Optimising Scheduling for Computed Tomography Imaging in a Healthcare Setting Using Discrete Event Simulation

MSc Research Project
Masters of Science in Data Analytics

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MSc Project Submission Sheet

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Optimising Scheduling for Computed Tomography Imaging in a Healthcare Setting Using Discrete Event Simulation

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Abstract

One of the big challenges facing the Irish healthcare system is managing the dramatic increase in the quantity and cost of radiological imaging. Waiting lists are predicted to soar as patient care becomes increasingly complex, and new imaging modalities are being developed and utilised. Discrete Event Simulation is a simulation technique that is used to model and test different scenarios in a virtual environment, to enhance real world decisions. This paper proposes a simulation model that will emulate a radiology department where patients are attending for their scheduled investigations. The model is created using domain-specific-knowledge, with many accurate features as well as incorporating stochastic processes, to best represent a real-life department. By analysing key patient flow factors, such as inter-arrival time and resource utilisation, insights are revealed into scheduling bottlenecks, which can then be addressed to improve the overall efficiency. This model will allow radiology departments to better inform their resource allocation, to increase their departments productivity and enhance patient care.

Keywords: Radiology, Computed Tomography, Discrete Event Simulation, Simulation, Operations Research, Ireland, Python

1 Introduction

Ensuring affordable and comprehensive healthcare for an ageing demographic is one of the most significant challenges that Ireland faces in the coming decades. The prevailing healthcare framework exhibits numerous deficiencies, most notably the prolonged outpatient waiting times and inpatient services stretched beyond their capacities. One area with increasing demands is that of radiology, the speciality of medicine that uses imaging technology to diagnose and treat disease.

Since its inception, radiology has benefitted immensely from real world advancements in physics and engineering, and has often been at the forefront of medical innovation, facilitating advancements in patient care. It has transformed significantly in the past 30 years and patients are more reliant on the speciality than ever before. Today, clinicians are leveraging advanced diagnostic tools like MRI, CT, and PET scans with increasing frequency. For example, a mere joint injury in orthopaedics can now require multiple MRI sequences. Furthermore, the sophistication of newer imaging techniques has added layers of complexity. Techniques like functional MRI (fMRI) and whole-body diffusion-weighted imaging not only provide a detailed view of the body but also require more extended imaging times due to their complexities. And with further imaging, arise further incidental findings in patients. For example, a cardiac CT could reveal not just cardiac irregularities but also suspicious findings in organs like the lungs or kidneys, which may require further imaging to investigate.

What occurs is that advanced imaging techniques become mandated by guideline directed care, with subsequent imaging demands and healthcare costs escalating, inflating healthcare expenses and leading to delays and waitlists for patients.

However, a beacon of hope lies in integrating artificial intelligence (AI) and machine learning (ML) into healthcare. These technologies are revolutionizing medical fields, especially radiology. The most recognised application is in swiftly navigating vast data produced by modern imaging techniques, making the diagnostic process streamlined. ML and AI assist in recognizing and categorizing anomalies in images with increased precision. However, there is also immense value in the role of operations research, in simulating and analysing current patient care pathways, to optimise them and better deliver patient care. Adopting these innovative methods can bolster resource efficiency by allowing healthcare professionals to spend less time on administrative duties and more on direct patient interactions. Providing high quality patient care depends just as much on efficient resource allocation as prescribing specialized drugs or surgery. Recognizing the pivotal role of radiology and the escalating pressures it faces, it's prudent to focus data science techniques on enhancing this sector of healthcare. Discrete event simulation (DES) is emerging as a significant tool for medical operations. DES, a computer-based modelling technique, mirrors real-world system operations over time. Instead of focusing on image data, it emphasizes workflows, patient flow, and resource allocation, making it exceptionally pertinent in healthcare settings. DES could help determine the optimal resource allocation to cater to patient demand, minimizing wait times while ensuring maximum equipment usage. By simulating various scenarios, healthcare professionals can foresee potential bottlenecks, evaluate the impact of different interventions, and develop strategies to improve service delivery and patient experience. Radiology departments are the nexus of diagnostic processes in healthcare. Efficient scheduling and queuing within these departments can ripple across the healthcare system, benefiting not only the patients but also the broader populace. For example, efficient scheduling can drastically trim waiting periods, ensuring patients receive radiological services swiftly. Prompt care can alleviate anxiety, leading to quicker diagnosis and treatment. Embracing advanced queuing and scheduling algorithms in radiology is not merely an operational enhancement; it redefines the patient experience, empowers healthcare practitioners, and benefits the overall healthcare ecosystem.

Radiology departments are characterized by multiple intertwined processes, each with its unique parameters and constraints. In Ireland, factors such as departmental sizes, patient demographics, and local disease prevalence can vary greatly, necessitating an approach that is both flexible and contextualized. The genius of DES lies in its capability to model these unique attributes in a virtual environment, accounting for many of the local nuances in delivering care. Beyond mere scheduling, DES brings a holistic approach. For instance, consider the diverse and often unpredictable Irish weather. On a day with extreme weather conditions, there might be increased patient drop-outs. A DES model can factor in these external variables, offering insights into optimal scheduling during such days or periods. In all healthcare analyses, it is important to have the proper environmental understanding and context, as the local factors are often the most critical elements for success. This paper shall be informed by the authors own clinical experience across multiple radiology departments in Ireland, and therefore be best placed to model an Irish radiology departmental setting and shall pertain to the challenges and nuances Irish clinicians and managers are likely to encounter in a resource constrained radiology department.

The paper will address this central research question:

- To what extent can a Discrete Event Simulation model, informed by domain specific knowledge in Irish healthcare systems, identify the key factors in patient flow through an Irish hospital's CT pathway?

There are several sub-questions to complement the overall objective:

- Can a model be created that adequately captures the complexity of healthcare delivery, yet does not lose interpretability?

- How can a DES model be utilized in the day to day allocation of resources and planning, for example if a radiographer was sick, or a CT scanner required maintenance?

- What role can DES play in overall hospital planning, such as in critical incident planning or in long term infection control planning?

In essence, this paper offers a comprehensive DES model tailored for optimizing CT scanner scheduling. Such a model, rooted in domain-specific knowledge and tailored to Irish clinical realities, holds transformative potential. The subsequent sections will explore previous works, domain-specific knowledge used, and the structure, design, and evaluation of the model. Through this paper, the aspiration is to provide a blueprint, a model that radiology departments across Ireland can emulate, ensuring patient-centric, resource-optimized care.

