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Crowd simulation-based knowledge mining supporting building evacuation design

Calin Boje*, Haijiang Li

School of Engineering, Cardiff University, Queens Building, the Parade, Cardiff CF24 3AA, UK

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ABSTRACT

Assessing building evacuation performance designs in emergency situations requires complex scenarios which need to be prepared and analysed using crowd simulation tools, requiring significant manual input. With current procedures, every design iteration requires several simulation scenarios, leading to a complicated and time-consuming process. This study aims to investigate the level of integration between digital building models and crowd simulation, within the scope of design automation. A methodology is presented in which existing ontology tools facilitate knowledge representation and mining throughout the process. Several information models are used to integrate, automate and provide feedback to the design decision-making processes. The proposed concept thus reduces the effort required to create valid simulation scenarios by applying represented knowledge, and provides feedback based on results and design objectives. To apply and test the methodology a system was developed, which is introduced here. The context of building performance during evacuation scenarios is considered, but additional design perspectives can be included. The system development section expands on the essential theoretical concepts required and the case study section shows a practical implementation of the system.

1. Introduction

The building design process has advanced significantly since the adoption of Building Information Modelling (BIM) tools and standards, leading to easier modelling and information sharing. However, there are currently very few ways in which to model and use information to provide knowledge outputs about the design, and thereby enhance the design decision-making processes. With increased interoperability and the use of common data formats such as IFC (Industry Foundation Classes), design disciplines can provide analysis models from various perspectives: costs, energy, fire safety, etc. However, most developments are focused on validation of BIM models [47] for various analyses and often apply prescriptive design rules [9] as opposed to performance-based analysis. The current state of using digital technologies for the building lifecycle is constantly developing and there is a need for more automatic, multi-disciplinary methods to deal with large data and interoperability issues [21].

In the field of fire safety, Crowd Simulation (CS) analysis tools are used to estimate building performance in terms of human movement behaviour [8]. This process requires several iterations in different scenarios following conventional workflows [34,5,20], which can be a very time-consuming process and can often lead to wrong estimations of the building performance [37]. There are currently no practical ways of leveraging building information and designer knowledge to enhance and speed up this process. The traditional process usually relies on designer judgement to identify performance problems, which cannot take into account all scenario types due to time-constraints, or the variance caused by human behaviour [22].

This research aims to bridge this gap by exploring the potential of representing information models, designer knowledge and design processes into semantic web ontologies. Using this methodology, ontologies can leverage information models through reasoning and data linking, thereby providing a more automatic process of analysing building performance. With the right operators in place, ontology rules and reasoning can provide insight from CS design scenarios. Another advantage which semantic web languages provide is a more complex integration of crowd simulation tools with BIM, but also with various other sources of information which are required the create realistic scenarios.

Succar [40] describes level 3 BIM as a network of integrated models and services which can be used beyond just the semantic properties of the used building models. Initiatives towards a BIM level 3 way of working [14] expect more intelligent model data and information, which can be leveraged to provide advanced and speedy design support

* Corresponding author.
E-mail address: BojeCP@cardiff.ac.uk (C. Boje).

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for various Architectural, Environmental and Construction (AEC) applications. Thus, it is expected that level 3 BIM and beyond to be able to provide more than just data and information, but also knowledge about building models.

The paper begins with presenting some of the most important related work in the field of fire safety analysis and current uses of ontology tools. The system development outlines the main requirements for representing the CS domain and its interactions with BIM and other sources of information. A conceptual knowledge mining process, for creating valid simulation scenarios and returning results in accordance to design objectives is described. A case study outlines the process of using the system prototype with the scope of identifying advantages and limitations. This is then followed by a discussion on the practical use of this approach and planned future work.

2. Related work

This section outlines crowd simulation models and ontologies in the fields of BIM collaboration efforts. A review of CS models and tools was necessary to assess their limitations, ways of working and their interoperability with BIM processes. The overall research aims to bridge interoperability and perform knowledge retrieval from vast simulation data, for which ontologies are chosen as tools to achieve this. A review of ontology tools is also presented to establish current methodologies, especially in the fields of BIM and fire safety.

2.1. Crowd simulation analysis tools

There are several comprehensive crowd model reviews, which offer critical analysis regarding methodologies used [13,19], application domains [19], scale [49], degree of realism [8] and high-rise buildings focused [35]. The afore-mentioned authors agree that there is no comprehensive model which can simulate all the complexities of human behaviour. Such a model would not be practical because as the complexity of the model grows, so does the computation time. Kuligowski [19] advises that each model should be used for very specific purposes and users should be aware of each model's practical application and limitations. Ronchi and Nilsson [35] mention that for a more comprehensive view, several models can be considered at the same time, which might reveal more information from different perspectives. Zhou et al. [49] and Duives et al. [8] agree that models can be divided into microscopic models (small population) which have high precision, and macroscopic (large population) models with lower precision. From literature, the most prevalent use case scenario is concerned with the emergency evacuation of a building.

Crowd simulation analysis tools are now widely used in design decision-making to assess building performance. Thus, they are expected to provide relevant information indicating building behaviour in crowded scenarios. However, it is not always clear how relevant the simulation output is, as it is dependent on a large number of parameters [15,20]. To compensate for this limitation, it is often required to conduct several simulations using different assumptions and scenarios [13]. This becomes overwhelming when in the context of several design iterations, making it a highly inefficient process. This suggests the need to integrate and automate the process with de facto design processes and standards.

A number of studies are focused on integrating crowd simulation tools into various systems: Jalali et al. [17] integrate different domain tools together for fire evacuation management scenarios; Wang et al. [44] use BIM platforms to provide building environment information into a system that perform calculations of escape routes - the authors present a sophisticated system using several tools to compare results across different design perspectives. For the above-mentioned studies, there is no consensus on information formats, but they regard BIM as the source of information. However, no use of IFC is mentioned, and the BIM data imported is limited to geometry. Despite these attempts, a gap in the interoperability layer between BIM tools and fire safety tools is evident, with no common methodology or information transfer protocols, also pointed out by Wang and Wainer [45]. Additionally, studies focused on fire evacuation with BIM support are only concerned with geometric objects, with no mention to the importance of a context of a simulation model which is defined by more than just geometric components.

Apart from the geometric information, additional object properties are often used in rules checking for fire safety. There are several attempts to automate the rules checking for fire evacuation safety evaluation, with one of the first comprehensive attempts by Dimyadi et al. [7]. The study presents a system which relies on IFC model data and user input, which is compared against a Regulatory Knowledge Model (RKM) consisting of the design rules applied to the process. The research checks output from multiple tools to assess fire safety performance of building designs and is IFC focused. Although a good step in the right direction, the process of integrating the information is not collaborative enough (due to expressing regulations in XML format) for more holistic design views or across the BIM lifecycle stages where higher expressivity of the model information is more beneficial. This is also explored by the same authors in another study [6], where they recommend using semantic web linked data formats (such as ontologies) to express regulatory knowledge, due to higher expressivity and interoperability, making it easier to access the relevant information required in this sort of multi-disciplinary process.

Malsane et al. [23] try to identify the requirements of integrating simulation safety tools and regulations. The scope of the research is limited to regulation in England and Wales, but it discusses in detail the level of knowledge formalisation and concludes that there is no overall consistency on how many fire sub-system rules are addressed. Fire design is a very complex problem to solve due to the multitude of subsystems that require audit and their inter-dependencies. The authors further state that with the use of the IFC standards, regulation formalisation should be more object-oriented, thus more specific and easier to assess. However, due to the complex nature of describing regulations, IFC alone cannot encapsulate all the necessary information for valid performance and rules-compliance audit, where user input and designer personal judgement are part of the process [6].

The studies discussed above rely heavily on IFC, but still face difficulties when expressing rules and regulations on top of building models when trying to evaluate the performance of a design. While IFC is the best option for storing structured data, it does not meet all the information requirements needs for inter-disciplinary design processes when in the context of performance assessment, which often requires significant user input [6]. Additionally, no study investigated the interoperability with BIM beyond geometric information, which is insufficient for CS purposes, and that valid simulation models require input from various other information sources, not just IFC. Finally, the studies have expressed less interest in conceptualising and representing the factors which are the indicators of fire design performance or how they can be used in the context of automation.

2.2. Ontology models for building design

Pauwels and Van Deursen [29] is one of the pilot studies investigating the capabilities of semantic web rule checking, applied to acoustic building design, closely tied to IFC concepts. They state that the limitations in the IFC schema expressivity of concepts are overcome by an ontology approach. Another pilot study on using ontology tools is by Scherer and Schapke [38], which describes a framework for using ontologies as a means of integration on the project level, which can include multiple models and processes. The main benefits identified seem to suggest that an ontology approach enables further expressivity and linking of the data, thus allowing for more flexible definitions of model data, which is crucial in including non-traditional design analysis under the BIM umbrella. Long before these developments, Rűppel et al. [36] proposed an ontology model framework for fire safety design, integrating different databases. This study was limited at the time due to insufficient technologies in the AEC sector. However, many developments today rely on the IFC format, which is seen as an underlying schema for structuring data, while IfcOwl [3,28] is its ontology representation which provides higher level interoperability and reasoning capabilities. Ontology representations of the IFC schema allow for a flexible and more robust backbone for interoperability requirements [43]. The computer-interpretable features of ontologies allow for validation methods and easier extensibility of other disciplines into the design process. However, this presents serious limitations when querying geometry data due to the object-oriented nature of the IFC schema. Pauwels et al. [31] investigate the optimisation issues around its representation in terms of geometry retrieval of the data. Farias et al. [10] also mention that the IFC STEP file was created for optimal information compression, but its object-oriented nature does not really align the same way semantically when represented in an ontology. Terkaj and Šojić [41] also aim to improve the semantics of the IfcOwl, to make it more adaptable and robust over different application domains. The IfcOwl is currently under the process of becoming an international standard [4], which would pave the way towards web-languages oriented BIMs.

