Automation in Construction 176 (2025) 106276

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Data integration for space-aware Digital Twins of hospital operations

Nicola Moretti [a],*, Yin-Chi Chan [b], Momoko Nakaoka [b], Anandarup Mukherjee [b], Jorge Merino [b], Ajith Kumar Parlikad [b]

[a] The Bartlett School of Sustainable Construction, University College London, London, WC1E 6BT, United Kingdom
[b] Institute for Manufacturing, University of Cambridge, 17 Charles Babbage Road, Cambridge, CB3 0FS, United Kingdom

ARTICLE INFO

Dataset link: https://github.com/yinchi/histopath-bim-des

Keywords:
Digital Twin
Process Digital Twin
Healthcare facilities
Operations management
Facilities management
Building Information Modelling
Industry Foundation Classes
Discrete Event Simulation
Histopathology

ABSTRACT

Healthcare facilities are complex systems where operational efficiency depends on space, processes, resources, and logistics. While many studies propose process-simulation-based improvements, few dynamically consider the built space's effect on process efficiency. The critical challenge here is the effective integration of data from these disparate domains. This article addresses this challenge by proposing an open Building Information Modelling (BIM) to Discrete Event Simulation (DES) data integration framework towards the development of a space-aware process Digital Twin (DT), with the goal of determining and controlling the impact of spatial layout and built asset performance on core-process throughput. A case study of a multi-storey Histopathology laboratory demonstrates how the impact of changes in travel time between process stages, due to a faulty lift and functional re-configurations, on laboratory turnaround time can be managed integrating up-to-date building information in modelling core business processes. This is achieved through the space-aware process DT architecture.

1. Introduction and background

Healthcare facilities are complex systems where the efficiency of the services depends on factors such as the quality of the built environment, resource utilisation, Human Resources (HR)[1], and supply chain management [1]. In particular, healthcare services do not operate in isolation; instead, their operational flow is significantly influenced by the spatial layout and physical condition of the building. From patient movement [2] to communication patterns of medical personnel [3], the design and infrastructure of a healthcare building play a crucial role in determining general efficiency and effectiveness. The complex interdependencies between healthcare operations and the built environment require advanced tools and approaches to address inefficiencies arising from the interaction between these factors, ensuring the delivery of high-quality healthcare services.

A key challenge faced by operations managers is balancing the use of constrained resources while safeguarding the quality and timeliness of services provided, thus increasing operational efficiency. A common technique used is simulation modelling, in which a digital replica of the system to be optimised is used for scenario analyses and to empower the decision-making process. In this context, one of the most widely used techniques is Discrete Event Simulation (DES) [4].

However, whereas many studies on process simulation for operations management and built environment analysis for patient safety exist, few consider how hospital infrastructure impacts operational efficiency, and fewer still do so in a dynamic manner — for example, being able to automatically detect core infrastructure failures that can create critical operational disruptions (such as lift breakdowns affecting patient transfers or access control failures delaying staff movement), immediately evaluate their effects on the facility's key performance indicators, and take actions to mitigate these effects as much as possible.

These complex decision-making and dynamism requirements are encapsulated within the concept of a Digital Twin (DT), which links a computational representation of a physical asset, entity (such as medical staff and patients), or process with its physical counterpart, with bidirectional flow of right-time data, forming a cyber–physical system. This powerful link between physical and digital can help monitor, optimise and remotely control the physical asset entity or process throughout its life cycle [5,6]. Recent advancements in research have demonstrated how assets and processes are digitalised to develop DTs, which simulate and predict performance under various conditions, and automate the systems' operation. [7].

* Corresponding author.
E-mail address: n.moretti@ucl.ac.uk (N. Moretti).
[1] A full list of abbreviations can be found in Table 1.

https://doi.org/10.1016/j.autcon.2025.106276
Received 9 May 2024; Received in revised form 7 May 2025; Accepted 8 May 2025

Table 1
List of abbreviations used in this paper.

Abbr.	Full name
ABS	Agent-Based Simulation
AECO	Architecture, Engineering, Construction, and Operations
BAS	Building Automation System
BMS	Building Management System
BIM	Building Information Modelling
BPMN	Business Process Modelling Notation
COBie	Construction-to-Operations Building Information Exchange
CT	Computed Tomography
DES	Discrete Event Simulation
DEVS	Discrete Event System Specification
DT	Digital Twin
FM	Facilities Management
HR	Human Resources
ICU	Intensive Care Units
IFC	Industry Foundation Classes
IoT	Internet of Things
IT	Information Technology
KPI	Key Performance Indicator
LtSFM	Low-trust Social Force Model
MAS	Multi-Agent System
M&S	Modelling and Simulation
O&M	Operations and Maintenance
OT	Operating Theatre
PIR	Project Information Requirements
RAAC	Reinforced Autoclaved Aerated Concrete
SOP	Standard Operating Procedure
TAT	Turnaround Time
UML	Unified Modelling Language
UWB	Ultra Wide Band
WBS	Work Breakdown Structure

However, a large part of DT research has focused on the digitisation, update, and curation of digital models of physical assets [8], e.g., equipment, building systems, elements, spaces, and infrastructures. In contrast, significantly less attention has been paid to the application of the DT concept to processes. In particular, additional research is needed on the ideation, development, and testing of interdisciplinary approaches that combine physical and geometric digital models, performance models, and process flow models into an integrated DT that delivers increased operational efficiency in healthcare facilities.

In Architecture, Engineering, Construction, and Operations (AECO), the DT concept is typically closely related to Building Information Modelling (BIM) [9], which is considered the main information management framework in this sector [10]. In this article, we refer to BIM as the set of processes, methods, and open data schemes defined in the ISO 19650 framework [10]. BIM data and information management techniques form a rich source of built asset information, which can be interoperated with Building Management and Automation Systems (BMS/BAS) and Internet of Things (IoT) data, for improved operations, maintenance and space management [11,12]. Therefore, it can be inferred that BIM provides the opportunity of using a variety of information, methods and tools, and rich sources of data supporting the development of DTs in healthcare facilities.

To address the research gaps identified in this paper (see a more detailed description in Section 2.5), we hypothesise and propose a space-aware process DT architecture and an integration framework through which building information, in this case BIM data, can be incorporated within a healthcare process simulation model (as part of the larger DT of hospital operations). As a proof of concept, the proposed framework is applied to a multi-storey Histopathology laboratory. The case study demonstrates how disruptions, such as a broken lift, increase travel times between process stages and how this delay can significantly impact the laboratory's overall turnaround time (TAT). Incorporating up-to-date building information into process simulation enables the proposed DT to inform Facilities and Operations Managers by anticipating, quantifying, and responding to such disruptions in a timely manner. Additionally, BIM data enables dynamic access to spatial and functional information, which is crucial for modifying the spatial assignment of process stages (e.g., for improving process efficiency).

1.1. Research question and hypothesis

In this paper, given the identified knowledge gaps, we formulate the following **research question**: How can information about the layout, built assets and systems be integrated with process simulation models to enable effective analysis and improvement of operations within complex healthcare facilities?

The research question is motivated by the findings that many inefficiencies in current healthcare facilities are related to the layout and factors of the built environment. A more detailed discussion of such identified inefficiencies is given in Section 2.1.

To answer our research question, we start by asking: How does the condition or layout of a building affect the main activities carried out inside it? And how can this kind of spatial information be used to support better decisions in managing those operations? We suggest that a practical way to connect this building information with operational decision-making is using existing BIM standards (ISO 19650 [10,13]), in particular the Industry Foundation Classes (IFC, ISO 16739-1 [14]). These standards provide structured data on building elements that can be used to link building conditions with process simulation models.

Accordingly, we define the following **hypothesis**: Integrating BIM-derived spatial and asset performance data with discrete event simulation models will significantly improve the facility's ability to anticipate and respond to disruptions, thereby reducing process bottlenecks and improving overall turnaround times.

In simple terms, our hypothesis states that where BIM information is available, IFC data can be used to bring together building layout and performance information with process simulations. This integration forms a decision support tool that helps to improve the efficiency with which healthcare processes are run. Using open standards like IFC also makes this integration easier because they ensure compatibility across different software tools, commercial or open source. The success of this approach depends on understanding exactly what data the simulation model requires, and building a data pipeline that extracts and transforms only that data. In this paper, we explore how to define those data needs and construct such a pipeline. This enables us to analyse how changes in the building's state affect operational efficiency, directly addressing our research question.

1.2. Contributions of this paper

In this paper, we present a framework that connects BIM data with DES to support more realistic and effective simulation of healthcare facility operations. Our approach enables the use of geometric and spatial data from BIM to model and manage the performance of a hospital laboratory in operation. Traditionally, BIM data has been underused during buildings' operational phase, especially for improving the efficiency and resilience of core service delivery. This work addresses that gap. We focus on using open standards, such as IFC, to build a flexible and interoperable data pipeline between BIM and DES. Using a BIM model and process data from a hospital in the East of England, we show how building-related disruptions such as a lift failure can be quantified and analysed in terms of their impact on core processes, such as laboratory TAT. Additionally, we demonstrate how updated BIM information can be used to inform the re-definition of the laboratory functional layout, given the constraints of the existing facility. By enhancing the DES model with spatial and asset performance data, our simulation becomes more realistic, reliable, and actionable. We planned this work within the broader scope of a space-aware process DT that supports better operational decision-making and we made the following specific contributions:

- Developed a BIM-DES integration framework that enables the use of building geometry and topology to inform and enrich process simulation.
- Proposed a space-aware process DT architecture that combines simulation and building state data for proactive and reactive decision-making.
- Demonstrated the practical use of open BIM standards (e.g. IFC) to improve core-process simulation interoperability and information exchange.
- Quantified the operational impact of infrastructure failures, such as lift outages, on laboratory performance using real hospital data.
- Showcased how BIM methods can be extended into the use phase to support both operations and Facilities Management (FM).
- Improved decision-making capabilities for Operations Managers and Facility Managers through a more integrated view of process and infrastructure performance.

2. Background and related work

2.1. Healthcare facilities operations inefficiencies

Healthcare facilities, and specifically hospitals, exhibit various operational inefficiencies when performing care activities, such as (i) delays in bed turnover [15] and (ii) patients' transfer [16], (iii) poor space utilisation [17], (iv) workflow disruptions [18], (v) high staff workload [19], and (vi) resource misallocation [20]. In particular, hospital layout inefficiencies significantly impact staff movement, patient care process, and workflow efficiency. Poor design in emergency departments and laboratories results in congestion and bottlenecks, slowing down operations and increasing turnaround times [17]. Beyond layout inefficiencies, poor space utilisation and ineffective building design create additional operational challenges. Underutilised hospital spaces can result in wasted resources, while overcrowded areas, such as phlebotomy labs, contribute to errors, distractions, and reduced efficiency. [18]. Operational inefficiencies in hospitals also impact staff well-being, TAT, and patient safety. Long walking distances and inefficient workflows due to poorly designed workspaces contribute to staff fatigue, burnout, and dissatisfaction [19]. Inefficient workflows further disrupt bed assignments, patient transfers, and overall hospital operations, leading to delays in care delivery and increased patient waiting times. Delays in bed turnover processes can extend waiting times for inpatient beds, causing patient care delays and decreased satisfaction [15]. The physical distance between wards and the Operating Theatre (OT) is a key factor in patient transfer, as greater distances can lead to unwanted delays in reaching the OT [16]. Addressing these inefficiencies requires data-driven approaches to optimise workflow efficiency, hospital layout, and resource management. In this regard, DTs and Simulation Models present innovative solutions that enable real-time tracking, predictive modelling, and process optimisation. Section 2.2 explores how DTs can transform hospital management by integrating real-time or right-time data, enhancing space utilisation, and reducing operational bottlenecks.

2.2. DT for improved complex healthcare facilities operations management

Trauer et al. [21] define a DT as "a virtual dynamic representation of a physical system, which is connected to it over the entire lifecycle for bidirectional data exchange". They also emphasise that "only data required for the respective use case should be entailed". In the field of manufacturing, DTs are covered by the ISO 23247 series [22]. However, there has also been a push towards defining a set of more general standards for DTs; so far, this has led to ISO 30173 [23].

In this section we consider not only the DTs, but also what Kritzinger et al. [24] define as *Digital Shadows* (i.e., digital systems in which there is a unidirectional automatic data flow from the physical to the digital counterpart), and *DT with human-in-the-loop*, where data flow from the digital to the physical counterpart (e.g., recommended actions) is reviewed by a human operator before being applied [25]. This allows us to broaden the scope of the analysis, understand how digital technologies can help solving healthcare facilities inefficiencies, including also those applications where full automation is not yet achieved. Table 2 summarises these applications, the inefficiencies addressed and the benefits achieved.

The reviewed applications summarise the benefits of healthcare DT development, though highlighting a main limitation, which is the narrow purpose of the applications developed. Each application, in fact, focuses exclusively on one domain area: either patient flow management, asset and facilities management, portering, or medical equipment management. However, processes do not operate in isolation, and this aspect requires a multi-disciplinary approach to modelling and simulation in order to deliver deeper insights and enhance the decision-making capabilities of hospital managers. In addition to this, all the reviewed applications either impact on or are constrained by space and building services. However, BIM data is seldom utilised to inform spatial and built asset variables, and this represents a missed opportunity, considering the rich information that can be used to inform the process operation through BIM approaches. For these reasons, Sections 2.3 and 2.4 delve into the problem of process modelling, simulation and openBIM (broadly defined as "seamless data sharing and collaboration across platforms and stakeholders"[2]), which is functional to the definition of an integrated space-process DT.

2.3. Simulation and its role in process improvement

Simulation techniques are essential for improving hospital operations by modelling complex processes and predicting outcomes [39]. Three widely used simulation methods in healthcare are DES [40, 41], Agent-Based Simulation (ABS), and hybrid models. DES models workflows as discrete events, useful for analysing patient flow and resource allocation, while ABS simulates individual behaviours of agents like staff and patients to understand movement patterns and decision-making.

There have been many studies on simulation modelling in healthcare and other fields of operational research [4,41–47]. Simulation modelling supports process managers in decision-making by enabling detailed process analysis, evaluating current and future scenarios, predicting the impact of changes, and optimising performance through risk-free experimentation [48]. In this subsection, we will focus mainly on simulation studies using DES, ABS or hybrid methods for healthcare which incorporate spatial information to optimise hospital layouts or improve indoor navigation systems for better movement of personnel and resources.

Simulation studies have been used to identify multiple bottlenecks in healthcare delivery, covering operational views such as patient flow and overcrowding [49,50], nurse travel distance [51], patient transfer delay [52], clinical laboratory throughput [53,54], utilisation of critical resources (e.g., bed or Computed Tomography — CT) [55], and appointment delays or cancellations [56]. Some have proposed actionable improvement measures for changeable design elements [49–51], while others have provided insights on operational policies about workplace behaviour, opening hours and access control [52]. However, while it has been found that many of the challenges faced in healthcare facilities (particularly hospitals) in the literature are related to the building layout, a large majority of publications which consider these challenges do not in fact make this association [57]. In the following text, we specifically study applications of space-aware simulation models in healthcare services delivery.

[2] https://www.buildingsmart.org/about/openbim/.

Table 2
Applications of DTs in hospital management with the related benefits.

Domain	Application	Inefficiency	Benefits
Patient flow management	Bed planning (trauma and orthopaedic) with dynamic update [26].	Delays in bed turnover.	Improved daily/weekly prediction of admissions.
	Agent-based emergency department simulation [25].	Patient transfer delays.	Improved management of patient pathways through what-if scenario analysis.
Asset and facilities management	NFC-based system for hospital discharge tracking and bed management [27].	Resource misallocation, Workflow disruptions.	Reduced bed turnaround time and automate the notification to the cleaning staff.
	Bluetooth/Wi-Fi-based [28] and Ultra Wide Band (UWB) [29] location system for movable assets.	Resource misallocation.	Dynamic asset tracking.
	BIM/IoT/OT enabled twin of a hospital [30,31].	Resource misallocation, Workflow disruptions.	Reduced energy consumption, facility faults, number of requested repairs, and enhanced the quality of daily maintenance work.
	Robot dispensary with a real-time stock management system [32,33].	High staff workload, Resource misallocation.	Reduced dispensing error and stock-out rates and high staff satisfaction. Reduced time for stock management.
	Intensive Care Units (ICUs) hybrid DES-ABS-based simulation [34].	High staff workload, Workflow disruptions.	Improved design and test different intervention strategies which can reduce clinicians' task durations and inform new discharge policy.
Portering	Robotic portering with automated guided vehicles [35].	Poor space utilisation, Workflow disruptions, High staff workload, and Resource misallocation.	Optimised decision variables and determined the best output for each supply chain. Avoid bottlenecks and congestion. Reduced staff workload.
	Indoor location-based hospital porter management system [36].	Workflow disruptions, Resource misallocation.	Real-time location information of porters, prioritise tasks and manage assignments.
Medical equipment management	Virtual patient with temporal evolution for mechanical ventilation through stochastic modelling [37,38].	Resource misallocation.	Optimised bedside mechanical ventilation guidance protocols through in-silico simulation and validation. Reduced need for lengthy, resource intensive, high cost clinical trials.

