

The registration staff in this simulation do not have any other job than registering new attendances in the A&E. Thus, their work is only scaled by the number of available staff. As a result, there are no specific characteristics, variables, or rules for these "agents". Their only mode of operation is to keep registering patients as long as there are people in the registration queue; they are idle otherwise.

3.5.3 Triage Nurses

Triage nurses are important agents in this simulation. They are charged with calling upon patients who are waiting to be triaged from the waiting area, escorting them to the triage unit, and effectively, place these patients into the suitable triage queue.

Characteristics of agent:
- Availability: available vs getting patient.
- Patient ID: this is the patient whom the nurse is currently dealing with.

The agent rules are given in the following table.

If	Then
Not dealing with a patient.	Go to the waiting room and call upon a patient. Escort patient back to the triage unit.
Dealing with a patient.	BUSY.

Table 9: Nurse Rules

3.5.4 Doctors

Doctors are as important as triage nurses in this simulation. They are charged with treating a patient in the treatment area.

Characteristics of agent:

- Availability: available vs getting patient.
- Patient ID: this is the patient whom the nurse is currently dealing with.

The agent rules are given in the following table.

If	Then
Not dealing with a patient.	Go to the waiting room and call upon a patient. Escort patient back to the triage unit.
There is a patient in ambulance queue.	Treat this patient as soon as possible.
Dealing with a patient.	BUSY.

Table 10: Doctor Rules

3.6 Statistical Data

3.6.1 Hospital A&E Units

The following table numbers all of the hospital A&E units included in the simulation.

#	Hospital
1	Barking, Havering And Redbridge University Hospitals NHS Trust
2	Barts Health NHS Trust
3	Beckenham Beacon Ucc
4	Central London Community Healthcare NHS Trust
5	Chelsea And Westminster Hospital NHS Foundation Trust
6	Croydon Health Services NHS Trust
7	Edmonton GP Walk In Centre
8	Epsom And St Helier University Hospitals NHS Trust
9	Guy's And St Thomas' NHS Foundation Trust
10	Harold Wood Walk In Centre
11	Homerton University Hospital NHS Foundation Trust
12	Hounslow And Richmond Community Healthcare NHS Trust
13	Imperial College Healthcare NHS Trust
14	King's College Hospital NHS Foundation Trust
15	Kingston Hospital NHS Foundation Trust
16	Lewisham And Greenwich NHS Trust
17	London North West Healthcare NHS Trust
18	Moorfields Eye Hospital NHS Foundation Trust
19	North East London NHS Foundation Trust
20	North Middlesex University Hospital NHS Trust
21	Orchard Village Walk-In-Centre
22	Royal Free London NHS Foundation Trust
23	St Andrews Walk-In Centre
24	St George's University Hospitals NHS Foundation Trust
25	The Barkantine Practice
26	The Hillingdon Hospitals NHS Foundation Trust
27	The Junction Hc - Unregistered Patients
28	The Ridgeway Surgery
29	The Whittington Hospital NHS Trust
30	University College London Hospitals NHS Foundation Trust
31	Urgent Care Centre
32	Waldron - Hurley Unregistered Practice

Table 11: Hospitals Included in the Simulation

3.6.2 Weekly Arrival Model

Using monthly attendances statistics obtained from the NHS website for the 2016-2017 tax year [19], we have each month's total attendances for each of the hospitals under examination. These are displayed in the table below.

#	Apr-16	May-16	Jun-16	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17
1	22,034	24,143	22,792	24,471	22,108	22,564	23,863	23,718	25,039	24,289	21,206	24,952
2	38,413	41,063	38,619	39,491	37,195	39,468	40,168	39,940	41,228	40,717	36,488	42,369
3	3,836	4,542	4,234	4,578	4,091	4,296	4,364	4,047	4,435	4,260	3,768	4,381
4	17,369	19,018	18,533	19,122	17,656	18,729	19,307	18,478	18,545	19,019	17,023	19,562
5	22,090	24,468	23,070	24,123	21,720	23,105	24,186	24,081	24,610	24,269	21,162	25,231
6	9,698	10,589	10,061	10,450	9,599	9,849	9,945	9,848	10,377	10,090	8,963	10,498
7	1,116	1,232	944	1,029	754	773	1,139	902	1,244	1,238	1,016	1,069
8	12,390	13,401	12,865	13,644	12,056	12,677	12,714	12,711	12,968	12,130	11,138	13,193
9	15,139	17,096	16,195	16,543	15,405	16,093	16,189	15,748	15,546	15,281	14,017	16,156
10	3,909	3,753	3,525	3,690	3,614	3,629	3,803	3,804	3,690	3,892	3,459	4,068
11	9,822	11,052	10,377	10,751	9,684	10,089	10,183	9,946	10,278	10,039	8,790	10,300
12	4,251	4,849	4,324	4,805	4,459	4,430	4,737	4,344	4,668	4,313	4,088	4,676
13	23,058	24,898	24,047	24,777	23,663	24,324	24,577	23,611	24,314	24,336	21,652	25,450
14	24,080	25,568	24,677	24,998	23,341	23,863	24,082	23,743	24,306	23,510	21,142	24,959
15	9,253	10,158	9,622	9,824	9,227	9,852	10,291	9,750	10,079	9,507	8,592	10,402
16	21,742	23,890	22,873	23,431	21,711	22,723	23,892	23,680	24,143	23,479	21,066	24,664
17	28,565	28,568	26,777	29,034	26,911	28,191	29,334	27,980	29,602	28,879	25,229	28,875
18	8,717	8,908	8,542	8,822	8,474	8,613	8,472	8,035	7,183	7,764	7,527	9,020
19	4,707	5,255	4,792	5,038	4,889	4,685	4,920	4,821	4,404	5,180	4,539	5,561
20	13,604	14,979	13,809	13,445	12,147	13,251	14,014	13,981	14,918	14,751	13,091	15,077
21	728	739	785	852	668	738	833	807	758	838	757	856
22	20,811	22,957	21,909	22,629	20,635	21,754	22,196	21,836	22,486	21,710	19,219	22,360
23	2,276	1,906	1,693	1,849	1,721	1,829	1,911	1,937	1,997	2,037	1,797	1,977
24	13,737	15,067	14,310	14,752	13,814	14,261	14,558	14,025	14,149	14,008	12,519	14,625
25	2,446	2,689	2,225	2,305	2,471	2,532	2,509	2,612	2,491	2,592	2,297	2,541
26	13,132	14,271	13,401	13,992	12,685	13,336	13,614	13,561	13,861	13,793	12,378	14,286
27	2,910	3,059	2,929	3,294	3,121	3,277	3,256	3,007	3,212	3,106	2,815	3,125
28	1,157	3,250	3,184	3,360	2,789	2,809	3,266	3,323	3,847	3,732	3,141	3,373
29	7,878	8,540	7,908	8,277	7,513	8,020	8,253	8,271	8,238	8,255	7,431	8,528
30	11,254	12,155	11,479	12,121	11,302	11,401	11,861	11,512	11,196	11,130	10,584	12,059
31	8,878	10,093	9,233	9,933	8,860	9,182	9,443	9,510	10,188	10,009	8,613	9,912
32	2,398	2,431	2,215	2,508	2,417	2,460	2,567	2,438	2,474	2,670	2,295	2,414

Table 12: Monthly Arrivals

As can be seen from the table above, the attendances vary from month to month and have great variances across different hospital A&E units.

Using the data in the table above, it was possible to obtain the average weekly arrival attendances for each of the hospitals as can be seen in the table below.

Table 13: Average Weekly Arrivals

#	Apr-16	May-16	Jun-16	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17
1	5,141	5,452	5,318	5,526	4,992	5,265	5,388	5,534	5,654	5,485	5,302	5,634
2	8,963	9,272	9,011	8,917	8,399	9,209	9,070	9,319	9,310	9,194	9,122	9,567
3	895	1,026	988	1,034	924	1,002	985	944	1,001	962	942	989
4	4,053	4,294	4,324	4,318	3,987	4,370	4,360	4,312	4,188	4,295	4,256	4,417
5	5,154	5,525	5,383	5,447	4,905	5,391	5,461	5,619	5,557	5,480	5,291	5,697
6	2,263	2,391	2,348	2,360	2,168	2,298	2,246	2,298	2,343	2,278	2,241	2,371
7	260	278	220	232	170	180	257	210	281	280	254	241
8	2,891	3,026	3,002	3,081	2,722	2,958	2,871	2,966	2,928	2,739	2,785	2,979
9	3,532	3,860	3,779	3,736	3,479	3,755	3,656	3,675	3,510	3,451	3,504	3,648
10	912	847	823	833	816	847	859	888	833	879	865	919
11	2,292	2,496	2,421	2,428	2,187	2,354	2,299	2,321	2,321	2,267	2,198	2,326
12	992	1,095	1,009	1,085	1,007	1,034	1,070	1,014	1,054	974	1,022	1,056
13	5,380	5,622	5,611	5,595	5,343	5,676	5,550	5,509	5,490	5,495	5,413	5,747
14	5,619	5,773	5,758	5,645	5,271	5,568	5,438	5,540	5,488	5,309	5,286	5,636
15	2,159	2,294	2,245	2,218	2,084	2,299	2,324	2,275	2,276	2,147	2,148	2,349
16	5,073	5,395	5,337	5,291	4,902	5,302	5,395	5,525	5,452	5,302	5,267	5,569
17	6,665	6,451	6,248	6,556	6,077	6,578	6,624	6,529	6,684	6,521	6,307	6,520
18	2,034	2,011	1,993	1,992	1,913	2,010	1,913	1,875	1,622	1,753	1,882	2,037
19	1,098	1,187	1,118	1,138	1,104	1,093	1,111	1,125	994	1,170	1,135	1,256
20	3,174	3,382	3,222	3,036	2,743	3,092	3,164	3,262	3,369	3,331	3,273	3,404
21	170	167	183	192	151	172	188	188	171	189	189	193
22	4,856	5,184	5,112	5,110	4,660	5,076	5,012	5,095	5,077	4,902	4,805	5,049
23	531	430	395	418	389	427	432	452	451	460	449	446
24	3,205	3,402	3,339	3,331	3,119	3,328	3,287	3,273	3,195	3,163	3,130	3,302
25	571	607	519	520	558	591	567	609	562	585	574	574
26	3,064	3,222	3,127	3,159	2,864	3,112	3,074	3,164	3,130	3,115	3,095	3,226
27	679	691	683	744	705	765	735	702	725	701	704	706
28	270	734	743	759	630	655	737	775	869	843	785	762
29	1,838	1,928	1,845	1,869	1,696	1,871	1,864	1,930	1,860	1,864	1,858	1,926
30	2,626	2,745	2,678	2,737	2,552	2,660	2,678	2,686	2,528	2,513	2,646	2,723
31	2,072	2,279	2,154	2,243	2,001	2,142	2,132	2,219	2,301	2,260	2,153	2,238
32	560	549	517	566	546	574	580	569	559	603	574	545

Of course, since the purpose of the simulation is to simulate a one-week period, the data in the above table is not enough as some months could have more than 4 weeks. For this purpose, the data above was used in conjunction with daily probabilities found in the next section in order to accurately represent the volume of attendances across each of the 52 weeks of the year for each of the 32 hospitals A&E units.

As a result, the following table possesses the data that went into building the simulation as it contains the most accurate approximations of each week's attendances. The following is only a section of the table corresponding to the first 12 weeks as the size of the table is too large.