Abanda et al. [1] offer an overview of ontology and semantic web linked data trends in research over the last decade, with clear interest in the fields of risk analysis, project management knowledge sharing and energy performance analysis. The authors mention that semantic linked data is a trend, as it facilitates interoperability between the large spectrums of application domains involved in the construction sector. However, they point out that very few applications exist commercially which are using ontology support. This is likely due to complex requirements for ontology-based collaboration in the field of design and construction. The study also identifies several research applications in energy performance analysis and building sustainability in general, but there was no mention of fire design performance analysis. This suggests a low level of research and development in the area.

Trento et al. [42] present a methodology to incorporate human behaviour in assessing building performance using ontology representations. However, this is beyond the rules and regulations for design compliance and does not address the requirements for using BIMs in practice. This is due to the focus on representing human behaviour and toward knowledge management. The authors argue that software tools have very limited capability of using ontologies, as they are abstract and require significant processing power. Onorati et al. [26] is an example of using ontology methods for aiding the evacuation process, whereby ontology and semantic web technologies are used in the building operation stage context.

Some studies represent certain regulations into ontology concepts and logical rules in order to facilitate a fast and automatic environment. Beach et al. [2] is one of the more recent studies which applies regulation checking using ontology representations due to it being easier to manage and having a more interoperable environment compared to traditional software tools. The study focuses on presenting a more viable way to quickly convert textual rules and procedures into valid ontology representations for model checking. The study was applied in the context of environmental assessment, which is a good example of multi-disciplinary and multi-domain design decision making. The authors mention that when the knowledge rules are executed, the rules check only for failure case, thus suggesting to the users why it failed. This is a limitation of the Open World Assumptions (OWA) to which ontologies as subjected to. The users also have to complement missing data with input in many situations. A step further from this, Zhou and El-Gohary [48] present a method which semi-automatically extracts information from design codes in order to facilitate the code-compliance schema against which models should be checked. However, this study is limited to the energy analysis domain. This could really speed up the process of interpreting design rules and regulations for automatic information retrieval. However, such methods are not suitable for the case of performance design review and feedback, where the ultimate decision lies with the designers.

Although many CS tools and models are used for evacuation design, the overall interoperability with BIM processes is low, being limited to geometry. Many studies regard IFC as the source of model information, which can be greatly enhanced using semantic web languages, offering the capability to link data and express knowledge, as some of the studies discussed have concluded. However, the related work which adopt an ontology approach do not consider the interactions of model data and knowledge required for a CS-based approach to model and assess building evacuation performance.

3. Methodology and system design

Based on the key findings discussed in the previous section, this research aims to test a methodology for automating the CS-based evacuation design by representing knowledge about this domain and processing it using knowledge retrieval concepts. This would in turn allow designers to identify design problems in a faster manner and on a larger scale, implicitly deriving new knowledge about the building performance. This is achieved by applying the Knowledge Mining concept which is defined as “a derivation of human-like knowledge from data and prior knowledge” [18]. This concept includes Databases, Knowledge bases and Operators, as outlined in Table 1.

Following the concept of Kaufman and Michalski [18], a conceptual framework which focuses on the knowledge mining of crowd simulation data is proposed. The framework aims to formalise the design knowledge using OWL ontologies and to retrieve new knowledge into the design loop in a BIM-oriented manner. There are several steps required, as listed below (see Fig. 1), and which are presented in more detail in Section 4:

(1) Representing information models – concerning the data and extent of the knowledge domains and tools involved in the process;
(2) Representing the processes – concerning the design procedures and assumptions made for evaluating building performance related to human behaviour in fire evacuation;
(3) Representing Knowledge Rules– the operators required to define the creation of new knowledge from the existing resources;
(4) Integration of the above processes – to achieve collaboration between system components and expressed knowledge bases by ensuring correct user input is provided (i), correct interpretation of the reasoning processes (ii) and that the users receive relevant feedback (iii).

Building on this knowledge mining framework for crowd simulation analysis, a software system was developed – Ontology Crowd Simulation (ONTOCS). Based on the system architecture, its 5 main components are:

Table 1
The main components for Knowledge Mining concept as described by [18], and their roles in the current developed system (ONTOCS).

Component	Description	ONTCS implementation
Databases	The raw data present across various sources of information	Information models which contain building and simulation data
Knowledge bases	The representation of existing knowledge	Web Ontology Language (OWL) representations of the information models and processes for analysis and feedback
Operators	Logical expressions used to supplement additional knowledge from existing knowledge bases	Semantic Web Rule Language (SWRL) rules, most commonly used to define knowledge on the Semantic Web and complement OWL ontologies [16]

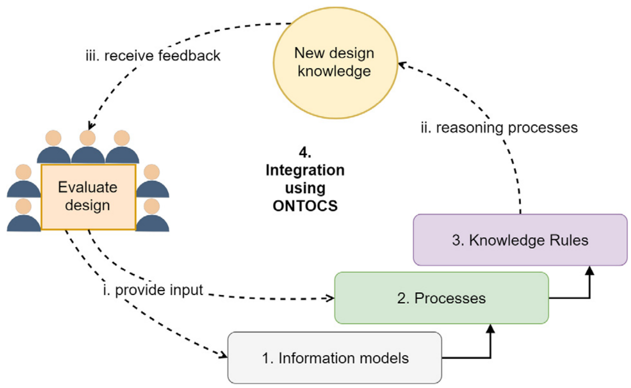


Fig. 1. The knowledge mining concept implemented in ONTOCS.

(1) Input models – provides all relevant input from building model information, user preferences and design constraints. Any other additional data such as sensor data or design variable tables, depending on the context, can be included;
(2) Ontology core – stores all the required information and knowledge representation in Resource Description Format (RDF) [12] databases. It includes the representations of various information models, the processes (described in Section 4.2), the reasoning rules and the alignment of all the ontologies used;
(3) Output models – there are two types corresponding to the process stages (see Section 4.2). The first output model types include the generated scenarios and the results they provide after execution. The second output type is provided by the ontology reasoning for analysis feedback;
(4) System manager – the main application used to coordinate the process by bridging the interfaces and managing the server-side databases;
(5) Interfaces – which are used for providing a user-friendly experience; they can be present at every application level, or as a web-service.

The interaction of the system components is shown in Fig. 2. The arrows indicate the flow of information and the collaboration between the several tools and ontologies. The process starts with the acquisition of all the necessary information via *input models* which are converted into the RDF format for processing. The ontology core is hosted on Stardog RDF databases [39] and the OWL ontologies shown reflect the framework described in Fig. 1. Stardog is a popular RDF store used more commonly in industries (including NASA, Samsung, eBay and others), but has also been used in academia in important related studies around BIM [30,33,10]. Stardog offers excellent OWL and OWL2 reasoning, also supporting the reasoning over SWRL rules and efficient querying using SPARQL 1.1. The tool is very well suited for large scale triple databases, which can work from physical or memory storage. The most important factor in choosing it was its capability to support different levels of reasoning, as this research employs a combination of OWL2 syntax with SWRL rules, and SPARQL queries to retrieve imbedded knowledge. Additionally, its web interface allows fast data querying and browsing of the RDF databases which was convenient for testing and development. Stardog is free to use, however, for a limited database size.

The information models act as resources for the processes involved. Firstly, the ontologies and rules make use of the underlying models and data to "understand" the model to a certain degree and then use this to generate valid scenario models. The system programming coordinates this process and outputs a file for the MassMotion [25] crowd simulation software used. The MassMotion software runs all the scenario simulations and the relevant results are uploaded into the RDF resources for the next stage of the process. Finally, the feedback rules are used to generate new knowledge, which is queried using SPARQL queries. Their results are then presented in a user-friendly way for further decision-making by safety engineers.

Considering the complexity of the entire process, and the several knowledge domains involved, it is preferred that the ontologies are developed on separate graphs, for easier maintenance, as recommended by Beach et al. [2]. These are linked using several *alignment ontologies* as can be seen in Fig. 2.

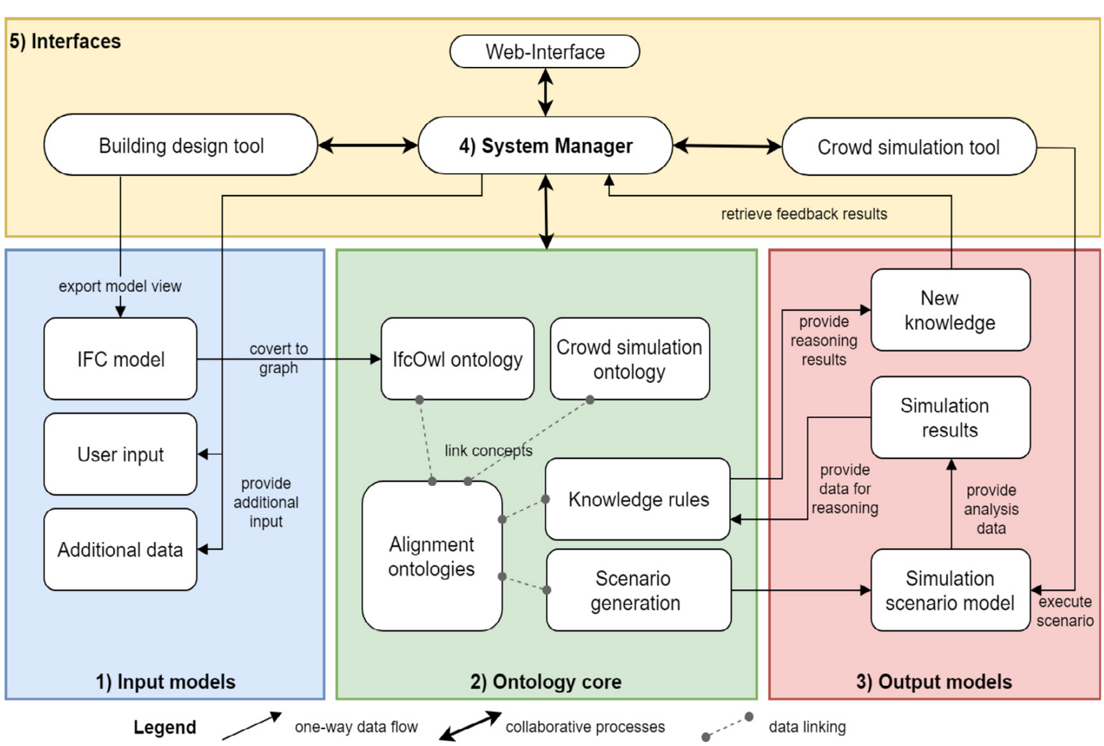


Fig. 2. ONTOCS system components interaction, categorised by their functionality.