Lee et al. [51] used ABS to model nurse travel distance in wards. They found that by revising the spatial layout of single, double, and multi-bed rooms, nurse travel distance was reduced by more than 15%, thus reducing fatigue and securing more nurse time for direct patient care. In particular, the common practice of grouping multi-bed rooms along one of the corridors was found to be inefficient; instead, single, double, and multi-bed rooms should be interspersed.

Li et al. [50] used a combination of mathematical optimisation and ABS to evaluate hospital ward design with respect to walking distance and human density. Locations in the ward were classified as fixed (patient rooms, lifts, stairwells) or movable (e.g., offices, nurse stations, storerooms). Then, mathematical methods were used to identify nine candidate layouts (A1–A3 along the Pareto front and six additional near-optimal layouts, labelled A4–A9), which were then compared using ABS, along with an additional layout A0 designed manually. Based on the simulation results, the automatically generated layout A2 was chosen as the best overall

Schaumann et al. [58] used a narrative-based simulation to explore potential implications of including or excluding a day room in the design of an internal medicine ward. It overcame the limitations of typical DES models and considered the movement and activities of individual occupants and the impact of building design on the flow of resources. The results of the simulation suggested that the presence of a day room reduces visitors' density in corridors and diminishes the number of staff–visitor interactions that can delay the scheduled medical procedures.

Xu et al. [59] applied DES with a low-trust social force model (LtSFM) to analyse passenger flow distribution and facility utilisation. It demonstrated that spatial planning in hospitals can be significantly optimised using improved simulation models. Improvement measures, such as removing two self-service check-in machines near the entrance of the outpatient hall, were compared to address density, queue time, facility usage, and infection risk.

Meephu et al. [52] used DES to optimise intra-hospital patient transfer. Among the key policies proposed is to prioritise critical patients (which require two accompanying staff instead of one), obtaining the next patient for transfer without the need to return to base, and choosing staff based on proximity rather than balancing workloads (however, this may not be desirable based on other criteria such as fairness). By combining these policies, the authors found that mean waiting time could be reduced by 21%. However, the spatial model of the hospital was not explicitly presented in the paper, nor was the methods of obtaining such a model discussed.

Ahmadi and Lather [49] They used DES to compare layouts for a walk-in vaccination clinic. It was found that perimeter-based layouts were more efficient than serpentine layouts in terms of average patient travel distance and time-in-system. However, since patients in the clinic model would only queue along the main path itself or outside the clinic (before the check-in point), the authors did not find any significant relationship between arrival load and average patient travel distance. The authors did not consider the case where heavy arrival load may lead to changes in the patient path configuration, for example, the introduction of holding areas for queuing patients.

Note that the publications listed above generally focus on one-off modifications to facility layouts for process improvement, but do not focus on layout resilience and actions for preventing or mitigating the effect of core infrastructure failures, e.g. lift outages or malfunctioning access card readers.

In summary, as the state of the built environment can change, it is important to study the ongoing interactions between the built environment and the processes carried out therein, particularly the core business processes in addition to those related to building maintenance. On the other hand, while there have been a few studies on the effect of building layout on process efficiency, especially for layout redesign, these do not consider naturally occurring changes to the building state,

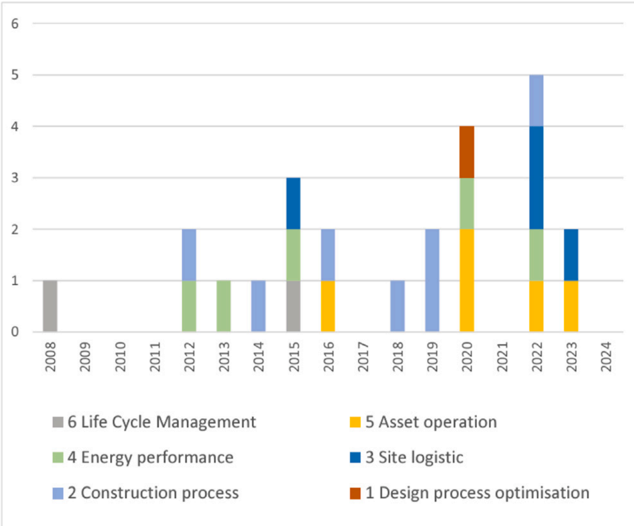

Fig. 1. Key studies on BIM-process M&S integration and applications, by year.

Table 3
Applications of BIM and process M&S integration.

Application	Papers
Design authorising	[74]
Construction process	[75–82]
Site logistics	[65,66,83,84]
Energy performance	[70,85–89]
Asset & operations management	[90–92]
Lifecycle management	[93]

Table 4
BIM and M&S techniques and integration approaches.

Technique	Papers
Business process model	[65,66,74,77,80,85,90,91]
Work Breakdown Structure (WBS) method	[65,66,83,89]
Activity network model	[74,79,81]
Simulation, discrete event	[65,79,87,88]
Simulation, energy	[85,87,88]
Simulation, fluid dynamics	[70,92]
Simulation, multi-agent	[66]
Particle swarm optimisation	[65]
Computer vision	[75,84]

e.g., due to random failures, and therefore cannot be used for day-to-day decision-making. This forms a knowledge gap which we elaborate upon in Section 2.5.

2.4. BIM as an enabler for space-aware process digital twins

In the context of developing building-level DTs, BIM improves the sharing of project and asset information among stakeholders throughout the building lifecycle, enhancing collaboration and decision-making [60,61]. For example, it is used as a static visualisation tool to enhance traditional building design, drawing modification, construction scheduling, and cost estimation [62]. BIM also integrates with green building practices, aiding in energy and thermal analyses, and supporting sustainable design and construction [63,64]. Other applications demonstrated how it can facilitate the Life Cycle Assessment by estimating environmental impacts and energy consumption during the design stages [63]. BIM supports construction process simulations, improving planning, scheduling, and productivity through dynamic visualisation and alternative design explorations [65–67]. It also enhances facility operation and maintenance by improving data exchange efficiency and supporting Operations and Maintenance (O&M) principles, though challenges in data interoperability remain [11,68,69]. BIM models are used for energy performance evaluations, optimising building energy efficiency and performance [70–72]. It also serves as a systematic risk management tool, integrating with other BIM-based tools for comprehensive risk analysis across the building lifecycle [73].

With a focus on the integration of BIM with process Modelling and Simulation (M&S), which is key for this article, the literature has been classified according to applications and techniques utilised, in Fig. 1 and Tables 3 and 4.

The review of the literature highlights that although BIM techniques are known to have an impact in the field of FM — e.g., through Construction Operations building information exchange (COBie) [94–96] and the ISO 19650 series [13] — its use in conjunction with M&S is still largely shifted towards the design and construction phase of a building's lifecycle, with only three articles [90–92] reporting the use of BIM for Asset & operations management, which primarily relates to the use phase. This is despite this phase accounting for a large part of a building's lifecycle, where BIM can inform space management, environmental monitoring, energy management, asset maintenance and other improvements, when integrated with IoT, BMS and BAS technologies [69]. In fact, BIM is primarily utilised to model and simulate building components for design and delivery; to enhance collaboration among construction professionals, support time and cost simulations in the construction process; and, in fewer cases, to provide enriched building information in asset performance monitoring and control.

With regard to the innovation proposed in this paper, when BIM data is available, it can be used beyond the current state-of-art, to inform the space variables and constraints of the healthcare facilities' operation process simulation, connecting two domains which are currently siloed. Although there are other possible sources of space and layout data, such as BMS, these sources would only work for modern buildings with a BMS built-in with such features. In contrast, our approach is agnostic to the availability of such technologies and relies on the availability of a BIM model, which if not existing could also be generated with relative ease to meet the space-aware simulation requirements described in Section 4.3. This builds on previous works on BIM to DES integration for building operation and addresses technical challenges such as modular design, data integration, simulation model development and validation [97]

A viable BIM-DES integration approach is the use of an intermediate open data format, which provides a view of the original BIM data in a manner tailored for the specific use case. The nature of this intermediate data will depend on the geometric and semantic building information needs (i.e., the Level Of Information Need, according to the ISO ISO7817-1:2024 [98]) of each specific use case. To enable the interoperation between the BIM model and the operational process model (e.g., a process simulation model, which we describe in this paper), the intermediate data format should be based on open standards — this is one of the core principles of openBIM [99]. The main interoperable data standard in this context is IFC [14], which we use in this work. Other open built environment data models exist, such as IndoorGML,[3] GreenBuildingXML[4] and BIMXML,[5] although they are beyond the scope of this paper.

[3] https://www.ogc.org/publications/standard/indoorgml/.
[4] https://www.gbxml.org/.
[5] https://bimxml.org/.

2.5. Identification of knowledge gaps

The review of the literature highlights some research gaps with respect to addressing the stated research question of this paper. Firstly, although many challenges and sources of inefficiency in healthcare settings are associated with space, most case studies do not study this association in depth [57]. Of those that do, many focus on one-off changes to layout or process design, and do not study the ongoing interactions between building state and process efficiency, as a DT would allow us to do. Conversely, many existing building-level DTs in academia and industry focus primarily on physical assets only, with less focus on the core business process that take place within the built spaces. Among DTs that focus on processes, most focus primarily on construction, manufacturing, or maintenance processes only. There is thus a lack of research on frameworks to not only integrate geometric, topological, semantic, and operational information from different sources, but to do so in a continuous manner as required for a space-aware process DT for core business operations. There is therefore a lack of research/evidence on how such frameworks and DT implementations can be used to inform the decision-making process and improve operational efficiency and resilience of business operations against failures in core building infrastructure, e.g. lifts, access card readers, etc.

3. BIM-DES integration methodology

In this paper, we develop a BIM-to-DES integration approach that enables the use of streamlined BIM data to inform the simulation of core-process operations in specialised buildings, i.e., facilities where the core business function is closely related to the built assets, such as hospitals. To define this approach, we used a mix of evidence-based research and empirical case-study-based research methodologies and general data processing methods, which simplify the data pipeline and can be deployed in any Python-based environment.

This section contains the generic aspects of the BIM-DES integration methodology. In Section 4, we provide specific implementation details relating to a case study of the Histopathology laboratory at Addenbrooke's Hospital, Cambridge, UK.

3.1. Discrete event simulation

In this paper, we used the Python library salabim [100][6] as a basis for our DES framework. A benefit of salabim is the inclusion of built-in statistics collection for resources and other simulation components. However, while salabim provides primitive constructs such as resources and events to support DES, the nature of our process model prompted us to create an additional framework layer for representing common tasks in the process logic, such as batching, collation, and delivery. To break the process logic into manageable code blocks, each step in the process is represented by an instance of `BaseProcess`, which includes the derived classes `Process`, `BatchingProcess`, `CollationProcess`, and `DeliveryProcess`, as shown in Fig. 2.

Each process instance defines an infinite loop:

- `Process` takes entities from its `in_queue` and launches the process defined by `fn` for each entity. To register a process, we make it a member function of the appropriate class using the code in Listing 1.

  Listing 1: Register a new function to a class. The function represents a task that operates on instances of the given `in_type`.

  ```
  setattr(self.in_type, self.name(), fn)
  ```

  The process defined by `fn` is responsible for forwarding entities to the `in_queue` of the next process in the process chain (unless it is the last process in the chain).
- `BatchingProcess` takes `batch_size` entities from its `in_queue` and places a `Batch` entity in the `in_queue` of the next process in the process chain, as defined by the string `out_process`.
- `CollationProcess` takes entities from its `in_queue` and collates them according to their `parent` attribute. When all child entities of a parent entity are collated (as tracked by the specified counter), the parent entity is placed in the `in_queue` of the next process in the process chain, as defined by the string `out_process`.
- `DeliveryProcess` takes entities (possibly `Batch` entities) and delivers them to the specified `out_process`, using one of `resource` and requiring time as defined by `durations`. `Batch` entities are unbatched before being placed in the `in_queue` of the output process.

Note that some process classes shown in Fig. 2 are analogous to logic blocks available in some graphical trajectory-based DES software, e.g. Process and Batch in Arena. However, the advantage of our Python-based DES approach is easier integration with other components such as the BIM component described in the following subsection.

3.2. OpenBIM and Industry Foundation Classes

In this paper, we use IFC4 ADD2 TC1.[7] The goal is to test the usability of IFC as data input for the process simulation component of our BIM-DES methodology. Therefore, we use both the semantic and geometric information represented within the IFC schema. For example, in our DES model, some system attributes, such as task duration (particularly for delivery tasks), are space-dependent, e.g., the time needed to reach room B in a building from room A or the waiting time in a lift to reach the desired floor. To feed these DES space-dependent variables with deterministic values, the location of any `IfcProduct` (e.g. a space, door, wall, stairwell, or lift) can be modelled in IFC and the schema can be parsed to extract all necessary geometric and semantic information required. However, the geometric representation of the IFC classes derived from the `IfcProduct` instances can differ, thus requiring different data discovery mechanisms to retrieve the geometric and spatial representations of the BIM objects.

In this article, we use the spatial representation of doors and walls and internal partitions in a building to feed the DES model, and we assume that the spatial containment relationships of the IFC schema are fulfilled. As an example, consider an `IfcDoor`. This door is spatially contained within an `IfcBuildingStorey` (through the `IfcRelContainedIn SpatialStructure` class), which is in turn contained within an `IfcBuilding`.[8] However, the door itself may be represented using `IfcExtrudedAreaSolid`, `IfcBooleanClippingResult`, or `IfcAdvancedBrep` and each of these geometries are represented differently in the IFC data model. Therefore, a variety of methods are required to obtain the location of `IfcDoor` instances relative to the global coordinate system, making the manual parsing of the IFC schema very complicated.

To automate the process of parsing these varied geometric representations of doors and walls in our IFC data file, in this article we use the ifcOpenShell Python library,[9] which we chose since our process

[6] https://www.salabim.org/manual/.

[7] https://standards.buildingsmart.org/IFC/RELEASE/IFC4/ADD2_TC1/HTML/.

[8] Although other hierarchies exist, e.g., involving `IfcSpace` or `IfcSite`, these are ignored in Listing 2, as the BIM model under study only consists of doors associated with building stories.

[9] https://ifcopenshell.org/.

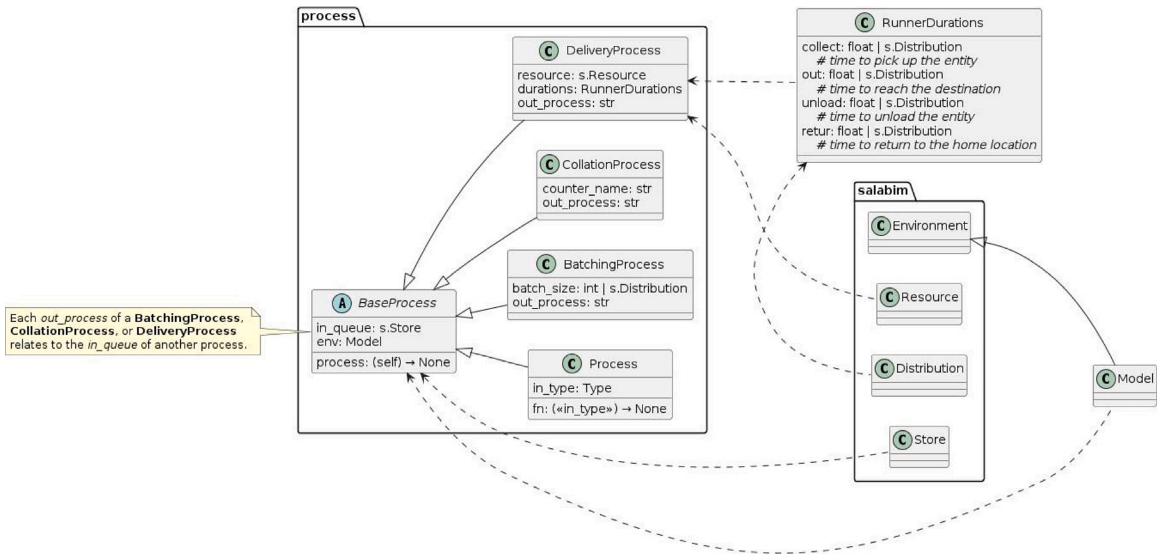

Fig. 2. UML Class diagram for the `BaseProcess` and related classes in our DES framework ("s" is an alias for salabim). Lines with white arrowheads denote class inheritance while dashed lines denote a general association. Key attributes (middle box) and methods (bottom box) of selected classes are also shown.

