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RESEARCH ARTICLE

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Using simulation for long-term bed modelling in critical care

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ABSTRACT
A simulation model of the University Hospital of Wales (UHW) Critical Care (CC) Department is presented. This is the first CC model that considers the impact of future demand on capacity, supporting planning decisions to build a new hospital. A combination of long-term demand trajectories and Discrete Event Simulation (DES) are used. The results suggest the unit will need at least 66 Intensive Care beds and 19 Post-Anaesthesia Care beds to fulfil predicted demand in 2040 while being at capacity less than 5% of the time. Non-critical care ward beds impact patient flow in CC, thus must be considered when planning a new hospital. This study's findings directly impact on decision making at UHW, having informed capacity planning of the planned unit. This paper contributes by presenting an infrastructure planning project using simulation as a decision-making tool, with transferable insights applicable to the planning of other CC units.

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KEYWORDS
Simulation; discrete event simulation; critical care; bed modelling

1. Introduction

1.1. Background

Critical Care (CC) provides organ support and monitoring to patients who have potentially reversible disease and who are at a high risk of dying or sustaining long-term morbidity. In Wales, CC beds are sparse, with an average of 3.2 beds per 100,000 people. This is lower than the average of 4 in England and visibly below the European average of 11 (All-Wales Implementation Group, 2014).

At the University Hospital of Wales (UHW), within Cardiff and Vale University Health Board (CAVUHB), the CC Department is split into two units with a protected space for elective patients. Generally, emergency demand is seen in the Intensive Care Unit (ICU) and elective demand in the Post-Anaesthesia Care Unit (PACU) with a small number of elective patients being transferred from PACU to ICU.

A full unit in CC with no capacity to admit more patients leads to CC patients being denied access or offered delayed care. In turn, this leads to patient harm and downstream system disruption, providing sub-optimal CC in sub-optimal locations. At UHW, this risk of denied patient access is compounded as the hospital is a Tertiary Centre where its CC capacity supports time critical services, such as Major Trauma and Neurosurgery, which currently cannot be provided in any other hospital in Wales.

CAVUHB have plans to build a new hospital ("UHW2") to offer, amongst other care services, CC in order to provide the facilities and space required to create a fit-for-purpose right-sized service (Cardiff and Vale UHB, 2019). The insights generated from this project are being used to inform the specification for CC in the business case for a UHW replacement. Timelines for this development initially suggested that the move from UHW to UHW2 would happen in 2030. Therefore, the two key time points for evaluation were 2030 and 2040 to ensure infrastructure in the new unit is adequate to support the service 10 years later. CAVUHB require the CC unit in UHW2 to be at capacity at most 5% of the time.

CC beds are costly, require specialist staff with extensive training and have complex infrastructure and equipment needs. Therefore, it is key to understand the demand trends and capacity requirements to effectively meet the current and future demand of the population. CC and health care in general have a high degree of variance over time, and therefore the level of detail captured in discrete-event simulation (DES) lends itself well to application in healthcare settings (Chahal et al., 2013).

DES is a suitable tool to model the flow of services in CC, whereby patients are dynamically represented to flow through a series of queues and activities within the CC system over time, governed by the availability of resources such as beds (Brailsford et al., 2009).

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Existing studies of CC use simulation to support planning of resources within existing ICU resources (Rodrigues et al., 2018; Williams et al., 2020). Some studies recommend creating capacity for emergency patients by a more effective scheduling of elective patient admissions or bed utilisation across other wards in the hospital floor, but to our knowledge, so far, there are no studies that focus on capacity planning of a new CC department incorporating interaction with the wider hospital bed base.

DES has already been used by analysts in NHS Wales as an appropriate method for modelling CC (Williams et al., 2020). This study differs from Williams et al. (2020) by capturing ICU and PACU, alongside the dependency on the rest of the hospital.

The aim of this paper is to report on the simulation model that combines long-range demand trajectories via judgemental forecasting and DES to support the demand and capacity of the CC Department over the next 20 years to ultimately determine the future physical combined number of emergency ICU beds and elective PACU beds and to ensure there is adequate infrastructure to support the service. The separation and specialisation of PACU is unusual in the UK and reduces the likelihood of elective surgeries being disrupted by surges in emergency activity. However, due to the specialisation of care in PACU, it is highly important that ICU is adequately resourced to stand alone.

The focus of this study is on the number of beds in the CC Department and related physical space requirements, rather than the scheduling of resources. The model incorporates projected changes in emergency and elective demand on CC services,looking at demand in the wider hospital setting and how this impacts the utilisation and performance of CC. This modelling does not include the Long-Term Ventilation (LTV) Service; this is a protected bed base within CC with no interaction effect with the rest of CC.

1.2. The rest of the paper is structured as follows

The next section provides a review of existing literature on the use of simulation to support capacity planning in ICU. This is followed by an overview of the materials and methods used to develop the simulation model. Next, the model results are presented followed by a discussion of the findings and practical implications for the hospital and ICU department, ending with conclusions.

2. Literature review of simulation modelling in critical care

A number of studies have examined demand and capacity planning in CC and/or intensive care. An overview of the studies found in the academic literature is presented in this section.

The main operational research methods used to support ICU management problems include exact mathematical, heuristics, and stochastic methods. In their review, Bai et al. (2018) found that the majority of studies, 80% of the 52 papers they included, consisted of stochastic methods comprising queuing theory, Markov Chains/MDP, and simulation, with the latter being used in 56% of the studies included. The higher take-up of simulation, as opposed to mathematical models and other stochastic methods (queuing theory and Markov Chains/MDP), can be explained due to the more flexible approach to modelling in simulation, which does not make restrictive assumptions about the particular types of arrival processes and Length of Stay (LOS) (Bai et al., 2018).

Several DES studies have examined demand and capacity planning in CC and/or ICUs, some examples include (Akkerman & Knip, 2004; Hasan et al., 2020; Williams et al., 2020; Zhong et al., 2022), while fewer system dynamics models have been found in the literature. For example, Demir et al. (2013) model the flow of patient pathways in the neonatal system to evaluate the impact of different policies related to reduction of LOS, such as the introduction of a new treatment procedure on unit performance. As a stochastic modelling approach, DES is well positioned to model the complexity inherent in ICU systems, representing patient flows, the capacity, and availability of expensive resources, such as beds and staff, to achieve optimal utilisation rates.

Of the studies found in the literature, some papers model specific ICUs in the hospital, such as the cardiac ICU (Akkerman & Knip, 2004; Yang et al., 2013), the neonatal/paediatric ICU (Adeyemi et al., 2010; Cochran & Roche, 2008; Demir et al., 2013), the surgical ICU (Troy & Rosenburg, 2009), or multidisciplinary ICU (Barado et al., 2012; Kolker, 2009; McManus et al., 2004) and others study a mixture of different ICUs (Lowery, 1992, 1993). The current study considers a multidisciplinary CC unit consisting of a variety of specialities with a protected area for PACU to be housed in the new hospital.

Many simulation studies consider ICU capacity problems by testing the impact of introducing different policies to CC, including management of patients flows, bed capacity management, patient triage and discharge policies, and LOS. We next consider the studies found by the type of problem studied.

Considering changes to the management of patient flows, studies consider the impact of overflow of intensive care patients (Litvak et al., 2008; Masterson et al., 2004), ICU admission, and discharge processes (Kim et al., 1999, 2000) For example, Williams et al. (2020) investigate the effects of increasing the ICU capacity, an increase in demand, and a reduction of delayed transfers of care (DTOC) on occupancy levels at an ICU and found that increasing the number of beds had less influence on the reduction of occupancy levels; however, reducing the number of patients with DTOC had the biggest effect on occupancy rates and average bed utilization, even when the demand is at its highest.

Introducing policies that reduce the time patients spend in the ICU could significantly improve capacity utilization rates (Griffiths et al., 2006), however relevant policies available and their effects can vary. For example, in a study of a neonatal unit, Demir et al. (2013) found that the introduction of policies related to reduction of LOS do not necessarily lead to substantial improvements in performance. While it may lead to an increase in the number of patients discharged home, the number transferred to other units or in the same hospital, they found that the numbers are the same whether LOS is reduced by 1 or 3 days. In addition, the study found that reducing LOS by 3 days for high dependency care patients leads to an increase in the number of patients refused entry to the unit, as the reduction in LOS after treatment means that patients' health worsens and they require further care, which is a counterintuitive effect of the behaviour of the system.