#	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11	Week 12
1	5427.239	5141.267	5141.267	5141.267	5185.651	5451.645	5451.645	5451.645	5451.645	5358.587	5318.133	5318.133
2	9313.446	8963.033	8963.033	8963.033	9007.257	9272.29	9272.29	9272.29	9272.29	9090.241	9011.1	9011.1
3	949.6977	895.0667	895.0667	895.0667	913.7348	1025.613	1025.613	1025.613	1025.613	999.3502	987.9333	987.9333
4	4264.153	4052.767	4052.767	4052.767	4087.318	4294.387	4294.387	4294.387	4294.387	4315.283	4324.367	4324.367
5	5469.267	5154.333	5154.333	5154.333	5207.343	5525.032	5525.032	5525.032	5525.032	5426.036	5383	5383
6	2325.303	2262.867	2262.867	2262.867	2281.199	2391.065	2391.065	2391.065	2391.065	2360.747	2347.567	2347.567
7	249.3725	260.4	260.4	260.4	262.9445	278.1935	278.1935	278.1935	278.1935	237.8185	220.2667	220.2667
8	2942.077	2891	2891	2891	2910.31	3026.032	3026.032	3026.032	3026.032	3009.166	3001.833	3001.833
9	3599.537	3532.433	3532.433	3532.433	3579.331	3860.387	3860.387	3860.387	3860.387	3803.544	3778.833	3778.833
10	915.8588	912.1	912.1	912.1	902.8553	847.4516	847.4516	847.4516	847.4516	830.0603	822.5	822.5
11	2311.524	2291.8	2291.8	2291.8	2320.945	2495.613	2495.613	2495.613	2495.613	2443.817	2421.3	2421.3
12	1029.003	991.9	991.9	991.9	1006.634	1094.935	1094.935	1094.935	1094.935	1034.992	1008.933	1008.933
13	5592.813	5380.2	5380.2	5380.2	5414.796	5622.129	5622.129	5622.129	5622.129	5614.349	5610.967	5610.967
14	5628.664	5618.667	5618.667	5618.667	5640.796	5773.419	5773.419	5773.419	5773.419	5762.649	5757.967	5757.967
15	2269.12	2159.033	2159.033	2159.033	2178.297	2293.742	2293.742	2293.742	2293.742	2259.862	2245.133	2245.133
16	5360.904	5073.133	5073.133	5073.133	5119.091	5394.516	5394.516	5394.516	5394.516	5354.451	5337.033	5337.033
17	6581.064	6665.167	6665.167	6665.167	6634.518	6450.839	6450.839	6450.839	6450.839	6309.437	6247.967	6247.967
18	2035.595	2033.967	2033.967	2033.967	2030.752	2011.484	2011.484	2011.484	2011.484	1998.694	1993.133	1993.133
19	1189.598	1098.3	1098.3	1098.3	1110.929	1186.613	1186.613	1186.613	1186.613	1138.883	1118.133	1118.133
20	3307.793	3174.267	3174.267	3174.267	3204.023	3382.355	3382.355	3382.355	3382.355	3270.657	3222.1	3222.1
21	183.4524	169.8667	169.8667	169.8667	169.4383	166.871	166.871	166.871	166.871	178.2291	183.1667	183.1667
22	4967.917	4855.9	4855.9	4855.9	4902.795	5183.839	5183.839	5183.839	5183.839	5133.837	5112.1	5112.1
23	481.9712	531.0667	531.0667	531.0667	516.6695	430.3871	430.3871	430.3871	430.3871	405.7455	395.0333	395.0333
24	3261.629	3205.3	3205.3	3205.3	3233.46	3402.226	3402.226	3402.226	3402.226	3358.157	3339	3339
25	572.497	570.7333	570.7333	570.7333	575.9471	607.1935	607.1935	607.1935	607.1935	545.8388	519.1667	519.1667
26	3157.941	3064.133	3064.133	3064.133	3086.777	3222.484	3222.484	3222.484	3222.484	3155.862	3126.9	3126.9
27	694.4542	679	679	679	680.6791	690.7419	690.7419	690.7419	690.7419	685.6478	683.4333	683.4333
28	555.1402	269.9667	269.9667	269.9667	336.305	733.871	733.871	733.871	733.871	740.1874	742.9333	742.9333
29	1888.937	1838.2	1838.2	1838.2	1851.097	1928.387	1928.387	1928.387	1928.387	1870.406	1845.2	1845.2
30	2682.232	2625.933	2625.933	2625.933	2642.914	2744.677	2744.677	2744.677	2744.677	2698.505	2678.433	2678.433
31	2168.196	2071.533	2071.533	2071.533	2101.21	2279.065	2279.065	2279.065	2279.065	2192.15	2154.367	2154.367
32	551.1601	559.5333	559.5333	559.5333	558.0178	548.9355	548.9355	548.9355	548.9355	526.5603	516.8333	516.8333

Table 14: Actual Weekly Arrivals

3.6.3 Daily Arrival Model

Through data obtained via HES's 2014-2015 statistics, it was possible to model the probability distribution of arrivals across the seven days of the week. These probabilities are of the given weekly attendance volume which can be found in the previous table [20].

The probabilities are used in the simulation and are shown in the table below.

Monday	0.158
Tuesday	0.145
Wednesday	0.139
Thursday	0.138
Friday	0.138
Saturday	0.139
Sunday	0.143

Table 15: Daily Probabilities

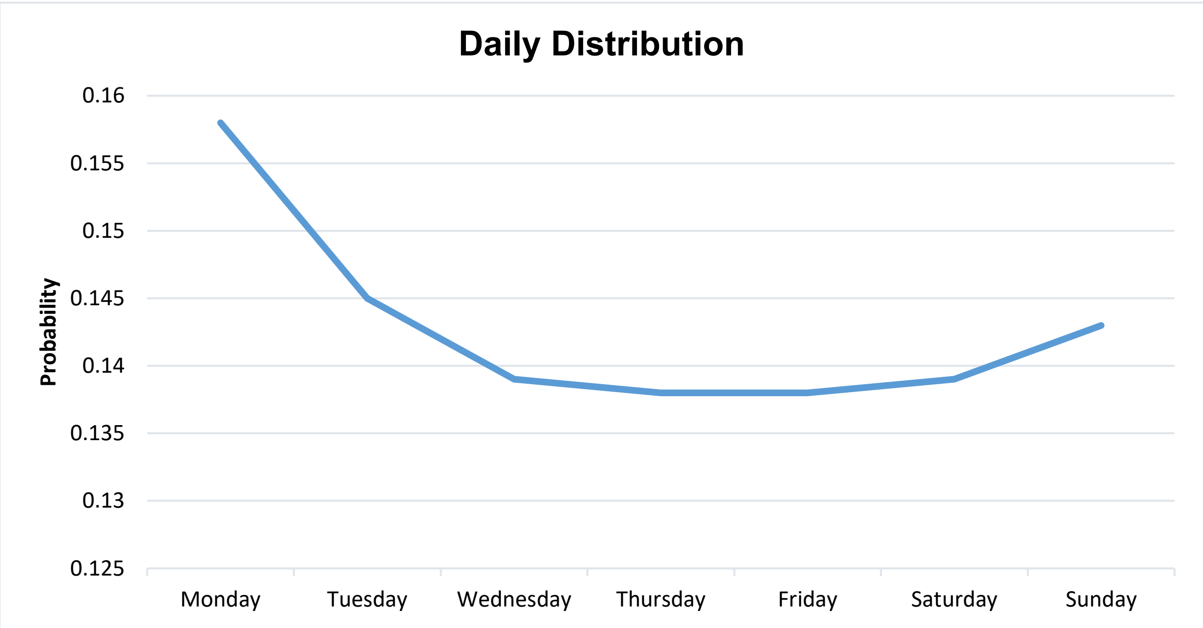

Figure 21: Daily Distribution

As can be seen, the peak of arrivals is on Monday, which then gradually goes down to start increasing again during the weekend. Modelling this is essential if the simulation were to be accurate and resembling reality. Simply spreading out the weekly arrivals evenly across the days will severely impact the results of each patient's waiting time in A&E. For this purpose, these probabilities aim to remedy any inaccuracy.

3.6.4 Hourly Arrival Model

Through data obtained via HES's 2014-2015 statistics, it was possible to model the probability distribution of arrivals across the 24 hours of a day. These probabilities are of the given daily attendance volume whose probabilities are in the previous section's table above [20].

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
0:00	0.0201	0.0213	0.0211	0.0217	0.0219	0.0247	0.0256
1:00	0.0136	0.0140	0.0144	0.0147	0.0150	0.0183	0.0197
2:00	0.0110	0.0114	0.0113	0.0119	0.0121	0.0157	0.0170
3:00	0.0095	0.0100	0.0099	0.0105	0.0105	0.0138	0.0151
4:00	0.0087	0.0090	0.0091	0.0095	0.0097	0.0124	0.0134
5:00	0.0085	0.0088	0.0088	0.0092	0.0092	0.0113	0.0122
6:00	0.0099	0.0101	0.0101	0.0102	0.0102	0.0116	0.0119
7:00	0.0168	0.0166	0.0167	0.0164	0.0167	0.0173	0.0168
8:00	0.0419	0.0405	0.0398	0.0394	0.0409	0.0382	0.0357
9:00	0.0706	0.0663	0.0655	0.0646	0.0651	0.0572	0.0550
10:00	0.0746	0.0697	0.0681	0.0681	0.0691	0.0705	0.0711
11:00	0.0743	0.0705	0.0691	0.0695	0.0701	0.0732	0.0744
12:00	0.0690	0.0659	0.0652	0.0655	0.0658	0.0694	0.0710
13:00	0.0664	0.0648	0.0652	0.0651	0.0653	0.0672	0.0674
14:00	0.0630	0.0628	0.0634	0.0637	0.0636	0.0659	0.0646
15:00	0.0606	0.0612	0.0615	0.0612	0.0611	0.0647	0.0620
16:00	0.0620	0.0622	0.0629	0.0627	0.0628	0.0611	0.0592
17:00	0.0603	0.0607	0.0608	0.0601	0.0611	0.0573	0.0566
18:00	0.0634	0.0650	0.0651	0.0638	0.0622	0.0537	0.0547
19:00	0.0577	0.0603	0.0607	0.0600	0.0566	0.0498	0.0526
20:00	0.0478	0.0510	0.0515	0.0514	0.0490	0.0459	0.0472
21:00	0.0380	0.0409	0.0415	0.0422	0.0410	0.0390	0.0394
22:00	0.0295	0.0324	0.0330	0.0333	0.0337	0.0335	0.0318
23:00	0.0226	0.0246	0.0254	0.0255	0.0274	0.0282	0.0255

Table 16: Hourly Probabilities

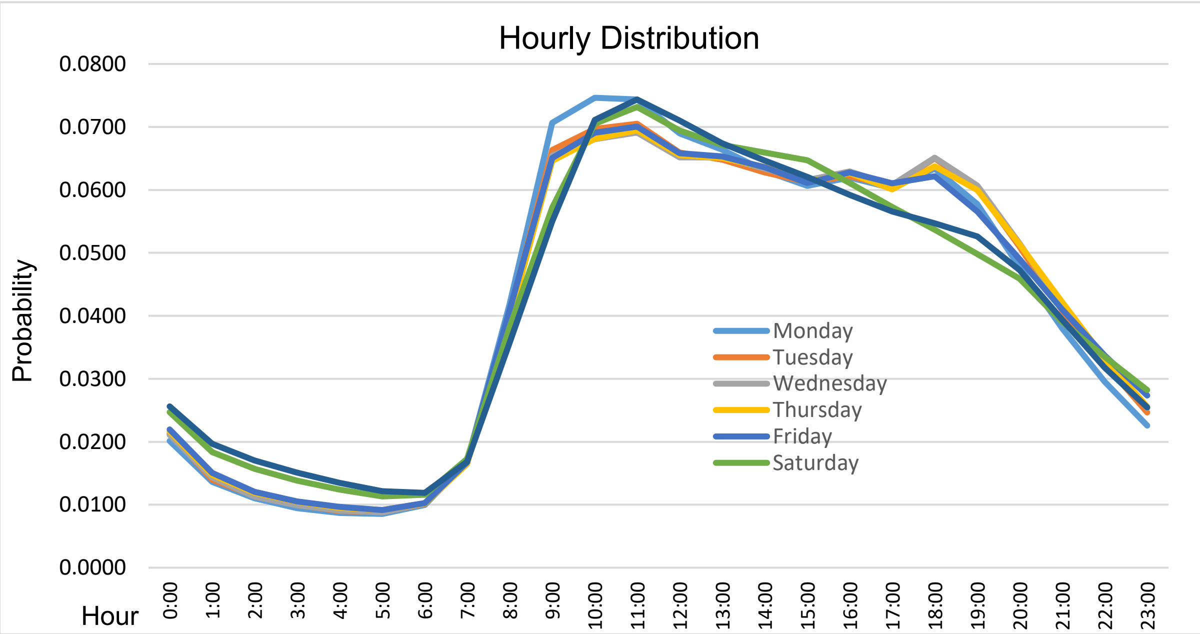

Figure 22: Hourly Distribution

3.6.5 Arrival Method Model

As mentioned in previous sections, arrival at the A&E can be via walk-ins or via ambulance. Amongst the total daily attendance, each of these arrival means carries a portion of these attendances. According to HES 2014-2015 statistics, these probabilities are as shown below in the table [20].