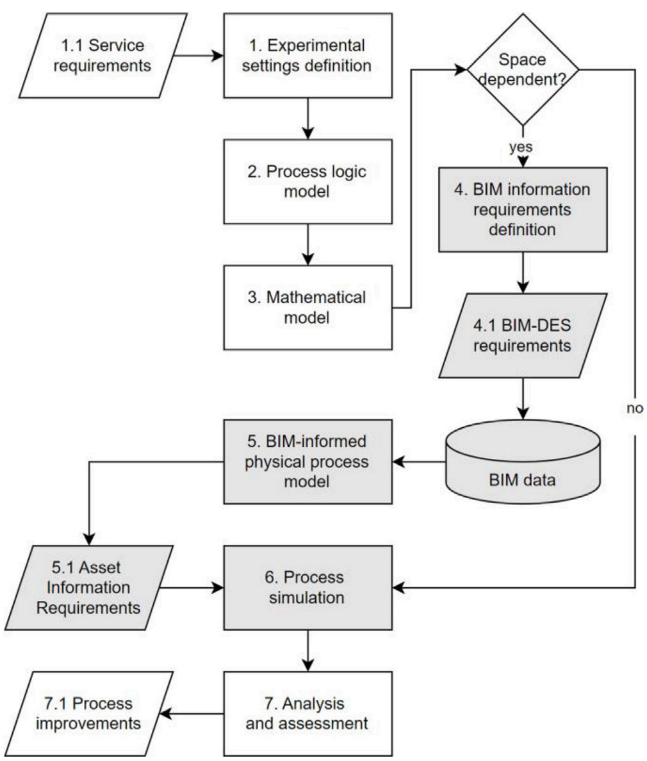

Fig. 3. Phases of research for our proposed BIM-DES integration approach. Phases addressed in this paper are highlighted in grey.

simulation was also developed in Python. IfcOpenShell offers a set of methods to navigate the geometry definitions in an IFC model; this is shown in Listing 2. In particular, the `get_level_name` function traverses the IFC object hierarchy to obtain the human-readable name for the `IfcBuildingStorey` each wall or door is on. Additionally, we have prepared the IFC model file such that all doors of interest have names of the form `d1`, `d2`, etc. Meanwhile, the `get_coords` function is used to obtain the bounding box of each wall or door. While the geometry definition of the IFC objects is much more complex than this, the current approach suffices for the model under consideration, in which all walls and doors are contained rectangular prisms aligned along the axes of the global coordinate system.

In our case study, detailed in Section 4, Autodesk Revit 2022 was used to prepare the BIM model, exported to IFC4, with the renamed doors.

3.3. BIM-DES integration approach

The DES techniques are used in our proposed integration approach to model the core processes in a healthcare facility, while the adoption of the openBIM methods enables the calculation of the durations of space-dependent activities. Fig. 3 represents the main phases of our proposed approach. Phase 1 (Experimental settings definition) involves defining the service requirements of the simulation with the key stakeholders. Since the focus is on the building's core processes, these stakeholders include Operations and Facilities Managers. This phase concerns the definitions of the desired capabilities of the process simulation, which will be used for decision-making in operation and process improvements. Phase 2 corresponds to process logic modelling, carried out via empirical research, collaboration with Operations Managers, and data extraction from Standard Operating Procedure (SOP) documents. This allows us to identify the main process stages, their inter-dependencies, the key process parameters, and the constraints/inputs/outputs of each stage, as described in [101]. Phase 2 also forms the basis of the mathematical modelling performed in Phase 3.

At this point, the space dependencies of the core processes can be identified, such that the process schema in Fig. 3 branches into two. If the modelled process is not space-dependent, the process simulation (Phase 6) can be developed without using BIM data; otherwise, BIM data is used to obtain the location, geometry, and semantics of the spaces and physical assets involved. However, since the BIM information is not usually created to support the simulation of core processes in buildings, the BIM-DES information requirements must be defined (Phase 4). In this phase, the geometric, alphanumerical Level Of Information Need [13,98] is defined (4.1 BIM-DES requirements) and mapped to the existing BIM data to ensure the BIM-DES integration. These information requirements are embedded into the BIM model (5.1: Asset Information Requirements — AIR) and can be also used as a

Listing 2: Import ifcOpenShell packages and obtain the required spatial/semantic data.

```
from ifcopenshell import geom as ifc_geom
from ifcopenshell.util import shape as ifc_shape

# Get the level that an IFC object is on.
def get_level_name(obj: ifc.entity_instance) -> str:
    return (
        obj.ContainedInStructure[0].RelatingStructure.Name
    )

# Get the list of elevations for each IfcBuildingStorey
# Our IFC file is known to express elevation in mm,
# convert to m.
elevations: dict[str, float] = reduce(
    lambda d1, d2: d1 | d2,
    map(
        lambda s: {s.Name: s.Elevation/1000.0},
        ifc_file.by_type("ifcBuildingStorey")
    )
)

# Get the bounding box of an IFC object; for our IFC file,
# all walls and doors are aligned to the xyz axes.
def get_coords(
        obj: ifc.entity_instance) -> dict[str, float]:
    shape = ifc_geom.create_shape(settings, obj)
    grouped_verts = ifc_shape.get_vertices(shape.geometry)
    return {
        'x0': min(map(lambda xyz: xyz[0], grouped_verts)),
        'y0': min(map(lambda xyz: xyz[1], grouped_verts)),
        'z0': min(map(lambda xyz: xyz[2], grouped_verts)),
        'x1': max(map(lambda xyz: xyz[0], grouped_verts)),
        'y1': max(map(lambda xyz: xyz[1], grouped_verts)),
        # 'z1': max(map(lambda xyz: xyz[2], grouped_verts))
    }

# Extract door data, only for doors labelled d1, d2, d3...
# through the IfcDoor.Name property
doors: list[ifc.entity_instance] = list(
    filter(
        lambda door: bool(re.match(r'd\d+$', door.Name)),
        ifc_file.by_type("IfcDoor")
    )
)
doors_coords = [get_coords(door) for door in doors]

# Extract wall data
walls = ifc_file.by_type("IfcWall")
wall_coords = [get_coords(wall) for wall in walls]
```

reference to inform the design process of similar buildings where a BIM-DES integration is needed.

The DES-informed AIRs are then used in the process simulation (Phase 6) to investigate how space and location impact process performance. Finally, Phase 7 corresponds to the analysis and assessment carried out to evaluate the simulated process performance against a set of Key Performance Indicators (KPIs) derived from the service requirements. The output of this phase is a set of process improvements in the form of recommendations, system automation, and notifications (7.1: Process improvements).

The phases highlighted in grey in Fig. 3 are addressed in Section 4 of this paper with respect to a case study of a clinical laboratory. Note, however, that the framework itself is general and can be applied to core business processes in other types of buildings.

4. Histopathology laboratory case study and implementation results

The proposed BIM-DES approach has been implemented in the Histopathology laboratory at Addenbrooke's Hospital in Cambridge, UK. The Histopathology laboratory provides crucial functionality for the efficient treatment of patients. Within the Histopathology department, histological specimens (i.e., a section of human tissue, once taken

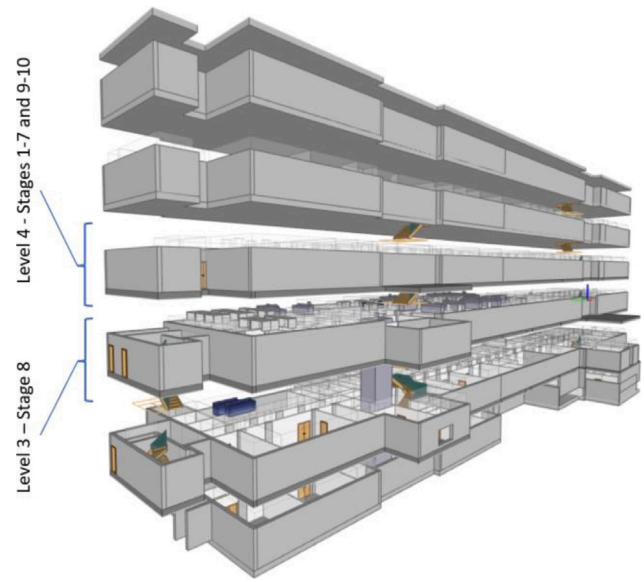

Fig. 4. 3D model in IFC of the Biomedical building of Addenbrooke's hospital. The Histopathology laboratory is hosted in Levels 3 and 4, corresponding to the first and second floors above the ground.

from a patient) undergo a series of stages until a pathological diagnosis is carried out and reported to the patient. These phases are enumerated in Table 5 (re-elaborated from [101]) and are located in the levels 3 and 4 of the building represented in Fig. 4, part of the Cambridge Biomedical Campus.

In this section, we first define (Section 4.2) our BIM-DES architecture, constructed using the BIM-DES integration approach in Section 3.3, and its context within a future DT. In Section 4.3, we complete Phase 4 of our integration approach (as shown in Fig. 3) by describing the requirements for parsing and processing the BIM data into a format usable by our BIM-informed physical process model. In Section 4.4, we describe how we use our DES framework (see Section 3.1) to create a simulation model (Phase 6 of the integration approach) for the Histopathology laboratory. Section 4.5 shows how the parsed and processed BIM data is fed into the process simulation model (Phase 5 of the integration approach) in order to compute the travel times between stages of the overall Histopathology process. Finally, two numerical examples are described in Sections 4.6 and 4.7 highlighting how our BIM-DES integration approach can be applied to quantify and evaluate the impact of state changes in a built space on the performance of processes conducted therein.

4.1. Case study overview

The main KPI used to assess the Histopathology service is the percentage of cases processed end-to-end within a given time frame, from case creation (when the sample is booked-in at the lab) to the issuing of a histopathologist report (i.e., the turnaround time or TAT). However, within the laboratory setting, the reporting time cannot be completely controlled, since it depends on the pathologists who are external to the laboratory (Stage 12 in Table 5). Therefore, we define the main laboratory process as Stages 1 to 11 in Table 5. The crucial KPI within the laboratory is thus the "lab TAT", which unlike overall TAT lies within the control of the laboratory's Operation Managers.

Between laboratory stages 1 to 10 in Table 5, the specimens are transferred individually or in batches between each pair of consecutive stages. In contrast, Stages 11 and 12 of the process are not dependent on

Table 5
Main histopathology process stages. Note that Levels 3 and 4 correspond to the first and second floors of the building, as illustrated in Fig. 4.

N	Stage	Level	Sample processing
1	Reception	4	—
2	Cut-up	4	Single
3	Processing	4	Batch
4	Embedding	4	Single
5	Microtomy	4	Single
6	Staining	4	Batch
7	Cover-slipping	4	Batch
8	Digital scanning	3	Batch
9	Collation	4	Single
10	Block check & quality check	4	Single
11	Case allocation	4	Batch
12	Reporting	—	Single

the physical movement of specimens. As a result of the physical movement of specimens between Stages 1 through 10, the laboratory TAT is affected by space–time variables. Furthermore, not all the process stages are executed in functional areas located on the same floor of the Addenbrooke's Hospital Biomedical building. In particular, since digital scanning (Stage 8) is located on a different floor from all the other stages (except Reporting), batches of specimens are transferred from Stage 7 to Stage 8 and from Stage 8 to Stage 9 using the lift. This ties the laboratory throughput to the maintenance condition of that asset — if the lift fails and is out of order, whoever carries the batch of specimens between floors (the "runner") must instead use the stairs, significantly impacting the laboratory TAT (see Fig. 4). However, the laboratory operations managers can only guess from experience the effect of this dependency, and have no detailed control over the laboratory process's throughput under this scenario, nor decision-making power over the lift inspection and maintenance schedule. At the time this study was carried out, the process was monitored using a combination of spreadsheets, the HR management system, the patients' records, and audio recordings, which do not allow tracking of the space and asset variables influencing the process. To fully quantify the effect of the built assets' state (such as lifts) on the Histopathology process, one needs an integrated DT that informs the Operations and Facilities Managers of the current shortest path for specimen transfer based on the current state of the built assets, and of the predicted TAT after any change of the transfer pathways. The current case study is intended as an initial step towards the construction of such a DT.

Corresponding to Step 4 of our approach as outlined in Fig. 3, we have identified, through co-operation with the laboratory operations team, the following requirements for this case study:

1. Support the team to identify where the bottlenecks are.
2. Predict what the impact of staff allocation is to TAT and service levels.
3. Determine what the staff-machine utilisation is.
4. Quantify the impact of equipment failure on the laboratory KPIs.
5. Quantify the effect of the layout organisation on flow and KPIs.

A DES-only solution addressing Requirements 1–3 above was previously proposed in [53]. In this article, we describe how our proposed solution addresses Requirements 4 and 5.

4.2. Developed BIM-DES Digital Twin architecture

As mentioned in the previous subsection, the current case study is intended as an initial step towards the construction of a DT that can fully quantify the effect of the built assets' state (demonstrated through the lifts operation) on the Histopathology process. The paradigm of "DT with human-in-the-loop" [25] was adopted for this use case. The Operations and Facilities Managers are considered to be the direct

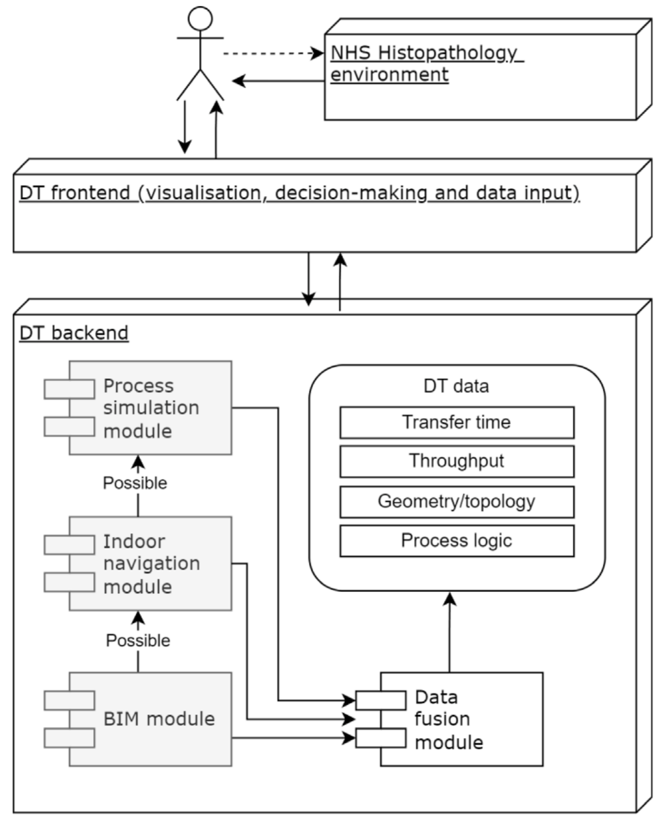

Fig. 5. Conceptual level Histopathology Laboratory DT UML architecture. Plain arrows represent the data flow. Dashed arrows represent the actuation flow. Greyed out parts represents aspects that are within the scope of this paper.

beneficiaries of the DT deployment, and play the role of the human in the "human-in-the-loop" design; thus, they can both input data into the DT environment and use its outputs to implement actions on the physical process.

A conceptual representation of our proposed BIM-DES DT architecture is depicted in Fig. 5, showing the loop formed by the NHS Histopathology laboratory environment, the DT environment, and the human-in-the-loop. The DT architecture is further composed of a frontend with decision-making and visualisation tools, and a backend composed of independent modules which we describe below. The backend modules are designed to address the need for data availability, accessibility, and timeliness in responding to the Histopathology lab's needs. In the current paper, we focus on the BIM, Indoor navigation, and Process simulation modules (highlighted in grey in Fig. 5), while the rest of the DT architecture is out-of-scope. The three modules are designed to run independently, enabling the parallel computation of the results used by the Data integration and fusion module. This fourth module aggregates and transforms the data from the other ones based on the data requirements of the frontend tools, which access the fit-for-purpose DT data via a backend access layer.