Studies on bed capacity management consider the efficient use of bed resources. The ultimate aim of all these models is to balance bed availability and occupancy levels, while minimizing the number of rejections from ICU admission. For example, Mohamed & Hussein (2021) developed a DES model to optimise bed capacity in an intensive care unit (ICU) in order to achieve target admission and utilisation levels. It is noted, however, that this study did not account for the natural growth in the population or the rise in the number of patients visiting the emergency department. Other examples include models that assess bed occupancy and patient transfers to other ICU facilities due to resource shortages (Steins & Walther, 2013); changes in patient flows by directing patients from ICU to intermediate care wards (Marmor et al., 2013; Rodrigues et al., 2018), to other hospital wards (Akkerman & Knip, 2004); the introduction of step-down beds as a less expensive alternative to ICU beds to deal with bed capacity issues (Rodrigues et al., 2018); improvement of bed management by distinguishing between emergency and elective surgery patients (Griffiths et al., 2013), or through effective scheduling of elective patient admissions to create capacity for emergency patients (Kolker, 2009; Ridge et al., 1998).

Admission and discharge policies can significantly affect occupancy levels in the ICU (Hasan et al., 2020). In real life, clinicians operating in a congested ICU are faced with the ethical dilemma of turning away a new patient in need of CC and admitting them. When all ICU beds are occupied, the clinician would need to make a bed available by prematurely discharging an existing patient occupying a bed, also known as the "last bed problem" (Azcarate et al., 2020; Teres, 1993). In practice, clinicians make patient discharge decisions considering aspects such as the upcoming surgical schedule for the day and ICU bed availability (Anderson et al., 2011).

Early simulation models, for example in Kim et al. (1999), model admissions as a first come first serve process, where the possibility of early discharge is checked first and then the decision to cancel a surgery is considered. Similarly Hagen et al. (2013); Lowery (1993); Shahani et al. (2008) incorporate early discharge in their simulation models. The latter found that prioritizing admissions could considerably reduce delays for critical cases while increasing the average waiting time for all patients. In addition, authors find that early discharges can raise readmission and mortality rates (Anderson et al., 2012; Hagen et al., 2013).

Azcarate et al. (2020) develop a simulation model that aims to accurately represent patient discharge decisions similar to real-life practice followed by clinicians by incorporating factors that influence patient discharge decisions. They model patient discharge as a function of the patients' current health status, the bed occupancy level, and the number of planned arrivals from elective surgery in the next days. The different patient states are represented in a phased-type distribution of patient LOS. Their model generates an optimal discharge policy that aims to balance patient rejections and LOS reduction as opposed to other studies that consider only the triage of the last bed. It is, however, noted that the model presented in the current paper does not incorporate the practice of the "last bed problem". Instead, a scheduled (elective) patient is delayed and not admitted if PACU beds are unavailable and patient LOS is not moderated based on the system business. The objective of the model presented in the current paper is to help with identifying the optimal number of beds required to support their forward planning. Moderating LOS is not a desirable operational practice, and the UHWCC team was not willing to have the system operating at full capacity for large periods of time, instead they wanted the model to reflect safe working practices for CC. The UHW CC team's focus was on understanding the probability that a bed would not be available for a patient to be admitted to CC, maintaining appropriate patient LOS.

Considering the review of studies above, it can be concluded that DES can be effectively used to model ICU capacity over time. Most studies found in the literature focus primarily on creating capacity for emergency patients primarily by developing more effective scheduling of elective patient admissions, bed utilisation policies in ICU or across other wards in the hospital floor, and patient admission and discharge policies. However, these studies do not consider the long-term demand and capacity for ICU beds by incorporating changes in population trends and the impact on patient demand for ICU services over time, as presented in the current study.

3. Materials and methods

This section provides details of the analytical work carried out to develop the simulation model. In order to help evaluate the required bed numbers for ICU and PACU in a new hospital department, a combination of potential long-term demand trajectories and DES were used. We next explain the data sources used and analysis carried out in preparation for use in the simulation model, the method used to calculate the demand trajectories for CC in Wales, and then the simulation model development.

The model development process was guided by best practices as presented in (Tako, 2015), with the focus switching between modelling topics as the project evolved. These topics included problem structuring, conceptual modelling, model coding, data inputs, model results and experimentation, implementation, verification, and validation. The model, data, and demand trajectories evolved through an iterative process of regular meetings with the UHW CC team to discuss all aspects of the modelling process and ensure that the model and outputs met the needs of CAVUHB. Additionally, ad hoc meetings with a subject matter expert on the data from CAVUHB took place to provide expert advice on specific data queries. Figure 1 is an illustration of the process undertaken, including the iterative cycles needed to ensure a robust simulation model was built.

3.1. Data

CAVUHB granted permission to use data from their WardWatcher database, which included CC admission level data and census care level data. The data spanned from April 2018 to November 2021. Due to the COVID-19 pandemic and changes to demand and working practices including new surge capacity, new "Nightingale"[1] hospitals, and cancelled elective surgery, the latest data for CC had to be treated differently from this study. After various stages of data cleansing, the dataset contained information for 2770 admissions. Figure 2 shows the time series of admissions to CC over this period with the notable impact of the COVID-19 pandemic.

[1]A temporary hospital located in Cardiff to help deal with the impact of the COVID-19 pandemic in Wales.

The WardWatcher data shared was a set of three tables and contained the following key information for this work. This list is not exhaustive of all the data items included.

- Patient's workstream, i.e., reason for admission.
- Date patient admitted to hospital.
- Date patient discharged from hospital.
- Date/Time patient admitted to CC.
- Date/Time patient ready for discharge from CC.
- Date/Time patient discharged from CC.
- Maximum care level of patient each day.
- Discharge location, e.g., death, ward, repatriation to local hospital.

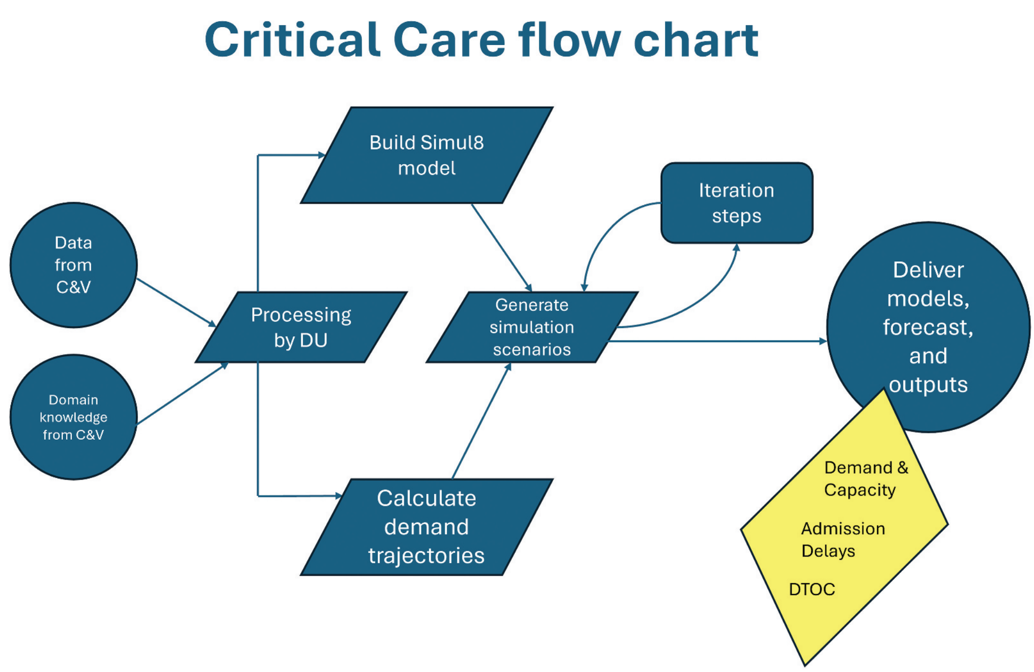

Figure 1. Flowchart outlining the iterative process followed in this study.