Table 2
The main information models used for ONTOCS.

Information model	Description	Roles
Building (BIM)	Ontology representation of the building environment which describes in detail its components, along with their geometry and other semantics	Provide data about the environment
Crowd simulation (CSIM)	Ontology representation of the crowd simulation analysis domain, where agents are used to mimic human movement behaviours within building environments in various situations	Provide data about human behaviour in the environment
Other	Ontology representations of other models or systems which can enhance or contribute overall to the aspect of human behaviour analysis knowledge domain (e.g.: building sensors ontologies)	Provide additional circumstantial data

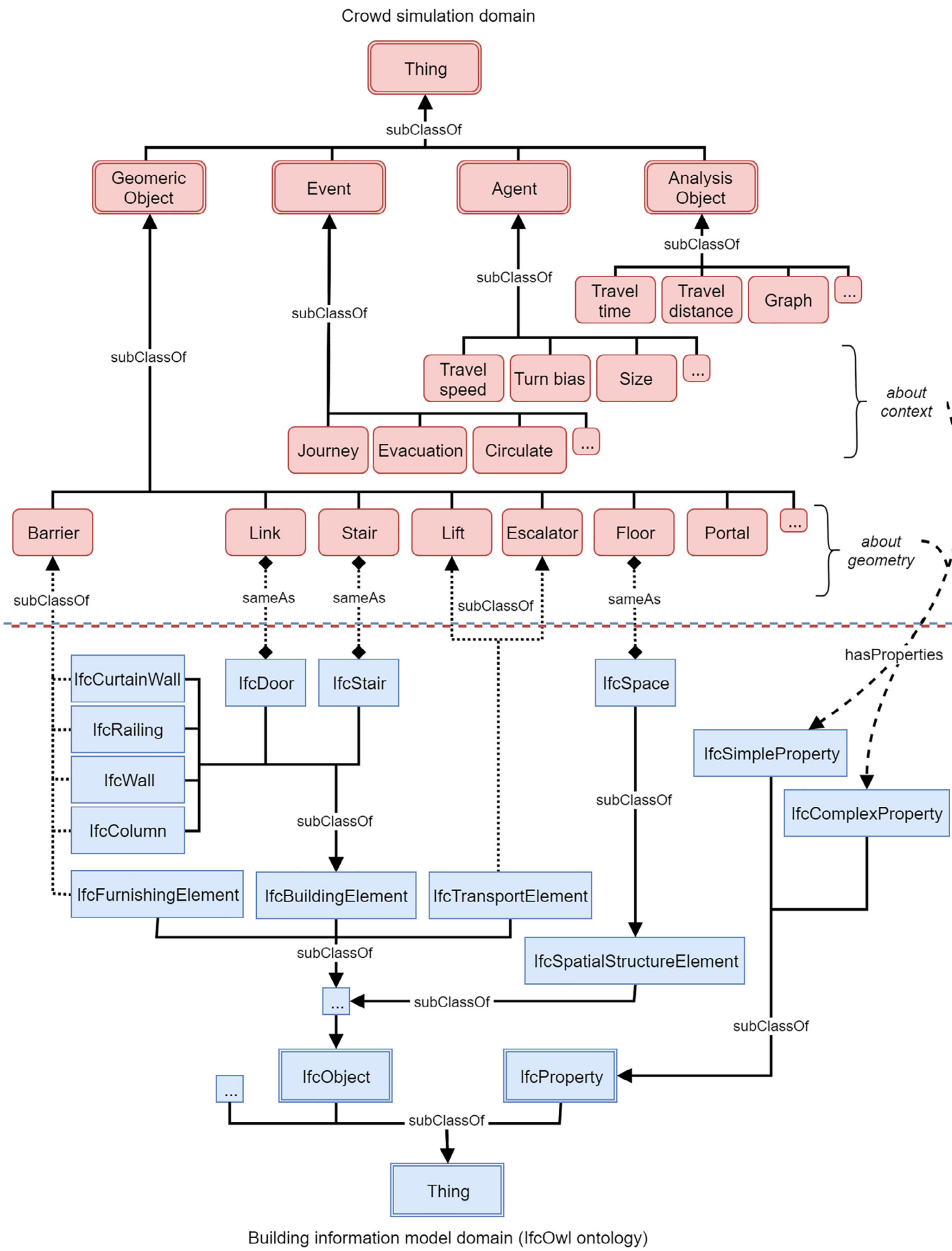


Fig. 3. Showing the difference in hierarchies between building ontology (IfcOwl) and crowd simulation ontology with common concepts and their alignment.

4. ONTOCS framework development & implementation

4.1. Representation of information models

In its current state, the system works with different information models (Table 2), including BIM models and Crowd Simulation Information Models (CSIM). Following the proposed methodology other models can be included as well depending on the application needs and future extensibility to other design domains.

The BIM model is seen here as the central provider of information. The IfcOwl ontology [4] was chosen to represent the building information and processes as it is best suited for design situations. The crowd simulation ontology was developed to work with crowd simulation tools, which includes 4 distinct categories (Fig. 3) of concepts:

(1) Geometry classes – entities with geometric representations in the crowd simulation environment which have impact on the movement of the agents;
(2) Event classes – entities which describe actions taken by agents within the environment in finite periods of time; they generally describe movement of people from one point to another within the defined boundaries of the building environment;
(3) Agent classes – entities concerning characteristics of agent behaviour and movement; they are intended to mimic the desired human behaviour;
(4) Analysis classes – concerns entities which are used by designers to objectively assess the performance and behaviours of agents during events simulated within the building environment.

Fig. 3 outlines some of the links between the developed CS ontology and IfcOwl. Due to different application domains, the ontology concepts can differ extensively. In fact, a relatively small number of classes are directly aligned. These are mostly those describing objects with geometric representations. Taking the example in Fig. 3, the classes for *IfcWall*, *IfcColumn*, etc. are classified as a *subClass* of *Barrier*. Even though in the BIM domain they are distinct entities, they all fulfil the same role: blocking the movement of actors. The fact that there are multiple types of *Barrier*, which are distinct in IfcOwl, means that the use of the *sameAs* axiom is not sufficient. The entities of *IfcDoor*, *IfcStair* and *IfcSpace* were identified as the only reasonable cases of declaring equivalency, where there is very little ambiguity. This approach is confirmed in part by crowd simulation tools which import the IFC format.

The hierarchy of entities represented in IfcOwl is very complex as it reflects the IFC schema which is object-oriented. This gives rise to some limitations when expressed in ontology formats, as it can make rules and alignment of data and individuals challenging, as well as slow for extraction. From practical experience whilst conducting this research, it is especially true when referring to the geometry data. This issue was also previously identified and addressed by Pauwels et al. [31].

While the common objects are related to geometry, there can be major differences in how the geometry is represented. The most well-known crowd models (such as the cellular automata) rely on mesh geometry objects, which are different from the 2D and 3D representations of IFC objects. In addition to that, the IFC schema expresses geometry in a compressed way to save memory, with complex geometric objects being defined by simple entities such as points and lines, which need to be extracted and re-constructed in memory following strict schema specifications. A low level of detail for geometric objects is often more than sufficient to import into the crowd simulation tools for full functionality. However, recreating the geometry in the crowd simulation context using IfcOwl with a combination of SWRL rules can be inefficient. Additionally, the SWRL rules for such a procedure were considered too complex and converting the geometry via software code was considered a better option. This approach is more straight forward and benefits from faster geometry construction, which is then put into the crowd ontology resources explicitly. The challenges behind using IfcOwl for querying geometry have been recognised previously [29,32], and are still a matter of debate.

Apart from the geometric information used to represent the environment, the IFC schema provides insufficient contextual information, which is vital for defining the *Agent* and *Event* entity types, needed to represent the actions and behaviours of agents within a specific crowd simulation scenario under analysis. In some cases, classes such as *IfcProperty* can provide partial information. This can be stated explicitly as values and need to be present in the BIM in the first place. Example of potential properties are occupancy densities of spaces, intended use of the spaces, or which spaces are designated for fire refuge.

4.2. Representation of processes

Representing knowledge concerning the process of creating and analysing crowd simulation scenarios is the second step required to facilitate knowledge mining. This usually requires several iterations of modelling and analysis and relies on the information models from the previous step. There are 2 main processes involved here:

(1) **Scenario generation** – the process of understanding the building environment and creating valid simulation scenarios from this, where several assumptions are made according to analysis requirements;
(2) **Analysis feedback** – the process of analysing scenario results and providing feedback for design decision-making.

4.2.1. Scenario generation

BIM model data is limited to geometry as most of the actual context information is not present explicitly. This information is usually provided by expert designers, who manually construct scenarios according to different objectives of the analysis stage. This knowledge is present with the designer, or sometimes in different design procedure guides which offer a concentrated summary of best practices and recommendations. It can be represented by ontologies in order to simulate the process of generating valid realistic crowd simulation models.

When considering the creation of simulation scenarios and as shown in Fig. 4a, two main categories of information input were identified which are required for valid scenarios:

(1) Geometric – provided by objects with geometry representation within the simulated environment; see Section 4.1 above.
(2) Contextual – information which defines the circumstances of the simulated environment, such as: numbers of inhabitants, exit choices, agent characteristics, etc.