2 Related Work

Medical professionals and hospital administrators are increasingly acknowledging the potential of data-driven solutions to enhance patient care quality and efficiency. Consequently, research in this domain is burgeoning. This literature review examines those recent or seminal publications within the domain of DES in clinical settings. The objective of this review is to identify potential challenges and knowledge gaps to best inform the proposed model. Primarily, this review emphasizes the practical application research regarding DES in real-world clinical settings.

A. **An Overview of the literature**

The article by Liu et al in 2020 provided an excellent starting point to explore the usage of discrete event simulation in health services and health care management, with publications reviewed from 1981 to 2014 (Liu et al., 2020). Analysing 483 journal papers from 230 journals, the study identified the growth trends and reasons for DES's adoption in the healthcare sector. The paper implies that up until recent years, DES has been underutilised in the healthcare setting, with a recent surge in interest in the past 10 years. The review highlighted various challenges like the need for operational research techniques in health programs and the difficulty in validating DES models. Despite these research limitations, the paper concludes that the growing popularity of DES will continue.

Another informative literature review on DES in healthcare settings was published in 2021 by Vázquez-Serrano et al (Vázquez-Serrano et al., 2021). The study systematically analysed 231 academic papers, revealing that nearly two-thirds combined DES with other analytical tools like optimization and process methodologies like 'Six Sigma'. The majority of applications were in emergency departments, aiming to enhance efficiency metrics, with Arena and Simul8 emerging as popular DES software. Interestingly, while DES's role in healthcare has grown, with 40% of the papers published in the past three years, less than 10% showcase real-world implementations following the modelling phase. This paper highlights the necessity for proper model formulation and the critical involvement of healthcare stakeholders for successful adoption. Notably, while the US, UK, and Canada lead in DES healthcare publications, the study emphasizes the global relevance and adaptability of this approach. The key takeaway point from this paper's model will be to acknowledge the complexities inherent in healthcare modelling, and to recognise the nuanced interactions between stakeholders, resources, and patient outcomes. This review also highlights the need for a clinical translation post design, which this model aspires to achieve.

Zhang in 2018 conducted a systematic review on the application of Discrete Event Simulation (DES) in health care decision making (Zhang, 2018). Analysing publications over two decades, the review encapsulated 211 articles and identified a surge in DES papers post-2010. The study sorted DES applications into four distinct categories: health and care systems operation (HCSO) at 65%, disease progression modelling (DPM) at 28%, screening modelling (SM) at 5%, and health behaviour modelling (HBM) at 2%. Interestingly, while HCSO dominated DES applications, there has been a notable trend towards modelling more integrated health systems. What comes through in this paper are the strengths of DES over other models like Markov models and decision trees, where DES's adaptability for complex health scenarios and its flexibility shine. This review suggests a growing embrace of DES in health care management and showcases its potential, especially in health system operations and economic evaluations. This is an important point, and this paper shall also discuss the important economic implications that arise from this proposal's model.

B. **Clinical Applications of DES**

In a recent study from 2018, Luo proposed a discrete event simulation (DES) approach to manage the scheduling of radiology patients in a hospital setting, particularly focusing on the radiology department in West China Hospital (Luo et al., 2018). Using operations research models, they developed an emergency reservation policy that considers both regular and emergency patients. The analysis revealed that by reserving capacity for emergency patients, there was an impressive 43.9% reduction in wait times for non-emergency patients, albeit with a slight decrease in equipment utilization. Interestingly, the comparison between various reservation policies found them to be quite robust, exhibiting negligible differences in patients' waiting times. Despite the positive findings, the study had some limitations, such as not accounting for patient behaviours like no-shows and basing the model on a single CT scanner's patient process. The study underscores the efficacy of DES in optimizing hospital resource utilization and can pave the way for further improvements in healthcare scheduling systems. One learning point from this research was the complexities of patient journeys in healthcare, and designing a system to facilitate these journeys. In contrast to Luo’s paper, the proposed model will test a variety of resource constraints.

What is evident from the literature is that many data scientists use off the shelf products to assist in their simulations. Johnston et al published in 2009 on using the Tecnomatix Plant Simulation® software to simulate patient flow and scheduling practices in a radiology department in an Australian public hospital (Johnston et al., 2009). Through visual displays, the model effectively illustrated the complex interactions between hospital departments. Data, collected over three months, was sourced from hospital records and direct observations, and was then validated through staff interviews. While the simulation demonstrated the potential to enhance patient flow by varying parameters like booking timeslot duration and staff resources, it was met with some challenges. The model's limitations included incomplete data sets, potential omissions of key parameters, and the software's manufacturing-centric nature which may not fully align with certain medical environments. Nevertheless, the visually simulated processes became a valuable tool for hospital staff, revealing inefficiencies and providing a concrete basis for suggesting changes. Findings such as these inspire this paper’s future work, which will be to design a Graphic User Interface (GUI) through Python, to reap the visualisation benefits.

Maass et al. in 2023 investigated the application of a discrete event simulation (DES) to evaluate the influence of radiology procedural adjustments on computed tomography (CT) access times in the emergency department (ED) of a large academic medical centre (Maass et al., 2021). The research acknowledged the intrinsic limitations of simulations in capturing every nuance of real-life procedures. Moreover, while the study highlighted operational enhancements, it emphasized the need for individual institutions to gauge the applicability of these interventions based on their unique processes and patient flow definitions. The research stands out for its innovative use of DES in pre-emptively assessing the impacts of operational changes in a setting with multiple CT machines and diverse patient categories. Notably, the insights derived from this research have been realized in actual practice, underscoring its practical value.

Baril et al. in 2014 delved into optimizing the performance of an outpatient orthopaedic clinic by investigating the interplay between patient flows, resource capacities, and appointment scheduling rules (Baril et al., 2014). By utilizing discrete event simulation, the study modelled patient flows within the clinic and tested various assignment strategies for doctors and nurses in conjunction with different scheduling rules and patient flow complexities. The findings suggest that by altering appointment scheduling rules tailored to specific patient flow types, there is potential for a significant reduction in patient lead time without affecting the clinical staff’s workload or the number of patients seen. Interestingly, the clinic under study could efficiently operate with fewer consulting rooms, allowing room for more orthopaedists, albeit requiring more nurses to maintain the desired performance level. Moreover, the authors emphasized the potential benefits of considering different patient flow types for scheduling, underscoring that the clinical workload can vary significantly on a weekly basis. Similar to previous studies, the proposed DES model doesn’t account for human factors such as punctuality. In contrast, this paper’s proposed model shall incorporate elements of uncertainty and unpredictable events, expected in a radiology department.