Walk-in	0.77
Ambulance	0.23

Table 17: Arrival Method Probabilities

3.6.6 Triage Model

During the A&E process, in the triage unit, patients are to be sorted and placed into three respective queues based on the acuity level of this condition. The following probabilities were obtained [21] and integrated into the simulation in order to mimic real-life situations by having realistic numbers of people in each priority queue.

Priority 1	0.344
Priority 2	0.344
Priority 3	0.311

Table 18: Triage Probabilities

3.6.7 Exit Model

At the end of the A&E process, there are three exit routes. The patient is either discharged, admitted into the hospital, or dead. The death probabilities were obtained through HES 2014-2015 statistics [20], while the admission rates were obtained through NHS 2016-2017 statistics [19]. The discharge rate is obtained by subtracting these two rates from 1. It is important to note that the death rate is day-specific in terms of the seven weekdays.

4 Implementation

4.1 Setting Up The Environment

4.1.1 Initializing the Grid

We begin by initializing the grid with different patch colours to represent pathways, walls, and different rooms throughout the hospital. The grid represents the floor plan of the A&E unit. This floor plan was chosen as to be as general as possible to be representative of all 32 hospitals included in the simulation.

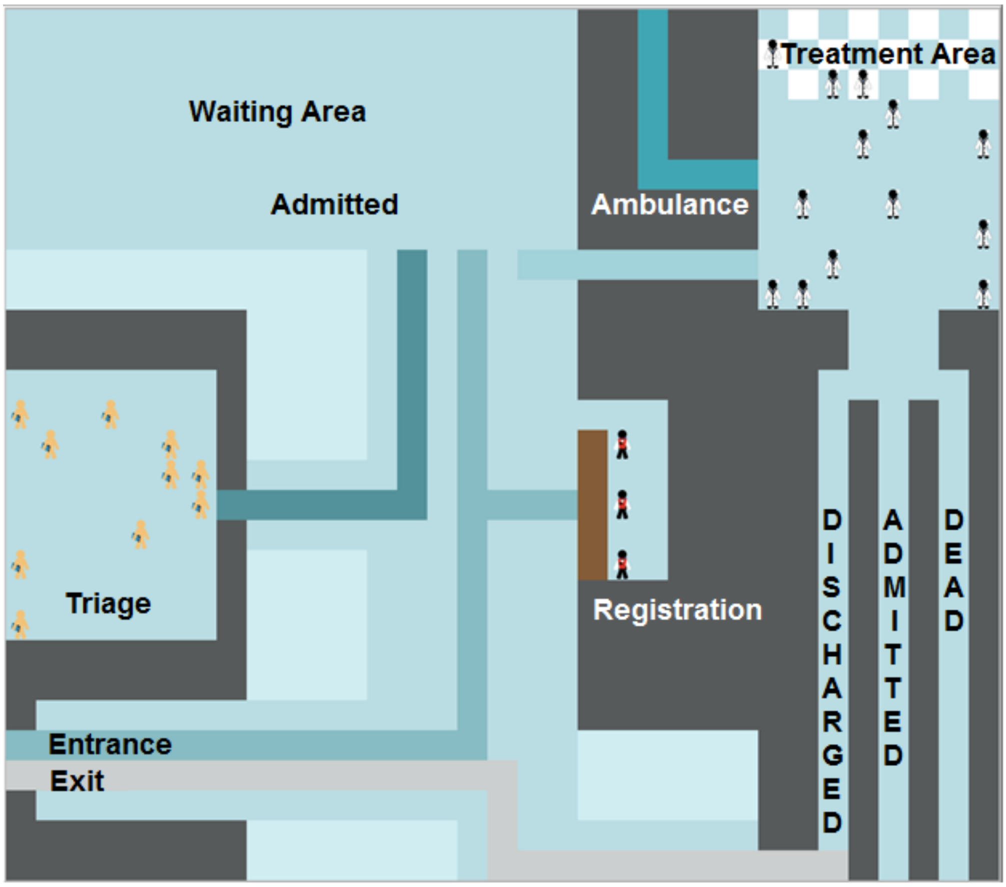

Figure 23: Simulation Floor Plan Screenshot

4.1.2 Files

We parse and read three input files before beginning the simulation.

- *Yearly file:*

This file contains data for each of the hospitals. Every five rows represent one hospital and every column represents one month. The 3rd, 4th, and 5th column correspond to monthly discharge rate, monthly admission rate, and monthly death rate respectively. We use this data to determine agent-doctor interaction outcomes (i.e patient death, admittance, discharge outcomes).

- *Weekly file:*

This file provides the weekly patient numbers across the 32 hospitals over the course of one year.

- *Hourly file:*

The file provides the patient distribution across every 24 hours of every day.

4.1.3 Other Constants

- Triage priorities (variable triage-priorities): This includes the triage priorities of priority 1, 2, and 3 patients.

- Week to day probabilities (variable week-to-day-probabilities): This represents the distribution of a week's patients across the days.

- Walk-in vs Ambulance patients: These are just constant values we use in the code, 77% of patients are walk-in patients while 23% are ambulance patients.

4.2 Agents

There are four different types of agents as discussed in the previous section:

- Registration staff: The number of these agents determined the throughput of the reception area. They do not move around the hospital and only serve the purpose of registering patients.

- Triage Nurses: Nurses can be available or unavailable, their job is to get patients from the waiting room and triage them.

- Doctors: Doctors can also be available or unavailable, their purpose is to get patients from the triage room and treat them. Doctors prioritize by choosing from the group of patients with the highest priority, within that group they pick the patient with the highest waiting time.

- Patients: Patients go through the following states/phases, 'in reception', 'in waiting room', 'in nurse room', 'in triage room', and 'in treatment/doctor room'. Patients can also have different priorities, patients with the highest priority are those arriving from the ambulance, they are coloured pink. The other patients with priority 1, 2, and 3 are coloured red, yellow, and green respectively.

4.3 Inputs

The following inputs discussed in this section are shown in the screenshot at the end of the section.

- Number of doctors (nb-doctors)
    - The number of doctors along with the number of beds determines the max number of patients that can be treated at once. The lower of the two values represent the treatment room's bottleneck.

- Number of beds (nb-beds)
    - The number of beds along with the number of doctors determines the max number of patients that can be treated at once. The lower of the two values represent the treatment room's bottleneck.

- Number of nurses (nb-nurses)
    - This determines the number of nurses which is equivalent to the max number of patients that can be triaged at once.

- Number of registration staff (nb-regis-staff)
    - This represents the number of registration staff available to register a patient.

- Average registration time (avg-regist-time)
    - This represents the speed of the registration staff at registering a patient.

- Average triage time (avg-triage-time)
    - This represents the speed of the nurse at triaging a patient.

- Average ambulance patient treatment time (avg-ambulance-treatment-time)
    - This represents the average time an ambulance patient needs to be treated in minutes.

- Average priority 1 patient treatment time (avg-priority-1-treatment-time)
    - This represents the average time a priority 1 patient needs to be treated in minutes.

- Average priority 2 patient treatment time (avg-priority-2-treatment-time)
    - This represents the average time a priority 2 patient needs to be treated in minutes.

- Average priority 3 patient treatment time (avg-priority-3-treatment-time)
    - This represents the average time a priority 3 patient needs to be treated in minutes.

- Week (week)
    - This represents which week will the simulation run for.

- Hospital selector (hospital)
    - This allows us to choose the hospital which we want to run the simulation for.

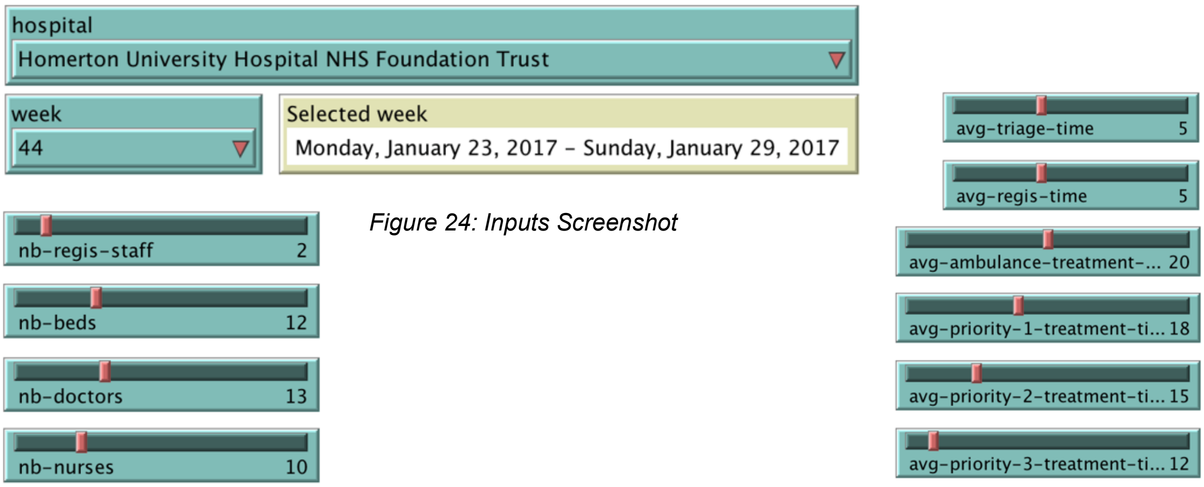

Figure 24: Inputs Screenshot

4.4 Data Processing

4.4.1 Patient Distribution

To establish this distribution, we first use the week to day percentage distributions to determine the number of patients that spawn every day using the weekly patient distributions file. Once the number of patients for each day is calculated, the data from the hourly file is used to establish the distribution of patients across all 24 hours of a day. We split this data between walk-in and ambulance patients based on our knowledge of this split. Finally, we establish spawn times for every patient by randomizing their spawn time across the hour they belong to. For example, if we have 150 patients for a given hour of the day their spawn values would be in the range of 0 to 3599 seconds.

4.4.2 Patient Outcomes

The calculations for this is much simpler, we just use the probability outcomes for the month of the chosen week when creating patients.

4.5 Moving the agents

4.5.1 Time

One NetLogo tick was chosen to represent one second.

The NetLogo Time Extension by Colin Sheppard and Steve Railsback [22] was also used to help with time simulation, adding/subtracting time periods, and establishing a relation between the selected inputs and the corresponding data.

<u>Simulation life:</u>

```
For every tick
  if any agent is moving to their destination
    move one patch forward
  if tick matches walk-in patient spawn time
    spawn patient
  if tick matches ambulance patient spawn time
    spawn patient and go to registration
  if any registration staff available and patient has reached
registration
    register patient and move to waiting room
  if a nurse available and any patients in waiting room
    dispatch nurse to patient with highest waiting time
  if nurse has obtained patient
    return with patient to triage room and triage patient for avg-
triage-time
  if patient has been triaged
    move to triage room
  if a doctor is available and any patients in triage room or ambulance
arrival queue
    dispatch doctor to patient with highest priority and highest waiting
time
  if doctor has obtained patient
    return with patient to treatment room and treat patient for avg-
treatment-time
```

The following screenshot is a mid-simulation screenshot showing the movement of agents throughout the A&E. In the middle, it can be observed that new patients are lined up in the registration queue. Two patients can be seen undergoing triage by the two triage nurses in the mid-left box. The patients coloured red, green, and yellow are those who have already been triaged and are waiting for treatment.