When launched for the first time, the BIM module parses and extracts the relevant BIM information from IFC, based on a set of process operations-based information requirements described in Section 4.3. The Indoor Navigation module then computes the shortest path for completing the transfer of the samples across the laboratory spaces and returns the transfer times for each process phase (see Section 4.5). Finally, the process simulation is utilised to compute the laboratory throughput and TAT (see Sections 4.4 and 4.5). At this stage, the Process Simulation and Indoor Navigation modules can be used to develop scenario analyses on the joint impact of space, built asset

Table 6
IfcDoor information requirements for the OpenBIM to DES Integration, representing the current laboratory configuration.

Level	IfcName	IfcDescription	Process phase
Level 3 First floor	d16	Digital pathology	Digital scanning
Level 3 First floor	d15	Corridor	
Level 3 First floor	d14	Corridor	
Level 3 First floor	d13	Lift	
Level 3 First floor	d12	Landing	
Level 4 Second floor	d11	Lift	
Level 4 Second floor	d10	Landing	
Level 4 Second floor	d9	Staining room	H&E staining, Slide cover-slipping
Level 4 Second floor	d8	Main lab	Microtomy/Slide printing, Case/slide collation, Block check and Quality check, Case allocation
Level 4 Second floor	d7	Corridor	
Level 4 Second floor	d6	Processing room (Embedding)	Cut-up
Level 4 Second floor	d5	Green room (Cut-up)	Cut-up
Level 4 Second floor	d4	Yellow room (Cut-up)	Cut-up
Level 4 Second floor	d3	White room (Cut-up)	Cut-up
Level 4 Second floor	d2	Lilac room (Cut-up)	Cut-up
Level 4 Second floor	d1	Specimen reception	Reception

conditions, staff allocation, and equipment capacity. Two numerical examples are presented in Sections 4.6 and 4.7 with a focus on the variation of built assets' condition and the functional layout of the laboratory.

Once the Indoor Navigation module is updated with the latest spatial and semantic data, it can run independently from the BIM module. In fact, the latter is updated only in case of changes to the building layout and components due to, for example, refurbishments and replacements, and can be used for other purposes. This simple and flexible architecture allows one to decouple the three modules and extend the DT architecture to incorporate additional service modules (e.g., IoT, Asset maintenance, etc.) without affecting the existing ones.

4.3. Defining the BIM information requirements

The principle adopted for the definition of the BIM information requirements is that any element which has an impact on the Histopathology laboratory throughput must be modelled in BIM with a certain level of geometric and semantic detail (see phases 4 and 5 in Fig. 3). Each Histopathology process has a physical location, and the samples follow the process logic, being physically moved across the laboratory spaces. The time spent by a runner to transfer the samples (or batches of samples) from one space-function (corresponding to the process stages) to another is computed using BIM data. Since the resolution of the process simulation does not require calculating the time for moving the materials within the same space, the door-to-door time is sufficient to inform the DES model.

To satisfy the above requirements, the doors (i.e., `IfcDoor` elements) used as access to the functional areas of Histopathology laboratory have been identified and tagged in IFC, as described in Section 3.2 and shown in Table 6. Additionally, to form the full topology of the building as it relates to the Histopathology process, certain doors have been included for connectivity purposes even though they are not directly associated with a functional area of the process. These doors are d7 and d10 to d15. This set of openBIM information requirements is sufficient to use the geometric definition of the assets and spaces modelled in BIM to enable the development of the BIM-informed physical model as described in Fig. 3.

4.4. Process simulation

Based on the methods outlined in Section 3.1, we implemented a DES simulation program in Python for the Histopathology laboratory (see Phase 6 in Fig. 3). To model the flow of entities through the histopathology lab, a class hierarchy of `Specimen`'s, `Block`'s, and `Slide`'s was defined. A generic `Batch` class was also defined to hold multiple specimens, blocks, or slides in a single entity, for machine processes and deliveries. Note that the output type of a process can be different from its input type if splitting is performed within the process. Additionally, `Process` instances may have multiple outputs, with each entity sent to one of the outputs based on the internal rules of the process.

A flowchart of the defined processes of the simulation program is given in Fig. 6. The colours of each process indicate the process type (green = `Process`, pink = `BatchingProcess`, orange = `CollationProcess`, blue = `DeliveryProcess`) as defined in Section 3.1. The arrow colours denote the type of entity being passed between processes (black = `Specimen`, red = `Batch[Specimen]`, blue = `Block`, green = `Batch[Block]`, pink = `Slide`, purple = `Batch[Slide]`).

Statistics collection for resources and queues in the simulation is enabled by default in the salabim Python library. For example, the `Resource` class contains a number of `Monitor` objects to track the number of claimed resources, the total capacity of the resource, and the number of waiting requests over time. In addition, we attach a Python dictionary to the simulation model to store specimen attributes, particularly timestamps recording the start and end of each process stage or group of stages. Note that, in Fig. 6, staining and coverslip application (Stages 6 and 7 in Table 5) have been combined, as further study of the Histopathology process revealed that these two stages are completed by the same combination machine (except for mega slides which are coverslipped manually). Finally, the `openpyxl` Python library[10] was used to extract simulation parameters from an Excel configuration file including:

- specimen arrival rates, hourly;
- task durations;
- batch sizes;
- staff allocation schedules;
- branching probabilities (e.g., cut-up type);
- process stage-to-door mapping for BIM-DES integration; and
- number of blocks and slides per specimen (set of random distribution parameters for each specimen and block type).

4.5. BIM-DES integration and pathfinding algorithm

The purpose of the BIM-DES integration is to inform the simulation model with the duration of the space-dependent specimen transfer

[10] https://openpyxl.readthedocs.io/.

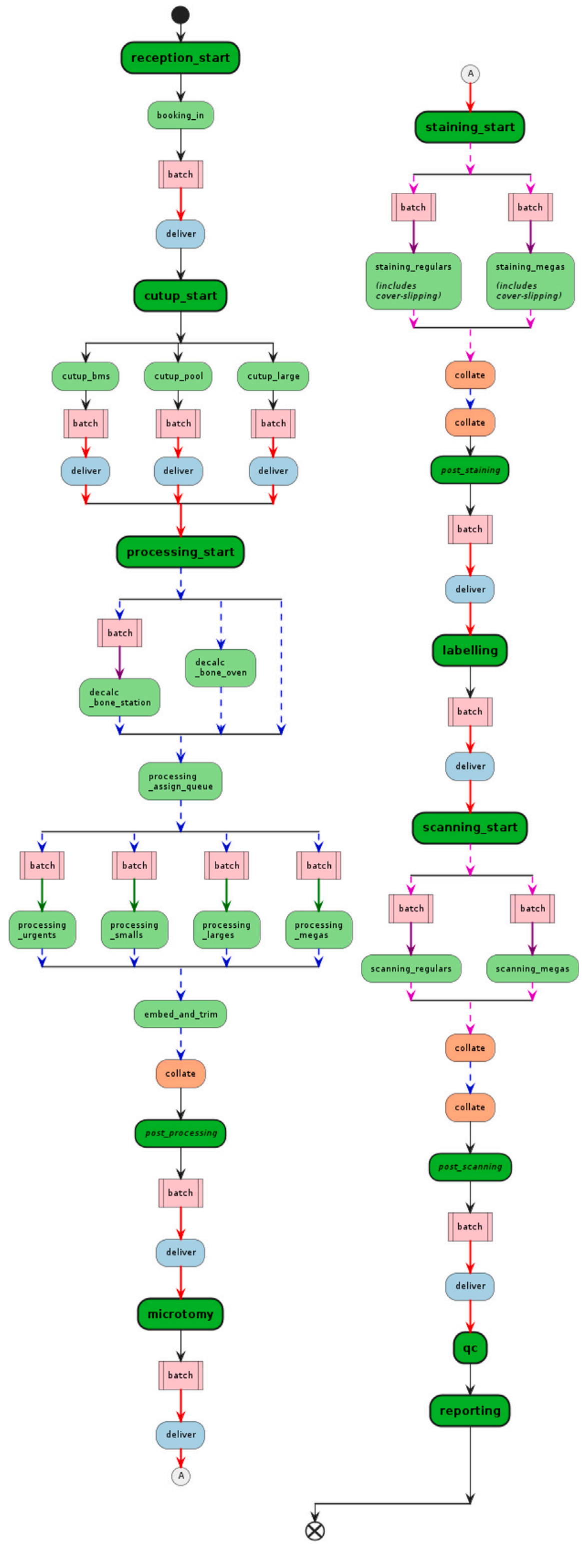

Fig. 6. The defined processes of the discrete-event simulation model as a UML activity diagram. See Section 4.4 for a detailed explanation, including colour codes.

times (see phase 6 in Fig. 3, when the process is space dependent). The steps followed to develop the integration are as follows:

1. For each door, wall, and column obtain the local coordinates.
2. Overlay a rectangular grid to each floor in the study and mark each grid square as open space (no containment of any of the previous objects), obstacle (contains wall or column), or door (contains a door).
3. For each pair of doors on the same floor:
   (a) Filter out all grid nodes blocked by an obstacle or door (other than the source and target door).
   (b) Add diagonal edges to the grid, but only inside complete rectangles of four non-diagonal edges.
   (c) Compute the distance and travel time between the two doors by applying Dijkstra's[11] algorithm to the marked grid, and a predefined walking speed for horizontal movement within a single floor.
4. Use the distances computed in Step 3 to build a logical graph of the floors under study. Add edges corresponding to transfer modes between floors, depending on the state of each transfer mode (for example, if the lift is out of order, do not add the corresponding edge to the logical graph). The reason we process each floor separately and add modes of transport between floors manually is because the movement speed for vertical movement (i.e., taking the stairs or lift) is generally different than for horizontal movement.
5. For each pair of consecutive stages, use Dijkstra's algorithm on the logical graph to compute the travel time between the doors corresponding to the two stages.
   (a) For the cut-up stage, which takes place in multiple cut-up rooms, all four room doors are treated as a single node and the average travel time used.

The Python code corresponding to the steps above is given in Listings A.1 and A.2, providing the `BimModel` and `ShapelyModel` classes, respectively. In particular, `BimModel` contains semantic and numerical coordinate data for each door and wall under study using a pair of Pandas dataframes, while `ShapelyModel` represents these doors and walls as `Polygon` objects using the Shapely library.[12] Plotting functionality was also added to the `ShapelyModel` class, resulting in the graphical output shown in Fig. 7. This `ShapelyModel` instance corresponds to the output of Step 1 above.

Figs. 8 and 9 show the rectangular grid and logical graph corresponding to Steps 2 and 4 above, respectively. They are computed and represented using the networkX Python library,[13] which is also used to execute Dijkstra's algorithm in Step 5. For each application of Dijkstra's algorithm, the graph nodes are the centroids of each open (white) grid square in Fig. 8, plus the squares corresponding to the source and target doors. The grid size of 0.5 m is defined to be always smaller than the minimum standard width of a door (which is 0.9 m). It can be seen that doors `d1` to `d7` and `d10` form a complete graph (free travel between any two doors in this group), whereas the remaining doors are more weakly connected to the core of the graph, with `d7` and `d10` forming bottlenecks that all specimens must pass through.

[11] Note that heuristic-based algorithms such as A* will still require exhausting *all* nodes reachable from the originating door if it is not connected to the destination door in our grid, thus performing no better than Dijkstra's algorithm.
[12] https://shapely.readthedocs.io/.
[13] https://networkx.org/.

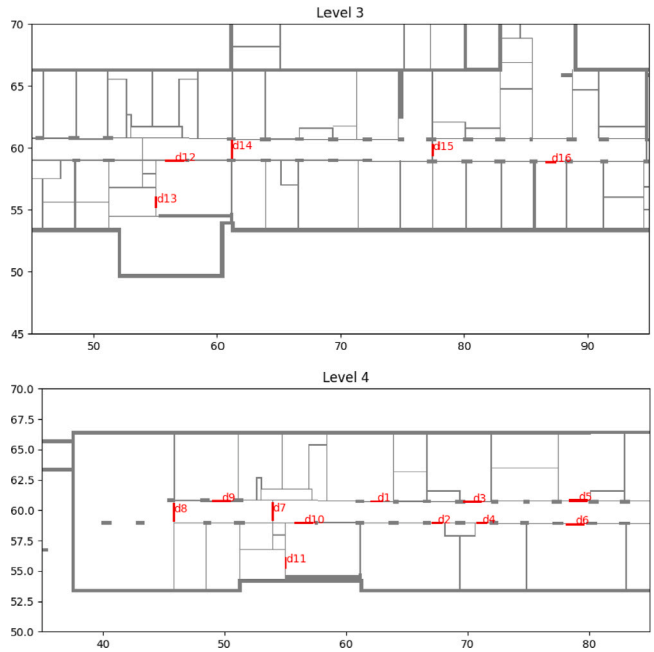

Fig. 7. Result of plotting the two `ShapelyModel` instances representing Levels 3 and 4 of the Histopathology laboratory, respectively.

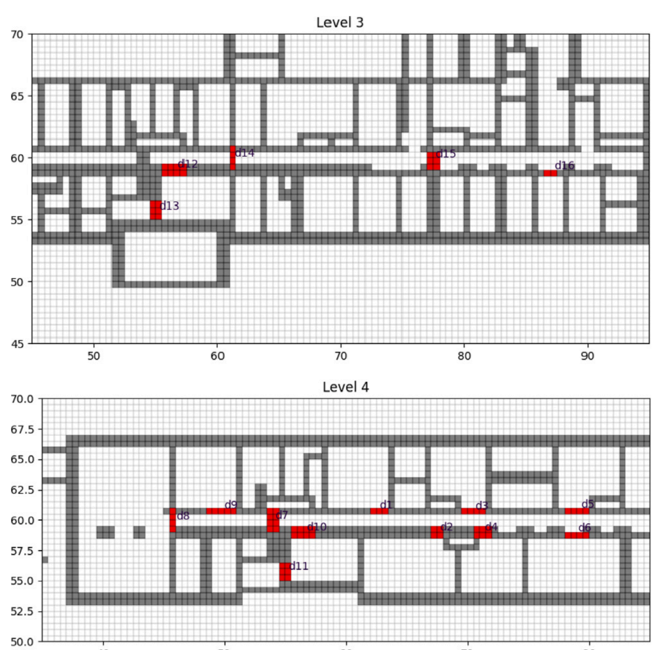

Fig. 8. Grid approximation of Levels 3 and 4 of the Histopathology laboratory, respectively.

Note the addition of diagonal edges in Step 3b. This helps to find edge lengths closer to the shortest possible path in free space. The reason we do not allow diagonal edges except within complete rectangles is illustrated in Fig. 10, where the diagonal line touches the corner of the obstructed grid square, leaving no space between the straight-line path and the obstruction.

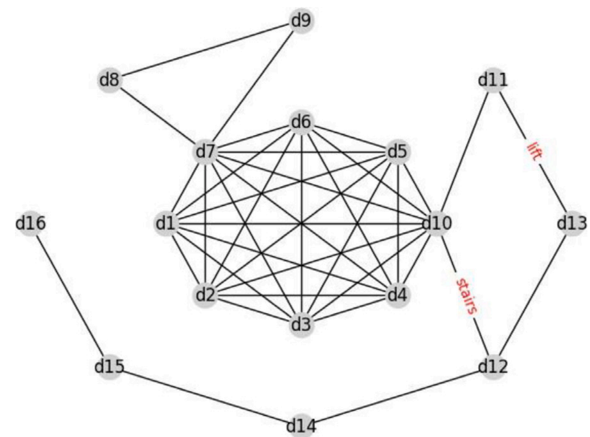

Fig. 9. Logical graph of the Histopathology laboratory process. A lift failure is modelled by removing the edge between doors `d11` and `d13`.

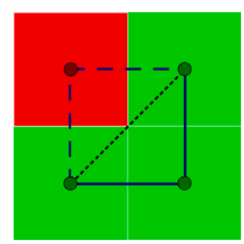

Fig. 10. A grid with three open (green) and one obstructed (red) square. Since the edge between the centres of the two diagonal open squares (black dashed) touches the obstructed square, only the two solid lines are considered as part of the final grid in Step 3b of the BIM-DES integration process.

4.6. Numerical example 1: impact of asset failure on the process performance

In this example, we quantify the impact of a change in the state of the physical process flow on the overall performance of the Histopathology laboratory (i.e., the core business). In particular, we demonstrate how a small change in travel times caused by a lift outage can result in a significant decrease in the proportion of specimen reports delivered in a timely manner. This numerical example addresses Requirement 4 in Section 4.1.