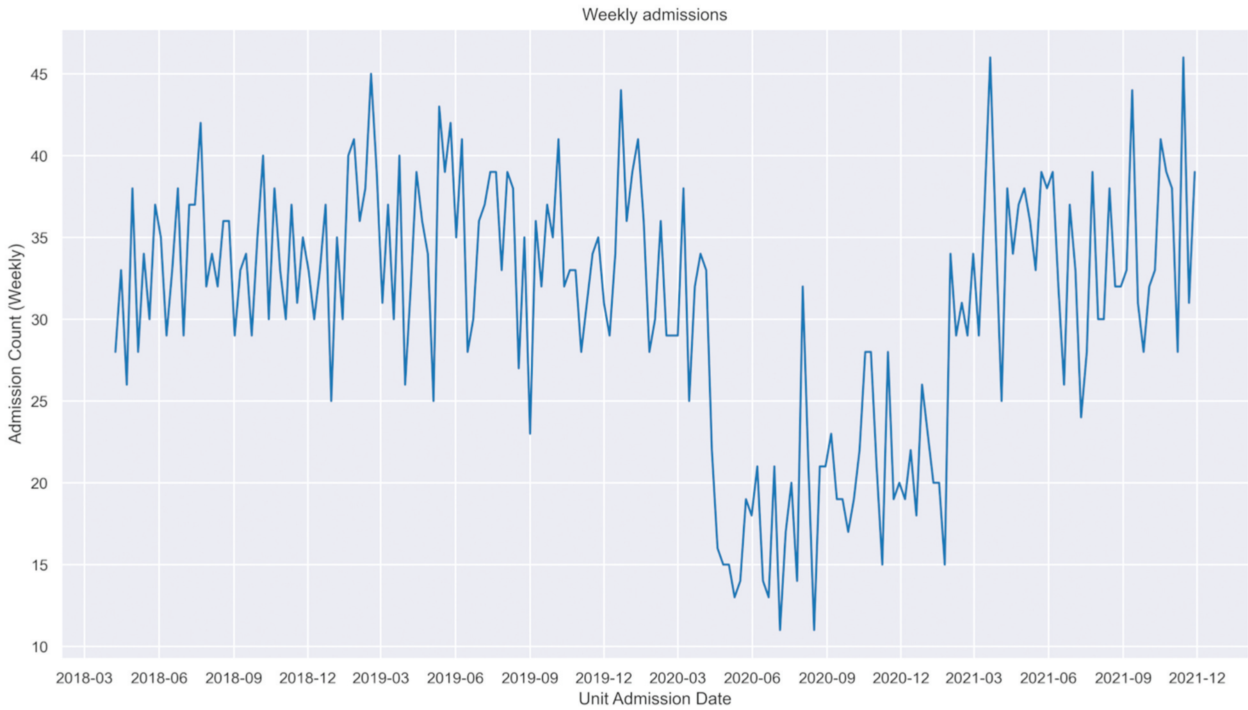

Figure 2. Weekly admissions to critical care.

- Patient demographics data (sex, age, Lower Super Output Area Welsh Index of Multiple Deprivation rank).

Additional data were shared by the Intensive Care National Audit and Research Centre (ICNARC) to provide a comparison with similar UK CC units in terms of demand and patient mix to help with benchmarking and quantifying the assumed unmet level 2 care demand.

The WardWatcher data was only able to give insight into patient stays within CC, and therefore the nationally available NHS Wales Admitted Patient Care dataset was required to add in the dependency between CC and the wider hospital.

In addition to the current activity seen at UHW CC, there is an understanding that services developments will be undertaken by the department in the future introducing new workstreams, and therefore additional ad-hoc data and insights were provided by domain experts to quantify the expected impact of these service developments.

A staged process was taken to generate a subset of the data provided that was then used in all analysis undertaken in this study. For example, this included the removal of a small number of patient records, which were incomplete due to changes in the level of data recorded. In some cases, data were manually overwritten when the clinicians consulted were aware of data entry issues. There were seven duplicated entries, which were removed along with seven additional patients who were assumed to have incorrectly recorded admission dates into PACU based on the unit's operational hours. Eight records were missing their "Hospital admission date", which was replaced with their "Unit admission date".

The "Admission delay" field is known to not be entirely reliable, but corrections could not be made due to a lack of information.

The decision was made to create two new workstreams, "Elective Other" and "Emergency Other", to avoid using very small volumes of patients in the modelling to ensure that the characteristics demonstrated were representative of the workstream and not specific to an individual patient. This grouping prevented the need to omit patients from the data.

4. Methods

4.1. Demand trajectories

This project required an understanding of projected hospital admissions for CC up to and including the year 2040 (i.e., a 19-year trajectory) and the use of forecasting with simulation as a hybrid approach has been used in healthcare as a decision support tool (Ordu et al., 2021) As this is a long-range demand trajectory, there is inevitably going to be a level of uncertainty in the numbers returned by this process (Granger & Jeon, 2007). This uncertainty needs to be considered when making further key decisions.

There were many constraints with the available CC data. These limitations included the following:

- The length of the data supplied did not provide an adequate training and test set to produce a 19-year long prediction.
- Various changes in both hospital and government policy relating to COVID-19 impacted the reliability of a large proportion of the demand data.
- Finally, the data supplied observed CC activity data and therefore does not capture historical "unmet demand", made up of patients who should have been admitted to CC but could not be admitted.

Time-series methods such as Prophet were explored but not successful in producing an accurate forecast. The prophet method, developed by Facebook (now Meta), is typically effective for time series that exhibit strong multiple seasonal patterns, such as day-of-the-week and yearly effects, which are prominent in Facebook traffic data (Taylor & Letham, 2017). However, its performance may decline in scenarios where these seasonal features are weak, particularly over long-term forecasting horizons, which is the case in our paper. Regarding the impact of COVID-19 on forecasting, although several strategies have been proposed (Hyndman & Rostami-Tabar, 2024) to address time series data influenced by the pandemic, it was decided that, given the described combination of data limitations, judgmental forecasting, which relies on the expertise of key personnel, was the most appropriate approach to adopt.

The main advantage of adopting a judgmental approach in our study was the ability to include useful information into the trajectories that cannot be derived from time series methods (Hyndman & Athanasopoulos, 2021) i.e. the new service changes and the reconciliation of the unmet demand. Incorporation of domain knowledge meant that the judgemental trajectories could take account of the following changes in future demand:

- There is some "unmet demand" from patients with lower care needs who are not admitted to CC.
- A range of new service developments which will impact the volume of patients requiring CC are due be introduced at various points over the modelled time period.
- The trend trajectories for increased demand for CC, based on expertise and analysis of historic demand including demographic and population, changes over the last 20 years (Jones et al., 2020).

Informed by Jones et al. (2020) and their own practical knowledge, the UHW CC teamconsidered that growth would be unlikely to be less than 3%, which is in line with their locally held data. Therefore, this figure was decided as the basis of the growth distribution.

Annual growth was sampled from the distribution $N(0.05, 0.025) + 0.03$ and considers knowledge of the CC department in CAVUHB, service developments impact on growth, and knowledge of other growth trends in similar UK CC departments. When the resulting growth was calculated at less than 3%, it was resampled to ensure a realistic level of demand growth each year. Demand for new workstreams was sought from business case proposals as well as liaising with wider colleagues in CAVUHB with specialised knowledge on the new services i.e., stroke specialists. During the iterative meeting cycles demonstrated in Figure 1, various demand trajectories were produced and validated with the CC team, who also disseminated the information amongst colleagues for a wider assessment and comment, which was brought back and incorporated.

The derivation of the projected demand did not explicitly incorporate population projections and are assumed to be captured in the trend proportion of the calculation. The CC department mainly treats CAVUHB patients, but due to UHW's position as a tertiary centre, it accepts patients from other locations in Wales with the clinical decision to transfer into or out of UHW being variable and complex. Therefore, the overall population served which would need to be included in analysis is complex and varies over time based on clinical need. This project did not analyse or include CC departments in other hospitals across Wales. Additionally, the population that the CC department is serving will change over time as service developments are incorporated (specialist services are provided by CAVUHB to health boards beyond CAVUHB), equally some services are provided for CAVUHB population at other hospitals in the health board.