Patients triaged into P3 are coloured green, those triage into P2 are coloured yellow, and those triaged into P1 are coloured red. A pink patient is an ambulance patient. As can be seen below, there is currently 1 ambulance patient waiting to be seen, while 3 other ambulance patients are being treated by the doctors.

It is also important to note that even though there are 4 beds in the screenshot, only 3 of them are in use since the simulation always considers the minimum between the number of doctors and the number of beds.

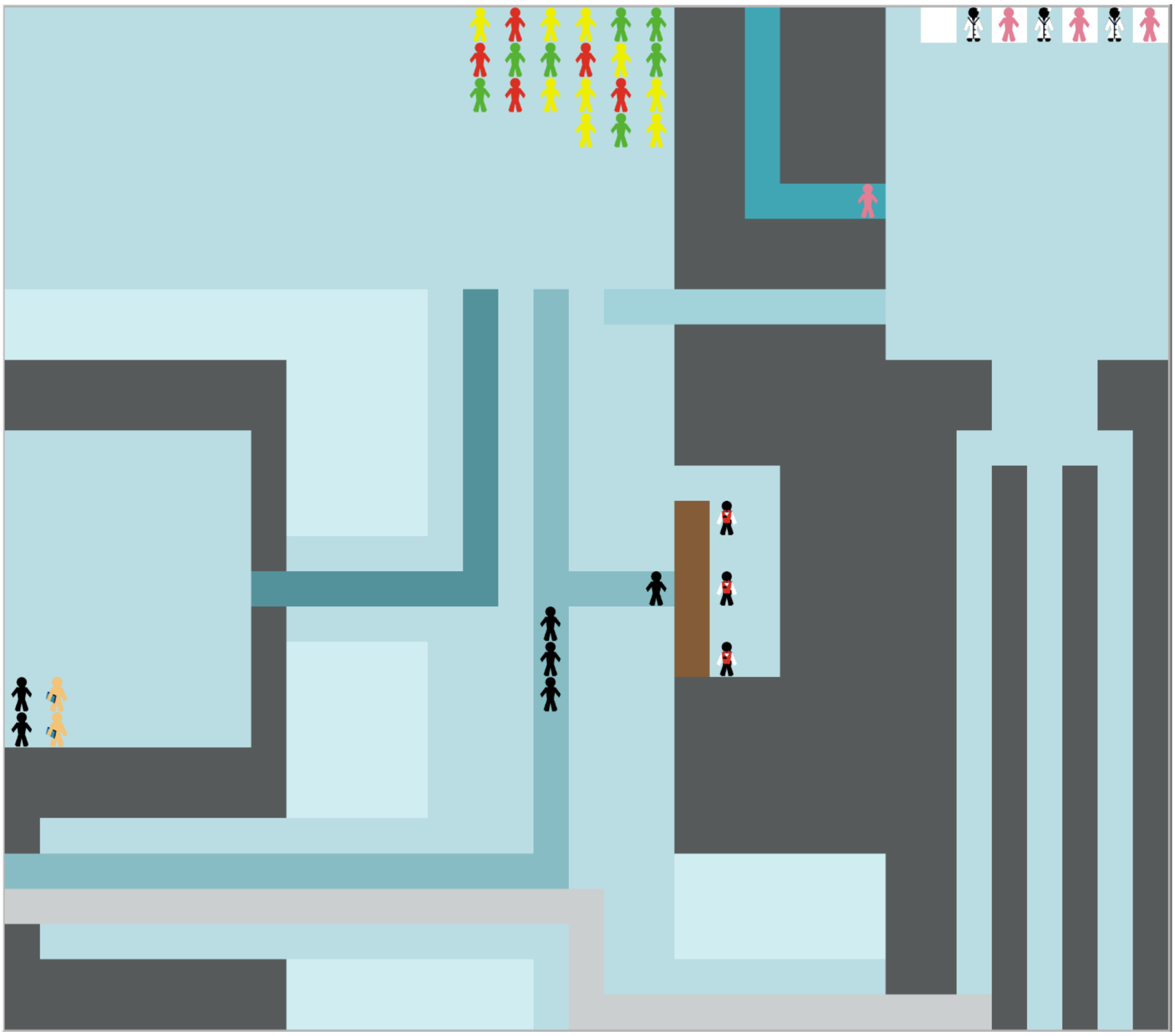

Figure 25: Mid-simulation Screenshot

4.6 Outputs

4.6.1 Monitors

- Number of patients being treated in the hospital
- Number of dead patients
- Number of admitted patients
- Number of discharged patients
- Longest wait time a patient had to go through
- Number of patients that waited more than four hours

The following figure shows screenshots of these monitors.

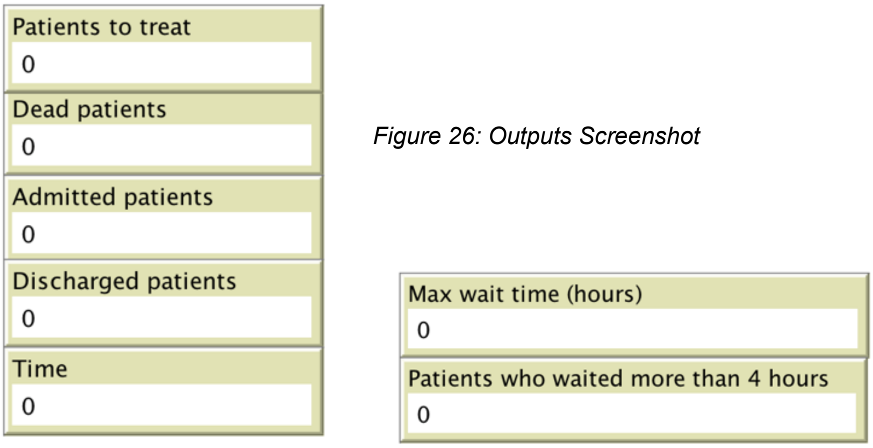

Figure 26: Outputs Screenshot

4.6.2 Output Files

The simulation also generates two output files, one which contains the priority of all the patients that waited more than 4 hours and another which displays how long did each of those patients wait.

5 Results, Analysis, and Evaluation

5.1 Experiment

In this experiment, we aim to evaluate the simulation in terms of repeatability and accuracy. The selected hospital A&E is Homerton University Hospital NHS Foundation Trust. The choice of this hospital is not random as the focus here is on those A&E units that break their 95% rule and have high overcrowding levels. This can be indicated by Homerton University Hospital A&E's record of 710 patients waiting more than 4 hours during a one-week period in January. Note that the total number of weekly attendances in January for this hospital is 2267. This yields that 31.3189% have had an LoS exceeding 4 hours, which clearly violates the NHS standard. As such, we are also choosing the last week of January as the week under examination for this repeatability experiment.

5.1.1 Repeatability

Setup:

- Number of registration staff: 2 minutes.
- Number of beds: 6 minutes.
- Number of doctors: 6 minutes.
- Number of triage nurses: 3 minutes.
- Average triage time: 5 minutes.
- Average registration time: 4 minutes.
- Average ambulance patient treatment time: 21 minutes.
- Average P1 treatment time: 23 minutes.
- Average P2 treatment time: 17 minutes.
- Average P3 treatment time: 10 minutes.

Since the simulation accepts as variables the number of registration staff, triage nurses, doctors, average triage time, average treatment times (according to each triage level or ambulance treatment), and average registration time, we will first keep these constant in order to examine the output across ten different trials. The results are documented below.

Table 19: Repeatability Trials

Trial	Number of patients waiting more than 4 hours
1	172
2	180
3	167
4	184
5	185
6	165
7	180
8	160
9	165
10	174
11	167
12	169
13	182
14	183
15	162
Average	172

As can be seen through examining the values of the table above, the mean of the samples was 172 patients who waited more than 4 hours. The range of all samples falls within [160, 185]. This shows that to some extent, the simulation's results are repeatable. The following is a screenshot showing the results of trial 10.

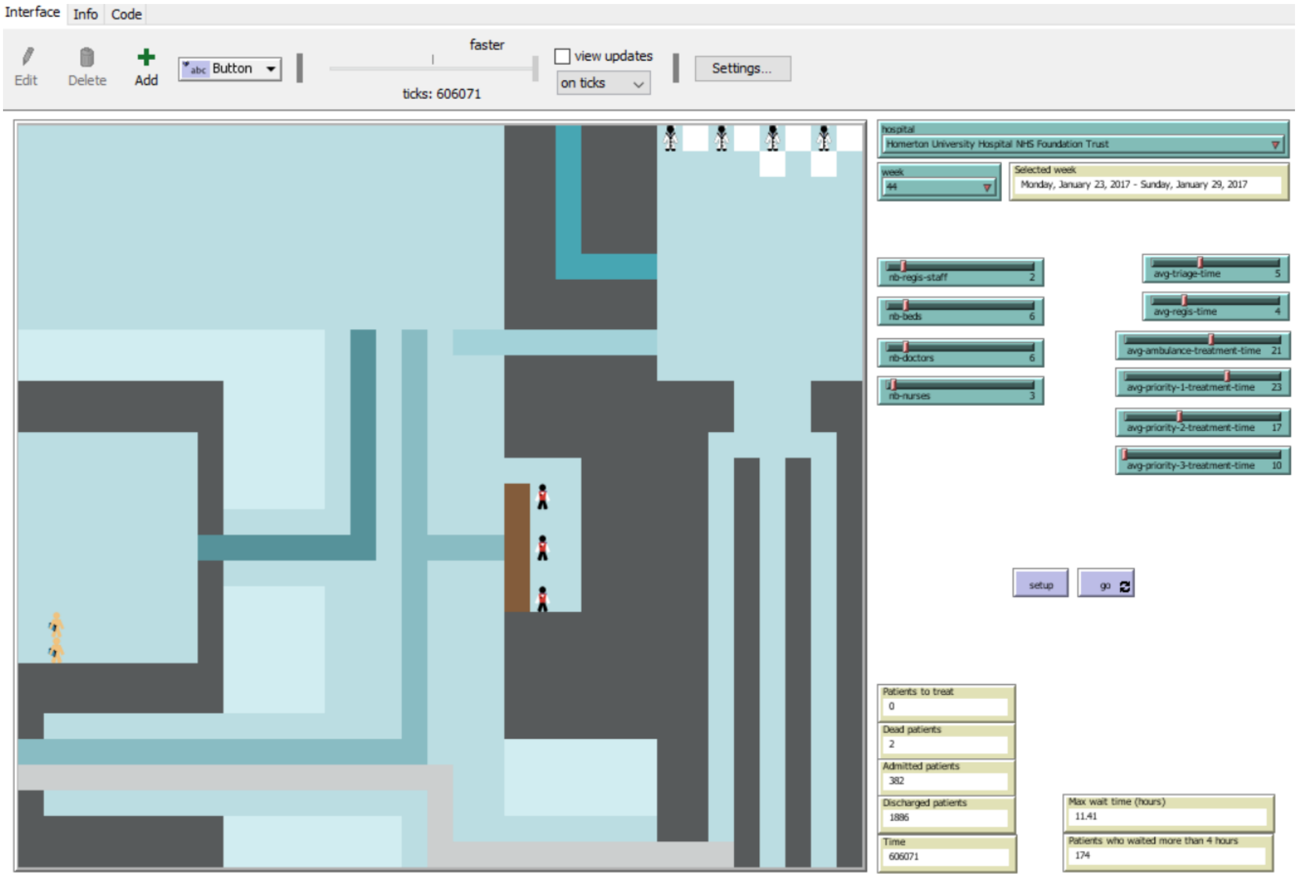

Figure 27: Simulation Screenshot

The tick count shown on the top left of the screen resembles the total running of the simulation. Since we have chosen to have 1 tick represent 1 second, this means that the simulation ran for a virtual 1 week and 21 minutes, given that 1 week is represented by 604800 ticks (24 x 7 x 3600).