Fig. 11 shows the runner times between each pair of doors in the Histopathology lab (Step 4 output) under normal operation, i.e., lift is working. This results in the total runner times between stages (Step 5 output) as shown in Table 7. It can be seen that the runner times to and from the Scanning stage are much longer than between any of the other process stages, due to the digital scanning room being located on a different floor (level 3 in Fig. 4) from the rest of the Histopathology lab (level 4 in Fig. 4). Note that Table 7 shows door-to-door runner times only; an additional duration of 30 s is added for all deliveries to represent pick-up and drop-off times within each room.

To test the capabilities of the integrated BIM-DES approach and verify the impact of the space variables on the process performance, we consider the scenario where the lift used to carry the slides from the main lab to the digital scanning and back (process phases 7–9 in Table 5) is out of order. Thus, the resultant runner times between stages

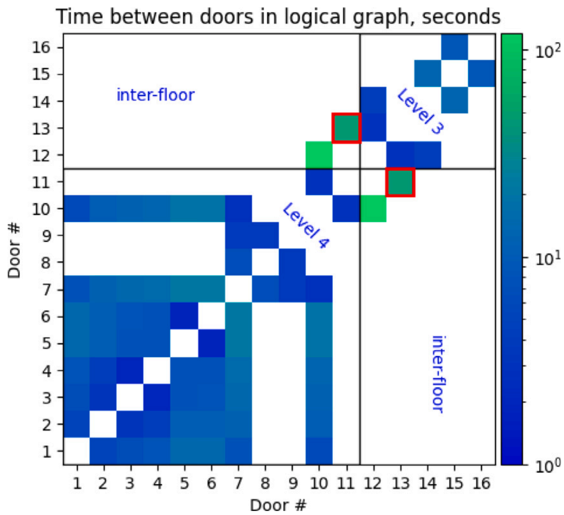

Fig. 11. Runner times between doors for the base scenario, using a speed of 1.2 m/s within each floor. For the lift-down scenario, the highlighted (red outline) entries, corresponding to the graph edge marked "lift" in Fig. 9, are removed.

Table 7
Runner times computed from the logical graph shown in Fig. 9.

Runner journey	Duration, seconds	
	Base scenario	Lift down
(reception, cutup)	8.452	8.452
(cutup, processing)	6.969	6.969
(processing, microtomy)	28.089	28.089
(microtomy, staining)	3.679	3.679
(staining, labelling)	3.679	3.679
(labelling, scanning)	86.898	155.863
(scanning, qc)	86.898	155.863

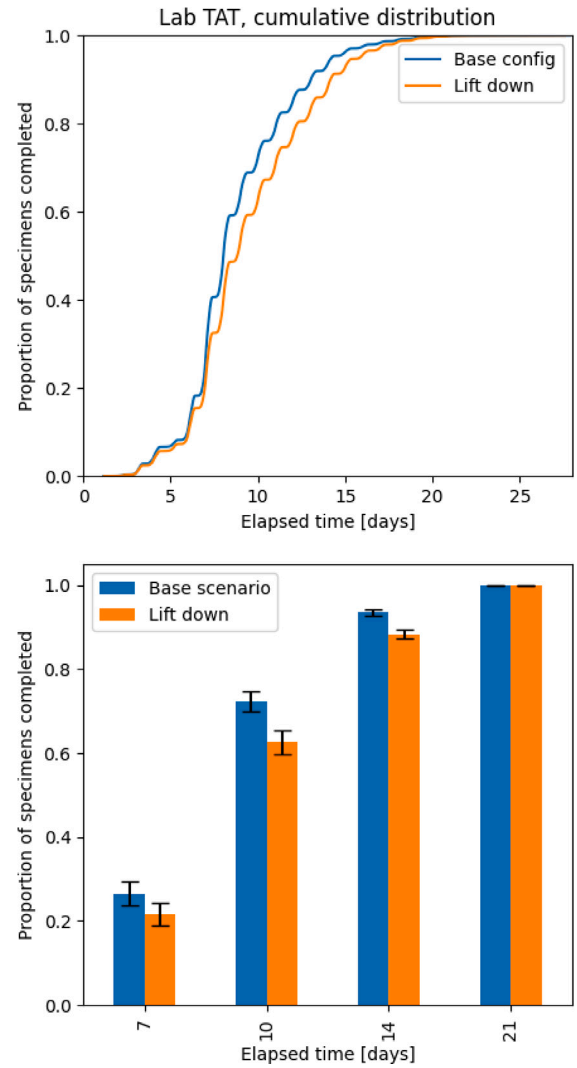

Fig. 12. Comparison of lab TAT for two scenarios with the lift working and out-of-order, respectively. The runner speed is set at 1.2 m/s within each floor for horizontal transfers. Error bars denote 95% confidence intervals based on 30 simulation runs.

must be computed considering the delay due to the use of the stairs instead. The glass slides are very fragile objects, and the runner needs to pay extra attention when they are moved through the stairs and when crossing doors, which are always closed for safety reasons in the lab environment. Also, the dimension of the batch can be large in some cases, and this may require breaking it down into smaller assemblies to be carried to the digital scanning one by one, as opposed to using a trolley and carrying all of them to the next stage using the lift. For these reasons, the runner times to and from the Scanning stage are estimated to be almost 80% higher than in the base scenario where the lift is working.

To gauge the impact of this increase, we ran the process simulation model for both sets of runner times, with results shown in Fig. 12. It is demonstrated that the increase in runner times under the lift-down scenario results in a lower service level of the laboratory. In particular, the difference in the proportion of specimens completed — Reception to Block & Quality Check stages as defined in Table 5, i.e., used to calculate the laboratory TAT — is statistically significant at the 7- and 10-day marks.

The result here can seem counterintuitive at first, as the mean lab TATs for the two scenarios are 8.6 and 9.4 days, respectively, corresponding to a TAT increase of 9.3% when the lift is out of order relative to the base scenario. On the other hand, the transfer of specimens between floors only accounts for a small percentage of this increase. This large performance loss relative to the small increase in runner times can be explained by the knock-on effects of increased staff utilisation on the queuing times of other tasks in the overall Histopathology process, some of which may be pushed to the next day due to shift scheduling caused by the longer time in moving samples (slides in this case) between floors.

4.7. Numerical example 2: impact of the redefinition of the laboratory layout on the process performance

The high travel time to and from the digital scanning room has a significant impact on lab efficiency, and, as shown in Fig. 12, causes the system to be quite sensitive to disruptions to lift connectivity between the two floors of the lab. We use the BIM-DES framework to predict the effect on the lab TAT of swapping the digital scanning room with a room on Level 4 of the lab — in particular, the amount of increase in specimens completed within a given number of days.

This scenario analysis serves as an example of the BIM-DES framework's ability to estimate runner times for new pathways in the histopathology lab, and demonstrates the system's sensitivity to the spatial layout, in response to requirement 5 in Section 4.1. The availability of BIM information allows us to check whether the two swapped rooms

Table 8
Room areas in the histopathology laboratory. The rooms marked with asterisks are those considered for reassignment of the Digital Scanning function.

IfcDescription	Area (m^2)	Level	Associated stages	Associated door
Main lab	102.112	4	Microtomy, Labelling, Block check/quality check	d8
Processing room (embedding)	42.976	4	Processing	d6
Lilac room cut-up	41.988	4	Cut-up	d2
Specimen storage	31.310	4	–	*(unnamed)*
Specimen reception	29.160	4	Specimen reception	d1
Staining room	27.772	4	Staining	d9
Yellow room cut-up	27.488	4	Cut-up	d4
Green room cut-up	26.867	4	Cut-up	d5
White room cut-up	26.103	4	Cut-up	d3
Main lab section leaders*	16.413	4	–	d19
Filing room*	14.239	4	–	d20
Ventilated stores*	14.012	4	–	d18
Block & slide*	13.815	4	–	d17
Digital pathology	12.651	3	Digital scanning	d16

in this scenario analysis are compatible with their newly assigned functions. For illustrative purposes, we use the room size and topology of the space-function configuration to choose the two alternative rooms for relocating the digital scanning function. However, we do not consider the effect of auxiliary tasks in the lab, under the assumption that the lab TAT is dominated by tasks on the critical path.

To identify spaces (`IfcSpace`) to which the digital scanning stage (Stage 8 in Table 5) can be relocated, we first obtain a list of all named spaces (non-empty `IfcDescription`) from the BIM module (as shown in Fig. 5) with a floor area equal or larger than current digital scanning room, using the code in Listing 3. The result of this search is shown in Table 8. Auxiliary spaces such as toilets and circulation areas have been excluded. Based on these results, we have several rooms as candidates for swapping functions with the current digital scanning room, which have a room area between 12.6 and 16.5 m^2, corresponding to the space needed to host the function.

Listing 3: Compute the floor area of an IfcSpace.

```
from ifcopenshell import geom as ifc_geom
from ifcopenshell.util import shape as ifc_shape

settings = ifc_geom.settings()
settings.set(settings.USE_WORLD_COORDS, True) #
    ↪ Find global coordinates

def get_area(x):
    shape = ifc_geom.create_shape(settings, x)
    geom = shape.geometry
    return ifc_shape.get_footprint_area(geom)
```

Running the Indoor navigation module for the new scenario analysis results in the runner times shown in Table 9. It can be seen that the runner times to and from the scanning stage are much reduced in the new cases compared to the d16 (base) case, while all other durations remain unchanged. Based on Table 9, we can identify the optimal relocation space for digital scanning to be the d17 Block & slide room option and all alternatives are shown to outperform the base case for all four thresholds shown in Fig. 13 compared to the base case. Note that Table 9 shows door-to-door runner times only; as in Numerical Example 1, an additional duration of 30 s is added for all deliveries to represent pick-up and drop-off times within each room.

Running the Process simulation module using the runner times in Table 9 leads to the lab TAT results shown in Fig. 13. It can be seen that swapping digital scanning functionality to a room on Level 4 leads to a higher proportion of specimens completed in a timely manner, especially for the 7- and 10-day thresholds. As an example, 78.7% of specimens can be completed when digital scanning is moved to Block & slide room, compared to 73.9% in the base case and 62.6% when digital scanning is kept in its current location in the Digital pathology room and the lift is non-functional.

The results in this subsection supports our finding in Section 4.6 (Numerical example 1) that small changes in runner times between histopathology stages can result in a significant change in overall lab

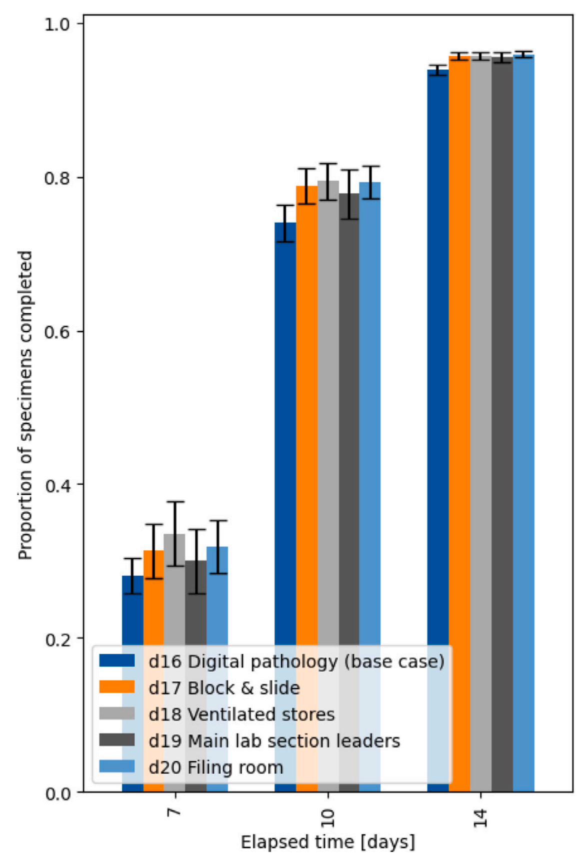

Fig. 13. Comparison of lab TAT with respect to room assignment for the digital scanning function. Legend labels show the current description for each candidate room and its associated IfcDoor. Error bars denote 95% confidence intervals based on 30 simulation runs.

Table 9
Runner times for the scenario analysis in Section 4.7. Descriptions for each room (associated doors d16 to d20) under the current process layout are given in Table 8.

Runner journey	Duration (s) when digital scanning is in:				
	d16 (Base)	d17	d18	d19	d20
(reception, cutup)	8.452	8.452	8.452	8.452	8.452
(cutup, processing)	6.969	6.969	6.969	6.969	6.969
(processing, microtomy)	28.089	28.089	28.089	28.089	28.089
(microtomy, staining)	3.679	3.679	3.679	3.679	3.679
(staining, labelling)	3.679	3.679	3.679	3.679	3.679
(labelling, scanning)	86.898	1.839	23.261	5.762	3.923
(scanning, qc)	86.898	1.839	23.261	5.762	3.923

efficiency, due to the proportion of lab TAT actually associated with manual tasks including specimen deliveries.

5. Discussion and conclusions

This paper presented a BIM-DES integration framework, using the open IFC data format for incorporating BIM data into a space-aware process DT for hospital operations. As shown by the two numerical examples, even a small change in travel times, such as that caused by the malfunction of critical building infrastructure (i.e., a lift) or a reorganisation of room-function assignments, can have a significant impact on core process performance in a specialised building. The proposed BIM-DES integration framework allows us to quantify such impacts, improving the Operations Managers' decision-making process when faced with such disruptions. The benefits of the proposed approach are discussed below.

Incorporating our BIM-DES integration framework into a DT architecture, as proposed in this paper, allows Facilities Managers to make reactive and proactive decisions for protecting process performance in response to continuous information updates regarding the building state. Adding space-awareness to the process simulation model also allows for the identification of inefficiencies in the core processes, so that normal operations can also be improved. Thus, Facilities Managers can use the results of the BIM-DES integration to define a prioritisation strategy for service-based asset maintenance, identifying and allocating more investment to parts of the building where disruptions have the highest impact on core business processes (e.g., see the results of Numerical example 1 in Section 4.6). This gives clear evidence of why Estates (healthcare facilities in this case) and clinical services should not be siloed, instead making decisions together based on the interdisciplinary insights provided by the space-process DT.

The DT architecture proposed in this paper provides a flexible and modular way to identify, parse, process and use multi-disciplinary BIM, Operations and Facilities Management information from multiple sources to make complex decisions in highly specialised and complex facilities. The data pipelines and algorithms allow for the flexible integration of additional modules (see Section 4.2), without compromising the functionality of the existing ones. In this paper, the effectiveness of the BIM, Indoor Navigation and Process Simulation modules have been tested. The proposed architecture sits outside the NHS environment and can run independently, complementing the functionality of legacy Information Technology (IT) systems and providing right-time data used to control the physical process.

For estimating the performance of the laboratory's core processes, comparable methods to the proposed BIM-DES integrated framework include DES alone and ABS. The advantages of the BIM-DES integrated framework are as follows:

- First, BIM information can be used to automatically reconfigure the BIM-DES simulation model parameters when changes occur to the process layout (reassignment of tasks to locations in the second numerical example in Section 4.7), whereas non-BIM-integrated DES and ABS models require this information to be incorporated into the simulation model manually.
- Second, the rich BIM information, including details on the areas of spaces, the activities they can support, and the distance between them, can be used to dynamically perform different scenario analyses using the BIM-DES integrated framework. In contrast, non-BIM-integrated DES and ABS models are typically built-for-purpose and may lack the information and capabilities required for new scenario analyses.
- Finally, by directly connecting core process performance to the available BIM information, we can model the effect of building design and state (numerical examples 1 and 2) on new process models while reducing the need for new data collection, such as measuring travel times between locations with a stopwatch. These new process models may reflect existing processes that have not been studied previously or optimisations to existing processes to reduce turnaround times. Note that the BIM standard covers not only geometric and spatial information but also semantic information, all of which can be used to inform the simulation model of the integrated BIM-DES framework.