Booker et al in 2015 delves into the transformative potential of discrete event simulation (DES) in enhancing the quality and processes within radiology (Booker et al., 2016). Emphasizing its proficiency in refining radiology workflows, the article provides a foundational guide on DES modelling, specifically tailored to medical imaging. The authors present a pragmatic approach to adopt a DES software package and introduces three illustrative radiology scenarios. One of these scenarios (Hours Versus Equipment) illustrates a common challenge of determining whether to extend operational hours or add another scanner to cater to increased outpatient business, highlighting the nuance in making capacity decisions. The article subtly champions the importance of simulations in enabling informed decisions, while acknowledging that the real-world dynamics of healthcare have an inherent uncertainty. Similar to Johnson et al, Booker et al also used an off-the-shelf product, the popular program ‘Simul8’, to design their model. The key finding is that DES as an underutilized tool that, when adeptly employed in a radiology department, can enhance patient flow, with both administrative and financial benefits.

In a study by Shakoor et al, the authors address the challenges facing a specific radiology department in a public hospital, using the Discrete Event Simulation (DES) technique to assess and improve its performance (Shakoor et al., 2017). Utilizing the Arena simulation program, data from over a year was gathered and evaluated to determine the efficacy and capacity of the MRI radiology division. One of the main outcomes suggested the inclusion of two more MRI scanning machines, making the total to three, as this emerged as the optimal scenario to significantly reduce waiting times and improve service quality. Despite these advancements, the study acknowledges its limitations, primarily the challenges tied to data quality, and the lack of a precise statistical distribution for patient arrival rates, and processing times. These ideas surrounding distributions and sampling better inform this paper’s proposed model, which seeks to be as accurate as possible.

Lim et al. in 2013 investigated the interactions between physicians and their delegates in an emergency department (ED) using a discrete event simulation (DES) modelling approach (Lim et al., 2013). In contrast to the typical patient-driven models where physicians mainly interact with patients, this study introduced an "interacting pseudo-agent" approach. This approach, validated using data from an Ontario hospital, represented physicians and delegates as entities with embedded decision logic that interact, reflecting their hierarchical roles in the ED. It found that the interaction between physicians and delegates resulted in longer ED stays and increased waiting times for beds. The study highlighted the importance of accurately modelling these interactions for optimal staff scheduling and resource allocation in the ED. A few limitations were noted, such as the omission of the entire patient flow and potential variations in patient routing. The study suggests future DES models in the ED should include physician-delegate interactions using the pseudo-agent approach for a more realistic representation of the ED environment. However, compared to an ED, entities in a radiology department would typically have less interactions, and there would be a less hierarchical nature.

In 2007, Coelli et al. published a highly influential paper which showcased a discrete-event simulation (DES) model based in a mammography clinic, specifically focusing on the patient flow (Coelli et al., 2007). Drawing inspiration from an existing public-sector clinic at the Brazilian Cancer Institute in Rio de Janeiro, the authors created two simulation models covering seven configurations, taking into account variations in patient arrival rates, equipment units, available personnel, equipment maintenance schedules, and exam repeat rates. Several key take home points about designing a DES model can be drawn from this paper. The paper demonstrates the importance of empirical validation in DES: the configuration closely representing the actual clinic matched well with historical data. An important observation was the clear limit to which adding more technicians or equipment units resulted in diminishing returns, indicating that there's an optimal configuration for efficiency. However, the paper also highlighted that implementing the results of such a study can be contingent on practical constraints, like infrastructure and human resource changes. Lastly, the paper suggests that real-world demand often varies from a clinic's actual capacity, emphasizing the importance of flexibility in designing healthcare systems. The major learning point for this proposed model is the complexity of representing real-world variability in healthcare simulations. It will be worth bearing in mind how small changes in patient flow, staffing, or equipment can have significant effects on the radiology department’s flow and efficiency.

A seminal paper in Annals of Emergency Medicine, Hoot et al. in 2008 presented a study where a DES model was developed specifically to predict patient flow and improve efficiency throughout an emergency department (Hoot et al., 2008). This DES model, termed "ForecastED", aimed to articulate ED crowding in terms of individual patients and their attributes, to forecast patient flow, and historical patient data was used to create theoretical distributions governing these patterns. The paper demonstrated a model with good results in predicting ED operational measures up to 8 hours into the future. Delving into the design intricacies of DES illustrated in this paper, several insights emerge. The study underscores the essence of focusing the simulation on individual patients and their specific characteristics, rather than solely relying on operational attributes. By doing so, the DES can produce a more refined and nuanced forecast. Despite its innovative approach, the study admits the focused scope of ForecastED, which was built exclusively for forecasting near-term operational metrics. This implies that while the simulation excels in its intended purpose, its application for other common simulation uses could be limited, which is reminiscent of the challenge in the healthcare sector where patients' journeys are multifaceted and non-linear. The key inspirations from this highly regarded paper were the importance of clearly defining the scope and objectives for a DES model.

Comas et al. in 2014 utilized a DES model to analyse the budgetary consequences of transitioning from screen-film mammography to full-field digital mammography in a population-based breast cancer screening program (Comas et al., 2014). This DES approach uniquely catered to women aged 50-69 years and started with an initial population of 100,000 women, reflecting upon the natural progression of breast cancer over a span of 20 years. Through the robust DES framework, the study uncovered statistically significant long-term savings in overall costs, treatment costs, and the expenses of additional tests when digital mammography was employed. While the initial investment in digital mammography is higher, the DES model highlighted the cost-saving benefits achieved, through fewer subsequent tests and treatment expenses. One key insight from the DES analysis was the reduced recall rate of digital mammography, which culminated in fewer additional tests and a subsequent cost reduction. Importantly, the DES findings remained consistent across various scenarios, showcasing its versatility and adaptability. However, the study's DES model did not include the potential costs linked to the transition between technologies. This criticism will also apply to this proposals model as doing a full cost analysis for a radiology department is outside the scope of this paper.

C. **Alternatives to Discrete Event Simulation**

Gharahighehi et al in 2016 highlighted a method to enhance the performance of an emergency department (ED) in a large Iranian hospital suffering from long waiting times, with notable effects of patient and staff dissatisfaction (Gharahighehi et al., 2016). Utilizing discrete event simulation (DES), the study modelled patient flow in the ED, focusing on identifying bottlenecks causing inefficiency. Two salient points their model included was that of the variable patient arrival based on the time of day and the time taken for specific medical tests. Data sourced from the hospital's HIS and staff interviews aided in creating a more accurate model. The study proposed several 'what-if' scenarios to address the bottlenecks, with criteria like waiting time, utilization, and cost guiding the selection process. This scenario prioritized services for patients based on the severity of their condition, which is comparable to what will occur in this paper’s proposed model.