5.1.2 Accuracy

In order to test for accuracy, this section of the experiment is concerned with simulating one week in each of the 12 months. Since we have the number of patients who actually spent more than 4 hours at the A&E at Homerton University Hospital obtained from NHS 2016-2017 statistics, this comparison will serve as an accuracy metric. Each of the 12 weeks will be simulated 5 times. The result of these 5 simulations will then averaged and compared to the actual real-life number. The results are documented in the table below.

Week	Trial	Simulated Result	Average	Actual	Accuracy (%)
1	1	160	151.4	146	96.30137
	2	150			
	3	139			
	4	151			
	5	157			
2	1	220	214.6	184	83.36957
	2	223			
	3	210			
	4	205			
	5	215			
3	1	222	213.6	186	85.16129
	2	214			
	3	207			
	4	205			
	5	220			
4	1	170	161.4	122	67.70492
	2	165			
	3	150			
	4	167			
	5	155			
5	1	60	65.8	85	77.41176
	2	65			
	3	63			
	4	70			
	5	71			
6	1	120	118.8	136	87.35294
	2	125			
	3	113			
	4	127			
	5	109			
7	1	200	188.6	170	89.05882
	2	193			
	3	175			
	4	201			
	5	174			
8	1	170	168.6	166	98.43373
	2	143			
	3	190			
	4	160			
	5	180			

9	1	180	178.6	161	89.06832
	2	167			
	3	168			
	4	170			
	5	208			
10	1	210	196	178	89.88764
	2	180			
	3	205			
	4	197			
	5	188			
11	1	106	112	127	88.18898
	2	101			
	3	93			
	4	120			
	5	140			
12	1	155	147.8	159	92.95597
	2	137			
	3	172			
	4	130			
	5	145			
				Average	**87.07461**

Table 20: Accuracy Trials

Note that the values of the input variables are kept the same as they were in the previous section when repeatability was examined. The accuracy results shown by this experiment indicate that the simulation is somewhat accurate with overall accuracy >85%. However, it is important to acknowledge that a more accurate assessment of accuracy would be to run multiple trials for each week of the 52 weeks. Another important note would be to realize that this data can be massively skewed by any change in the input variables. This is why it is more valuable to examine whether or not the simulated trend of patients who spent more than 4 hours in A&E is consistent with the actual one. Both curves can be found below. From the curve plots, we can see that the two trends are similar, thus validating our simulation. The blue curve represents the simulated data while the orange curve represents the actual data. The x-axis constitutes the different examined weeks while the y-axis represents the number of patients who waited more than 4 hours. Note that this is the key factor in quantifying overcrowding.

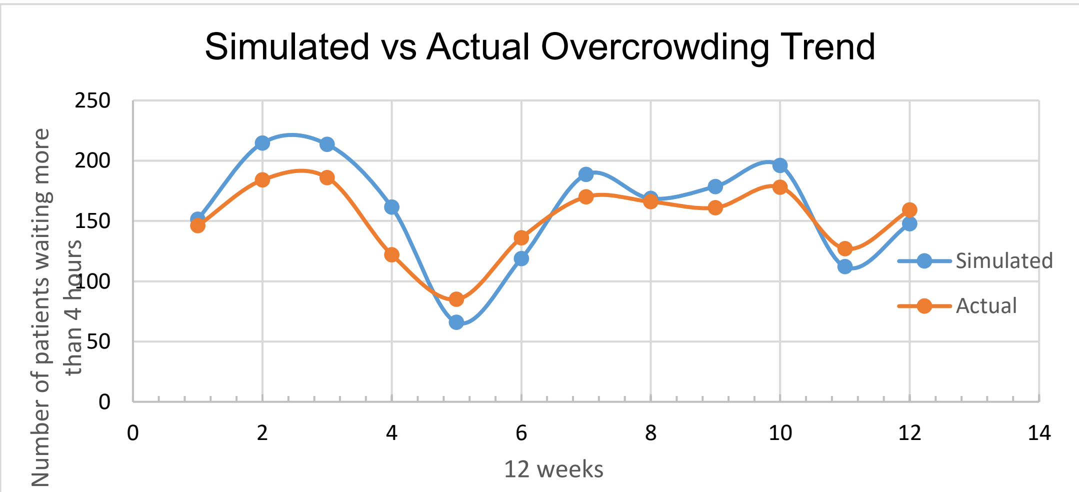

Figure 28: Accuracy Trend

5.1.3 LoS Distribution

Since the simulation has an output file listing each of the patients who waited for more than 4 hours, it is important to examine the spread of this data in order to examine LoS patterns for those in the overcrowding category.

For this purpose, the data of trial 7 in Experiment 1 (Repeatability) is gathered and plotted. A total of 180 patients waited for more than 4 hours during this simulation, with a maximum waiting time reaching 12.36 hours. The following plot shows the distribution of the waiting times in the order of these patients' arrival at the A&E.

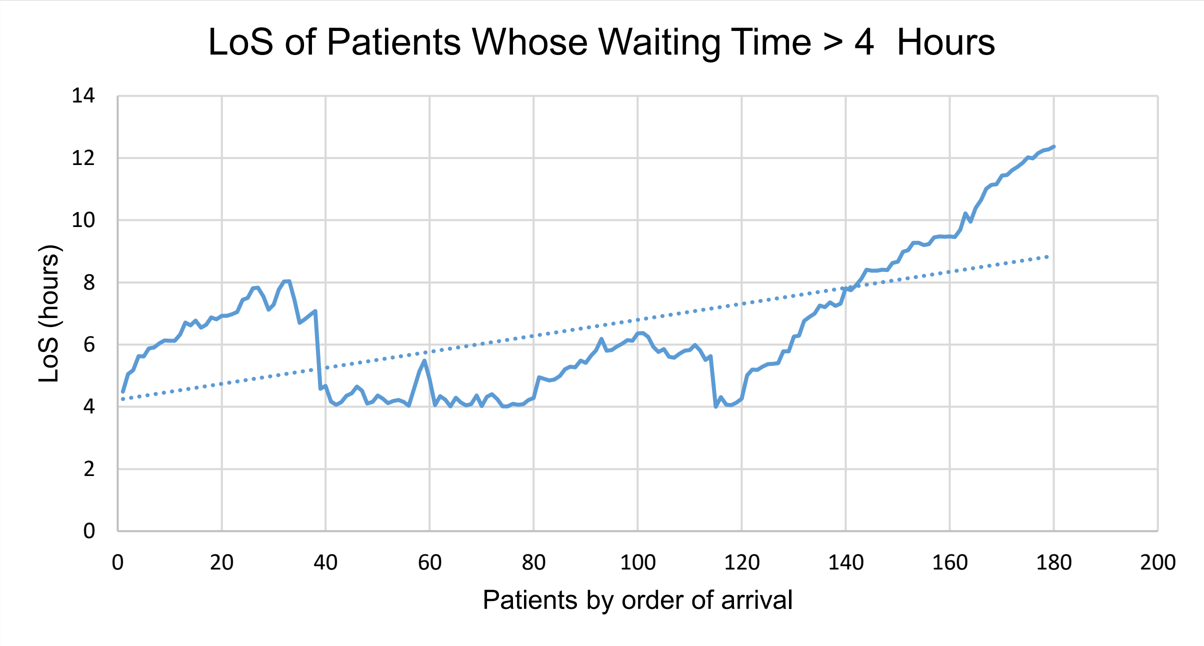

Figure 29: Overcrowding LoS

The dotted line shows the trendline of this distribution. We can notice that the distribution starts off with an LoS of 4 hours which is logical considering this data is only logged for those patients whose LoS exceeds 4 hours. As time progresses and more patients arrive at the A&E, more and more patients start to fall into the overcrowding category. From the trendline, we can notice that LoS is on an increase from the first patient whose LoS exceeds 4 hours and until the last one. This also makes sense since the more patients there are in this category, the longer those who come after them have to wait. As for the sub-trends, we can notice that after approximately 40 patients in this overcrowding category, the LoS drops and almost remains constant until the 120th patient in this category. This makes sense since approximately 40 patients wait for more than 4 hours during the first two days of the week. These first 40 patients have an LoS higher than those who come after them during the mid-week. This can be validated by the fact that the first two days of the week have a substantially greater volume of the weekly attendances in A&E than the rest of the week. However, after approximately 120 patients have waiting for more than 4 hours, the LoS for those after them is even higher, reaching more than a 12-hour wait. This is again validated by the fact that at the end of the week, attendances start to go up again as we go into the weekend. Pairing this fact with the fact that there are already a lot of patients waiting for more than 4 hours, the LoS starts to increase rapidly for the arrivals on Saturday and Sunday.

Evaluating this distribution, it seems to follow basic logic rules and is backed up by the statistical data of each of the days and the varying trendline of attendances on each of those days. This means that the simulation is capable of producing a realistic distribution of patients who wait for more than 4 hours, which is an indicator of A&E overcrowding as previously mentioned.

5.2 Overcrowding Reduction

In this section, several suggestions to solve the overcrowding problem will be provided. The simulated effect of carrying out each of these changes is recorded and discussed.

5.2.1 Suggested Solutions

In order to carefully come up with ways that lead to less people spending more than 4 hours in A&E, one has to examine the process flow of these patients in order to identify possible bottlenecks. As a result, the effect of the following changes will be examined in the next sub-section. The suggested solutions to examine are:

1. Increasing the number registration staff.
2. Increasing the number of triage nurses.
3. Increasing the number of doctors.
4. Decreasing the average triage time.
5. Decreasing the average treatment time of Priority 1 patients.
6. Decreasing the average treatment time of Priority 2 patients.

5.2.2 Effects

In order to examine the effect of each of the suggestion in the previous sub-section, we need to start off with reference data based upon which comparison and contrast could be made. For this reason, the following table has the recorded data from Trial 7 in section 5.1.1. This is because the output of this simulation is closest to the actual number of patients whose LoS exceeded 4 hours (177 patients). Each of the solutions will be examined in terms of incremental change in the direction of improving LoS. Note that overcrowding level for the reference data is 31.3189%, obtained by dividing the total number of people who wait for more than 4 hours by the total number of attendances.

Number of registration staff	Number of beds	Numbers of doctors	Number of triage nurses	Average triage time (mins)	Average registration time (mins)	Average ambulance treatment time (mins)	Average P1 treatment time (mins)	Average P2 treatment time (mins)	Average P3 treatment time (mins)	Number of patients whose LoS > 4 hours
2	7	6	3	5	4	21	23	18	10	180

Table 21: Reference Values

1. Increasing the number of registration staff:

Number of registration staff	Number of beds	Numbers of doctors	Number of triage nurses	Average triage time (mins)	Average registration time (mins)	Average ambulance treatment time (mins)	Average P1 treatment time (mins)	Average P2 treatment time (mins)	Average P3 treatment time (mins)	Number of patients whose LoS > 4 hours
3	7	6	3	5	4	21	23	18	10	165

Table 22: Suggestion 1 Values

By increasing the registration staff number by 1, 15 fewer patients wait more than 4 hours This is equivalent to an improvement by 8.3333% from the reference value of 180 patients. The makes for 660 patients waiting for more than 4 hours during this month, where the total attendances are 2267 patients. Overcrowding level, thus, goes down to 29.1133%.

2. **Increasing the number of triage nurses:**

Number of registration staff	Number of beds	Numbers of doctors	Number of triage nurses	Average triage time (mins)	Average registration time (mins)	Average ambulance treatment time (mins)	Average P1 treatment time (mins)	Average P2 treatment time (mins)	Average P3 treatment time (mins)	Number of patients whose LoS > 4 hours
2	7	6	4	5	4	21	23	18	10	110

Table 23: Suggestion 2 Values

By increasing the triage nurses number by 1, 70 fewer patients wait more than 4 hours. This is equivalent to an improvement by 38.8888% from the reference value of 180 patients. The makes for 660 patients waiting for more than 4 hours during this month, where the total attendances are 2267 patients. Overcrowding level, thus, goes down to 19.4089%.