The demand trajectories were created using a simulation approach, comprising of 1000 simulations (runs).

The output is a range of total admissions for each year per workstream between 2022 and 2040 and can be seen in Figure 3. Work was required to disaggregate the admissions down to accommodate the simulation requirements; first, to a weekly level and then down to three-hour periods based on the previous admission patterns identified in WardWatcher data. Any new workstreams implemented as part of a service development follow a uniform pattern from week to week with the three-hour proportions based on the workstream's elective or emergency status. The final demand trajectories that were used in the simulation model were discussed and approved by the CC team.

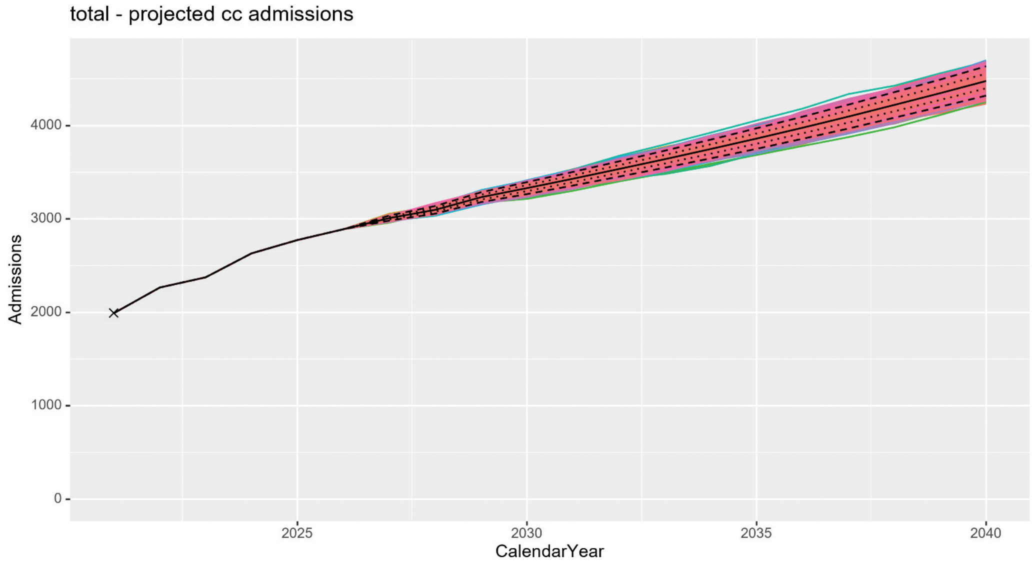

Figure 3. Visualisation of the calculated admission numbers through to 2040.

The projected demand for CC is an input into the simulation model showing what the implications on CC beds are if the CC arrival demand is at a particular level. The demand figure can be changed and alternative scenarios run to explore capacity requirements at different demand levels.

4.2. Introduction to the critical care simulation model

Here we describe a DES model of the CC department in UHW developed to help with the planning of provisions through to 2040. The simulation model is described in the following sections using the STRESS guidelines (Monks et al., 2019

Purpose of the model: To study the performance of the CC department assuming demand levels for various years. Due to the margin of error that comes with long-range trajectories, this is a modelling tool for use by the health board in the future as more accurate demand data and forecasts emerge.

Model outputs: patient level data and hourly census data capturing patient LOS, a count of admission delays over 4 hours, and the number of hours at capacity.

Experimentation aims: To calculate the expected bed requirements and provide details on how varying bed numbers and changes to service decisions can impact patient spells, based on the demand levels calculated in the trajectories for the years 2030 and 2040.

4.3 Model logic

The model captures the flow of patients during their entire hospital spell both within and outside of CC. The model captures the CC department broken down into an ICU and a PACU where patients spend time either receiving level 2 (L2) or level 3 (L3) care.

Due to the complex nature and variation in patients within CC, the demand is considered in workstreams, where each workstream corresponds to either an elective or emergency grouping. For context, Emergency General Medicine, Elective General Surgery, and Emergency Neurosurgery are some of the larger workstreams seen in the CC department. These workstreams therefore comprise of patients with similar characteristics and, for cases when patient admissions in a workstream are rare, workstreams with similar characteristics have been combined based on clinical judgement.

4.3.1 Base model logic

The model is a flow, Figure 4, capturing the journey into, out of, and within CC (split into ICU and PACU) for a single workstream. This structure is repeated in the model for each workstream operational in the scenario.

Patients are admitted into the CC unit for either an elective or emergency stay. They transition around units/beds as their care needs change. Patients may have a delayed admission if an appropriate bed is not available. For patients with a bed already assigned, any delay time spent waiting to transfer to another unit will be spent in their current bed. Patients may face a delay between being registered fit for discharge and the process of being discharged in order to follow the current discharge pattern where no discharges happen overnight. PACU stays are generally short due to their elective nature; however, any patients who require more than 72 hours of critical care are transferred to ICU for care.

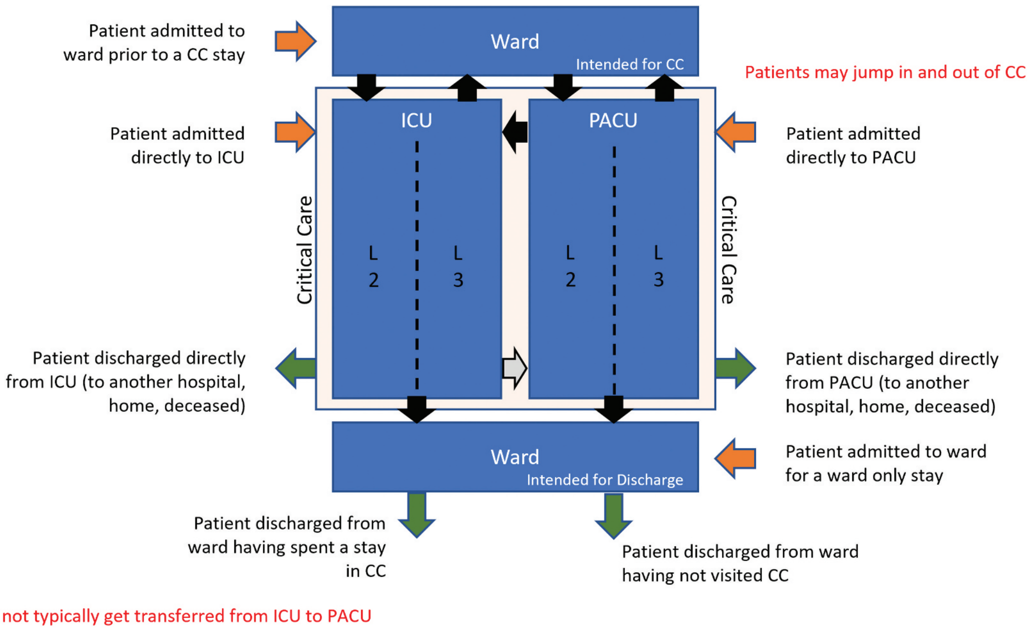

Figure 4. Model flow diagram.

4.3.2 Scenario logic

In the base model, PACU is shut from Saturday noon to Monday noon with any patients still requiring care being transferred to ICU. In the future scenarios for 2030 and 2040, the operating hours for PACU are changed to be open seven days a week. The future scenarios involve PACU running at a lower capacity over the weekend, retaining the equivalent admission pattern of Monday to Friday but with an additional few admissions on the weekend, meaning that any patients who would have traditionally been transferred to ICU on a Saturday now continue their stay in PACU.

The impact of discharge times on occupancy was an additional point of interest during the work. Two scenarios were developed looking at adjusting the likelihood of being discharged. In the first scenario, the probability profile used for discharge by hour was inflated from the baseline scenario while retaining the same shape; however, for the second scenario, discharge was equally likely across all daytime hours.

4.4 Algorithms

4.4.1 Patient flow

The movement of a patient through CC is determined by a transition matrix outlining each state a patient may be in: admission, ICU L2, ICU L3, PACU L2, PACU L3, or discharge. A matrix has been defined for each workstream to encompass the typical treatment received by a patient of that specialty (Table 1).