The importing of geometric information, which appears to be a typical format conversion and interoperability issue, has been explored by several research studies mentioned in Section 2. These related works have failed however to address the implicit information which can be reasoned using the appropriate rules, whereby the ontology system is able to “understand” the BIM and therefore create a context for the CS domain.

As opposed to geometry, context information provides important assumptions about each scenario and directly influences *Agent* and *Event* entities within the CS ontology. To benefit from fully automatic ways of creating simulation scenarios, it is necessary to define the relevant contextual information for crowd analysis and how it can be acquired using intelligent methods. Contextual information can be hard to compute, due to its various sources. The minimum requirements for a functional crowd simulation scenario were identified, as shown in Fig. 4a. Four principal domains (Fig. 4b) which can provide information input emerge:

(A) **User input** – refers to the choices that the designer is using to

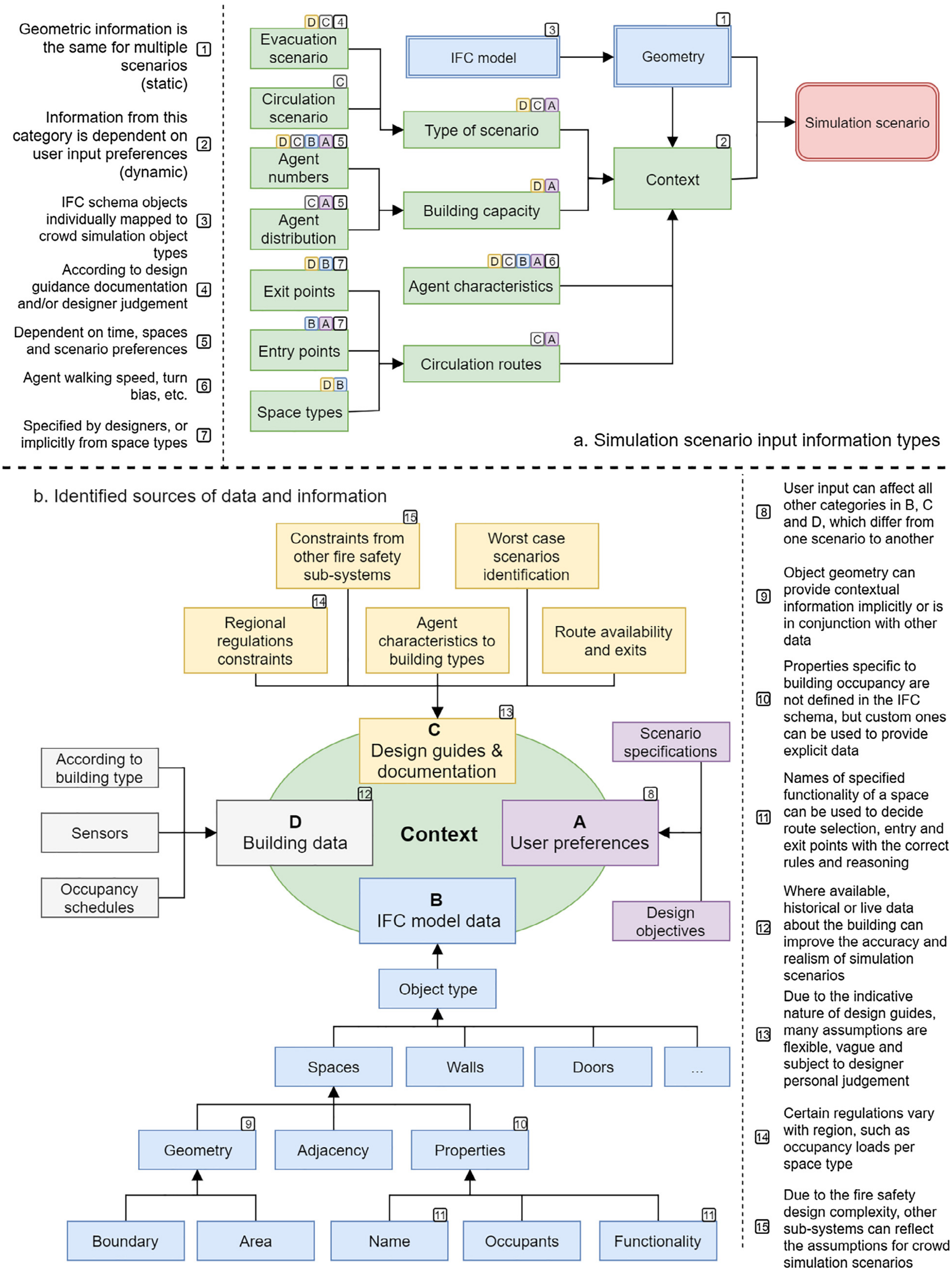
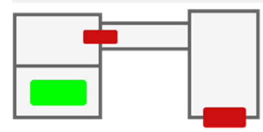
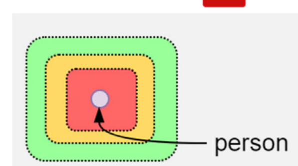


Fig. 4. a. Shows the concepts which provide the relevant information for a fully functioning scenario with emphasis on contextual data types which are influenced by other information domains shown below; b. shows the four domains which influence the concepts in a. and their identified relevant factors.

Table 3
Identified PIFs which are used to assess building performance during evacuation scenarios.

	PIF	Description	Visual representation	Source
1	Travel time	The time it takes for agents to reach a destination point from a specific origin in the environment		BS7974
2	Exit capacities	The flow capacity of a corridor, door or exit portal the total time required by agents to reach a safe point		BS7974
3	Escape time	The total time required by agents to reach a safe point		BS7974
4	Population density	Density factor at a specific point in time, in a specific area of the environment		BS7974
5	Fruin's Levels of Service (LOS)	A way to quantify traffic density, describing the service state of a specific area in the environment		Simulation tools
6	Other PIFs	Situational or ad-hoc factors	N/A	N/A

generate a variety of scenarios which are relevant to the situation. For example, the designer should specify what type of scenario is chosen, what is the desired simulated building capacity, or which data sets and ontologies are used to do reasoning or for importing data;

(B) **IFC model data** – provides relevant building data, from geometric to contextual information. The data should be stated explicitly through specific properties for faster processing. There are no defined standards for crowd simulation purposes, but the IFC schema allows the custom creation of properties at object level;

(C) **Design guides & documentation** – when it comes to scenario assumptions, a variety of documentation guides and published documents can provide an overview of the factors to be considered. However, due to their indicative nature, much of the information is highly interpretable and circumstantial. The available information is spread across several documents. For instance, the PD7974 (2004), part 6 [34] is one of 7 documents published in the UK which were used to gather knowledge for the ontology representations of the process during this research. However, information concerning occupant densities was vague, so local official regulation documents were consulted instead.

(D) **Building data** – live or historical data which refers to occupant traffic that might be relevant to the simulated building environment, e.g. data recorded from sensors, traffic cameras or exact numbers of occupants per space within a facility. This is more relevant at the operation stage of the building lifecycle.

4.2.2. Analysis feedback

The second part in representing the knowledge processes looks at the act of evaluating simulation model data. This resembles the act of knowledge mining whereby gathered simulation data is analysed by the ontology rules and returned to designers. The feedback is highly dependent on the inputs provided in the system from the generation stage and it needs to be tailored to designer's objectives. This means that the feedback stage must consider the user input (Fig. 4b) for the generation of relevant knowledge.

To assess design performance objectively, certain performance indicator factors need to be established, as they can allow both ontology reasoners and human decision-makers to distinguish between different scenarios.

After careful consideration, Table 1 shows a list of concepts which can act as performance indicator factors (PIF) when assessing crowd behaviour in evacuation scenarios. The main sources in developing these performance indicators are dependent upon design guidance on assessing evacuation performance, available data provided by the simulation software and ad-hoc factors sought by designers. The most representative of performance and easiest to assess are those related to travel times of agents towards the exits (factors 1 and 3 in Table 3). More complex assessment can rely on area factors such as plotted density maps (factors 4 and 5 in Table 3), which designers have to visualise and manually assess. The evaluation of occupant densities can be done more automatically by adopting a scale such as Fruin's Level of Service (LOS) [11], which grades area traffic according to a density scale.

The combination of various inputs which constitute the contextual information can lead to a variety of different scenarios. This makes the iteration of the design easier and faster through automation. However, as the entire process is dependent on user input, there is a limit to the degree of automation which can be achieved. This is further limited to the PIFs used and how they can be expressed in an automation context.