Shukla et al. in 2015 introduced a systematic methodology for developing a discrete event simulation (DES) model based on the role activity diagram (RAD) notations for healthcare service delivery processes (Shukla et al., 2015). Traditional DES models often utilized oversimplified flow charts representing patient flow, which might neglect crucial interactions between patients, clinical staff, and equipment. The methodology, rooted in RAD notations, captures roles, interactions, actions, and decision questions. The workflow involves: (1) crafting a RAD model of the service delivery process; (2) creating a data model for this RAD-based process; (3) evolving a DES model influenced by RAD; and (4) introducing dynamic attributes and validating the DES model. Their method was validated through a case study of the magnetic resonance (MR) scanning process in a large hospital's radiology department. The paper also describes a software tool that translates RAD concepts into DES models efficiently, which aids in rapid analysis and improvements. By integrating RAD with simulation modelling, there's a significant timesaving in developing models for hospital simulations. Findings such as these guide this paper’s future work to design visualisation models for a DES.

D. **Irish / UK Healthcare examples**

This papers proposal is focusing on an implementing a DES model for a radiology department in Ireland. As evidenced from the previous studies, it is vital to recognize the local factors involved in patient care to implement a successful solution.

The NHS presents a similar paradigm to the Irish healthcare system and lessons are often learnt from one another. In light of mounting pressures on the NHS concerning demand and capacity in radiology, a paper by Singla in 2020 sought to elucidate MRI usage to enhance MRI capacity (Singla, 2020). By employing Discrete Event Simulation (DES), the research sought to optimize NHS hospital resources within the radiology department, targeting a round-the-clock service availability for outpatients. This intended service revamp promises reduced waiting times and better resource deployment, all while achieving a balance between staff, resources, and MRI demand. Notably, the DES simulations, run under various scenarios, spotlighted moments when resources were dormant and patient treatment lagged. The findings of proposed models underscored remarkable enhancements, such as the reduction of MRI waiting room time from 17 minutes to a mere 5. Additionally, the average duration outpatients spent within the system plummeted by 20 minutes in a specific scenario. An insightful takeaway from this research is the profound impact of resource optimization on patient throughput and the elimination of bottlenecks in patient flow. While this research offers a promising perspective, it also hints at the potential of integrating cost as a key performance indicator. Furthermore, the feasibility of an agent-based model—categorizing patients, radiographers, clerks, and radiologists as distinct agents—might offer a more granular analysis, albeit with a longer setup time. A hybrid model, merging DES with agent-based modelling, emerges as a potential avenue for future research, particularly for strategic planning and cost estimation in healthcare.

A DES model based on an Irish hospital was published by Keshtkar et al in 2020, with its aim to investigate bed capacity issues and resource management in a busy Irish tertiary hospital (Keshtkar et al., 2020). The simulated model found that improving transfer rates between wards within the hospital has a significant impact on freeing up bed space in acute departments such as an ED. The caveat from this is that DES alone cannot rectify bed capacity issues, but only help identify what can be done to address it. Akin to prior papers, the authors conclude that human factors and inadequate resources such as staffing are often the main barriers.

E. **Summary of literature review**

In conclusion, the above literature review has illustrated many important learning points for the development of a DES model in a radiology department in Ireland. There is a clear consensus that the clinical context and environmental background is essential for a successful and realistic CT scheduling model. It appears to be best restricted to small-to-moderate complexity systems, in more predictable environments where human behaviour has less impact. There appears to be a gap in the literature for the appropriate DES model for an Irish radiology department, that can capture the nuances of the healthcare environment.

3 Research Methodology

A comprehensive research methodology was established and followed to answer the research question. The Cross-Industry Standard Process for Data Mining (CRISP-DM) was utilized in designing this approach. CRISP-DM is a structured approach to planning and executing data mining projects. It consists of six phases: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. When adapting the CRISP-DM framework for creating a discrete event simulation for CT scan appointment scheduling, the process begins with understanding the specific business needs (or, in this case, the intricacies of CT scan scheduling). Next, the current data, such as patient flow and machine availability, is assessed and prepped to fit the simulation model. The modelling phase then involves creating the discrete event simulation itself, followed by an evaluation to ensure its effectiveness. Finally, the optimized scheduling system can be evaluated in various virtual hospital settings. Thus, while CRISP-DM is traditionally used for data mining, its structured approach can be effectively tailored for simulation projects, which assists in comprehensive planning and execution.

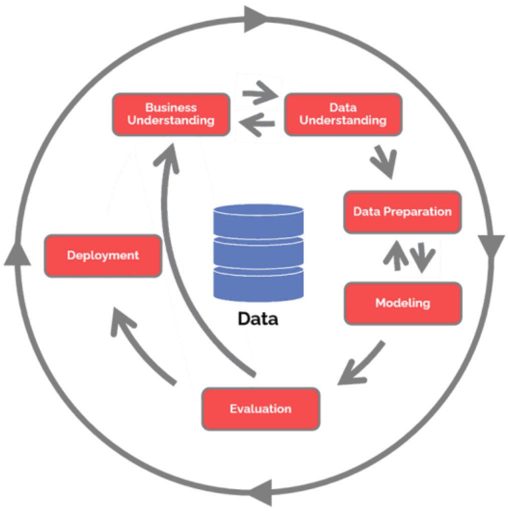


Figure 1. CRISP-DM lifecycle

A. Discrete Event Simulation model

Discrete Event Simulation (DES) is a modelling and simulation technique used to represent and analyse sequential events in a system. DES works by simulating a sequence of individual events over time. Each event occurs at a specific instant and marks a change of state in the system. Instead of focusing on continuous change, DES jumps from one event to the next, which makes it especially suitable for systems where change occurs at distinct points rather than continuously.

Key components include:

- **Entities**: things flowing through the model, in a sequential process.
- **Generators**: way in which entities enter the model/come into being.
- **Inter-arrival times**: specify the time between entities being generated (time between arrivals).
- **Activities**: what happens to the entities.
- **Activity times:** the time it takes for an activity to occur to an entity.
- **Resources**: these are necessary for the required activity to take place.
- **Queues**: entities wait until an activity has capacity and the required resources to begin.
- **Sinks**: how entities leave the model.

B. Domain Understanding

Having experienced various imaging departments as a medical professional, the author of this paper is well disposed to utilize domain-specific knowledge relating to radiology departments. Doctors possess firsthand knowledge of the patient flow, the time typically taken for different types of scans, potential complications that might extend an appointment, and the urgencies associated with specific medical conditions. This will significantly enhance the accuracy and relevance of this DES model.