Typically, elective patients stay in PACU with a small number of transfers to ICU, while emergency patients will exclusively stay in ICU. Once a patient has finished their stay in their current state, the matrix is used to determine their next destination.

If a patient is to move from one unit to another, and no bed is available, they will continue receiving care in their current bed/unit and will be moved as soon as a bed is available.

4.4.2 Discharge

How and where a patient is discharged to varies from workstream to workstream, and this has been captured using different distribution parameters per workstream (example shown in Table 2) The model splits up discharges into three methods, discharged to ward in UHW, discharged to home/another medical facility, or deceased. This method of discharge is sampled when the entity is first initialised in the model.

The unit tries to maintain the practice of only discharging patients during the day, and therefore the model has been parameterised to model a varying likelihood of being discharged in daytime hours and a 0% chance of being discharged at night in order to replicate the working practice. Patient deaths can happen at any time.

Table 1. Percentage of patients transitioning between activities when ready to leave an activity - example from one workstream.

Elective General Surgery	ICU_2	ICU_3	PACU_2	PACU_3	Discharge
Arrivals	0.0	0.4	98.9	0.7	0.0
ICU_2	0.0	10.0	0.0	0.0	90.0
ICU_3	66.7	0.0	0.0	0.0	33.3
PACU_2	1.8	1.1	0.0	0.0	97.1
PACU_3	50.0	50.0	0.0	0.0	0.0
Discharge	0.0	0.0	0.0	0.0	0.0

4.5 Model components

4.5.1 Entities

Entities in the model represent individual patient spells in UHW and are either categorised as CC patients and non-CC patients. A CC patient is defined as a patient who spends the entirety or some of their hospital spell in CC whereas, non-CC patients do not enter CC during their spell.

4.5.2 Activities

The activities in the model can be thought of in three groups: assign bed activities, stay activities, and discharge activities.

In the assign bed activities, a bed resource of the required type is assigned to the entity. The patient retains the bed until they are discharged or are transferred to another unit.

The stay activities are where entities spend their intended time in a hospital bed; an example of one workstreams intended stay is in Table 3.

The activities represent either L2 or L3 care received in ICU or PACU or care received in a ward bed outside of the CC units.

There are additional "dummy" activities in the model used to implement model logic including sampling distributions for entities.

4.5.3 Resources

The model contains three different bed resources, ICU beds, PACU beds and Ward beds for use in their respective parts of the model. The bed resources were constrained to varying levels across the scenarios to mimic the finite pool of beds available or were set to very high levels to test an unconstrained environment.

Within the model, staff and resources were not directly modelled, and therefore no patients experience a delay when changing care level. Staffing resources are assumed to match the number and type of bed; thus, they were not simulated and can be directly calculated as a result of the modelling.

4.5.4 Queues

Entities are subject to queuing when a bed resource is not available. This delay time is captured in the model outputs.

Table 2. Percentage of patients to discharge destinations - Example for two workstreams.

Workstream	Ward	Other hospital	Home/Non-medical	Died
Elective General Surgery	93.9	4.3	0.4	1.4
Emergency General Surgery	83.1	1.7	1.4	13.8

4.5.5 Entry/Exit points

Entities enter the simulation at an entry point relevant to their specialty workstream, and their patient categorisation is a CC patient or a non-CC patient.

Entities exit the model once they have completed a full hospital spell. For each workstream, there are a set of exit points that represent the discharge type, i.e., discharged from ward and discharged from PACU to home.

4.6 Data

4.6.1 Data sources

The model logic and input parameters are informed by the WardWatcher CC data, demand projections, and domain knowledge from the project implementation team. As discussed in the Data Section, the data spanned from April 2018 to November 2021. In total, full records for 2770 admissions were used to inform the model input parameters.

4.6.2 Input parameters

The model input parameters are unique to each workstream and are laid out in the model input file. (Summarised in Table 4 and 5). The input parameters have been developed using past data, which spans from 2018 to 2019 for emergency admissions and the year 2021 for elective admissions. It has been assumed that over the modelling period, there are no changes to individual patient activity, and therefore for example the likelihood of an Elective Vascular Surgery patient being discharged to ward is the same in 2021 and it is in 2030.

4.6.3 Pre-processing

Details of the pre-processing required to shape the model inputs can be found in the Data section.

4.6.4 Assumptions

The data used to populate the model is from past patient spells and therefore it is assumed that previous patient behaviour will be representative of future patient behaviour, i.e., there will be no changes in patient LOS, or levels of care received over time. As mentioned above, the data used to build these characteristics spanned from 2018 to 2019 for emergency admissions and the year 2021 for elective admissions.

The profile used for determining discharge has been built off the current patterns on discharge seen across the day and therefore the model assumes that there are no changes in practice and/or policy that will change patient discharge times and release of a bed.

4.7 Experimentation

A number of scenarios were run as part of this study to ascertain the capacity levels required in CC based on the demand trajectories discussed in the demand trajectories Section. The scenarios are listed below and assesses the impact that bed availability has on patient waiting times, ICU, and PACU utilisation and how often ICU and PACU run at capacity. These run under three different constraint levels: all beds unconstrained, CC beds constrained, and all beds constrained. This was used as an approximation of the cancellation/postponement of surgeries as elective patients were unable to reserve a ward bed in advance of their surgery. Two further scenarios tested the adoption of two different discharge profiles, the observed discharge profile displayed in Figure 5, and a proposed uniform profile of discharging between 08:00 and 22:00 (Figure 6).

Scenarios:

- Baseline;
- 2030;
- 2040;
- Discharge profile 1 (using 2030 input parameters);
- Discharge profile 2 (using 2030 input parameters).

Results of each scenario were analysed and visualised before being discussed with the project implementation team for review.

4.8 Model validation

During the model building phase, the model structure and outputs were regularly discussed with the project implementation team to ensure their expert judgement informed the logic implemented in the model. In addition, where a set of indicators derived from the model were monitored and analysed to evaluate the performance of the unit in comparison to real-world activities and behaviours that can be pulled out from the past WardWatcher data.

For validation purposes, the model was run for a historic period, April 2 2018 to April 7 2019, which is the most recent 1-year period not impacted by the COVID-19 pandemic. This allowed for the model results to be compared against the real patient-level data captured in the WardWatcher dataset. The model was run for 100 runs to account for the variability in the system. The model mean LOS was 133 hours compared to the 127 hours seen in the actual data, suggesting that the model provides an accurate representation of reality (See Table 6). Figure 7 and 8 show that the model tracks occupancy across the year in line with the actual data points.

A fundamental part of the validation was to fine-tune the profile used for discharges to ensure they mimic the working practices of the department. The UHW CC team was consulted with the results during the validation process to ensure the model behaviour, and the results were in line with their expectations and experiences.

Table 3. Activity timing per workstream example.

workstream	Activity	Distribution	Parameter1
Elective General Surgery	ICU_2	NEG_EXP	0.785972222
Elective General Surgery	ICU_3	NEG_EXP	4.689236111
Elective General Surgery	PACU_2	NEG_EXP	0.952860809
Elective General Surgery	PACU_3	NEG_EXP	1.213541667
Elective General Surgery	Ward_Stay_For_CC	FIXED	0
Elective General Surgery	Ward_Stay_For_Disch	NEG_EXP	9.287923177

5. Results

Modelling was performed assuming a desired proportion of time spent at maximum capacity of 5%, as agreed with CAVUHB.

The demand for CC is an input scenario into the model showing the implications on CC beds if CC arrival demand is at a particular level. Evaluating the performance in 2030 with the current physical capacity of 48 ICU beds and 12 PACU beds available to be commissioned, when using the projected level of demand as an input, the model suggests that the department is expected to be at capacity 9% of the time. An additional 3 ICU beds would need to be added in order to facilitate a service where bed capacity is not reached more than 5% of the time (Table 7).

Table 4. Input parameters.