One building design is usually tested in several performance scenarios, following conventional workflows [20,34], or defining ad-hoc contexts. When considering such large numbers of scenarios under evaluation, data can accumulate very quickly, and it needs to gain

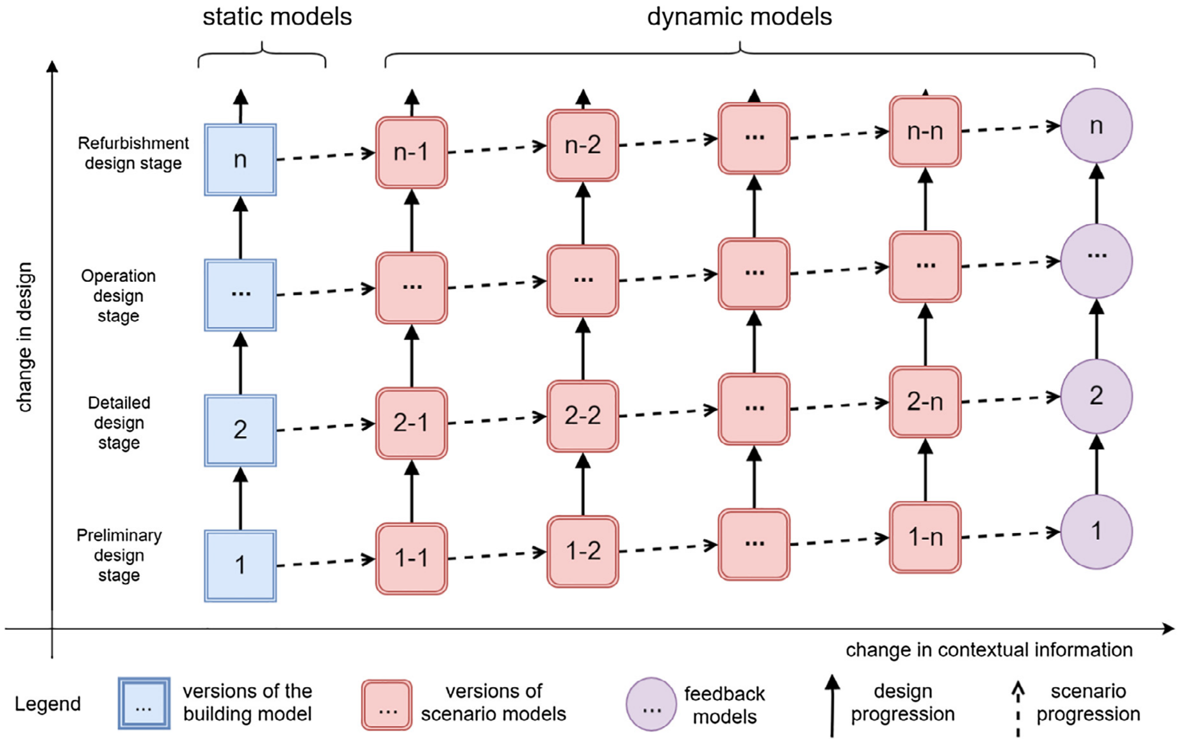


Fig. 5. Static and dynamic information model progression with design change.

certain structure within the system. This means that certain mechanisms need to be in place for this sort of system to handle the large amounts of generated data and structured information.

IFC models are considered central information providers, which is then leveraged using ontology representations and rules. In turn, this means that for every IFC model iteration, a multitude of simulation scenario models will emerge, as shown in Fig. 5. As such, it is important to describe the difference between the two types of models in use:

- Static models – versions of the building models under design assessment;
- Dynamic models – extensions of the static models, which bring in additional analysis related data, information and knowledge.

A link between the two types of models is necessary as in practice, the static model and its dynamic models refer to the same real-life object. If an '*IfcSpace_01*' object represented in the IFC model refers to an actual space, its correspondents in simulation models each contain data about the same actual space, but in different circumstances. This can create conflicts of identity across multiple OWL individuals which refer to the same '*IfcSpace_01*'.

4.3. Rules construction

An ontology representation of model data brings forth the opportunity to apply reasoning and infer additional information and knowledge with the right rules in place. The two types of information as defined by Xiao Hang Wang et al. [46], are:

- Explicit – it refers to data which is directly stated in a model, such as: "IfcSpace_01 has Area_01 as 2 m^2". This sort of data is usually related to geometry components, element properties and connections, and is always present and stated as "true" in the BIM model;
- Implicit – it refers to data and information which is not directly stated in the model, but is something that might be inferred by logical reasoning as being "true", if the evaluated rules return "true".

Fig. 6 shows one example of implicit information being created from some basic building element properties, which are used for the scenario generation stage of the ONTOCS system.

Explicit information is required to correctly extract the context from the above defined sources (Fig. 4b). However, if the information is not found or doesn't exist, user input and validation is required.

Relying solely on performance factors is not always enough to make decisions regarding certain design. At times, some factors may not explain the cause of certain results and their behaviour. As such, it is required to leverage the embedded knowledge and the relationships that exist between the different assumptions. Let's consider the example of a forming bottleneck in a certain area in a building, like *Space 3* shown in Fig. 7. High traffic density in certain areas is caused by the influx of agents provided by various origin points, i.e. *Spaces 1 and 2*. However, determining which origin point has more impact in causing the bottleneck is a complicated problem, as it is dependent on many factors such as agent characteristics, geometry of the spaces, distribution of agents, etc. Complex rules in place could be represented in ontology knowledge that could help determine the causes of such circumstances, thus indicating higher degree of implicit knowledge. This process is limited however to the semantics and expressivity of the developed ontologies and rules. When considering such rules, careful consideration is required along with validation that expressed knowledge correctly reflects design procedures and judgement. The retrieval of such knowledge is more complicated to assess due to a lack of clearly defined PIFs used in practice. Additionally, this can also be limited by the expressivity that ontologies and SWRL rules can provide, making certain rules un-decidable. This is mainly due to the "Open World Assumptions" which governs ontology reasoning, where evaluation of rules can not only be "true" and "false", but also "unknown", and certain imbedded knowledge can be very hard to retrieve or take a very long time to process.

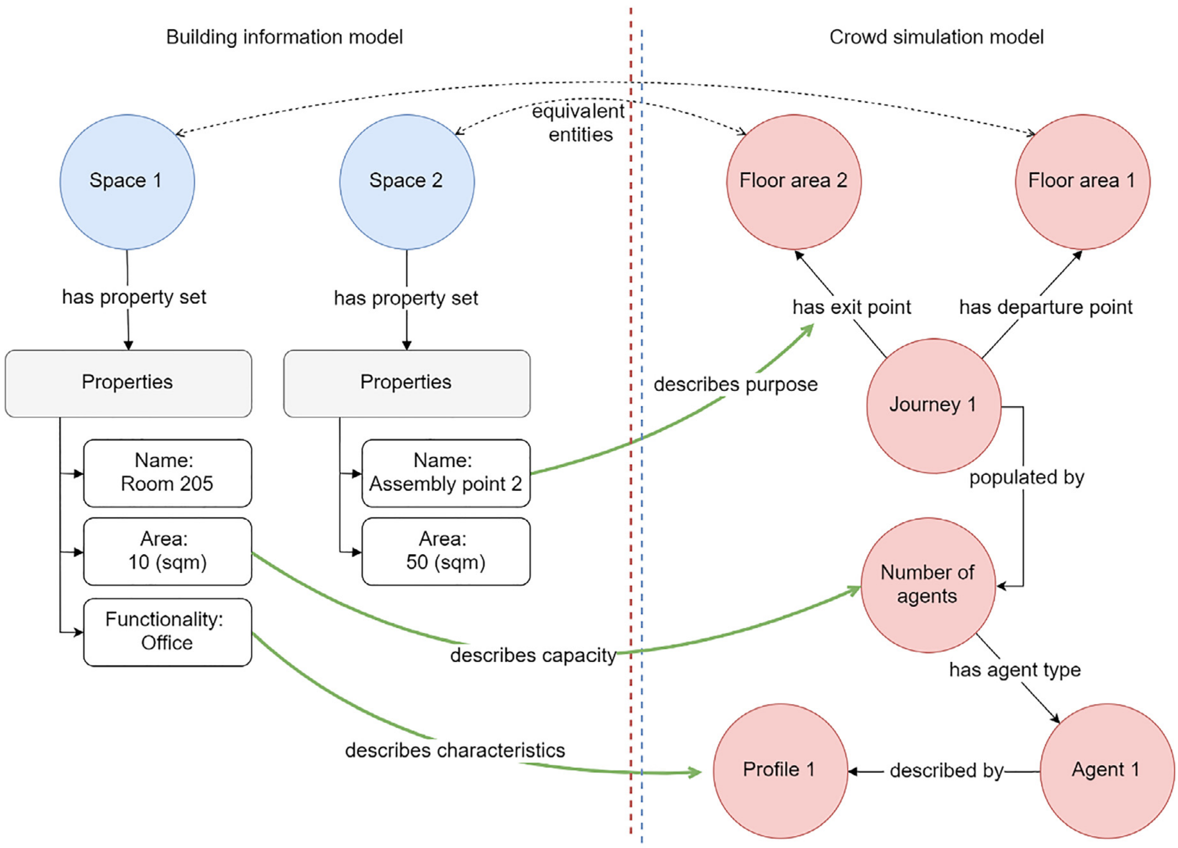


Fig. 6. Example of retrieving implicit information from BIM data, which can describe contextual data.

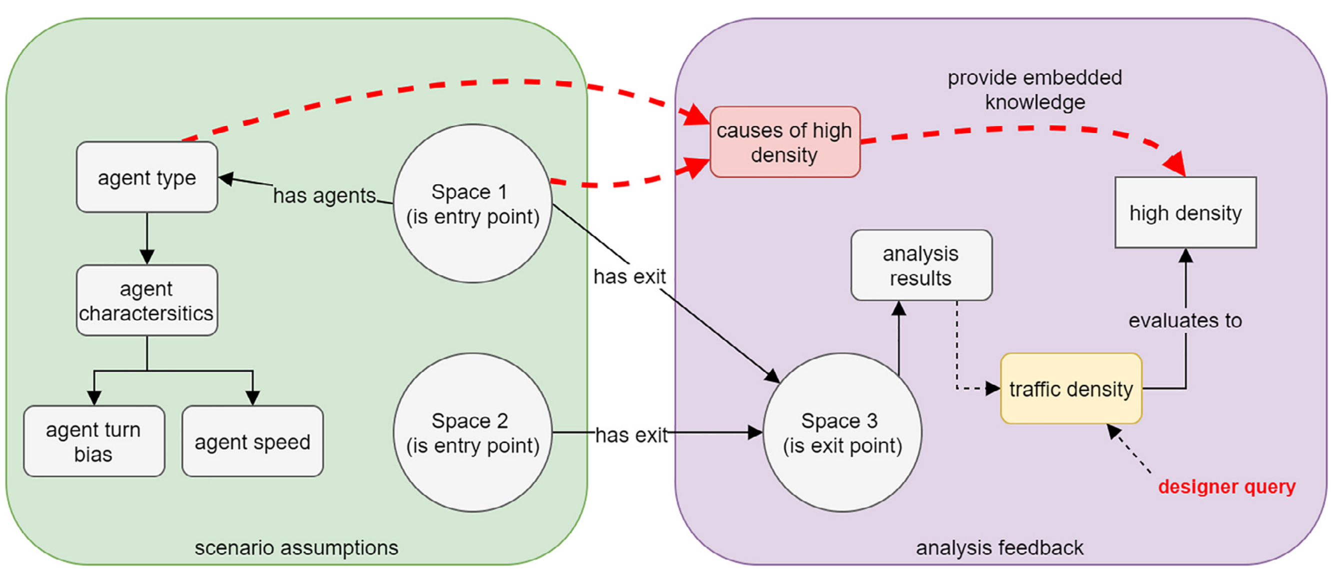


Fig. 7. Example of objects and properties (contextual and geometric) influencing the final analysis result. The dashed arrows indicate how certain knowledge rules can be embedded to provide more relevant feedback.