3. **Increasing the number of doctors:**

Number of registration staff	Number of beds	Numbers of doctors	Number of triage nurses	Average triage time (mins)	Average registration time (mins)	Average ambulance treatment time (mins)	Average P1 treatment time (mins)	Average P2 treatment time (mins)	Average P3 treatment time (mins)	Number of patients whose LoS > 4 hours
2	7	7	3	5	4	21	23	18	10	26

Table 24: Suggestion 3 Values

By increasing the number of doctors by 1, 154 fewer patients wait more than 4 hours. This is equivalent to an improvement by 85.5555% from the reference value of 180 patients. The makes for 104 patients waiting for more than 4 hours during this month, where the total attendances are 2267 patients. Overcrowding level, thus, goes down to 4.6017%. The hospital in this case **no longer violates the 95% standard** and overcrowding is extremely reduced.

4. **Decreasing the average triage time:**

Number of registration staff	Number of beds	Numbers of doctors	Number of triage nurses	Average triage time (mins)	Average registration time (mins)	Average ambulance treatment time (mins)	Average P1 treatment time (mins)	Average P2 treatment time (mins)	Average P3 treatment time (mins)	Number of patients whose LoS > 4 hours
2	7	6	3	4	4	21	23	18	10	170

Table 25: Suggestion 4 Values

By increasing the registration staff number by 1, 10 fewer patients wait more than 4 hours. This is equivalent to an improvement by 5.5555 % from the reference value of 180 patients. The makes for 680 patients waiting for more than 4 hours during this month, where the total attendances are 2267 patients. Overcrowding level, thus, goes down to 29.9955%.

5. **Decreasing the average treatment time of Priority 1 patients:**

Number of registration staff	Number of beds	Numbers of doctors	Number of triage nurses	Average triage time (mins)	Average registration time (mins)	Average ambulance treatment time (mins)	Average P1 treatment time (mins)	Average P2 treatment time (mins)	Average P3 treatment time (mins)	Number of patients whose LoS > 4 hours
2	7	6	3	5	4	21	22	18	10	150

Table 26: Suggestion 5 Values

By increasing the registration staff number by 1, 30 fewer patients wait more than 4 hours. This is equivalent to an improvement by 16.6666% from the reference value of 180 patients. The makes for 600 patients waiting for more than 4 hours during this month, where the total attendances are 2267 patients. Overcrowding level, thus, goes down to 26.4666%.

6. **Decreasing the average treatment time of Priority 2 patients:**

Number of registration staff	Number of beds	Numbers of doctors	Number of triage nurses	Average triage time (mins)	Average registration time (mins)	Average ambulance treatment time (mins)	Average P1 treatment time (mins)	Average P2 treatment time (mins)	Average P3 treatment time (mins)	Number of patients whose LoS > 4 hours
2	7	6	3	5	4	21	23	17	10	152

Table 27: Suggestion 6 Values

By increasing the registration staff number by 1, 28 fewer patients wait more than 4 hours. This is equivalent to an improvement by 15.5555% from the reference value of 180 patients. The makes for 608 patients waiting for more than 4 hours during this month, where the total attendances are 2267 patients. Overcrowding level, thus, goes down to 26.8195%.

5.2.3 Discussion

After examination of the data obtained by implementing any of the above suggestions, it is clear that the bottleneck in A&E is the number of doctors. All other changes could not massively impact the overcrowding level. Meanwhile, increasing the number of doctors by a mere increment dropped the overcrowding level from 31.3198% to 4.6017%, thus, allowing the A&E to satisfy its 95% standard.

5.3 Limitations

It is important to make note of the different limitations of this simulation in order for the evaluation to be sound and complete.

1. The simulation hugely depends on the input variables. Any incremental change in these values greatly skews the output. As a result, simulating Homerton A&E is only possible in this paper due to the somewhat realistic knowledge of this hospital's resources in terms of staffing, number of beds, and the different average durations.

2. In some hospitals, there are four levels of triage. This simulation takes into consideration only three of those levels. This may affect the simulation's ability to represent those A&E units that use the four-level triage standard.

3. Average triage time should be replaced by two separate input variables instead. This is because triage time varies by more than a couple of minutes depending on whether or not the nurse's initial assessment includes the recording of vital signs.

4. In purpose of making the simulation as general as possible to ensure representation of the included A&E units, the variables: average P1 treatment time, average P2 treatment time, and average P3 treatment time were integrated. However, this is not completely accurate as depending on the patient cases, the distribution of treatment times even within the same triage queue could greatly vary.

5. Also in terms of these three variables in the previous point, each of the average durations is assumed to include all the durations of any tests that need to be done in addition to any medical imaging requirements. This leaves the patient idle while the result of these tests or images are produced, during which the doctor is capable of examining other patients (in the case of bed availability). This fact may affect the accuracy of the simulation and the extent to which it resembles reality.

6. The simulation starts off with an empty initial state where the hospital is simulated as empty. This fast-tracks the process for the patients who arrive first on Monday post Sunday midnight. This is not realistic as there will be patients from the previous week still waiting and being treated at the A&E. The solution implemented to counter this inaccuracy was to have the simulation terminate after the last patient who arrives on Sunday is treated and his/her journey ends. Possibly more accurate solutions would be to run the simulation for more than just a week, where data starts getting recorded after a virtual week passes to best resemble reality.

6 Conclusion

In conclusion, simulations are used to identify improvements and understand how a certain facility works. They are capable of showing real variabilities, diminish usage and testing expenses, and help limit the risk of mistakes caused by the blind implementation. Agent-based modelling (ABM) is a class of such simulations which demonstrate the point of view of its constituent parts. Systems are displayed as a collection of agents [6]. These agents possess different properties, practices, and interactions that endeavour to capture real properties of people by being a “bottom-up” indicator of overall system level. Agents are both versatile and independent entities that are able to assess a situation, make decisions, content or participate with each other on the premise of a set of rules, and adjust future practices on the premise of past interactions [6]. The foundational premise and the theoretical profundity of ABM are that simple tenets of individual behaviour will join to form a complex or emergent phenomenon that is not particularly encoded by the modeller and that can't be anticipated or clarified by the agent level rules.

By using such simulation to model the A&E unit, we hoped to examine the problem of overcrowding within this department from the agent's perspectives and implement fixes that hope to solve this problem. Through research, we find that a multitude of factors is at play causing this increased overcrowding. These factors range from obvious demand growth, A&E resource efficiency, and budget cuts. The agent-based simulation discussed in this paper addresses the first and second factor whereby demand growth is estimated and positive effect of resource changes can be examined.

After implementing this simulation, we reach the following results. The simulation can be considered repeatable and somewhat accurate. It is capable of correctly modelling patient arrival models but less capable of correctly estimating the number of patients who wait for more than 4 hours. This is a key factor since it is the metric we use in order to measure overcrowding at the A&E. As a result, the performance of the simulation can be considered satisfactory. After that, different changes were suggested in order to combat the overcrowding problem, after which the effect of each suggestion was examined. We conclude that the best way to fight overcrowding and allow hospitals to meet their 95% rules is by increasing the number of doctors. Increasing this number by a mere increment resulted in an overcrowding level drop by more than twenty-five percentage points, as the doctors were deemed to be the bottleneck of the A&E process. The NHS invests around 102 million pounds a year in consultant salaries. If a portion of this spending could be directed towards PR improvement, the image of working at the NHS would improve. This would allow more doctors to apply for jobs at the NHS which really solves the overcrowding problem completely.

While using an ABM with real data serves to improve legitimacy and believability of the model and facilitates the understanding of the simulation results, ABMs do have some shortcomings [6]. These include vigorous approval and confirmation strategies which the ABM research community agrees upon. This difficulty is faced by most simulation models. Different troubles emerge from the test of creating precise models of agent behaviours and interactions, as well as data extracted from the systems being modelled [6]. In brief, the simulation’s accuracy in predicting effects of the change to simple actions is only as accurate as the data used to build the simulation in the first place.

Possibilities for future work on this simulation would be to address the six limitations discussed in the previous section as well as to fine tune the triage percentages and ambulance percentages, and factor in the separation between the children’s A&E section of the department. This split could result in major result changes and it would make the simulation a more valuable tool for real-life use.