Input Parameter	Description
Entity Arrival Distributions	Due to the variation is arrivals across the day, the inter-arrival distributions are reparametrised every 3 hours. Since they are non-stationary, the distributions are set to match the busiest period while for quieter periods a proportion of the arrivals are removed from the model, using the simplification method of thinning (Lewis & Shedler, 1979)
Activity Timings	The intended LOS for each unit/care level stay is sampled from the respective distribution every time an entity enters a stay activity.
Discharge Method Distributions	Patients can be discharged in a number of ways. The method is set for an entity just after it has been generated in a dummy activity. The likelihood of each discharge method is specific to each workstream.
Transitions	The routing between care levels and unit is informed via a transition matrix for each workstream i.e., from a L3 bed in PACU, there is a 25% chance a patient moves to a L3 bed in ICU.
Number of Critical Care Stays Distributions	Since each entity represents a patients hospital stay, an entity can route through the CC activities more than once. In general, for over 96% of admissions patients only have one episode in CC.

Table 5. Yearly input parameter Summary.

	Baseline	2030	2040
Demand	Synthetic arrival profile (based on elective year 2021, emergency years 2018-2019)	Predicted 2030 arrival profile including proposed service developments	Predicted 2040 arrival profile including proposed service developments
Workstreams	20 workstreams (8 Elective, 12 Emergency)	29 workstreams • (11 Elective, 18 Emergency)	29 workstreams • (11 Elective, 18 Emergency)
PACU hours	PACU open 5 days	PACU open 7 days, 4 elective arrivals per weekend	PACU open 7 days, 4 elective arrivals per weekend

Table 6. Validation results summary (mean and standard deviation)

	Modelled Output	Wardwatcher Data
Average Number of Patients Seen in CC (SD)	1910 (46.2)	1816
Average LOS hours (SD)	133 (4.4)	127 (233.4)
Average Daily Beds Occupied in ICU (SD)	30 (5.9)	28 (2.8)
Average Daily Beds Occupied in PACU (includes days when unit closed) (SD)	2 (2)	3 (1.7)

With the expectation of a new department being commissioned prior to 2040, there were no constraints on the number of beds to initially test in the 2040 scenario, and therefore runs of the model were used to determine reasonable levels of ICU and PACU beds. With the projected level of demand in 2040, constraining at 70 ICU and 19 PACU beds resulted in the expectation of being at capacity only 1% of the time. Through consultation with the UHW CC team and further model runs an alternative, less generous capacity of 66 ICU and 19 PACU beds is suggested to achieve maximum occupancy approximately 5% of the time (Table 7).

The impact of the hospital ward beds outside of CC becomes obvious when the 2030 demand is run through a scenario with ward bed capacity set to typical level of occupancy seen in the baseline scenario. With ward beds capacity not increasing in line with either the increased number of admissions of CC and non-CC patients, or the increased capacity in CC, a growing level of unmet demand that never recovers can be observed (see Figure 9). The prioritisation of critical care patients in the model ensures flow is maintained in the department; however, access for non-CC patients is challenging.

Adjusting the discharge profile proved to have an effect on the proportion of occupancy lost to DTOC. With the current discharge profile, the outputs showed that occupancy lost to DTOC on average was

Table 7. 2030 and 2040 CC department constrained results summary (mean and 95% confidence intervals).

	2030		2040	
	ICU: 48 PACU: 12	ICU: 51 PACU: 12	ICU: 66 PACU: 19	ICU: 70 PACU: 19
Mean number of patients waiting over 4hrs to access Critical Care (95% CI)	18.2 (12.1–24.3)	3.3 (2.0–4.5)	5.6 (4.1–7.2)	0.9 (0.3–1.4)
Mean number of days at capacity in ICU (95% CI)	28.4 (25.6–31.2)	10.4 (9.1–11.7)	13.4 (11.6–15.2)	3.5 (2.9–4.1)
Mean number of days at capacity in PACU (95% CI)	14.1 (13.5–14.8)	15.2 (14.4–16.0)	1.8 (1.6–2.0)	1.9 (1.7–2.0)
Mean ICU utilisation (95% CI)	78.2% (77.7% – 78.6%)	73.5% (73.1% – 73.9%)	76.4% (76.1% – 76.8%)	72.1% (71.8% – 72.4%)
Mean PACU utilisation (95% CI)	48.5% (48.2% – 48.8%)	48.8% (48.4% – 49.1%)	40% (39.8% – 40.3%)	40.2% (40.0% – 40.5%)

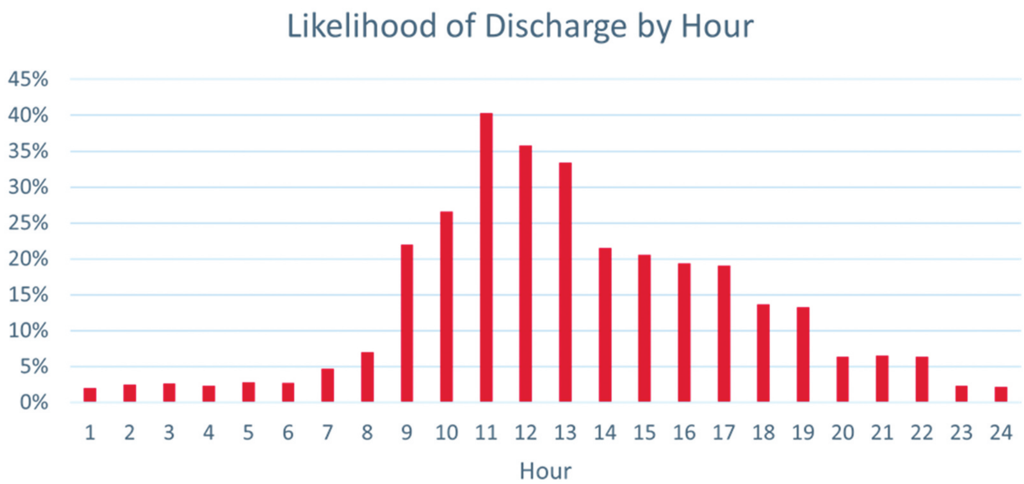

Figure 5. Inflated discharge profile, mimicking shape of profile used in baseline version of model.

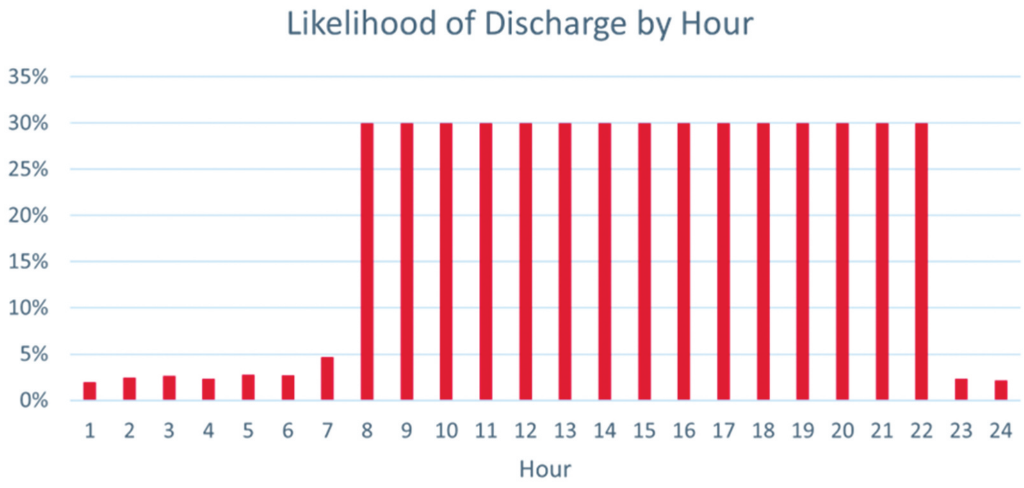

Figure 6. Consistent discharge profile across daytime hours.