5. Case study testing

The purpose of this case study is to show the benefits of using the developed ONTOCS system which uses an ontology approach for aggregating simulation and BIM data in an automatic manner, while also providing insight about the building design performance in accordance to design objectives. To show this, a test case of a building is presented, as an example of its functionality.

The developed system was tested on a simplified model from an existing Cardiff University building. The building environment was

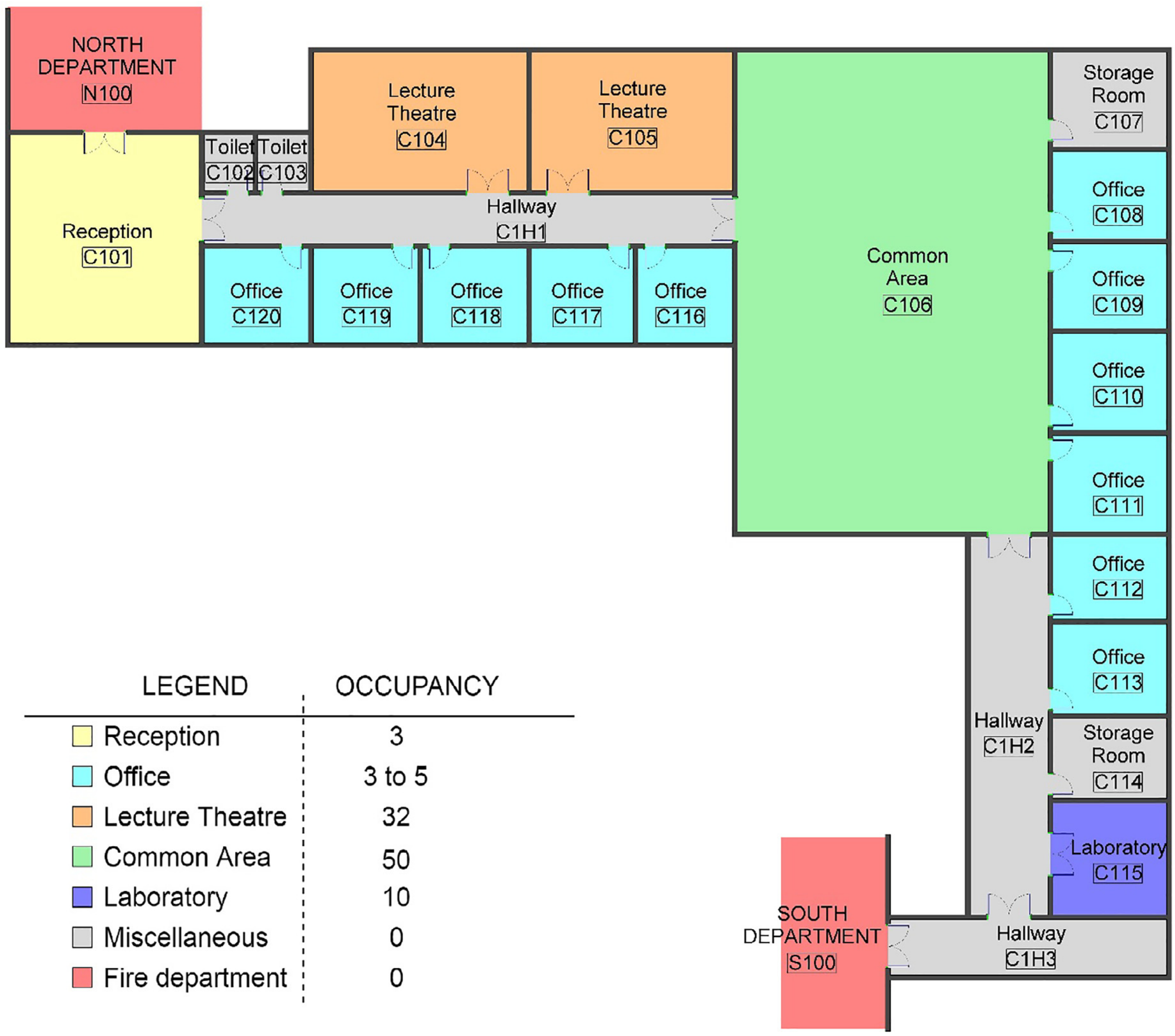


Fig. 8. Plan view of the case study building being tested, split by space functionality. Circulation areas are assumed to have no inhabitants, as per regulations.

modelled using Autodesk Revit 2017 and exported to IFC. The IFC file was converted using a third party software [27] to the IfcOwl format and then put on the system. The interface guides the users through the entire process via web browser pages.

5.1. Building model analysed

The tested building model can be seen in Fig. 8. The building is a representation of an academic environment with a good mix of offices, lecture rooms and a common room. The areas in red represent other parts of the building, as divided by fire compartments. Should a fire event occur, people are expected to evacuate to a safe refuge place to either of the adjacent departments. Each of the space types has a value for occupancy attached as a property in the IFC model being exported, also shown below.

The design problem is to assess the evacuation travel times of agents under various population capacity conditions. An initial design population was prescribed (Fig. 8 legend), which was then multiplied in order to determine the limits of the building design and establish a realistic egress time.

5.2. Scenarios setup and assumptions

The model defined above was put into the ONTOCS system where several scenarios were created, each with a gradual increase in population, in 10% increments. Each scenario was given to simulate the environment for 5 min, which was considered a reasonable amount of time for all agents to evacuate, and which is also above the desired egress time objectives defined for the case study (see section 5.3).

The native MassMotion agent profile was chosen, along with other default settings. The assumptions can be seen in Fig. 9, as part of the system interface. The agents were chosen to appear spontaneously, meaning that from each entrance portal in the model, all agents would be present at the beginning of the simulation. Any additional data was provided by the IFC model itself, which is processed by ontology rules and the software itself. For example, an ontology rule was used to determine egress destinations, which was described by the Uniclass [24] code for each space. This is part of the scenario generation stage, as described in Section 4.2.1.

Initial assumptions were set for 20 scenarios, with varying population multipliers from 10 to 200%. After this, the scenarios were generated and executed for simulation results. All created scenarios were generated successfully, creating independent model files for the crowd

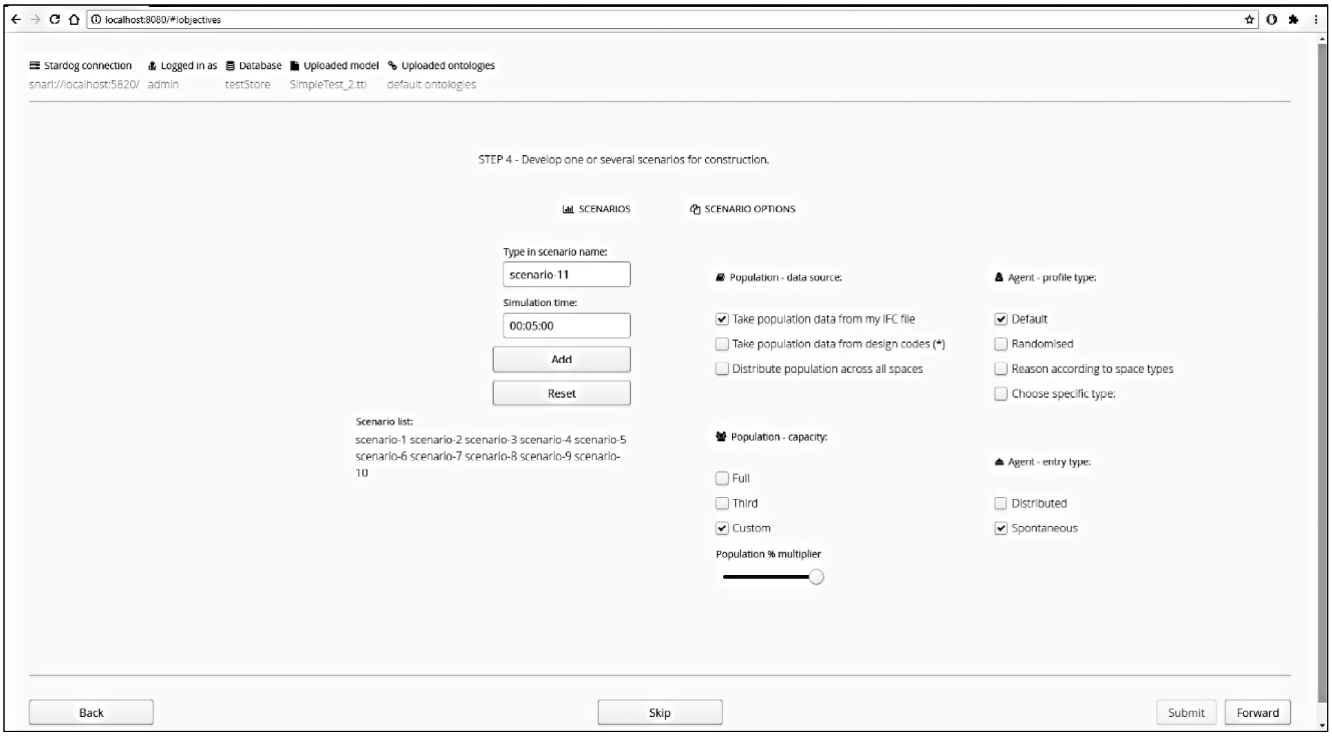


Fig. 9. ONTOCS system assumptions page. Each scenario can be set with different assumptions and added for generation and analysis.

software to use. These were validated via the interface and in the MassMotion software, to check for any scenario generation inconsistencies or errors. The simulation files were then executed automatically and generated databases of results for each scenario. These results were used for the analysis feedback stage.