A brief description of a patient's typical journey for a scheduled CT scan appointment would look like the following:

- Patient arrives for scheduled appointment time.
- Patient checks in at reception.
- Patient is greeted by the radiographer and prepared for the CT scan.
- CT scan occurs.
- Patient leaves the department.

On the surface, the majority of patient journeys are straightforward and unhindered. However, the proposed model aims to incorporate the additional elements to accurately reflect the real-world complexity.

- Preparation for a CT scan can vary in time, with some patients requiring venous cannulation prior, and other requiring additional safety checklists to assess pregnancy status or renal function. Therefore, the radiographer time in the model will vary.
- CT scan time varies depending on the types of phases to be acquired during a CT scan for a given indication. For example, a CT scan looking for the cause of blood in the urine (haematuria) has 3 radiation phases to acquire, while a CT scan looking for a kidney stone has only 1 phase.
- CT scan time will also vary depending on the cleaning to be done after use. For patients who are colonised by drug resistant bacteria, e.g. Methicillin Resistant Staphylococcus Aureus (MRSA), or with an infectious disease e.g. COVID, the CT scanner will receive additional cleaning.
- In many departments, the CT scanner is utilized by both scheduled CT imaging and emergency CT imaging requests. If a patient requires an emergency CT scan, they take priority.

C. Radiology Department Model

The following is a description of the model and visual diagram demonstrating the patient flow:

Component	***Description***
Entities	○ Patients presenting for scheduled CT scan appointments ○ Patients for emergency CT scans from a different location e.g. from ED
Generators	○ Patients self-presenting for their scheduled appointment time ○ Patients being brought to the department on an emergency, unplanned basis by a hospital porter
Inter-arrival times	○ Time between appointments ○ Time between unscheduled emergencies
Activities	○ Getting checked in by the receptionist ○ Getting prepared for the CT scan by the radiographer e.g. safety checklist, IV cannulation ○ Having the CT scan e.g. variable time durations based on indication for CT
Activity times	○ Time taken for receptionist / radiographer / CT scan event to complete
Resources	○ Receptionist ○ Radiographer ○ CT scanner
Queues	○ Waiting for a receptionist / radiographer / CT scan to be free
Sinks	○ The patient completes the scan and leaves the radiology department

Table 1. Describing Radiology DES Model Components

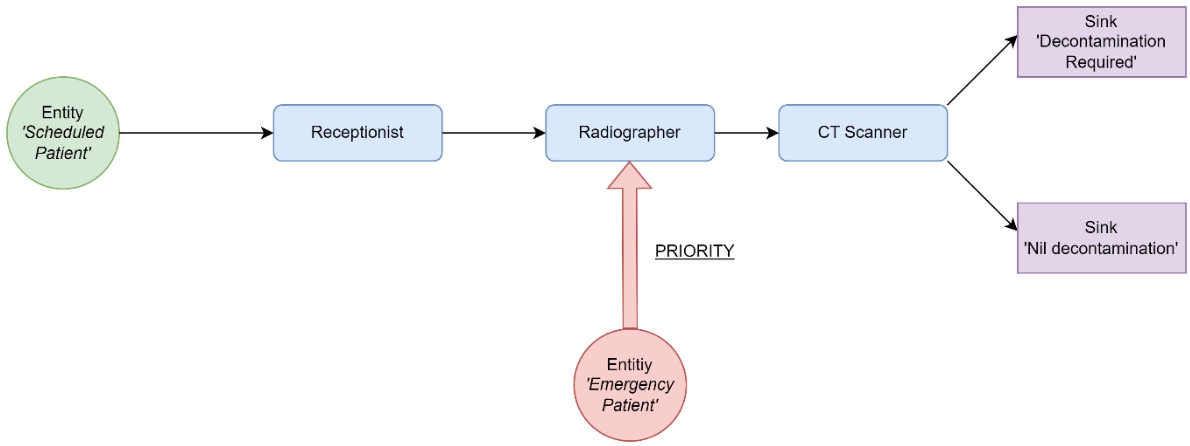


Figure 2. Radiology Department illustration

A priority resource can be specified in a DES model, so that an entity can be prioritized in a queue. In the proposed model, an 'Emergency' priority is created to emulate those patients with critical pathologies needing emergency imagining. This reflects real world practice where, for example, suspected stroke or major trauma patients would automatically go to the CT scanner, causing delays for scheduled, non-emergent patients.
In a DES model, a warmup period can be created for systems which don't start empty and are always running e.g. an emergency department. However, this model shall not utilise this as it concerns itself with a planned schedule of daytime appointments, which start and end on a fixed time.

The large benefit of using DES models is that one can implement stochastic elements into the model, which more accurately reflect real-world uncertainties. Unlike deterministic models, which assume fixed values and produce consistent outcomes, stochastic models incorporate probability distributions for one or more variables, allowing the system to respond differently under various simulation runs. This randomness in the model mirrors the natural variability that would be observed in a radiology department. For example:

- Medical emergencies
- Receptionist, radiographer, and CT scan timing

When choosing to sample from a stochastic distribution, it is important to pick a distribution that accurately mirrors that of real life. For example, it stands to reason that a medical emergency would have a normal distribution, with the majority of cases taking a certain length of time. The following table documents the chosen distributions used. These choices have been guided by the literature review conducted above.

Time taken	**Type of distribution**
Receptionist	*Exponential distribution*
Radiographer	*Exponential distribution*
Scheduled CT	*Gausian distribution*
Emergency CT	*Gausian distribution*
Decontamination	*Gausian distribution*

Table 2. Chosen distributions

Given the stochastic nature of a DES model, it must be run multiple times in order to generate a statistically significant result. A simulation of one-hundred runs was determined as large enough to generate a statistically significant sample size, and yet remain still computationally feasible.

When creating a DES model, it is imperative, as demonstrated in the literature, to understand the environment to be simulated. Simulation models cannot completely convey the real world, and therefore must have some assumptions.

Below is a list of assumptions for the DES model:

- There is no travel time taken into account for resources
- Emergency patients are given priority
- The resources designated are always available e.g. no machine dysfunctions/staff sickness/breaks
- The CT scheduling times, other than emergency, are by appointment only
- Appointments are scheduled on a 15 minute basis
- Patients will always arrive on time for their appointment
- There are unlimited capacities for the waiting areas
- The CT scans only need to be performed, not reported on
- There is only timeframe during the day, mimicking an 8am-6pm schedule.