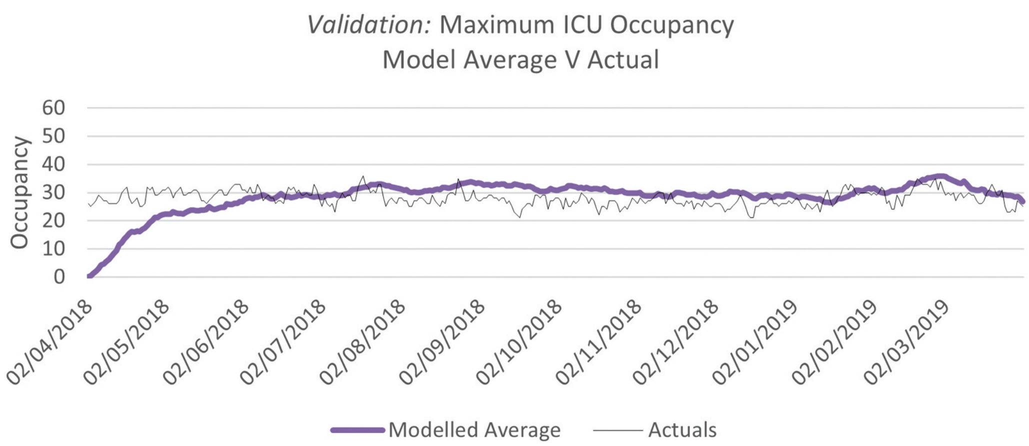

Figure 7. Daily maximum ICU occupancy from 18/19 actual data compared to the average from model runs note model warming up for approximately 3 months to hit a steady state.

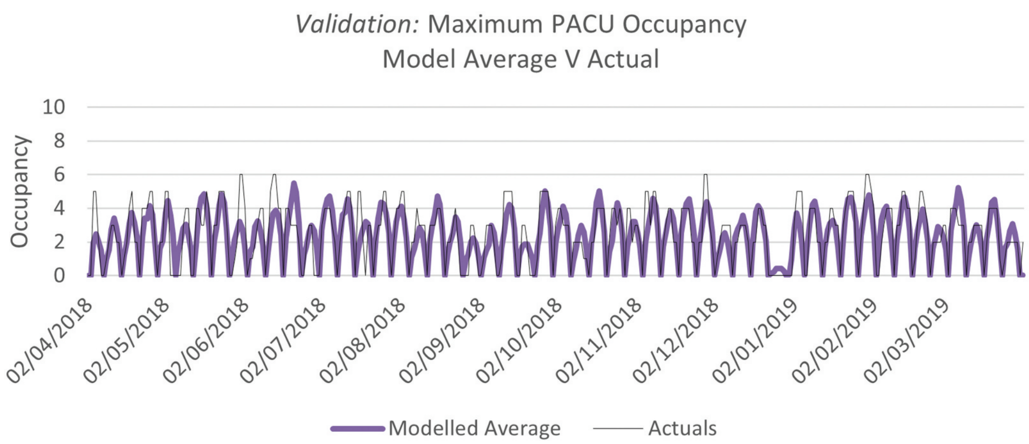

Figure 8. Daily maximum PACU occupancy from 18/19 actual data compared to the average from model runs.

8%. However, when we inflate the likelihood of discharge equally across the daytime hours, leaving the overall shape of the model's inputted discharge profile to follow its original pattern, there is an improvement of only 5% of the occupancy being delayed. When the likelihood of discharge is flat and equally highly likely across the day, the percentage of occupancy lost to DTOC improved further to only 3%. Despite these improvements, the delays observed did not follow the same pattern. Our results show that the delays experienced by patients waiting to access CC were lower when the discharge profile follows its current

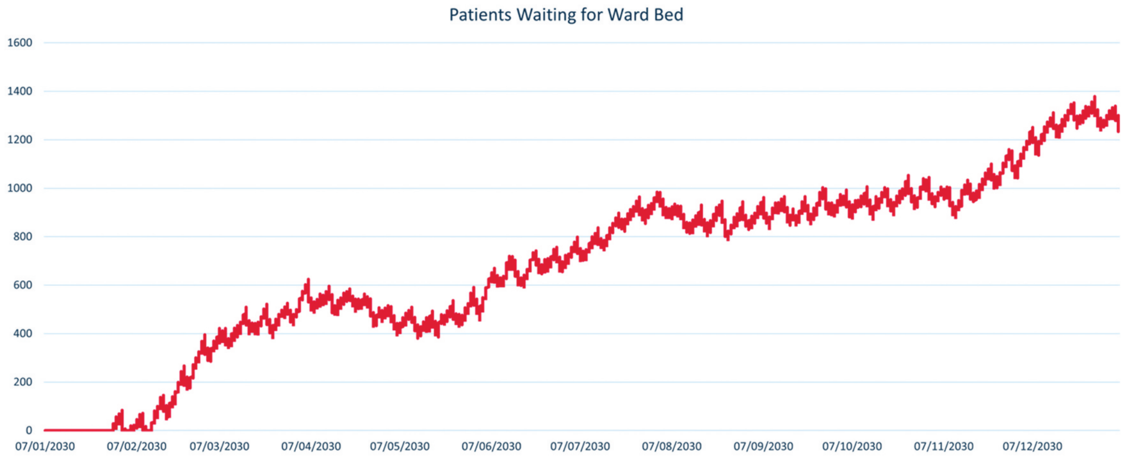

Figure 9. Outputs from a single extreme scenario run showing the escalation of unmet demand if ward beds are not increased in accordance with critical care growth.

shape but with an increased likelihood of discharge. This highlights the key relationship between admission and discharge times and the need to get patients discharged earlier in the day in advance of the peak admissions (Figures 10 and 11).

6. Discussion

This study has provided CAVUHB with a flexible DES model that can be re-run with different calculated demand profiles when service decisions are made in order to ascertain the optimal capacity for the functioning of the CC department and to increase the robustness of future plans. The current simulation model is different to other CC models presented in the literature (Williams et al., 2020), in that a high-level CC model is presented, capturing bed requirement capacity separately at ICU and PACU, alongside that for the rest of the hospital as the key factor to ascertain optimal capacity levels for the CC department.

The model offers a wider picture of the impact different bed capacity levels have on the demand for hospital beds faced from ICU patients. In addition, similarly to the Ordu et al. (2021) study, our model incorporates expected long-range demand to generate expected demand. Capturing expected trends in patient growth is important in order to generate suitable patient demand for beds which can inform hospital's capacity planning strategy. The demand takes

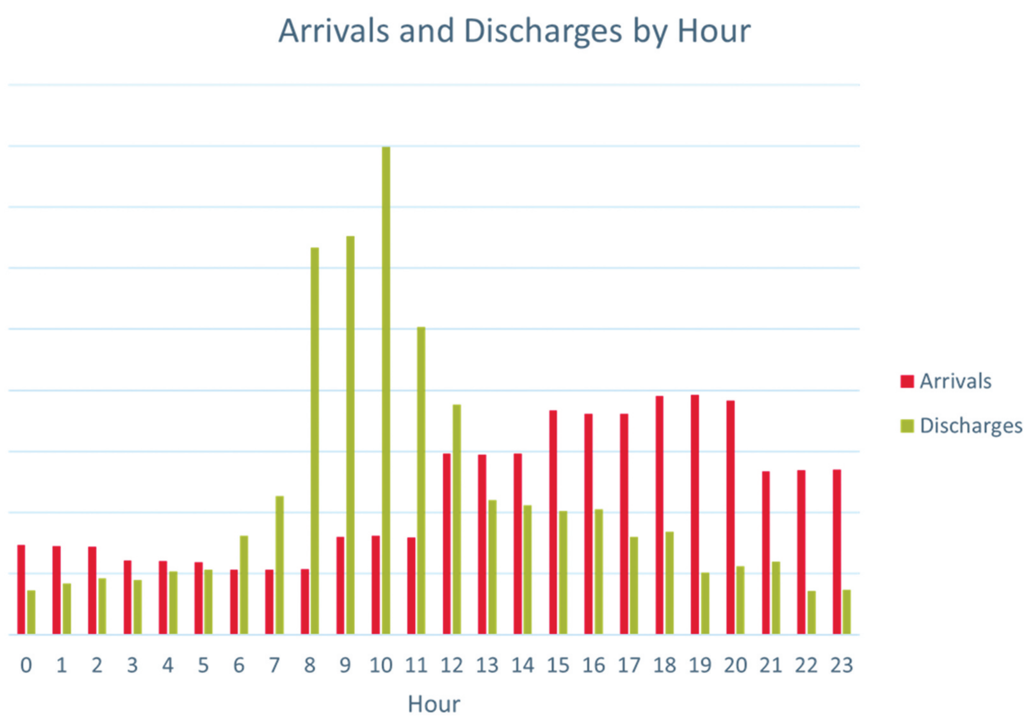

Figure 10. Frequency of admissions and discharges in CC department by hour based on the discharge profile seen in Figures 5. Note, the peak in discharges in this figure is more extreme than seen in Figure 11.