Overall, the proposed approach can increase the laboratory resilience and helps to find viable solutions in the case of disruptions to the core process. The numerical example in Section 4.6 describes a scenario in which the Histopathology process needs to be re-routed using the existing built environment (space and asset performance) constraints. The same framework has been used to assess multiple space-functional reconfiguration alternatives to identify the best option for the laboratory performance. Assuming that BIM data is available, the proposed approach can be extended and used in the case of a temporary decamp or when the entire function needs to be moved to a new building, with the latter being a real need expressed by the Addenbrooke's Histopathology Operations team. Leveraging the proposed methods, the new sample transfer time is automatically obtained using IFC data, shortest path calculation, and DES, saving decision-making time and ensuring efficient operation under the effect of a built-environment-related process disruption. Having clarity on this issue can save time-critical resources and help control the backlog of medical cases. For example, key medical facilities may be forced to temporarily or permanently relocate due to various factors such as risk of contamination (a typical situation during the COVID-19 emergency) or the presence of highly degraded Reinforced Autoclaved Aerated Concrete (RAAC). RAAC was widely used in mid-20th century in the UK and its service life is now coming to an end [102], posing a serious problem for the NHS Estates.

5.1. Limitations and future work

In this subsection, we highlight the remaining research gaps and limitations, thus setting the direction for future work.

5.1.1. Improved BIM-based indoor navigation

The indoor navigation algorithm used in this paper only allows travel in the eight ordinal directions. A more advanced pathfinding algorithm may allow travel in a straight line between any two grid points, as long as the path between them is unobstructed (any-angle path planning) [103]. Moreover, we used a weighted graph method to compute the travel time in 3D (through the stairs and the lift). Although more advanced navigation methods exist in literature [104,105], in the current implementation, which serves as a proof-of-concept of BIM-DES integration, we have chosen simplicity of pathfinding algorithm over optimality. In fact, we have used the distance between doors as a proxy for the runner time between process stages, while ignoring the internal geometries of each room involved in the Histopathology process, e.g. workbenches and machines.

The relevant spatial variables for the Histopathology laboratory were originally identified and described in [101], and are modelled in BIM at a low level of geometric detail in accordance to the information requirements needs of the current use case. This depends on the fidelity of the process simulation, which has been developed to support decision-making at the whole-laboratory level. However, the original BIM model supports a higher level of granularity, which can be used to compute internal travel times within each space. This presents an opportunity for additional research to further develop the integration approach.

5.1.2. Real-time data communication

The simulation model in this paper can, with some modification, be used for short-term forecasting of the process performance by reading in a fresh building state (i.e., whether the lift is working) and process state (i.e., the status of all work-in-progress specimens) at the beginning of each simulation round. This will require a data serialisation format for reading and writing the full simulation state from and to a file, e.g., JSON (ISO 21778), MessagePack or HDF5. A method of estimating residual task durations based on time elapsed is also required, i.e., generating random variates from the truncated probability distribution (i.e., the distribution of a task's remaining duration conditioned on the time already elapsed). Rejection sampling is suitable for this but requires further study to minimise the rejection rate for computational efficiency.

Alternatively, the process flow logic of the simulation model can be used to track the progress of the specimens within the laboratory in real-time. Combined with the results of the process simulation, this can enhance control operations. However, such fine-grained progress tracking of specimens requires location tracking and real-time data collection (e.g., using barcode scanners or sensors to ensure that the specimens are where they are supposed to be according to the process logic). Further research is required to determine the granularity of the real-time process tracking and the simulation-based forecasting.

Under the FM perspective, the performance of the built assets has been considered as an input for the scenario analysis presented in Section 4.6. However, this is a simplified model of asset performance containing a single high-risk situation (i.e., a faulty lift), used to demonstrate the impact of a critical asset on overall process performance. In contrast, built asset performance can be modelled with a higher level of detail, and the condition of both the built assets and spaces can be defined using a statistical approach or data-driven methods — e.g., using environmental and asset monitoring sensors such as IoT or BMS and BAS data, if available. For example, this integration can enable to automatically check whether the swapped rooms in the scenario analysis in Section 4.7 are compatible with their newly assigned functions, considering building services constraints. This requires to develop new Facilities Management and IoT engines for our proposed DT architecture, which requires further research work.

Moreover, the performance of the clinical equipment has not been considered in the process simulation model, as staffing is the primary resource constraint in the current case study. On the other hand, the condition of these assets (which can be monitored via sensors as well) represents a critical factor, and similarly to the built assets, any disruption to clinical equipment could heavily impact the core process. The integration of this data represents a further research opportunity and a closer relationship with the Clinical Engineering team to define an additional Asset Management engine. The authors are currently working at further developing and testing the proposed approach in additional case studies, where built asset and clinical equipment monitoring data can be integrated in the DT ecosystem.

5.1.3. An ontology for the hospital Digital Twin

To realise the full potential of the proposed BIM-informed DT architecture, M&S, AM, FM, and IoT information must be structured in a consistent and interoperable manner. For example, within the BIM domain, the IFC schema is an application-agnostic and non-proprietary data schema which offers the opportunity to access and use building information using a variety of software and libraries (such as IfcOpenShell in this paper). IFC also contains classes for process modelling, including `IFCProcess` corresponding to the processes described in Fig. 2 and `IfcWorkCalendar` to define the allocation of staff resources. Therefore, it may be possible to describe the operations of the Histopathology laboratory within the IFC schema.

However, IFC does not contain enough classes representing the clinical assets, other than the generic `IFCProduct`. Furthermore, it may be preferable to describe these processes using other modelling schemas, such as UML, particularly activity and sequence diagrams, or BPMN (ISO 19510). To describe the events (corresponding to `IfcEvent`) of these processes and corresponding changes to the laboratory state, formal specifications include the Discrete Event System Specification (DEVS) and its extensions [106], as well as stochastic Petri nets [107].

Finally, research on ontologies and knowledge graphs for the built environment has demonstrated the possibility of enriching existing schemes and standards with a wide variety of data models [108], which increase capability of representing any asset, spatial, process object, physical and virtual agents. The scope is potentially much broader and creates the opportunity of developing a full-hospital DT ontology, including clinical services, logistics and remote patient monitoring.

5.2. Conclusions

The research on healthcare facilities DTs has flourished in the past few years. Here we reiterate the knowledge gaps and how they have been addressed.

1. *Isolated Process Improvements*: Most research has focused on isolated process improvements without a multi-disciplinary approach. This gap is addressed by modelling the joint effect of space and asset performance on core processes using a BIM-DES integration approach.
2. *Building Layout and Process Efficiency*: Few studies consider the effect of building layout on process efficiency, especially with naturally occurring changes. This gap is addressed by developing a space-aware process DT architecture that handles multi-source data and provides insights based on a DT-with-the-human-in-the-loop paradigm.
3. *Focus on Physical Assets*: Many existing DTs focus on physical assets rather than core business processes within built spaces. This gap is addressed by using IFC as an openBIM standard to inform space variables and constraints in an integrated process simulation of hospital operations, connecting currently siloed domains.

In summary, this paper answers the research question by proposing a BIM-DES integration approach and showing how it can be integrated into a DT architecture for a histopathology laboratory. In particular, we used IFC data to generate a logical graph of the histopathology laboratory, from which the travel times between stages of the histopathology process can be computed. This processed data was then used to create a BIM-informed physical process model, upon which we used DES to compute the KPIs of the histopathology process, in particular the proportion of specimens completed within a certain lab TAT threshold. Finally, we demonstrated how the effect of changes in the building's state due to a lift failure and the laboratory's functional configuration on the histopathology process's KPIs can be quantified and estimated.

The results of this paper support our hypothesis in Section 1.1 that, where BIM is available, valid IFC can be used to integrate this data with simulation modelling to form a decision-making framework. This BIM data provides our framework with information about the layout, systems, and fabric of our facility, thus informing actions for improving core-process efficiency, particularly within complex healthcare facilities, as specified in our stated research question. Operations and facilities managers can use our approach to:

1. simulate failures of critical built assets and their impact to the core processes,
2. build scenario analyses and compare the performance of the facility under current and hypothetical situations, and
3. develop a strong business case for allocating additional investments on spaces and built assets, allowing more efficient operations and resilience against any disruptions to the workflow.

Furthermore, because our proposed methodology, as implemented in this paper, is developed using open-source technologies, it is compatible with a wide range of BIM editing software, as long as export to the IFC format is supported and meets the standard schema requirements. Additionally, the generic nature of the proposed space-aware process DT architecture means it can be applied to a variety of buildings across various applications.

CRediT authorship contribution statement

Nicola Moretti: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yin-Chi Chan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Momoko Nakaoka:** Writing – original draft, Visualization, Methodology, Formal analysis. **Anandarup Mukherjee:** Writing – review & editing, Data curation, Conceptualization. **Jorge Merino:** Writing – review & editing, Data curation, Conceptualization. **Ajith Kumar Parlikad:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research is funded by the Cambridge University Hospitals NHS Foundation Trust. We deeply thank Zahrah Rosun and Colin Carr from the Department of Histopathology, Addenbrooke's Hospital, for giving us access to the laboratory and sharing their knowledge. We also thank the Lifecycle Management Group Ltd team for the fruitful conversations on histopathology process modelling.

Appendix. Program listings

Program listings for Section 4.5 (BIM-DES integration and pathfinding algorithm) are given in Listings A.1 and A.2.

Listing A.1: `BIMModel` class definition for the BIM-DES integration.

```
from dataclasses import dataclass
from functools import reduce
from itertools import islice, product

import ifcopenshell as ifc, ifcopenshell.geom as ifc_geom, ifcopenshell
    ↪ .util.shape as ifc_shape
import matplotlib.axes, natsort, networkx as ntx, numpy as np, pandas
    ↪ as pd, re, shapely as shp

from os import PathLike
from typing import Self
from shapely.plotting import plot_polygon

import sys
if '..' not in sys.path: sys.path.append('..')

from histopath_bim_des.config.runners import RunnerConfig

(settings := ifc_geom.settings()).set(settings.USE_WORLD_COORDS, True)
    ↪  # Find global coordinates

@dataclass
class BimModel:
    elevations: dict[str, float]
    doors: pd.DataFrame
    walls: pd.DataFrame

    @staticmethod
    def from_ifc(path, door_filter = r'd\d+$'):
        ifc_file = ifc.open(path)
        elevations: dict[str, float] = reduce(
            lambda d1, d2: d1 | d2,
            map(lambda s: {s.Name: s.Elevation/1000.0}, ifc_file.by_type
                ↪ ("ifcBuildingStorey")))

        def get_level_name(obj): return obj.ContainedInStructure[0].
            ↪ RelatingStructure.Name

        def get_coords(obj):
            shape = ifc_geom.create_shape(settings, obj)
            v = ifc_shape.get_vertices(shape.geometry)
            return {'x0': min(map(lambda xyz: xyz[0], v)), 'x1': max(map(
                ↪ lambda xyz: xyz[0], v)),
                'y0': min(map(lambda xyz: xyz[1], v)), 'y1': max(map(
                    ↪ lambda xyz: xyz[1], v)),
                'z0': min(map(lambda xyz: xyz[2], v))}

        # Extract door data
        doors = list(filter(lambda door: bool(re.match(door_filter,
            ↪ door.Name)),
                        ifc_file.by_type("IfcDoor")))
        doors_coords = [get_coords(door) for door in doors]
        doors_df = pd.DataFrame({
            'door_name': [door.Name for door in doors], 'floor': [
                ↪ get_level_name(door) for door in doors],
            'x0': [box['x0'] for box in doors_coords], 'x1': [box['x1'] for
                ↪ box in doors_coords],
            'y0': [box['y0'] for box in doors_coords], 'y1': [box['y1'] for
                ↪ box in doors_coords],
            'z0': [box['z0'] for box in doors_coords],
        })\
        .sort_values(by='door_name',key=natsort.natsort_keygen())\
        .reset_index(drop=True)

        # Extract wall data
        walls = ifc_file.by_type("IfcWall")
        wall_coords = [get_coords(wall) for wall in walls]
        walls_df = pd.DataFrame({
            'wall_name': [wall.Name for wall in walls], 'floor': [
                ↪ get_level_name(wall) for wall in walls],
            'x0': [box['x0'] for box in wall_coords], 'x1': [box['x1'] for box
                ↪ in wall_coords],
            'y0': [box['y0'] for box in wall_coords], 'y1': [box['y1'] for box
                ↪ in wall_coords],
            'z0': [box['z0'] for box in wall_coords]})
        return BimModel(elevations,doors_df,walls_df)

    def to_shapely(self, level: int) -> 'ShapelyModel':
        """Returns a Shapely representation of a floor in the `BimModel`.
            ↪ """
        wall_shapes = [
            shp.box(wall.x0, wall.y0, wall.x1, wall.y1, ccw=False)
            for wall in self.walls.loc[self.walls.floor.str.contains(f'
                ↪ Level {level}')].itertuples()]
        door_shapes = {
            door.door_name: shp.box(door.x0, door.y0, door.x1, door.y1,
                ↪ ccw=False)
            for door in self.doors.loc[self.doors.floor.str.contains(f'
                ↪ Level {level}')].itertuples()}
        for s in wall_shapes + door_shapes.values(): shp.prepare(s)
        return ShapelyModel(wall_shapes, door_shapes)
```

Data availability

The key code used in this paper is available in the Appendix. The full Python code base for this paper can be found at https://github.com/yinchi/histopath-bim-des.

Listing A.2: `ShapelyModel` class definition for the BIM-DES integration. See Listing A.1 for required `import` statements.

```
@dataclass
class ShapelyModel:
    """Shapely representation of a single floor in the Histopathology lab."""
    wall_shapes: list[shp.Polygon]
    door_shapes: dict[str, shp.Polygon]

    def is_valid_box(self, box: shp.Polygon, ok_doors: list[str]):
        """Determines if box intersects with a wall or door except for `ok_doors`."""
        ok_door_shapes = [self.door_shapes[x] for x in ok_doors]
        shp.prepare(box)
        return (
            (True, 'ok_door') if any(box.intersects(ok_door_shapes))
            else (False, 'wall') if any(box.intersects(self.wall_shapes))
            else (True, 'empty'))

    def shortest_path(self, from_door: str, to_door: str, grid_size=0.5,bottom_left=(30, 45), top_right=(90, 70)):
        """Find the shortest path between two doors in the model."""
        x_min, y_min = bottom_left
        x_max, y_max = top_right
        n_x, n_y = len(np.arange(x_min, x_max, grid_size)), len(np.arange(y_min, y_max, grid_size))

        # Create base grid
        grid = ntx.grid_2d_graph(n_x, n_y)
        for i, j in grid.nodes:
            grid.nodes[(i, j)]['box'] = shp.box(
                x0 := x_min + i*grid_size, y0 := y_min + j*grid_size, x0+grid_size, y0+grid_size, ccw=False)
            shp.prepare(grid.nodes[(i, j)]['box'])
            grid.nodes[(i, j)]['pos'] = ((centroid := grid.nodes[(i, j)]['box'].centroid).x, centroid.y)

        selected_nodes = [n for n, v in grid.nodes(data=True)
                          if self.is_valid_box(v['box'], ok_doors=[from_door, to_door])[0]]
        grid2 = ntx.Graph(grid.subgraph(selected_nodes))

        # Add diagonals to grid2 within each complete "box" of 4 edges
        for _, _, v in grid2.edges(data=True): v['weight'] = 1.0
        for x, y in grid2.nodes:
            if ((x+1, y) in grid2.nodes and (x, y+1) in grid2.nodes and (x+1, y+1) in grid2.nodes):
                grid2.add_edge((x, y), (x+1, y+1), weight=2**0.5) # northeast direction
            if ((x+1, y) in grid2.nodesand (x, y-1) in grid2.nodes and (x+1, y-1) in grid2.nodes):
                grid2.add_edge((x, y), (x+1, y-1), weight=2**0.5) # southeast direction

        # Get node indexes for from_door and to_door
        from_node = [n for n, v in grid.nodes(data=True) if v['box'].intersects(self.door_shapes[from_door].centroid)][0]
        to_node = [n for n, v in grid.nodes(data=True) if v['box'].intersects(self.door_shapes[to_door].centroid)][0]

        path_nodes = ntx.shortest_path(grid2, from_node, to_node, weight='weight')
        path_edges = list(zip(path_nodes[:-1], path_nodes[1:]))
        path_graph = ntx.Graph()
        for i, n in enumerate(path_nodes): path_graph.add_node(i, pos=grid2.nodes(data=True)[n]['pos'])
        for i, e in enumerate(path_edges): path_graph.add_edge(i, i+1, weight=grid2.edges[e]['weight'])
        path_length = ntx.shortest_path_length(grid2, from_node, to_node, weight='weight') * grid_size
        return path_length, path_graph

    def plot_floor(self, ax: matplotlib.axes.Axes, title: str, bottom_left=(30, 45), top_right=(100, 80)):
        """Plots the floor model using Matplotlib."""
        for p in self.wall_shapes: plot_polygon(p, ax, facecolor='gray', add_points=False, linewidth=0)
        for n, p in self.door_shapes.items():
            plot_polygon(p, ax, facecolor='red',add_points=False, linewidth=0)
            ax.text(p.centroid.x, p.centroid.y, n, color='red')
        ax.axis('square')
        x0, y0 = bottom_left
        x1, y1 = top_right
        ax.set(xlim=(x0, x1), ylim=(y0, y1), title=title)

def logical_graph(model: ShapelyModel, speed: float):
    """Construct a logical graph representation of a floor."""
    graph = ntx.Graph().add_nodes_from(keys := list(model.door_shapes.keys()))
    for i, k1 in enumerate(keys):
        for _, k2 in islice(enumerate(keys), i+1, None):
            try:
                path_len, _ = model.shortest_path(k1, k2)
                graph.add_edge(k1, k2, weight=path_len/speed)
            except ntx.NetworkXNoPath:
                continue
    return graph

def runner_times(model: BimModel, cfg: RunnerConfig) -> dict[tuple, float]:
    """Compute runner times between process stages in the Histopathology model."""
    target_levels = [re.match(r'Level (\d+)', s).group(1) for s in model.doors.floor.unique()]
    logical_graphs = {level: logical_graph(model.to_shapely(level=level), speed=1.5)
                      for level in target_levels}
    full_logical_graph = ntx.compose_all(logical_graphs.values())
    for path in cfg.extra_paths: full_logical_graph.add_edge(*path.path, weight=path.duration_seconds)

    d = cfg.door_map.model_dump()
    pairs = list(zip(k := list(d.keys()), k[1:]))

    ret = {}
    for u, v in pairs:
        if 'cutup' in (u, v):
            du, dv = d[u] if u == 'cutup' else [d[u]], d[v] if v == 'cutup' else [d[v]]

            # compute the average runner time for all cutup rooms
            ret[(u, v)] = np.average(
                [
                    ntx.shortest_path_length(full_logical_graph, d1, d2, weight='weight')
                    for d1, d2 in product(du, dv)
                ], weights=cfg.cutup_dist
            )
        else:
            ret[(u, v)] = ntx.shortest_path_length(full_logical_graph, d[u], d[v], weight='weight')
    return ret
```

References

[1] Y. Li, X. Pan, Y. Han, J.E. Taylor, Sustainable healthcare facilities: A scoping review, J. Constr. Eng. Manag. 147 (12) (2021) 03121007, http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0002170.