D. Model Scenarios

Radiology departments vary greatly depending on the location and hospital. Those departments in large hospital such a major trauma centre or quaternary hospital, have vast resources, with often dedicated CT scanner, full complement of staff and high patient turnover. Radiology departments in smaller hospitals often have a far more limited capacity, with restricted hours, typically only 1 dedicated CT scanner, and have fewer emergencies. There also exists, outside of the public hospital sphere, private imaging companies which patients are referred to for an outpatient investigation, and these facilities do not encounter emergencies. This paper will focus on a medium size, tertiary hospital centre, as it broadly will be applicable to the other size facilities.

E. Evaluation

The data from the simulations was collated and then analysed. This was done by collecting the average time from each simulation. A mean, median and mode were then calculated for that model. Histograms were charted to visually assess the model's performance.
This result was then critically appraised and analysed in its real world context, for example, the significant financial costs of having an additional CT scanner versus the efficiency derived from it.

4 Design Specification

4.1 Data storage and architecture

All research was carried out on Toshiba Satellite Laptop with an Intel i5 Core processor, 16GB of RAM and a dedicated Nvidia GPU. The operating system was Windows 10 and the Python 3 programming language was utilized. The study utilised Jupyter Notebooks as a programming environment, as no cloud storage or cluster capabilities were required. Local storage was used to store the generated data.

Below is a list of the packages used as part of the model:

pandas	Data analysis and manipulation.
statistics	To compute statistical metrics like mean.
simpy	For discrete-event simulation.
random	To generate random numbers for modelling uncertain times.
matplotlib	For plotting.
numpy	Mathematical and logical operations.
csv	To read and write CSV files.
seaborn	For graph visualisations

Table 3. Python modules used

4.2 Object Orientated Programming

The model utilises the principles of Object-Orientated Programming (OOP). OOP is a programming paradigm centred on the concept of "objects". These objects are designed to represent real-world entities, making the software more intuitive, modular, and organized. There are numerous benefits for utilizing this approach for a radiology department model.
For example, each component of the radiology department, such as CT scanners, patients, and radiographers, can be represented as individual objects. Once these objects are created, they can be reused in different simulations or scenarios, which allows for easier flexibility.
Furthermore, as the radiology model changes, OOP makes it easier to update and maintain the model. For instance, for adding in a new entity or resource, one can simply extend an existing object or create a new one without overhauling the entire model. Both OOP and DES aim to represent real-world entities and interactions. In the context of a radiology department, this means having individual patient objects interact with scanner objects, capturing nuances like wait times, procedure lengths, and equipment availability.
In essence, OOP offers a structured, intuitive, and scalable approach to developing a DES model for a radiology department, aligning closely with the real-world operations and interactions inherent in such a setting.

4.3 Model Design

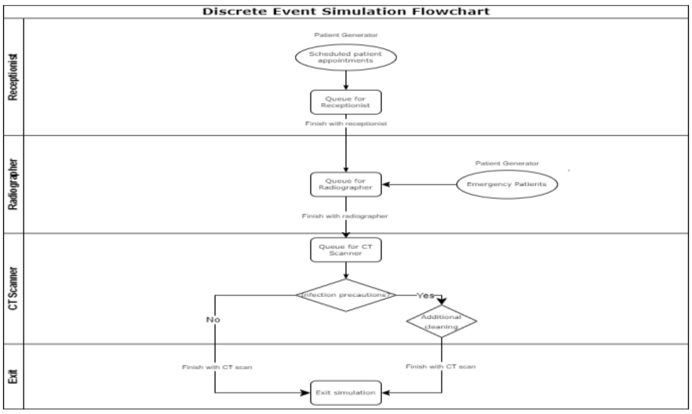


Figure 3. DES flowchart

The above diagram illustrates a patient’s journey through the radiology department, demonstrating the flow of entities through the model.

5 Implementation

The code simulates the flow of both scheduled and emergency patients through a radiology department, focusing on the CT scan process. It is programmed with an Object-Oriented style. It considers different variables such as the need for decontamination and different patient priorities. The simulation is run multiple times, and the results are then analysed to determine average waiting times and visualize them.

The classes operate as follows:

- ‘g’ houses various constants to control the simulation parameters, including:
  - Average reception, radiographer, and CT times
  - Scheduled and emergency patient inter-arrival times
  - Simulation time and number of simulations
  - Capacities for resources
  - Decontamination-related variables

- ‘CT_patient’ represents a scheduled CT patient. The class tracks the patient's waiting times in the reception, radiographer, and CT queues.
- ‘emergency_patient’ represents an emergency patient.
- ‘emergency_CT_model’ represents the journey of an emergency patient through the radiographer and CT scan process, considering potential decontamination times.
- ‘Radiology_dept_model’ handles the journey of scheduled patients through the reception, radiographer, and CT scan process. Also manages storing of patients' waiting times into a pandas DataFrame and writing the results to a CSV file.
- ‘Multiple_Run_Results_Calculator’ handles the data analysis across multiple simulation runs.

The script also contains the following functions:

- ‘setup_simulation(env, run_number)’ configures the simulation by creating priority resources for reception, radiographer, and CT scanner. Initializes the radiology and emergency models and initiates the processes for scheduled and emergency patient generation.
- ‘generate_scheduled_patients(env, radiology_model)’ generates scheduled patients based on the specified scheduled inter-arrival time.
- ‘generate_emergency_patients(env, emergency_model)’ generates emergency patients based on an exponential distribution of specified emergency inter-arrival time.

The script is designed to be run directly and goes through the following steps:

[1] Creates CSV files to store results.
[2] Runs the simulation multiple times (as defined by NUMBER_OF_SIMS in the g class).
[3] At the end of each run, the simulation results are stored in the CSV files.
[4] After all runs are completed, the average results over all runs are computed and stored.
[5] Visualizes waiting times for scheduled CT patients using Matplotlib and Seaborn.

An example of a scheduled patient journey would be as follows:

- The ‘g’class variables are defined, such as scheduled patient arrival times.
- A patient enters the queue for the receptionist.
- The receptionist processes the patient, and a processing time is generated.
- The patient then moves to the radiographer’s queue. If emergency patients are generated, they will go ahead of the scheduled patient.
- The radiographer processes the patient, and a processing time is generated.
- The patient then moves to the CT scanner queue. Emergency patients take priority in the queue.
- The CT scan will occur. A processing time is generated, and this length will be affected by whether the patient required infection precautions or not.
- Patient then exits the simulation.

6 Evaluation

The aim of this model was to discern if a discrete event simulation model could be designed to fit an Irish radiology department to assist in resource allocation and improve a department's efficiency.
The results obtained by following the above methodology are presented below.

6.1 Tertiary size hospital radiology department

The table below shows the various 'base' chosen entities which further models were benchmarked against.