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Appendix 1: Source Code

```
extensions [csv time]

globals [
  data
  selected-week
  nb-dead
  nb-admitted
  nb-discharged
  hospitals
  days
  time-multiplier
  week-to-day-probabilities
  walk-in-patients-to-spawn
  ambulance-patients-to-spawn
  triage-priorities
  hourly-week-rates
  walk-in-patient-spawn-times
  ambulance-patient-spawn-times
  max-wait-time
  nb-waited-more-than-four-hours
]  ; globals

breed [ doctors doctor ]
breed [ regs reg ]
breed [ nurses nurse ]
breed [ patients patient ]

nurses-own [
  available
  getting-patient
  the-patient
]

doctors-own [
 available
 getting-patient
 the-patient
]

patients-own [
  in-reception
  time-alive
  in-wait-room
  in-nurse-room
  in-triage-room
  in-doctor-room
  in-treatment-for-x-ticks
  outcome
  from-ambulance
  priority
]

to setup
```

```
clear-all

ask patches [set pcolor [187 221 226]]

setup-floor
setup-reception
setup-pathway
setup-nurses
setup-doctors
setup-beds

show-selected-week

set time-multiplier 60
set hourly-week-rates 0
set max-wait-time 0
set nb-waited-more-than-four-hours 0

set hospitals (list
  "Barking, Havering And Redbridge University Hospitals NHS Trust"
  "Barts Health NHS Trust"
  "Beckenham Beacon Ucc"
  "Central London Community Healthcare NHS Trust"
  "Chelsea And Westminster Hospital NHS Foundation Trust"
  "Croydon Health Services NHS Trust"
  "Edmonton GP Walk In Centre"
  "Epsom And St Helier University Hospitals NHS Trust"
  "Guy's And St Thomas' NHS Foundation Trust"
  "Harold Wood Walk In Centre"
  "Homerton University Hospital NHS Foundation Trust"
  "Hounslow And Richmond Community Healthcare NHS Trust"
  "Imperial College Healthcare NHS Trust"
  "King's College Hospital NHS Foundation Trust"
  "Kingston Hospital NHS Foundation Trust"
  "Lewisham And Greenwich NHS Trust"
  "London North West Healthcare NHS Trust"
  "Moorfields Eye Hospital NHS Foundation Trust"
  "North East London NHS Foundation Trust"
  "North Middlesex University Hospital NHS Trust"
  "Orchard Village Walk-In-Centre"
  "Royal Free London NHS Foundation Trust"
  "St Andrews Walk-In Centre"
  "St George's University Hospitals NHS Foundation Trust"
  "The Barkantine Practice"
  "The Hillingdon Hospitals NHS Foundation Trust"
  "The Junction Hc - Unregistered Patients"
  "The Ridgeway Surgery"
  "The Whittington Hospital NHS Trust"
  "University College London Hospitals NHS Foundation Trust"
  "Urgent Care Centre"
  "Waldron - Hurley Unregistered Practice"
 )

set days (list
  "Monday"
  "Tuesday"
```

```
    "Wednesday"
    "Thursday"
    "Friday"
    "Saturday"
    "Sunday"
  )

  set week-to-day-probabilities (list
    0.158
    0.145
    0.139
    0.138
    0.138
    0.139
    0.143
  )

  set triage-priorities (list
    0.344
    0.344
    0.311
  )

  read-hospital-files

  ; Outputs
  set nb-dead 0
  set nb-admitted 0
  set nb-discharged 0

  ; Shapes
  set-default-shape patients "person"
  set-default-shape nurses "person student"
  set-default-shape regs "person service"
  set-default-shape doctors "person doctor"

  reset-ticks
end

to setup-floor

  ask patches with [pycor > 6] with [pxcor > 2 and pxcor < 9] [set
pcolor [87 90 91]]

  ask patches with [pycor = 5 and pxcor > 2 and pxcor < 9] [set pcolor
[87 90 91]]

  ask patches with [pycor = 3 or pycor = 4] with [pxcor < -8 or (pxcor
> 2 and pxcor < 12) or pxcor > 14] [set pcolor [87 90 91]]

  ask patches with [pycor = 2] with [pxcor = -9 or (pxcor > 2 and
pxcor < 11) or pxcor = 16] [set pcolor [87 90 91]]

  ask patches with [pycor = 1 or pycor = 0 or pycor = -1] with [pxcor
= -9 or pxcor = 6 or pxcor = 7 or pxcor = 8 or pxcor = 9 or pxcor =
10 or pxcor = 14 or pxcor = 12 or pxcor = 16] [set pcolor [87 90 91]]
```

```
  ask patches with [pycor = -2] with [(pxcor > 5 and pxcor < 11) or
pxcor = 14 or pxcor = 12 or pxcor = 16] [set pcolor [87 90 91]]

  ask patches with [pycor = -3 or pycor = -4] with [pxcor = -9 or
(pxcor > 5 and pxcor < 11) or pxcor = 14 or pxcor = 12 or pxcor = 16]
[set pcolor [87 90 91]]

  ask patches with [pycor = -5 or pycor = -6] with [pxcor = -9 or
(pxcor > 2 and pxcor < 11) or pxcor = 14 or pxcor = 12 or pxcor = 16]
[set pcolor [87 90 91]]

  ask patches with [pycor = -7 or pycor = -8] with [pxcor < -8 or
pxcor > 2 and pxcor < 11 or pxcor = 14 or pxcor = 12 or pxcor = 16]
[set pcolor [87 90 91]]

  ask patches with [pycor = -9] with [pxcor < -15 or pxcor > 2 and
pxcor < 11 or pxcor = 14 or pxcor = 12 or pxcor = 16] [set pcolor [87
90 91]]

  ask patches with [pycor = -11 or pycor = -10] with [pxcor = 9 or
pxcor = 10 or pxcor = 14 or pxcor = 12 or pxcor = 16] [set pcolor [87
90 91]]

  ask patches with [pycor = -12] with [pxcor < -15 or pxcor = 9 or
pxcor = 10 or pxcor = 14 or pxcor = 12 or pxcor = 16] [set pcolor [87
90 91]]

  ask patches with [pycor = -13] with [pxcor < -8 or pxcor = 9 or
pxcor = 10 or pxcor = 14 or pxcor = 12 or pxcor = 16] [set pcolor [87
90 91]]

  ask patches with [pycor = -14] with [pxcor < -8 or pxcor = 14 or
pxcor = 12 or pxcor = 16] [set pcolor [87 90 91]]

end

to setup-reception
  create-regs 1 [set xcor 4 set ycor 0 set color black]
  create-regs 1 [set xcor 4 set ycor -2 set color black]
  create-regs 1 [set xcor 4 set ycor -4 set color black]
  ask patches with [pycor < 1 and pycor > -5] with [pxcor = 3] [set
pcolor [131 92 59]]
end

to setup-pathway
  ; entrance
  ask patches with [pycor = -10 and pxcor <= -1] [set pcolor [ 137
188 195 ] ]
  ask patches with [pxcor = -1 and pycor > -10 and pycor < 7] [set
pcolor [ 137 188 195 ] ]
  ask patch 0 -2 [set pcolor [ 137 188 195 ] ]
  ask patch 1 -2 [set pcolor [ 137 188 195 ] ]
  ask patch 2 -2 [set pcolor [ 137 188 195 ] ]

  ; exit
```

```
  ask patches with [pycor = -11 and pxcor <= 0] [set pcolor [204 207
207]]
  ask patches with [pxcor = 0 and pycor < -10] [set pcolor [204 207
207]]
  ask patches with [pxcor > 0 and pxcor < 12 and pycor = -14] [set
pcolor [204 207 207]]

  ; doctor
  ask patches with [pycor = 6 and pxcor > 0 and pxcor < 9] [set pcolor
[163 210 217]]

  ; nurse
  ask patches with [pxcor = -3 and pycor > -3 and pycor < 7] [set
pcolor [ 86 146 154 ]]
  ask patches with [pycor = -2 and pxcor < -3 and pxcor > -10] [set
pcolor [ 86 146 154 ]]

  ; ambulance
  ask patches with [pxcor = 5 and pycor > 9] [set pcolor [71 166 179]
]
  ask patches with [pycor = 9 and pxcor >= 5 and pxcor < 9] [set
pcolor [71 166 179] ]

  ; overcroud areas
  ask patches with [pxcor > 2 and pxcor < 9 and pycor < -9 and pycor
> -13] [set pcolor [209 237 241]]
  ask patches with [pxcor > -9 and pxcor < -4 and pycor < 5 and pycor
> -1] [set pcolor [209 237 241]]
  ask patches with [pxcor > -9 and pxcor < -1 and pycor < -12] [set
pcolor [209 237 241]]
  ask patches with [pxcor > -9 and pxcor < -4 and pycor < -3 and pycor
> -9] [set pcolor [209 237 241]]
  ask patches with [pxcor < -4 and (pycor = 5 or pycor = 6)] [set
pcolor [209 237 241]]
end

to setup-nurses
  let nbnurses nb-nurses
  loop [
   let x -16 + random 7
   let y -6 + random 9
   if not any? turtles-on patch x y [
      create-nurses 1 [
        set xcor x
        set ycor y
        set color [241 194 125]
        set getting-patient false
        set available true
        set heading 90
        set the-patient -1
      ]
      set nbnurses nbnurses - 1
      if nbnurses = 0 [stop]
    ]
  ]
end
```

```
to setup-doctors
  let nbdoctors nb-doctors
  loop [
   let x 9 + random 8
   let y 5 + random 10
   if not any? turtles-on patch x y [
      create-doctors 1 [
        set xcor x
        set ycor y
        set color black
        set getting-patient false
        set available true
        set the-patient -1
        set heading 270
      ]
      set nbdoctors nbdoctors - 1
      if nbdoctors = 0 [stop]
    ]
  ]
end

to setup-beds
  let j 14
  let nbbeds nb-beds
  while [ j > 4 and nbbeds > 0] [
    let i 16
    while [ i > 8 and nbbeds > 0 ] [
      if j mod 2 = 0 and i mod 2 = 0 [
        ask patch i j [set pcolor white]
        set nbbeds nbbeds - 1
      ]
      if j mod 2 = 1 and i mod 2 = 1 [
        ask patch i j [set pcolor white]
        set nbbeds nbbeds - 1
      ]
      set i i - 1
    ]
    set j j - 1
  ]
end

; End setup

to go
  spawn-patient
  spawn-ambulance-patient
  move-nurses
  patients-go-forward
  ambulance-patients-go-forward
  nurse-patient
  move-doctors
  doc-patient
  exit-patients
  if ticks >= 604800 and ambulance-patients-to-spawn = 0 and walk-in-
patients-to-spawn = 0 and count patients = 0 [
```

```
    stop
  ]
  tick
end

to spawn-patient
  if walk-in-patients-to-spawn > 0 and position ticks walk-in-patient-
spawn-times != false [
    create-patients 1 [
      set color black
      set xcor -15
      set ycor -10
      set heading 90
      set in-reception false
      set time-alive 0
      set in-wait-room false
      set in-nurse-room false
      set in-triage-room false
      set in-doctor-room false
      set outcome 0
      set in-treatment-for-x-ticks avg-regis-time * time-multiplier
      set from-ambulance false
    ]
    set walk-in-patients-to-spawn walk-in-patients-to-spawn - 1
  ]
end

to spawn-ambulance-patient
  if ambulance-patients-to-spawn > 0 and position ticks ambulance-
patient-spawn-times != false [
    create-patients 1 [
      set color pink
      set xcor 5
      set ycor 14
      set heading 180
      set in-reception false
      set time-alive 0
      set in-wait-room false
      set in-nurse-room false
      set in-triage-room false
      set in-doctor-room false
      set outcome 0
      set from-ambulance true
      set priority 0
    ]
    set ambulance-patients-to-spawn ambulance-patients-to-spawn - 1
  ]
end

to move-nurses
  if any? nurses with [available] [
    if any? patients with [in-wait-room] [
      let nursepatient -1
      ask max-one-of patients with [in-wait-room] [time-alive] [
        move-to patch -3 6
        set in-wait-room false
```

```
        set nursepatient self
      ]
      ask one-of nurses with [available] [
        set getting-patient true
        set available false
        set the-patient nursepatient
      ]
    ]
  ]
  ask nurses with [getting-patient] [
    nurse-get-patient self
  ]
end

to nurse-get-patient [moving-nurse]
  if-else xcor < -9
    [
      set xcor -9
      set ycor -2
    ]
    [
      let nursexcor xcor
      let nurseycor ycor
      if heading = 90 [
        if-else  xcor < -3 [
          fd 1
        ][
          set heading 0
        ]
      ]
      if heading = 0 [
        if-else ycor = 5 [
          set heading 180
          ask the-patient [set heading 180]
        ][
          fd 1
        ]
      ]
      if heading = 180 [
        if-else ycor = -2 [
          set heading 270
        ] [
          ask the-patient [fd 1]
          fd 1
        ]
      ]
      if heading = 270 and xcor > -10 [
        if-else xcor = -9 [
          set getting-patient false
          set-nurse-and-patient self
        ][
          fd 1
          ask the-patient [if ycor = -2 [set heading 270] fd 1]
       ]
      ]
    ]
```

```
end

to set-nurse-and-patient [the-nurse]
  let i -16
  let moved false
  while [ i < -9 and not moved] [
    let j -6
    while [ j < 3 and not moved ] [
      if not any? patients-on patch i j [
        ask [the-patient] of the-nurse [set xcor i set ycor j set in-
wait-room false set in-nurse-room true set in-treatment-for-x-ticks
avg-triage-time * time-multiplier]
        ask the-nurse [set xcor i + 1 set ycor j]
        set moved true
      ]
      set j j + 1
    ]
    set i i + 2
  ]
end

to patients-go-forward
  ask patients with [from-ambulance = false] [
    set time-alive time-alive + 1
    if pcolor = [ 137 188 195 ]  [
        if pxcor = -1 and pycor = -10 [
          set heading 0
        ]
        if pycor = -2 and pxcor = -1 and count patients with [in-
reception] < nb-regis-staff [
          set in-reception true
        ]
        if pxcor = -1 and in-reception [
          if-else heading = 270
            [set heading 0 set in-reception false]
            [set heading 90]
        ]
        if pxcor = 2 [
          if in-treatment-for-x-ticks > 0 [
            set in-treatment-for-x-ticks in-treatment-for-x-ticks - 1
          ]
          if in-treatment-for-x-ticks = 0 [
            set heading 270
          ]
        ]

        if in-reception and not (pxcor = 2 and in-treatment-for-x-
ticks > 0) [
          fd 1
        ]
        if not in-reception [
          if-else ycor = -3 [
            if count patients with [in-reception] < nb-regis-staff [
              fd 1
            ]