[2] A.O.B. Sari, W. Jabi, Architectural spatial layout design for hospitals: A review,

J. Build. Eng. (2024) 110835, http://dx.doi.org/10.1016/j.jobe.2024.110835.

[3] L. Lim, M. Moore, J.R. DuBose, B. Obeidat, R. Stroebel, C.M. Zimring, Spatial influences on team awareness and communication in two outpatient clinics: a multiple methods study, J. Gen. Intern. Med. 35 (7) (2020) 1987–1996, http://dx.doi.org/10.1007/s11606-020-05790-6.

[4] J.J. Forbus, D. Berleant, Discrete-event simulation in healthcare settings: A review, Modelling 3 (4) (2022) 417–433, http://dx.doi.org/10.3390/modelling3040027.

[5] AIAA Digital Engineering Integration Committee, DIGITAL TWIN: Definition & VALUE an AIAA and AIA position paper, 2020, https://www.aia-aerospace.org/wp-content/uploads/Digital-Twin-Institute-Position-Paper-December-2020-1.pdf. (Accessed 07 May 2025).

[6] UK Government Office for Science, RTA: Digital twins - GOV.UK, 2023, https://www.gov.uk/government/publications/rapid-technology-assessment-digital-twins/rta-digital-twins. (Accessed 07 May 2025).

[7] V.V. Tuhaise, J.H.M. Tah, F.H. Abanda, Technologies for digital twin applications in construction, Autom. Constr. 152 (2023) 104931, http://dx.doi.org/10.1016/j.autcon.2023.104931.

[8] D. Davletshina, V.K. Reja, I. Brilakis, Automating construction of road digital twin geometry using context and location aware segmentation, Autom. Constr. 168 (2024) 105795, http://dx.doi.org/10.1016/j.autcon.2024.105795.

[9] C. Boje, A. Guerriero, S. Kubicki, Y. Rezgui, Towards a semantic construction digital twin: Directions for future research, Autom. Constr. 114 (November 2019) (2020) 103179, http://dx.doi.org/10.1016/j.autcon.2020.103179.

[10] ISO, 19650-1:2018. Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM) - information management using building information modelling. Part 1: Concepts and principles, 2018, https://www.iso.org/standard/68078.html. (Accessed 07 May 2025).

[11] J. Patacas, N. Dawood, M. Kassem, BIM for facilities management: A framework and a common data environment using open standards, Autom. Constr. 120 (June) (2020) 103366, http://dx.doi.org/10.1016/j.autcon.2020.103366.

[12] N. Moretti, X. Xie, J. Merino, J. Brazauskas, A.K. Parlikad, An openBIM approach to IoT integration with incomplete as-built data, Appl. Sci. 10 (22) (2020) 8287, http://dx.doi.org/10.3390/app10228287.

[13] ISO, 19650-3:2020. Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM) — Information management using building information modelling — Part 3: Operational phase of the assets, 2020, pp. 1–46, https://www.iso.org/standard/75109.html. (Accessed 07 May 2025).

[14] ISO, 16739-1:2024 - Industry Foundation Classes (IFC) for data sharing in the construction and facility management industries — Part 1: Data schema, 2024, https://www.iso.org/standard/84123.html. (Accessed 07 May 2025).

[15] C.L. Percell, Smoothing Patient Flow by Improving Bed Turnover Time (Ph.D. thesis), Walden University, 2021, https://scholarworks.waldenu.edu/dissertations/10061. (Accessed 07 May 2025).

[16] R. Haldar, D. Gupta, H. Pandey, S. Srivastava, P. Mishra, A. Agarwal, Patient transportation delays and effects on operation theatres' efficiency: A study for problem analysis and remedial measures, Anesthesia Essays Res. 13 (3) (2019) 554–559, http://dx.doi.org/10.4103/aer.AER_75_19.

[17] D. Sancho, R. Acero Cacho, M.J. Lavilla, M. Corral, A. Carrillo-López, A. Rezusta, Optimizing the supply chain of intensive care unit blood culture samples to clinical microbiology laboratory using lean six sigma, in: 10th Manufacturing Engineering Society International Conference (MESIC 2023), in: Advances in Science and Technology, Vol. 132, Trans Tech Publications Ltd, 2023, pp. 394–404, http://dx.doi.org/10.4028/p-n04TQG.

[18] D. DelDotto, M.A. Yusif, An analysis of work flow in the phlebotomy, chemistry, hematology, and urinalysis laboratories at the edith nourse rogers memorial veterans hospital in bedford, MA, 2012, https://digital.wpi.edu/concern/student_works/g158bh574?locale=de. (Accessed 07 May 2025).

[19] A. Ley-Chavez, T. Hmar-Lagroun, P. Douglas-Ntagha, C.L. Cumbo, Layout improvement study to reduce staff walking distance in a large health care facility: How to not walk an extra 4740 miles, Qual. Manag. Heal. Care 25 (3) (2016) 134–140, http://dx.doi.org/10.1097/QMH.0000000000000095.

[20] L. Deng, F. Cheng, X. Gao, W. Yu, J. Shi, L. Zhou, L. Zhang, M. Li, Z. Wang, Y.D. Zhang, Y. Lv, Hospital crowdedness evaluation and in-hospital resource allocation based on image recognition technology, Sci. Rep. 13 (1) (2023) 299, http://dx.doi.org/10.1038/s41598-022-24221-6.

[21] J. Trauer, S. Schweigert-Recksiek, C. Engel, K. Spreitzer, M. Zimmermann, What is a digital twin? – Definitions and insights from an industrial case study in technical product development, in: Proceedings of the Design Society: DESIGN Conference, Vol. 1, Cambridge University Press (CUP), 2020, pp. 757–766, http://dx.doi.org/10.1017/dsd.2020.15.

[22] ISO, ISO 23247-1:2021 Automation systems and integration — Digital twin framework for manufacturing — part 1: Overview and general principles, 2021, https://www.iso.org/standard/75066.html. (Accessed 07 May 2025).

[23] ISO, ISO/IEC 30173:2023 Digital twin — Concepts and terminology, Standard 30173:2023, ISO, 2023, https://www.iso.org/standard/81442.html. (Accessed 07 May 2025).

[24] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital twin in manufacturing: A categorical literature review and classification, IFAC- Pap. 51 (11) (2018) 1016–1022, http://dx.doi.org/10.1016/j.ifacol.2018.08.474.

[25] T. Moyaux, Y. Liu, G. Bouleux, V. Cheutet, An agent-based architecture of the digital twin for an emergency department, Sustainability 15 (2023) 3412, http://dx.doi.org/10.3390/su15043412.

[26] T. England, D. Gartner, E. Ostler, P. Harper, D. Behrens, J. Boulton, D. Bull, C. Cordeaux, I. Jenkins, F. Lindsay, R. Monk, L. Watkins, Near real-time bed modelling feasibility study, J. Simul. 15 (2021) 261–272, http://dx.doi.org/10.1080/17477778.2019.1706434.

[27] W.J. Phua, M.Y.H. Low, N. Venkatarayalu, J. Koh, NFC-based smart notification system for hospital discharge process and bed management, in: 2018 IEEE International Conference on Service Operations and Logistics, and Informatics, SOLI, IEEE, 2018, pp. 143–147, http://dx.doi.org/10.1109/SOLI.2018.8476736.

[28] S. Yoo, S. Kim, E. Kim, E. Jung, K.-H. Lee, H. Hwang, Real-time location system-based asset tracking in the healthcare field: lessons learned from a feasibility study, BMC Med. Inform. Decis. Mak. 18 (2018) 80, http://dx.doi.org/10.1186/s12911-018-0656-0.

[29] S. Shyam, S. Juliet, K. Ezra, Tracking and monitoring of medical equipments using UWB for smart healthcare, in: 2022 6th International Conference on Computing Methodologies and Communication, ICCMC, IEEE, 2022, pp. 631–637, http://dx.doi.org/10.1109/ICCMC53470.2022.9753719.

[30] Y. Peng, M. Zhang, F. Yu, J. Xu, S. Gao, Digital twin hospital buildings: An exemplary case study through continuous lifecycle integration, Adv. Civ. Eng. 2020 (2020) http://dx.doi.org/10.1155/2020/8846667.

[31] Y. Song, Y. Li, Digital twin aided healthcare facility management: A case study of Shanghai Tongji Hospital, in: Construction Research Congress 2022, American Society of Civil Engineers, Reston, VA, 2022, pp. 1145–1155, http://dx.doi.org/10.1061/9780784483961.120.

[32] C.G. Rodriguez-Gonzalez, A. Herranz-Alonso, V. Escudero-Vilaplana, M.A. Ais-Larisgoitia, I. Iglesias-Peinado, M. Sanjurjo-Saez, Robotic dispensing improves patient safety, inventory management, and staff satisfaction in an outpatient hospital pharmacy, J. Eval. Clin. Pract. 25 (2019) 28–35, http://dx.doi.org/10.1111/jep.13014.

[33] S. Vekaria, G. Boardman, K. Tam, J. Kho, B. Jenkins, M. Rawlins, Implementation of robotics in the Australian hospital pharmacy dispensary: adding to the evidence, J. Pharm. Pr. Res. 51 (2021) 552–553, http://dx.doi.org/10.1002/jppr.1764.

[34] X. Zhong, F.B. Sarijaloo, A. Prakash, J. Park, C. Huang, A. Barwise, V. Herasevich, O. Gajic, B. Pickering, Y. Dong, A multidisciplinary approach to the development of digital twin models of critical care delivery in intensive care units, Int. J. Prod. Res. 60 (2022) 4197–4213, http://dx.doi.org/10.1080/00207543.2021.2022235.

[35] W. Liu, W. Zhang, B. Dutta, Z. Wu, M. Goh, Digital twinning for productivity improvement opportunities with robotic process automation: Case of Greenfield Hospital, Int. J. Mech. Eng. Robot. Res. (2020) 258–263, http://dx.doi.org/10.18178/ijmerr.9.2.258-263.

[36] C.-R. Lee, E.T.-H. Chu, H.-C. Shen, J. Hsu, H.-M. Wu, An indoor location-based hospital porter management system and trace analysis, Heal. Inform. J. 29 (2023) http://dx.doi.org/10.1177/14604582231183399.

[37] C.Y.S. Ang, J.W.W. Lee, Y.S. Chiew, X. Wang, C.P. Tan, M.E. Cove, M.B.M. Nor, C. Zhou, T. Desaive, J.G. Chase, Virtual patient framework for the testing of mechanical ventilation airway pressure and flow settings protocol, Comput. Methods Programs Biomed. 226 (2022) 107146, http://dx.doi.org/10.1016/j.cmpb.2022.107146.

[38] C.Y.S. Ang, Y.S. Chiew, X. Wang, E.H. Ooi, M.B.M. Nor, M.E. Cove, J.G. Chase, Virtual patient with temporal evolution for mechanical ventilation trial studies: A stochastic model approach, Comput. Methods Programs Biomed. 240 (2023) 107728, http://dx.doi.org/10.1016/j.cmpb.2023.107728.

[39] J.I. Vázquez-Serrano, R.E. Peimbert-García, L.E. Cárdenas-Barrón, Discrete-event simulation modeling in healthcare: A comprehensive review, Int. J. Environ. Res. Public Heal. 18 (22) (2021) http://dx.doi.org/10.3390/ijerph182212262.

[40] A.M. Law, Simulation Modeling and Analysis, fifth ed., McGraw-Hill Education, New York, 2015.

[41] J.I. Vázquez-Serrano, R.E. Peimbert-García, L.E. Cárdenas-Barrón, Discrete-event simulation modeling in healthcare: A comprehensive review, Int. J. Environ. Res. Public Heal. 18 (22) (2021) 12262, http://dx.doi.org/10.3390/ijerph182212262.

[42] S. Almagooshi, Simulation modelling in healthcare: Challenges and trends, Procedia Manuf. 3 (2015) 301–307, http://dx.doi.org/10.1016/j.promfg.2015.07.155.

[43] C.M. Macal, Everything you need to know about agent-based modelling and simulation, J. Simul. 10 (2) (2016) 144–156, http://dx.doi.org/10.1057/jos.2016.7.

[44] S. Abar, G.K. Theodoropoulos, P. Lemarinier, G.M. O'Hare, Agent based modelling and simulation tools: A review of the state-of-art software, Comput. Sci. Rev. 24 (2017) 13–33, http://dx.doi.org/10.1016/j.cosrev.2017.03.001.

[45] H. Cai, J. Jia, Using discrete event simulation (DES) to support performance-driven healthcare design, HERD: Heal. Environ. Res. Des. J. 12 (3) (2018) 89–106, http://dx.doi.org/10.1177/1937586718801910.