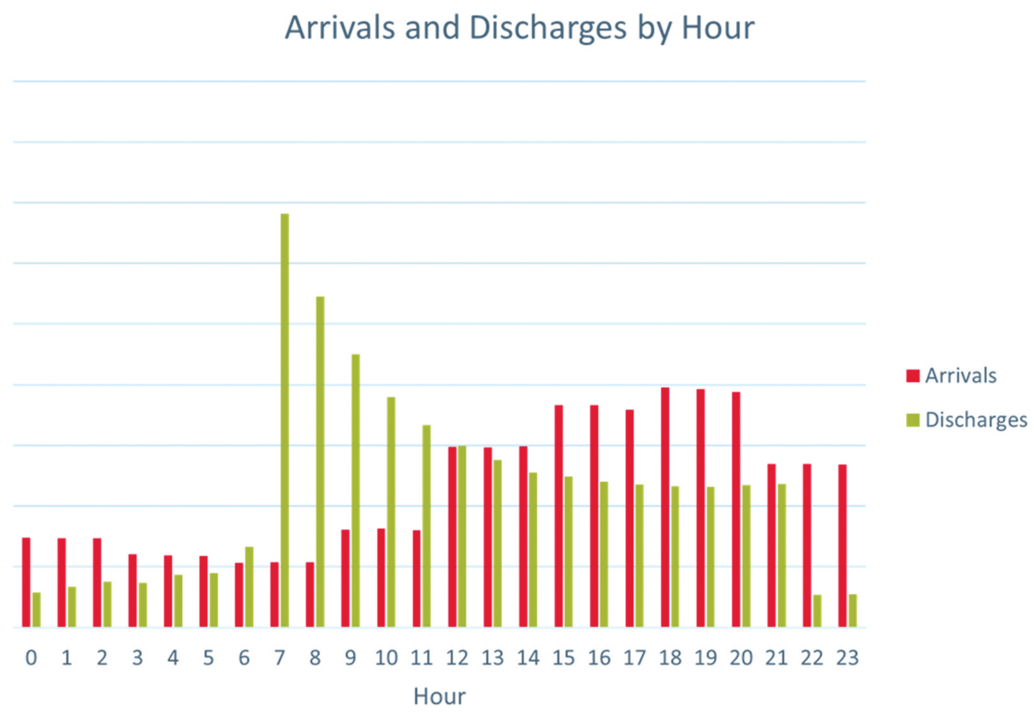

Figure 11. Frequency of admissions and discharges in CC department by hour based on the discharge profile seen in Figure 6.

into account trends in the future using long-range trajectories and subject matter expertise of demand to represent patient need in the form of patient inter-arrivals.

The simulation model presented in this paper shows that there is a need for an increased number of beds for both ICU and PACU in UHW for 2030 in order to meet the expected demand generated from the projections. CAVUHB have been provided with the simulation model and logic used to form the demand trajectories and, therefore are in the position to update the modelling and improve conclusions with any changes made to the planned services developments and general CC trends.

Based on the demand trajectories calculated for 2040, the recommendation is to commission 66 ICU beds and 19 PACU beds to effectively manage the service and ensure patients are seen in a timely manner.

This work shows that increased demand on CC will cause capacity issues across the hospital if ward bed numbers are not adjusted accordingly. The discharge scenarios have shown that, on average, with arrivals peaking late afternoon, enough discharges need to have occurred in advance to allow free flowing admissions to CC. To conclude, the relationship between admissions and discharges are key to maintaining flow in CC, and this relationship needs to be considered within all decision making as changing one will affect the other.

The model results, as presented in the previous section, show that additional beds are needed for UHW to fulfil future capacity requirements.

Furthermore, the model shows that by 2030, the current physical infrastructure of UHW's current CC Department will be outmatched by the calculated demand trajectory, leading to the maximum occupancy being reached 9% of the time. This finding is concerning since the opening date of UHW2 has been moved, and as stated before, the CC Department at UHW provides crucial services that are unavailable elsewhere in Wales.

The new CC Department in UHW2 will need to be approximately 42% bigger than the existing one to satisfy predicted requirements in 2040 (from 48 to 66 ICU beds and from 12 to 19 PACU beds).

Modelling was also done by varying other levels of desired time spent at capacity, showing that, in 2040, 1% time at maximum occupancy can be achieved with an additional 4 ICU beds over the number needed for 5% (for a total of 70 beds).

The effects of DTOC were also investigated, and it was found that simply reducing the DTOC may not be enough to reduce delays accessing critical care; however, the key consideration is the dependency across the day between discharges and admissions.

7. Practical implications, impact and limitations

The work presented in this paper has practical implications for the hospital CC unit and their decision making. The results and insights drawn from the model have been considered by the senior leadership teams at CAVUHB in order to inform their business case for the new UHW2 CC department. The work has been presented as an industrial case study talk at the OR Society Simulation workshop (Lentle & Sachser, 2023) and been shared by the CC consultant to both medical peers and at strategic meetings within CAVUHB to inform their strategic planning.

The UHW CC team can now be supported by the modelling team to continue updating the model assumptions and parameters and use it to make more informed decisions regarding CC capacity in the future.

There are a number of limitations that affected the way the model was developed and the analysis undertaken. This concern primarily the data available to develop both the model and the demand forecasts generate. The data available only explains what happened to patients receiving CC and not what should have happened as those who were denied a CC bed are not captured in the data.

The model developed focuses on the use of bed-related resources, and it was agreed that staff resources would not be included as staff numbers can be derived from bed numbers using well established ratios set at a national level (The Faculty of Intensive Care Medine, 2022).

Predicting the long-term changes in demand and other input parameter inherently comes with a high level of uncertainty. The work presented in this paper assumes that input parameters described in Table 4 such as LOS remain unchanged in 2040. The input variable of demand is calculated using experienced historical trend patterns and includes a level of unmet demand, service knowledge, policy decisions, and advancements in technologies and treatments. The data and knowledge around the facilitation of new workstreams is generally quite poor in comparison to the richness of the data we have for the existing larger workstreams. Population changes were considered a lesser driver to changes in demand compared to the local and UK wide trends in admission service developments, and the unmet demand population change is assumed to be incorporated in the trend patterns. Capturing the changes in the population demographic is made more complicated by the fact that UHW is a tertiary centre and causes variability over time in the base population.

8. Conclusions

This paper presents a case study of an ICU department in Wales that illustrates how simulation modelling was used as a decision-making tool to help inform the size of the CC department within a new hospital in South Wales. Ensuring the physical size of the CC department is suitable at the new site is crucial due to the challenges of expanding the department size when physical space is limited.

Data provided by CAVUHB, including admissions, discharges, and transitions between units and ward, was used to simulate patient flow within the CC department and interactions of these patients with the wider hospital. The model incorporated a variety of behaviours observed in the CC department rather than an idealised scenario, e.g., discharge patterns.

The simulation outputs show that additional ICU and PACU beds will be needed for UHW2 to fulfil demand and capacity requirements. Different levels of "risk appetite" were considered, reflected in the requirement to adhere to 5% and 1% of time spent at maximum capacity.

A concerning finding was that, due to the delay in building the new UHW2 hospital, the existing hospital will be unable to maintain the desired maximum time spent at occupancy of 5%. The interaction between the CC department and other wards is a key relationship that must be considered in future decision making as insufficient ward beds directly impacts CC.

Simulation modelling provides a useful tool in the planning of healthcare services. It provides amechanism to test varying capacities and conditions to understand the impact on patients without causing harm or disruption to flow. The work presented in this industrial case study paper has had real-life impact in the health care domain, informing a key element of an infrastructure planning project using simulation as a decision-making tool, with transferable insights applicable to the planning of other future CC units.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data used for this project is highly sensitive, and confidential patient data thus cannot be made publicly available.

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