          ][
```

```
            if not any? turtles-on patch-ahead 1 [fd 1]
          ]
        ]
    ]
    if pxcor = -1 and pycor = 7 [
      move-to-first-free-spot self
      set in-wait-room true
    ]
  ]
end

to ambulance-patients-go-forward
  ask patients with [from-ambulance = true] [
    set time-alive time-alive + 1
    if pcolor = [71 166 179] [
      if pxcor = 5 and pycor = 9 [
        set heading 90
      ]
      if pxcor = 7 and pycor = 9 [
        set in-triage-room true
      ]
      if pxcor != 8 or pycor != 9 and not any? turtles-on patch-ahead
1 [
        fd 1
      ]
    ]
  ]
end

to move-to-first-free-spot [agent]
  let i -16
  let moved false
  while [ i < -4 and not moved] [
    let j 14
    while [ j > 6 and not moved ] [
      if not any? turtles-on patch i j [
        ask agent [move-to patch i j]
        set moved true
      ]
      set j j - 1
    ]
    set i i + 1
  ]
  if not moved [
    move-to-random-crowded-spot agent
  ]
end

to nurse-patient
  ask patients with [in-nurse-room] [
    if-else in-treatment-for-x-ticks > 0
      [ set in-treatment-for-x-ticks in-treatment-for-x-ticks - 1 ]
      [
        let x random-float 1

        if-else x <= item 0 triage-priorities [
```

```
          set color red
          set priority 1
        ][
          if-else x <= item 0 triage-priorities + item 1 triage-
priorities [
            set color yellow
            set priority 2
          ][
            set color green
            set priority 3
          ]
        ]

        set in-nurse-room false
        let patientx xcor
        let patienty ycor
        ask one-of nurses with [available = false and pxcor = patientx
+ 1 and pycor = patienty] [set available true set heading 90]
        move-to-first-free-post-triage-spot self
        set in-triage-room true
      ]
  ]
end

to move-to-first-free-post-triage-spot [agent]
  let j 14
  let moved false
  while [ j > 7 and not moved] [
    let i 2
    while [ i > -4 and not moved ] [
      if not any? turtles-on patch i j [
        ask agent [move-to patch i j ]
        set moved true
      ]
      set i i - 1
    ]
    set j j - 1
  ]
  if not moved [
    move-to-random-crowded-spot agent
  ]
end

to move-doctors
;  print list count doctors with [available or getting-patient] count
patients-on patches with [pcolor = white]
  if count doctors with [getting-patient] + count patients-on patches
with [pcolor = white] < nb-beds [
    if any? doctors with [available] [
      if any? patients with [in-triage-room] [
        let docpatient -1

        let pinkpatients count patients with [in-triage-room and color
= pink]
        let redpatients count patients with [in-triage-room and color
= red]
```

```
        let yellowpatients count patients with [in-triage-room and
color = yellow]
        let greenpatients count patients with [in-triage-room and
color = green]


        if-else pinkpatients > 0 [
          ask max-one-of patients with [in-triage-room and color =
pink] [time-alive] [
            move-to patch 1 6
            set in-triage-room false
            set docpatient self
          ]
        ] [
          if-else redpatients > 0 [
            ask max-one-of patients with [in-triage-room and color =
red] [time-alive] [
              move-to patch 1 6
              set in-triage-room false
              set docpatient self
            ]
          ] [
            if-else yellowpatients > 0 [
              ask max-one-of patients with [in-triage-room and color
= yellow] [time-alive] [
                move-to patch 1 6
                set in-triage-room false
                set docpatient self
              ]
            ] [
              ask max-one-of patients with [in-triage-room and color
= green] [time-alive] [
                move-to patch 1 6
                set in-triage-room false
                set docpatient self
              ]
            ]
          ]
        ]

        ask one-of doctors with [available] [
          set getting-patient true
          set available false
          set the-patient docpatient
        ]
      ]
    ]
  ]
  ask doctors with [getting-patient] [
    doc-get-patient self
  ]
end

to doc-get-patient [moving-doc]
  if-else xcor > 8
    [
```

```
      set xcor 8
      set ycor 6
    ]
    [
      let docxcor xcor
      let docycor ycor
      if heading = 270 [
          fd 1
      ]
      if heading = 90 [
        if-else xcor = 8 [
          set getting-patient false
          set-doctor-and-patient self
        ][
          fd 1
          ask the-patient [fd 1]
        ]
      ]
      if xcor = 2 [
        set heading 90
        ask the-patient [set heading 90]
      ]
    ]
end

to set-doctor-and-patient [the-doctor]
  let j 14
  let moved false
  while [ j > 4 and not moved] [
    let i 16
    while [ i > 8 and not moved ] [
      if not any? patients-on patch i j [
        if j mod 2 = 0 and i mod 2 = 0 [

          ask [the-patient] of the-doctor [
            set xcor i set ycor j set in-triage-room false set in-
doctor-room   true   set   in-treatment-for-x-ticks   (report-agent-
treatment-time [the-patient] of the-doctor)
          ]
          ask the-doctor [set xcor i - 1 set ycor j]
          set moved true
        ]
        if j mod 2 = 1 and i mod 2 = 1 [
          ask [the-patient] of the-doctor [
            set xcor i set ycor j set in-triage-room false set in-
doctor-room   true   set   in-treatment-for-x-ticks   (report-agent-
treatment-time [the-patient] of the-doctor)
          ]
          ask the-doctor [set xcor i + 1 set ycor j]
          set moved true
        ]
      ]
      set i i - 1
    ]
    set j j - 1
  ]
```

```
end

to doc-patient
  ask patients with [in-doctor-room] [
    if-else in-treatment-for-x-ticks > 0
      [ set in-treatment-for-x-ticks in-treatment-for-x-ticks - 1 ]
      [
        let x random-float 1
        let docx xcor
        let docy ycor

        if-else x <= discharge-percent [
          set outcome 1
          set xcor 12
          set ycor 4
        ][
          if-else x <= discharge-percent + admit-percent [
            set outcome 2
            set xcor 13
            set ycor 4
          ][
            set outcome 3
            set xcor 14
            set ycor 4
          ]
        ]

        set heading 180
        set color black
        set in-doctor-room false
        if-else docy mod 2 = 0 [set docx docx - 1] [set docx docx +
1]
        ask one-of doctors with [available = false and pxcor = docx
and pycor = docy] [set available true set heading 270]
      ]
  ]
end

to exit-patients
  ask patients with [(outcome > 1 and ycor = -14) or (outcome = 1 and
xcor = -16)] [
    if outcome = 1 [
      set nb-discharged nb-discharged + 1
    ]
    if outcome = 2 [
      set nb-admitted nb-admitted + 1
    ]
    if outcome = 3 [
      set nb-dead nb-dead + 1
    ]
    set max-wait-time max list max-wait-time time-alive
    if time-alive > 14400 [
     set   nb-waited-more-than-four-hours   nb-waited-more-than-four-
hours + 1
     file-open "output-time-alive.csv"
     file-print time-alive
```

```
      file-close
      file-open "output-priority.csv"
      if priority = 0 [
        file-print "Ambulance"
      ]
      if priority = 1 [
        file-print "Priority 1"
      ]
      if priority = 2 [
        file-print "Priotiy 2"
      ]
      if priority = 3 [
        file-print "Priority 3"
      ]
      file-close
     ]
     die
   ]
   ask patients with [outcome = 1] [
     if ycor = 2 [
       set heading 270
     ]
     if xcor = 11 [
       set heading 180
     ]
     if ycor = -14 [
       set heading 270
     ]
     if xcor = 0 and ycor = -14 [
        set heading 0
     ]
     if xcor = 0 and ycor = -11 [
        set heading 270
     ]
     fd 1
   ]
   ask patients with [outcome = 2] [
     fd 1
   ]
   ask patients with [outcome = 3] [
     if ycor = 2 [
       set heading 90
     ]
     if xcor = 15 [
       set heading 180
     ]
     fd 1
   ]
end


;; File Processing

; 5 row format
; 12 columns 1 for each months
; 1st row attendance
```

```
; 2nd row more than 4 hours wait time
; 3rd row % discharged
; 4th row % admitted
; 5th row % dead
to read-hospital-files
  file-open "yearly-data.csv"
  let yearresult (list)
  while [ not file-at-end? ] [
    let i 0
    let monthresult (list csv:from-row file-read-line)
    while [i < 4] [
      let row csv:from-row file-read-line
      set monthresult lput row monthresult
      set i i + 1
    ]
    set yearresult lput monthresult yearresult
    set i 0
  ]
  file-close
  set data yearresult

  file-open "weekly-data.csv"
  let i 0
  let row 0
  while [ not file-at-end? and i <= hospital-index] [
    set row csv:from-row file-read-line
    set i i + 1
  ]
  file-close
  let weeklypatients item (week - 1) row

  let nb-patients-by-day (list round (weeklypatients * (item 0 week-
to-day-probabilities)))
  set nb-patients-by-day lput round (weeklypatients * (item 1 week-
to-day-probabilities)) nb-patients-by-day
  set nb-patients-by-day lput round (weeklypatients * (item 2 week-
to-day-probabilities)) nb-patients-by-day
  set nb-patients-by-day lput round (weeklypatients * (item 3 week-
to-day-probabilities)) nb-patients-by-day
  set nb-patients-by-day lput round (weeklypatients * (item 4 week-
to-day-probabilities)) nb-patients-by-day
  set nb-patients-by-day lput round (weeklypatients * (item 5 week-
to-day-probabilities)) nb-patients-by-day
  set nb-patients-by-day lput round (weeklypatients * (item 6 week-
to-day-probabilities)) nb-patients-by-day

  file-open "hourly-data.csv"
  set i 0
  let walk-in-patients-hourly (list)
  let ambulance-patients-hourly (list)
  while [ not file-at-end?] [
    set hourly-week-rates csv:from-row file-read-line
    set walk-in-patients-hourly sentence walk-in-patients-hourly map
[[hourly-week-rate] -> round (hourly-week-rate * item i nb-patients-
by-day * 0.77) ] hourly-week-rates
```

```
    set ambulance-patients-hourly sentence ambulance-patients-hourly
map [[hourly-week-rate] -> round (hourly-week-rate * item i nb-
patients-by-day * 0.23) ] hourly-week-rates
    set i i + 1
  ]
  file-close

  set walk-in-patient-spawn-times remove-duplicates (spawntimes walk-
in-patients-hourly)
  set ambulance-patient-spawn-times remove-duplicates (spawntimes
ambulance-patients-hourly)
  set walk-in-patients-to-spawn length walk-in-patient-spawn-times
  set ambulance-patients-to-spawn length ambulance-patient-spawn-
times
end

to-report death-percent
  let hospitaldata item hospital-index data
  let deathdata item 4 hospitaldata
  let monthindex time:get "month" time:plus selected-week 6 "days"
  ifelse monthindex < 4 [
    set monthindex monthindex + 9
  ] [
    set monthindex monthindex - 4
  ]
  report item monthindex deathdata
end

to-report admit-percent
  let hospitaldata item hospital-index data
  let admitdata item 3 hospitaldata
  let monthindex time:get "month" time:plus selected-week 6 "days"
  ifelse monthindex < 4 [
    set monthindex monthindex + 9
  ] [
    set monthindex monthindex - 4
  ]
  report item monthindex admitdata
end

to-report discharge-percent
  let hospitaldata item hospital-index data
  let dischargedata item 2 hospitaldata
  let monthindex time:get "month" time:plus selected-week 6 "days"
  ifelse monthindex < 4 [
    set monthindex monthindex + 9
  ] [
    set monthindex monthindex - 4
  ]
  report item monthindex dischargedata
end

; Util methods

to-report hospital-index
  report position hospital hospitals
```

```
end

; show selected week indicator
to show-selected-week
    set selected-week time:plus time:create "2016/3/28" (week - 1)
"weeks"
end

to-report spawntimes [patientsbyhour]
  ; list format number of patients in each hour
  let j 0
  let spawntimeslist (list)
  foreach patientsbyhour [
    [x] ->
      let i x
      while [i > 0] [
        set spawntimeslist lput (j * 3600 + random 3600)
spawntimeslist
        set i i - 1
      ]
      set j j + 1
  ]
  report sort spawntimeslist
end

to move-to-random-crowded-spot [agent]
  ask one-of patches with [pcolor = [209 237 241]] [
    let redpxcor pxcor
    let redpycor pycor
    ask agent [move-to patch redpxcor redpycor]
  ]
end

to-report report-agent-treatment-time [p]
  if [color] of p = pink [
    report avg-ambulance-treatment-time * time-multiplier
  ]
  if [color] of p = red [
    report avg-priority-1-treatment-time * time-multiplier
  ]
  if [color] of p = yellow [
    report avg-priority-2-treatment-time * time-multiplier
  ]
   if [color] of p = green [
    report avg-priority-3-treatment-time * time-multiplier
  ]
end
```