[46] S.C. Brailsford, T. Eldabi, M. Kunc, N. Mustafee, A.F. Osorio, Hybrid simulation modelling in operational research: A state-of-the-art review, European J. Oper. Res. 278 (3) (2019) 721–737, http://dx.doi.org/10.1016/j.ejor.2018.10.025.
[47] E. Ouda, A. Sleptchenko, M.C.E. Simsekler, Comprehensive review and future research agenda on discrete-event simulation and agent-based simulation of emergency departments, Simul. Model. Pr. Theory 129 (2023) 102823, http://dx.doi.org/10.1016/j.simpat.2023.102823.
[48] M. Ruiz, E. Orta, J. Sánchez, A simulation-based approach for decision-support in healthcare processes, Simul. Model. Pr. Theory 136 (2024) http://dx.doi.org/10.1016/j.simpat.2024.102983, Cited by: 2; All Open Access, Hybrid Gold Open Access.
[49] S.Y. Ahmadi, J.I. Lather, Determining the impact of facility layout methods on walk-in Covid-19 vaccine clinics: a theoretical exploration, in: 2023 Winter Simulation Conference, WSC, IEEE, 2023, pp. 1100–1111, http://dx.doi.org/10.1109/wsc60868.2023.10407119.
[50] Y. Li, P. Liao, Y. Song, H. Chi, A systematic decision-support approach for healthcare facility layout design integrating resource flow and space adjacency optimization with simulation-based performance evaluation, J. Build. Eng. 77 (2023) 107465, http://dx.doi.org/10.1016/j.jobe.2023.107465.
[51] J. Lee, H. Lee, M. McCuskey Shepley, Exploring the spatial arrangement of patient rooms for minimum nurse travel in hospital nursing units in Korea, Front. Archit. Res. 9 (4) (2020) 711–725, http://dx.doi.org/10.1016/j.foar.2020.06.003.
[52] E. Meephu, S. Arwatchananukul, N. Aunsri, Enhancement of Intra-hospital patient transfer in medical center hospital using discrete event system simulation, in: Y.-H. Kuo (Ed.), PLOS ONE 18 (4) (2023) e0282592, http://dx.doi.org/10.1371/journal.pone.0282592.
[53] Y.-C. Chan, A. Mukherjee, N. Moretti, M. Nakaoka, G. Yilmaz, M. Sasidharan, J. Merino, Z. Rosun, C. Carr, D. McFarlane, A.K. Parlikad, A process simulation model for a histopathology laboratory, in: Proceedings of the 2024 Winter Simulation Conference, Orlando, Florida, 2024, http://dx.doi.org/10.1109/WSC63780.2024.10838731.
[54] K. Pongjetanapong, C. Walker, M. O'Sullivan, M. Lovell-Smith, N. Furian, Exploring trade-offs between staffing levels and turnaround time in a pathology laboratory using discrete event simulation, Int. J. Heal. Plan. Manag. 34 (2) (2019) http://dx.doi.org/10.1002/hpm.2748.
[55] S.L.M. Abhijit Gosavi, C.M. Masek, Analysis of clinic layouts and patient-centered procedural innovations using discrete-event simulation, Eng. Manage. J. 28 (3) (2016) 134–144, http://dx.doi.org/10.1080/10429247.2016.1195664.
[56] R.M. Wood, Modelling the impact of COVID-19 on elective waiting times, J. Simul. 16 (1) (2020) 101–109, http://dx.doi.org/10.1080/17477778.2020.1764876.
[57] Z. Jia, P. Nourian, P. Luscuere, C. Wagenaar, Spatial decision support systems for hospital layout design: A review, J. Build. Eng. 67 (2023) 106042, http://dx.doi.org/10.1016/j.jobe.2023.106042.
[58] D. Schaumann, N.P. Pilosof, M. Gath-Morad, Y.E. Kalay, Simulating the impact of facility design on operations: a study in an internal medicine ward, Facilities 38 (7) (2020) 501–522, http://dx.doi.org/10.1108/F-10-2018-0132.
[59] J. Xu, Y. Peng, C. Ye, S. Gao, M. Cheng, Hospital flow simulation and space layout planning based on low-trust social force model, IEEE Access 12 (2024) 90135–90144, http://dx.doi.org/10.1109/ACCESS.2024.3420406.
[60] R. Volk, J. Stengel, F. Schultmann, Building Information Models (BIM) for existing buildings – literature review and future needs, Autom. Constr. 38 (2014) 109–127, http://dx.doi.org/10.1016/j.autcon.2013.10.023.
[61] Z. Liu, Y. Lu, L.C. Peh, A review and scientometric analysis of global building information modeling (BIM) research in the architecture, engineering and construction (AEC) industry, Buildings 9 (10) (2019) 210, http://dx.doi.org/10.3390/buildings9100210.
[62] M. Deng, Y. Tan, J. Singh, A. Joneja, J.C. Cheng, A BIM-based framework for automated generation of fabrication drawings for façade panels, Comput. Ind. 126 (2021) 103395, http://dx.doi.org/10.1016/j.compind.2021.103395.
[63] B. Soust-Verdaguer, C. Llatas, A. García-Martínez, Critical review of bim-based LCA method to buildings, Energy Build. 136 (2017) 110–120, http://dx.doi.org/10.1016/j.enbuild.2016.12.009.
[64] Y.T. Chang, S.H. Hsieh, A review of building information modeling research for green building design through building performance analysis, J. Inf. Technol. Constr. 25 (2020) 1–40, http://dx.doi.org/10.36680/j.itcon.2020.001.
[65] H. Liu, M. Al-Hussein, M. Lu, BIM-based integrated approach for detailed construction scheduling under resource constraints, Autom. Constr. 53 (2015) 29–43, http://dx.doi.org/10.1016/j.autcon.2015.03.008.
[66] B. Liu, B. Yang, B. Zhang, M. Dong, S. Jiang, J. Xiao, Spatio-temporal deduction of floor construction based on the agent modeling of construction actors, Autom. Constr. 142 (2022) http://dx.doi.org/10.1016/j.autcon.2022.104487.
[67] A. Mtya, A. Windapo, Drivers and barriers to the adoption of building information modelling (BIM) by construction firms in South Africa, Innov. Prod. Constr.: Transform. Constr. Through Emerg. Technol. (2019) 215–223, http://dx.doi.org/10.1142/9789813272491_0013.
[68] M.K. Dixit, V. Venkatraj, M. Ostadalimakhmalbaf, F. Pariafsai, S. Lavy, Integration of facility management and building information modeling (BIM) A review of key issues and challenges, Facilities 37 (7/8) (2019) 455–483, http://dx.doi.org/10.1108/F-03-2018-0043.
[69] X. Gao, P. Pishdad-Bozorgi, BIM-enabled facilities operation and maintenance: A review, Adv. Eng. Inform. 39 (2019) 227–247, http://dx.doi.org/10.1016/J.AEI.2019.01.005.
[70] J. Clarke, J. Cockroft, A. Cowie, J. Hand, N. Kelly, A. Samuel, D. Tang, On the High-Resolution simulation of building/plant systems, in: 14th International Conference of IBPSA - Building Simulation 2015, BS 2015, Conference Proceedings, 2015, pp. 90–97, http://dx.doi.org/10.26868/25222708.2015.2327.
[71] A.M. Maglad, M. Houda, R. Alrowais, A.M. Khan, M. Jameel, S.K.U. Rehman, H. Khan, M.F. Javed, M.F. Rehman, Bim-based energy analysis and optimization using insight 360 (case study), Case Stud. Constr. Mater. 18 (2023) e01755, http://dx.doi.org/10.1016/j.cscm.2022.e01755.
[72] C.-J. Chen, S.-y. Chen, S.-h. Li, H.-t. Chiu, Green BIM-based building energy performance analysis, Comput.- Aided Des. Appl. 14 (5) (2017) 650–660, http://dx.doi.org/10.1080/16864360.2016.1273582.
[73] Y. Zou, A. Kiviniemi, S.W. Jones, A review of risk management through BIM and BIM-related technologies, Saf. Sci. 97 (2017) 88–98, http://dx.doi.org/10.1016/j.ssci.2015.12.027.
[74] S. Kouhestani, M. Nik-Bakht, IFC-based process mining for design authoring, Autom. Constr. 112 (2020) http://dx.doi.org/10.1016/j.autcon.2019.103069.
[75] C.-S. Park, D.-Y. Lee, O.-S. Kwon, X. Wang, A framework for proactive construction defect management using BIM, augmented reality and ontology-based data collection template, Autom. Constr. 33 (2013) 61–71, http://dx.doi.org/10.1016/j.autcon.2012.09.010.
[76] J. Jia, S. Dou, S. Yang, Y. Wu, F. Cao, B. Li, H. Cui, Study on the application framework of BIM in the life cycle management of offshore wind farms, in: Proceedings of the International Offshore and Polar Engineering Conference, 1, 2019, pp. 513–520, http://dx.doi.org/10.1201/b12516-145.
[77] H.-J. Shin, H.-S. Cha, Proposing a quality inspection process model using advanced technologies for the transition to smart building construction, Sustain. (Switzerland) 15 (1) (2023) http://dx.doi.org/10.3390/su15010815.
[78] A.D. Chasey, S. Pindukuri, Information exchange requirements for capital equipment and facility infrastructure for semiconductor facilities, in: Construction Research Congress 2012: Construction Challenges in a Flat World, Proceedings of the 2012 Construction Research Congress, 2012, pp. 437–446, http://dx.doi.org/10.1061/9780784412329.044.
[79] W. Lu, T. Olofsson, Building information modeling and discrete event simulation: Towards an integrated framework, Autom. Constr. 44 (2014) 73–83, http://dx.doi.org/10.1016/J.AUTCON.2014.04.001.
[80] E. Alreshidi, M. Mourshed, Y. Rezgui, Cloud-based BIM governance platform requirements and specifications: Software engineering approach using BPMN and UML, J. Comput. Civ. Eng. 30 (4) (2016) http://dx.doi.org/10.1061/(ASCE)CP.1943-5487.0000539.
[81] F.R. Correa, Cyber-physical systems for construction industry, in: Proceedings - 2018 IEEE Industrial Cyber-Physical Systems, ICPS 2018, 2018, pp. 392–397, http://dx.doi.org/10.1109/ICPHYS.2018.8387690.
[82] L. Gebken, P. Drews, I. Schirmer, Enhancing the building information modeling lifecycle of complex structures with IOT: Phases, capabilities and use cases, in: Proceedings of the Annual Hawaii International Conference on System Sciences, Vol. 2019-January, 2019, pp. 5929–5938, http://dx.doi.org/10.24251/HICSS.2019.715.
[83] H. Guo, X. Ye, Q. Ren, L. Zhubang, Automatic generation of construction schedules based on BIM and rule reasoning, J. Tsinghua Univ.(Sci. Technol.) 62 (2) (2022) 189, http://dx.doi.org/10.16511/j.cnki.qhdxxb.2022.22.001.
[84] Y. Dong, Y. Zhang, F. Sang, Construction process simulation of building decoration based on BIM and computer-aided technology, Comput.- Aided Des. Appl. (2023) http://dx.doi.org/10.14733/cadaps.2023.S15.294-308.
[85] D. Ioannidis, D. Tzovaras, C. Malavazos, Occupancy and business modeling, in: EWork and EBusiness in Architecture, Engineering and Construction - Proceedings of the European Conference on Product and Process Modelling 2012, ECPPM 2012, 2012, pp. 919–930, https://www.researchgate.net/publication/235412763_Occupancy_and_Business_Modelling. (Accessed 07 May 2025).
[86] R. Heikkilä, M. Marttinen, Development of BIM based rehabilitation and maintenance process for roads, in: ISARC 2013 - 30th International Symposium on Automation and Robotics in Construction and Mining, Held in Conjunction with the 23rd World Mining Congress, 2013, pp. 1216–1222, http://dx.doi.org/10.22260/isarc2013/0136.
[87] G. Gourlis, I. Kovacic, Energy efficient operation of industrial facilities: The role of the building in simulation-based optimization, in: IOP Conference Series: Earth and Environmental Science, Vol. 410, 2020, http://dx.doi.org/10.1088/1755-1315/410/1/012019.
[88] G. Gourlis, I. Kovacic, A holistic digital twin simulation framework for industrial facilities: BIM-based data acquisition for building energy modeling, Front. Built Environ. 8 (2022) http://dx.doi.org/10.3389/fbuil.2022.918821, Cited by: 6; All Open Access, Gold Open Access.
[89] F. Meng, Q. Wang, Y. Liu, Y. Zhang, Design and BIM-based technology on a new cross-sea bridge in Xiamen, China, Proc. Inst. Civ. Eng.: Civ. Eng. 176 (3) (2023) 121–127, http://dx.doi.org/10.1680/jcien.22.00229.

[90] M. Eguaras-Martínez, C. Martín-Gómez, M. Vidaurre-Arbizu, T. Brennan, S. Krinidis, D. Ioannidis, D. Tzovaras, Architectural simulation of the integration of building information modelling (BIM) & Business Process Modelling (BPM), in: Proceedings of the 10th European Conference on Product and Process Modelling, ECPPM 2014, 2015, pp. 805–811, http://dx.doi.org/10.1201/b17396-130.

[91] Z. Wang, T. Bulbul, J. Lucas, A case study of BIM-based model adaptation for healthcare facility management - Information needs analysis, in: Congress on Computing in Civil Engineering, Proceedings, Vol. 2015-January, (January) 2015, pp. 395–402, http://dx.doi.org/10.1061/9780784479247.049.

[92] M. Xu, D. Peng, Pyrosim-based numerical simulation of fire safety and evacuation behaviour of college buildings, Int. J. Saf. Secur. Eng. 10 (2) (2020) 293–299, http://dx.doi.org/10.18280/ijsse.100218.

[93] V. Popov, V. Juocevicius, D. Migilinskas, S. Mikalauskas, Application of building information modelling and construction process simulation ensuring Virtual Project Development concept in 5D environment, in: ISARC 2008 - Proceedings from the 25th International Symposium on Automation and Robotics in Construction, 2008, pp. 616–624, http://dx.doi.org/10.3846/isarc.20080626.616.

[94] B. East, Using COBie, Wiley, 2013, pp. 107–143, http://dx.doi.org/10.1002/9781119572633.ch5,

[95] S. Lavy, N. Saxena, M. Dixit, Effects of BIM and COBie database facility management on work order processing times: Case study, J. Perform. Constr. Facil. 33 (2019) http://dx.doi.org/10.1061/(ASCE)CF.1943-5509.0001333.

[96] K. Schwabe, M. Dichtl, M. König, C. Koch, COBie: A specification for the construction operations building information exchange, in: Building Information Modeling, Springer International Publishing, 2018, pp. 167–180, http://dx.doi.org/10.1007/978-3-319-92862-3_9.

[97] A.H. Behzadan, C.C. Menassa, J.L. Tishman, A.R. Pradhan, Enabling real time simulation of architecture, engineering, construction, and facility management (AEC/FM) systems: a review of formalism, model architecture, and data representation, ITcon 20 (1) (2015) 1–23, Accessed:07/05/2025 http://www.itcon.org/2015/1, Vol. 20, Pg. 1- 23.

[98] ISO, ISO 7817-1:2024 - Building information modelling — level of information need — Part 1: Concepts and principles, 2024, https://www.iso.org/standard/82914.html. (Accessed 07 May 2025).

[99] buildingSMART International, Activity proposal. ISO41000 FMBIM protocol, IDS and CDE AKA "facilities management and openBIM"', 2020, https://app.box.com/s/q4gy4lzw1kkuxynt0d5e13u98qmy4t12. (Accessed 07 May 2025).

[100] R. van der Ham, Salabim: discrete event simulation and animation in Python, J. Open Source Softw. 3 (27) (2018) 767, http://dx.doi.org/10.21105/joss.00767.

[101] A. Mukherjee, N. Moretti, Y.-C. Chan, G. Yilmaz, M. Sasidharan, J. Merino, Z. Rosun, C. Carr, D. McFarlane, A. Kumar Parlikad, Healthcare process and variable mapping for identifying digitalisation opportunities and building a hospital digital twin, in: EC3 CIBW78 Joint Conference 2023, 2023, http://dx.doi.org/10.35490/EC3.2023.270.

[102] A. Mafi, NHS trusts are told to prepare to evacuate hospitals with crumbling concrete, 2023, http://dx.doi.org/10.1136/bmj.p2045.

[103] T. Uras, S. Koenig, An empirical comparison of any-angle path-planning algorithms, Proc. Int. Symp. Comb. Search 6 (1) (2021) 206–210, http://dx.doi.org/10.1609/socs.v6i1.18382.

[104] L. Liu, X. Wang, X. Yang, H. Liu, J. Li, P. Wang, Path planning techniques for mobile robots: Review and prospect, Expert Syst. Appl. (2023) 120254, http://dx.doi.org/10.1016/j.eswa.2023.120254.

[105] J. Zhu, M.O. Wong, N. Nisbet, J. Xu, T. Kelly, S. Zlatanova, I. Brilakis, Semantics-based connectivity graph for indoor pathfinding powered by IFC-Graph, Autom. Constr. 171 (2025) 106019, http://dx.doi.org/10.1016/j.autcon.2025.106019.

[106] Y. Van Tendeloo, H. Vangheluwe, DEVS: Discrete-event modelling and simulation for performance analysis of resource-constrained systems, in: Foundations of Multi-Paradigm Modelling for Cyber-Physical Systems, Springer International Publishing, 2020, pp. 127–153, http://dx.doi.org/10.1007/978-3-030-43946-0_5.

[107] P.J. Haas, Colored stochastic Petri nets, in: Stochastic Petri Nets, Springer New York, 2002, pp. 385–445, http://dx.doi.org/10.1007/0-387-21552-2_9.

[108] C. Ramonell, R. Chacón, H. Posada, Knowledge graph-based data integration system for digital twins of built assets, Autom. Constr. 156 (2023) 105109, http://dx.doi.org/10.1016/j.autcon.2023.105109.