5.3. Objectives and reasoning results

For this step, several objectives were set in order to assess an appropriate egress time for the building department, along with a maximum population cap, as seen in Table 4. Each set includes 2 separate objectives, each answering specific questions:

(a) Total egress time – what is the total time for all the agents to travel to the exits?
(b) Capacity egress – by what time can x% of the population be evacuated?

By applying several rules, the system was able to provide answers for the sets of objectives chosen. After the simulations were executed,

Table 4
Objective sets for the feedback analysis stage. Each row describes 2 separate objectives, which both have to be met.

Objectives	(a) Total egress time (s)	(b) Capacity egress		Valid scenarios
		Population (%)	Time limit (s)	
1	90	50	45	1–9
2	90	75	45	1–5
3	120	75	60	1–10
4	120	95	90	1–13

overall results are stored in various resources graphs and presented on the interface in a table, as can be seen in Fig. 10. Below that, analysis objectives can be chosen by designers, which is submitted and evaluated using ontology reasoning.

Once the *Evaluate* button (Fig. 10) is pressed, the application sends SPARQL queries to the RDF databases. Fig. 11 shows the two rules (1) and (2) responsible for answering the two types of objectives under analysis. The rules work with classes and properties defined in a developed feedback ontology. The system is able to query data across various databases from simulations, and process the results with reasoning flags, categorising each scenario in accordance to user objectives, as seen in Fig. 12. The results are summarised in Table 4, showing which scenarios meet both objectives. Reasoning results are reported back and presented on page as shown in Fig. 12. The basic functionality here is to categorise the various scenarios in accordance to each rule.

Some scenarios are both valid and invalid under certain sections, as can be observed from Fig. 12. This is because certain scenarios can achieve one objective but fail another. Therefore, it can belong to both categories at the same time. To mitigate this limitation, another rule is put in place (rule (3) in Fig. 11) which checks that all objectives are met, categorising it as a "*FullyValidScenario*" class within the developed feedback ontology and effectively intersecting rules (1) and (2).

The process time seems to increase with the complexity of the rules in place, as well as with the number of tested scenarios. For example, when rules (1) or (2) are called by corresponding queries to the database, they usually take up to 2 s to process the reasoning. However, when rule (3) is called, the time increases significantly, to 33 s, due to it implicitly relying on multiple rules.

5.4. Validating the results

The results received by the rules were checked against the raw data generated by the crowd simulation software. The data showing the

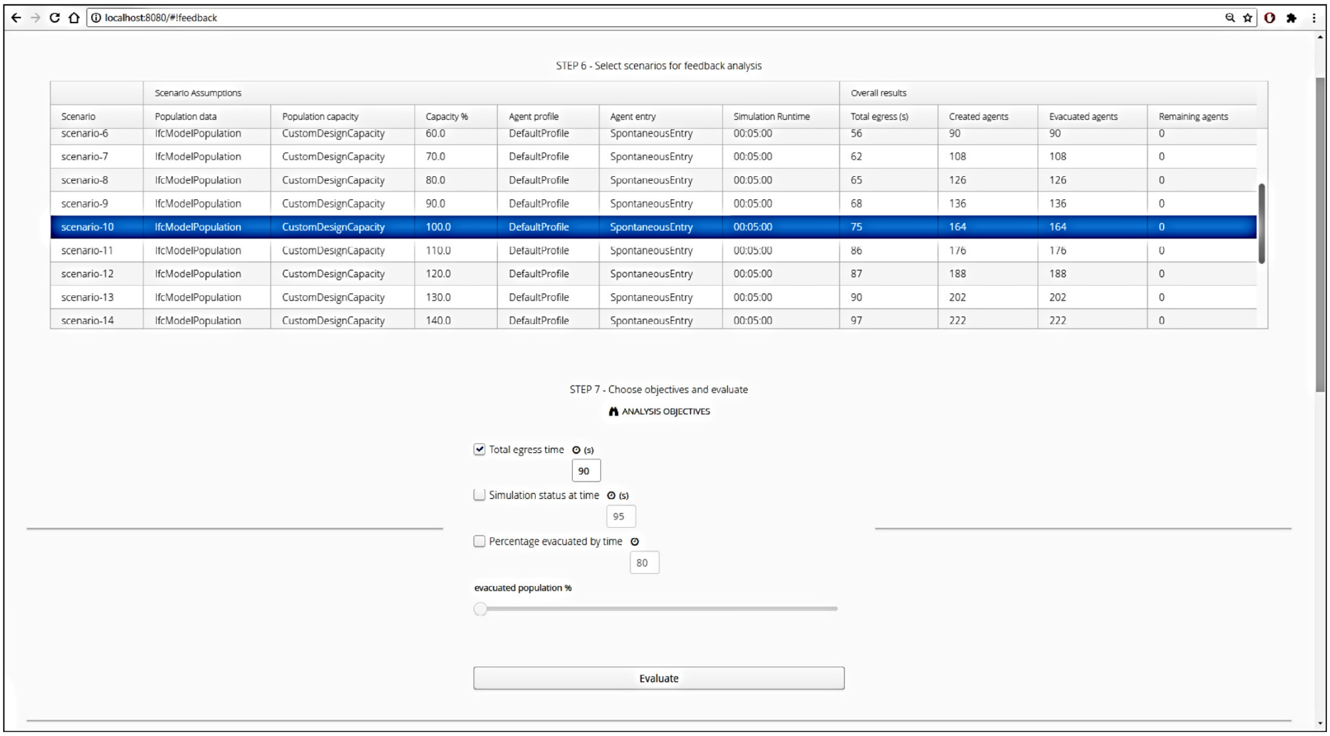


Fig. 10. ONTOCS initial results reporting & objectives page.

```
Rule (1)

Reasoning: If a scenario result has below or equal the required time,
           it becomes a ValidTotalEgressScenario.

fbo:hasObjective(?objectivesSet, ?objective) ^ fbo:FindTotalEgressTime(?objective) ^
fbo:hasTimeLimit(?objective, ?requirement) ^ fbo:timeInSeconds(?requirement, ?timeLimit) ^
fbo:appliesToScenario(?objectivesSet, ?scenario) ^ fbo:hasEndResult(?scenario, ?result) ^
fbo:TotalEgressTime(?result) ^ fbo:timeInSeconds(?result, ?timeResult) ^
swrlb:lessThanOrEqual(?timeResult, ?timeLimit) ^ fbo:hasResult(?scenario, ?popResult) ^
fbo:PopulationResult(?popResult) ^ fbo:numberRemainingAgents(?popResult, ?remainingAgents) ^
swrlb:equal(0, ?remainingAgents)

 -> fbo:ValidTotalEgressScenario(?scenario)

-----------------------------------------------------------------------------------------------------

Rule (2)

Reasoning: If an intermediate result has a certain capacity of the population evacuated below a
           certain time, it becomes a ValidCapacityEgressScenario.

fbo:hasObjective(?objectivesSet, ?objective) ^ fbo:FindCapacityEgressStatus(?objective) ^
fbo:hasTimeLimit(?objective, ?timeRequirement) ^ fbo:timeInSeconds(?timeRequirement, ?timeValue) ^
fbo:hasPopulationCapacity(?objective, ?percentageRequirement) ^
fbo:percentageRequired(?percentageRequirement, ?percentageValue) ^
fbo:appliesToScenario(?objectivesSet, ?scenario) ^
fbo:hasIntermediateResult(?scenario, ?simulationTimeResult) ^ fbo:SimulationTime(?simulationTimeResult) ^
fbo:timeInSeconds(?simulationTimeResult, ?timeResult) ^ swrlb:lessThanOrEqual(?timeResult, ?timeValue) ^
fbo:percentageEvacuated(?simulationTimeResult, ?percentageResult) ^
swrlb:equal(?percentageResult, ?percentageValue)

 -> fbo:ValidCapacityEgressScenario(?scenario)

-----------------------------------------------------------------------------------------------------

Rule (3)

Reasoning: If a scenario is a ValidTotalEgressScenario and ValidCapacityEgressScenario,
           it is also a FullyValidScenario.

fbo:ValidTotalEgressScenario(?scenario) ^ fbo:ValidCapacityEgressScenario(?scenario)

 -> fbo:FullyValidScenario(?scenario)
```

Fig. 11. Example feedback SWRL rules for assessing which scenarios have valid results. The 'fbo' prefix stands for the developed feedback ontology.