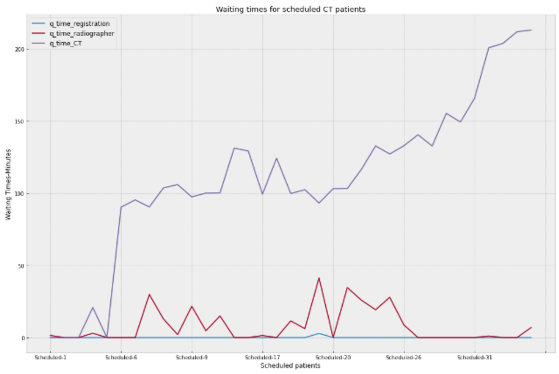
Chosen Parameters	
Entities	**Values**
Receptionist capacity	1
Radiographer capacity	1
CT scanner quantity	2
Emergency patient interarrival time	30
Scheduled patient interarrival time	10
Emergency CT average time	15
Scheduled CT average time	15
Percentage of decontamination patients	20%

Table 4. Chosen parameters

Data from 100 simulation runs **Total Wait Times in minutes**	
Mean	54.8
Median	50.4
Max	159
Minimum	10.8

Table 5. Simulation data

The below graph demonstrates a time series from a single simulation of waiting times for scheduled patients. There is clear evidence of an unsustainable queue for CT waiting times building. The radiographer and receptionist appear to be stable and can potentially handle increased patient loads. The graph alongside it demonstrates a histogram of the mean total wait times per 100 runs. The mean appears around 50, and the distribution appears to have a positive skew.



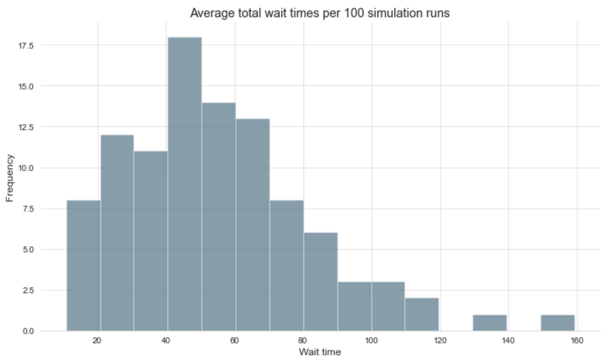


Figure 4. Time series of CT Department

Figure 5. Histogram for CT department

The bottleneck at the CT scanner was identified and a subsequent model with increased capacity (one extra CT scanner) was analysed. The graphs below show the subsequent changes. There is considerable improvement in the overall waiting times as evidenced by the graphs and histogram below.

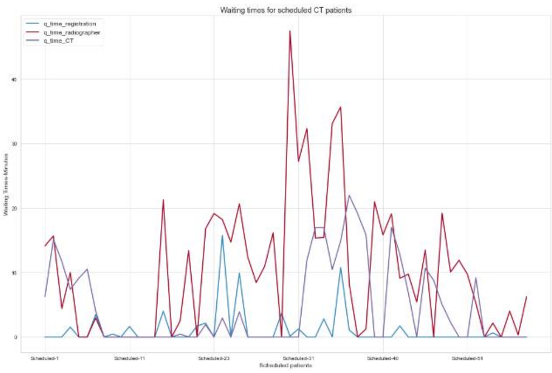


Figure 6. Time series with increased CT scanner

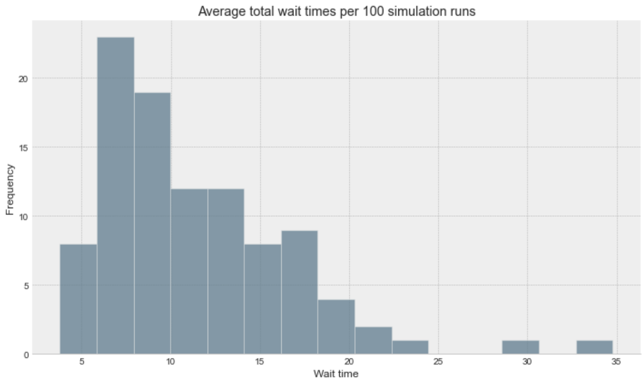


Figure 7. Histogram for increased CT scanner

A major critical incident is when the quantity of hospital presentations or the severity of patient injuries exceeds the hospital's capacity. All hospitals have a policy and procedure on file in case exceptional circumstances were to occur, such as a natural disaster or a terrorist attack. This can be simulated in the DES model by changing the interarrival time of the emergency patients to a more frequent arrival. The interarrival time for emergencies was changed to every 15 minutes and the below graphs demonstrate the change in waiting times.

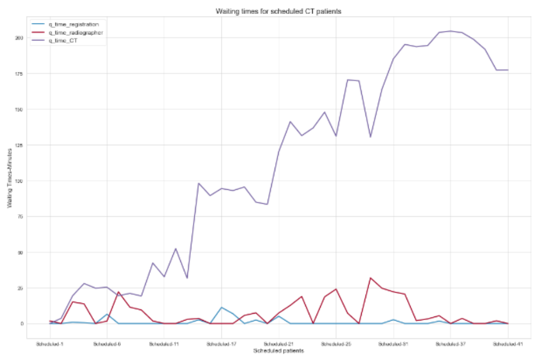


Figure 8. Time series with critical incident

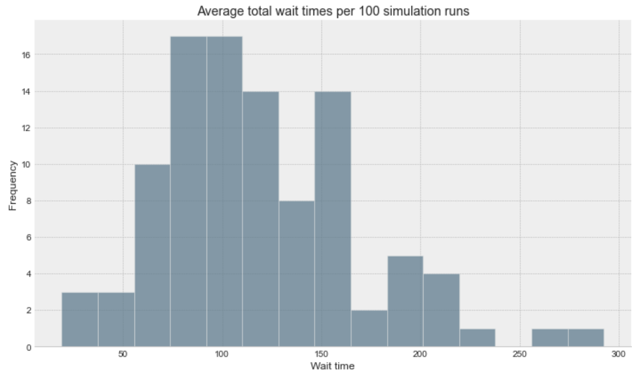


Figure 9. Histogram for critical incident

With increasing rates of hospital acquired infections and antibiotic resistance, a hospital may plan for lengthier equipment utilisation time. This would also be applicable during a pandemic, as what happened during the COVID pandemic, with some hospitals operating separate CT scanners for COVID positive and COVID negative patients. Both of these scenarios can be simulated by increasing the percentage of patients designated for infectious precautions. This percentage was changed to 75% and the below graphs demonstrate the change in waiting times.

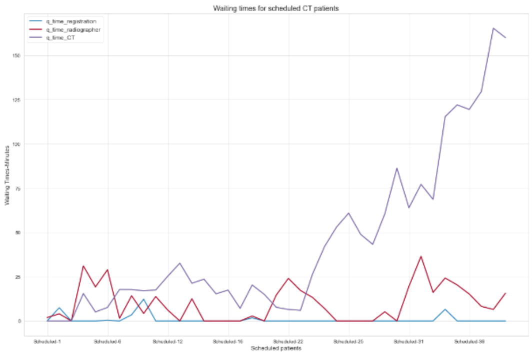


Figure 10. Time series of high decontamination rates

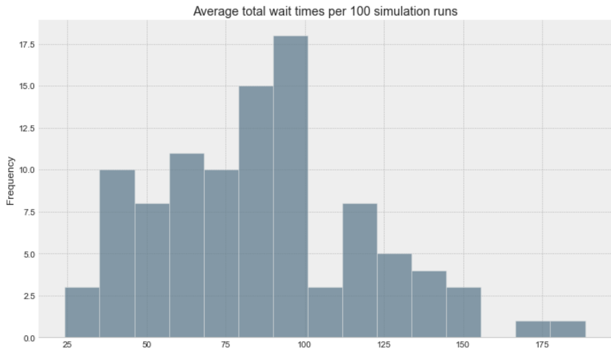


Figure 11. Histogram of high decontamination rates

In both a critical incident and pandemic, scheduled CT appointments are severely disrupted, with a compounding effect for those with appointments later in the schedule.

Table 6 below gives a breakdown of the overall wait times per activity. The mean registration time does not vary across the scenarios, which indicates there is often additional capacity in this resource. The mean radiographer time is not affected by an additional CT scanner, however during a critical incident, the time triples to a 20-minute wait on average. The mean CT time roughly doubles during a critical incident but has a tenfold decrease if a new CT scanner is acquired. It also increases by roughly 50% during pandemic times. It appears that only when there is a very large demand on the hospital, that radiographer resources become a barrier. Otherwise, a CT scanner is always the main bottleneck. The increase at times during a pandemic may signal a trend towards increasing CT scanner queue times given the increasing intensity of infection control precautions in hospitals. Hospital systems must weigh up the significant economic costs versus the improved service delivery of investing in additional CT scanners.

Time in Minutes	**Mean Registration Time**	**Mean Radiographer Time**	**Mean CT Scan Time**	**Total Wait Time**
Regular model	1.2	6.6	47.0	54.8
Extra CT scanner	1.1	6.0	4.5	11.4
Critical Incident	1.1	20.4	105.9	127.4
Pandemic	1.2	6.8	77.6	85.6

Table 6. Mean time results from models

6.2 Discussion

Overall, the model performs well and simulates a CT schedule with success,

It has both public and private applications. Public hospitals can utilise it to provide more efficent imaging services, which would offload the pressure in also running an acute emergency service. Also, there are private imaging services who could use the model to further evaluate their own pathway and potentially justify investing in a large capital expense such as a CT scanner. The utilisation of this model could have broad implications across healthcare services, with better resource allocation allowing for decreased patient waiting time as well as a more efficient response to emergencies. Additionally, it would facilitate quicker and more expedited diagnosis of conditions and potentially decreasing overall healthcare costs. Hospital management could utilise the model and correlate it with Key Performance Indicators (KPI's) to guide overall hospital policy:

- Staff utilisation (radiographer, receptionist)

- Average waiting time
- Total CT exams performed

This model corroborates the findings of the literature review in that DES provides a powerful tool for resource utilisation in a healthcare setting. It managed to intuitively diagnose where resources could be utilised better to decrease wait times. And while this model focused on CT scanning, it is generalisable to MRI, Ultrasound and PET-CT scanning. However, similar to the points made above, it lacks a clinical trial or implementation. Furthermore, unlike some studies published above, the data used to guide variable choices and values were not sampled from local hospital data. It was outside the scope of this paper to perform a cost analysis for addressing the bottlenecks the model identifies.

Addressing the research questions, this DES model is based on the Irish healthcare system and succeeds in identifying key factors in patient flow in a radiology department. As demonstrated, it is flexible so that it can be tailored to various scenarios and settings. Furthermore, it captures various nuances of hospital practice, yet is not opaque and still interpretable. Not only can it be utilised in both day to day departmental planning with staff or machine maintenance, and but in long term hospital policies such as in planning for a critical incident. Future work could focus on creating a GUI or a visualisation platform to further facilitate insights. It could also involve gathering local data on wait times and flow, and comparing and adjusting the model with these insights. Overall, this model contributes further to the growing body of research on improving resource allocation in hospitals, and it develops on this concept in an Irish radiology setting.

7 Conclusion and Future Work

The research question posed at the beginning was *'To what extent can a Discrete Event Simulation model, informed by domain specific knowledge in Irish healthcare systems, identify the key factors in patient flow through an Irish hospital's CT pathway?*

Taking a critical look at the paper, the proposed model does appear to meet this objective and is appropriate to the Irish healthcare environment. Factors such as the inclusion of infection precautions, unscheduled emergencies, and variable CT lengths allow for a good deal of realism while maintaining the models interpretability.

In keeping with the findings of the literature review, this model is limited by its lack of a clinical deployment, as well as not analysing the cost-benefit analysis and economic arguments involved in resource allocation.

However, a more streamlined radiology department undoubtedly reduces overhead costs associated with prolonged patient stays, overtime for staff, and inefficient use of equipment. These savings can then be reallocated to other vital areas, bolstering the overall quality of healthcare services.

Efficient scheduling and queuing algorithms prepare the healthcare system for this increased demand, ensuring scalability and adaptability to future needs.

This model has shown that it is often the CT scanner which is the resource bottleneck. And while purchasing a CT scanner is a large capital investments, efficient queuing ensures maximum utilization of expensive radiological equipment. With optimized schedules, machines like MRI or CT scanners can operate at full capacity without unnecessary idle times, thus maximizing the return on investment and potentially extending the life of the equipment due to regular, efficient usage patterns.

Future work would focus on visualisations of the DES, and utilising local data on patient flow through the department to validate and tune the model. There are commercial opportunities to be explored in private radiology, with private clinics seeking for resource optimisation as well.

In summary, integrating advanced queuing and scheduling algorithms into radiology departments is not just a matter of operational efficiency; it's about enhancing patient experiences, empowering healthcare professionals, and fostering a robust, responsive healthcare ecosystem. As technology continues to evolve, embracing these tools will be paramount in delivering world-class care to patients and ensuring a healthful future for the larger community.

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