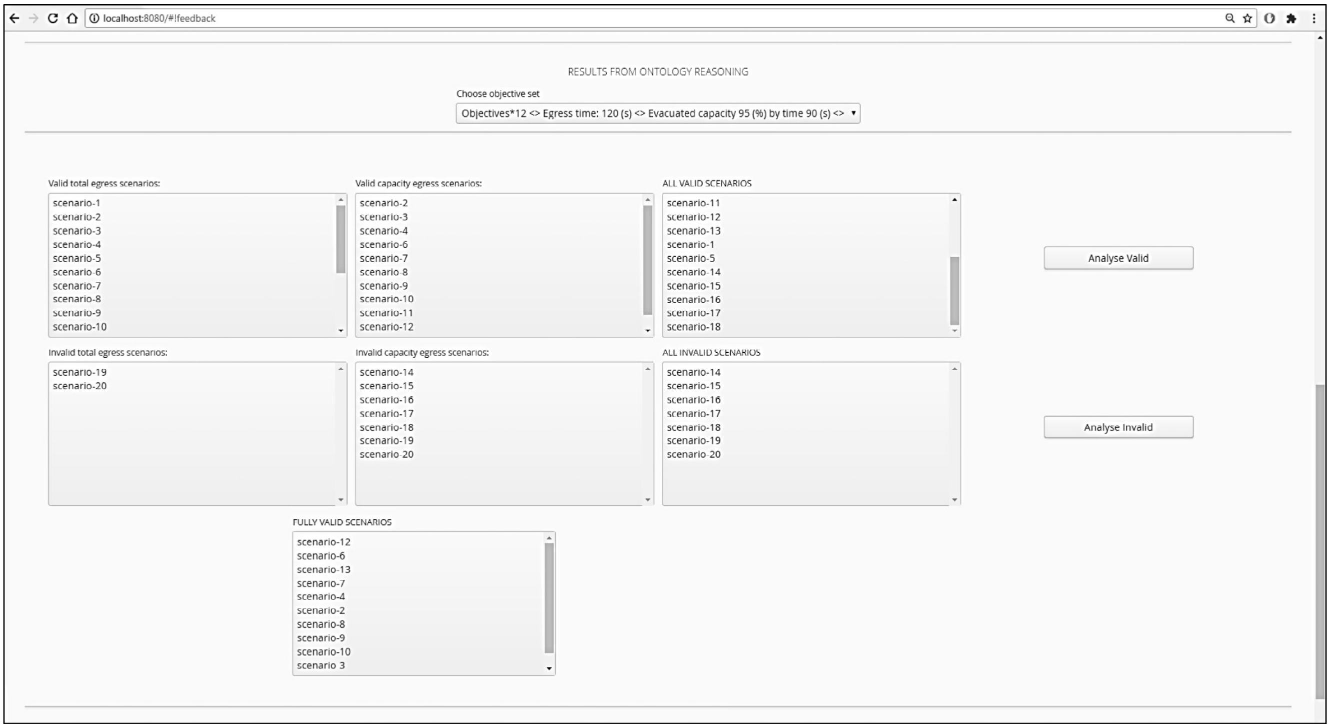


Fig. 12. ONTOCS reasoning results page.

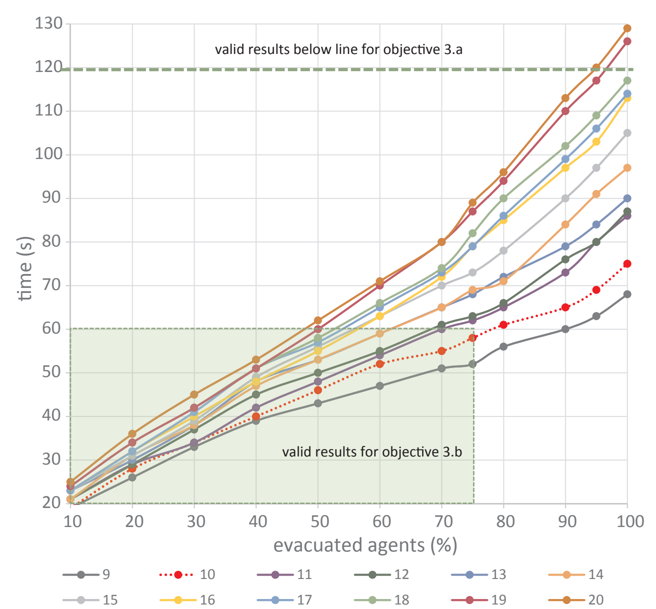


Fig. 13. Plotted results of the egress progression for each tested scenario. Scenario 10 is depicted by the dotted line, which assumes 100% population capacity for the building.

progress of the evacuation procedure was plotted in Fig. 13. Only scenarios from 9 to 20 are shown, to achieve better clarity on the chart. The trend lines for each scenario look quite similar, suggesting no anomalies or large bottlenecks forming. However, as the population increases, it becomes clear that the evacuation time increase significantly, which puts more pressure on the exit capacities of the building.

The horizontal dashed line and the overlayed rectangle show the areas in which results are met for objective set 3, from Table 4. While objective 3.a is met for most scenarios, the amount reduces significantly when a secondary objective is present. Objective 3.b is more relevant to finding out how much time is left before the exit capacities become problematic, thus increasing the evacuation time. From these results it can be observed that the reasoning results are performing correctly. However, with more design restrictions, it is possible that at times no result is found, should data not be present for one of the objectives to be met.

6. Discussion

Due to the multi-disciplinary nature of the design involving human behaviour assessment, it is clear that an ontology approach would greatly benefit the integration of all the required data and information concepts, in order to achieve a BIM-based way of working. This would bring forth the benefits of more automation and therefore faster and more efficient ways of evaluating building performance. However, the same multi-disciplinary nature creates a complex system, ranging from software, data transfer protocols, human factors and design procedures. Each of these factors are research and practical problems on their own. While the data models can rely heavily on IFC, software tools used for analysis will evolve and change, and so can design procedures.

The IFC format is essentially a representation of structured data for the use in the construction sector. Due to its standardised schema, it can provide a reliable base for constructing information automation rules and ontology representations. However, structured data still needs to be specified in the first place, especially when trying to create the context for simulation scenarios, as discussed in Section 4.2.1. For example, in an IFC model there is no specific property defined as “Number of Occupants” for a specific space, and therefore this property needs to be defined explicitly by a BIM platform or tool, and its corresponding value be inputted by the user somewhere along the process. In this context, ontology rules and representations must be based on existing and already defined properties within the BIM model. This implies that rules are highly dependent on model templates and its source modelling platform, as each modelling platform exports IFC differently. This presents a serious limitation to using ontologies and rules for this purpose, which ends up with high maintenance costs. A standardised way is recommended for providing and expressing data referring to building occupancy use. Alternatively, more complex rules can be set in place, which are able to identify the functionality of model objects based on their names, descriptions or even geometric arrangement and relationships with other objects within the model.

Apart from the advantages of automation and reasoning, the main limitation of this approach is that the extent to which knowledge needs to be represented is quite large. This implies a need for validation of the ontologies, which is currently still ongoing. However, once validated, an ontology approach offers great extensibility to this methodology, allowing multiple design domains to merge. The same way as ONTOCS allows the view of a model in IFC or in CS, it would allow a view of the model in energy analysis or other analysis models. The IFC schema is a good example of a robust structured data format, however it lacks these things in the crowd simulation analysis domain. The diverse information which is required in this domain comes from the 4 main sources discussed in Section 4.3.1. While user preferences can always change, the extent of the available options can be narrowed down to basic ingredients and is not expected to change. Design regulations and guidance differ by region, meaning that some local occupancy factors or assessment objectives need to be represented separately. This can lead to the assessment of the same model in different contexts. However, the maintenance of these ontologies and their rules requires extensive knowledge of the involved domains and their interactions.

The simplified example in the case study tries to showcase the benefits of automation and the use of multi-objective design assessment. This mainly tries to solve the problem of aggregating data across multiple models, while the BIM model acts as the single point of truth from the designer's perspective. The ontology representation of the models is beneficial when the correct mapping is in place, essentially allowing the formation of a comprehensive building model in various dimensions. However, for more advanced processing, such as reasoning rules for feedback, providing new knowledge about the design can be achieved in various ways. The one explored in Section 5 involved simpler rules, where answers are provided based on threshold PIFs values limited by objectives. This effectively provides knowledge by notifying the designers of which scenarios are performing in accordance to their objectives and which are not. This can be useful when evaluating several scenarios iteratively. However, a more meaningful way for feedback is detecting the cases of design problems and bringing them forward as new knowledge, as suggested in Section 4.3. This however can become problematic, as each it is hard to determine if an answer is always true or false, in order to express a valid ontology rule.

7. Conclusion and future work

From the literature in Section 2.1, working with crowd analysis for building design is lacking behind in BIM standards, being effectively limited to geometry, with little consensus on common data formats, apart from the use of IFC as a source model. Because of the multi-disciplinary nature of fire safety and its process requiring multiple sources of information input, an ontology approach is proposed, as it is suited best for both interoperability and knowledge representation and retrieval. Similar ontology models and methodologies were also reviewed in Section 2.2, and IfcOwl was identified as the most suitable representation of the building environment. A methodology on knowledge representation and mining about building performance is introduced in Section 3, along with the prototype system architecture (ONTOCS) which was developed for testing. This approach was described conceptually in Section 4 as a framework to achieve interoperability, representing information models and design processes for crowd simulation analysis and a way to perform knowledge mining using rules on top. An initial alignment between a CS domain and the IfcOwl is proposed, along with factors influencing the input for the CS analysis domain, in Section 4.1. Using these identified sources of information, scenario rules are created to allow the ONTOCS system to "understand" the models and create valid scenarios for further analysis, in Section 4.2. The feedback stage presents the complexities of aligning user design objectives as well as the capabilities of rules to bring forth new knowledge about the designs, and how the knowledge models and objects interact conceptually, in Section 4.3.

The framework was tested on a on a building model representing an academic-office department, in Section 5. The case study shows the design process for identifying a suitable overall building capacity in terms of its population. Some rules which are used to assess scenario results are presented, and how they can provide knowledge about the building performance by aggregating the relevant results data. The expressivity of the SWRL language allows for some basic categorisation of scenarios into valid or invalid types, which are in-line with design objectives. The results are limited to the available data and assumptions and the cost of reasoning increases with the number of rules applied in conjunction with each other.

The overall limitations of this approach are discussed in Section 6. The multi-disciplinary nature of fire safety assessment results in a complex system with inter-dependent components. While the web ontologies bring overall greater interoperability and reasoning capabilities, they are hard to maintain.

Ongoing work involves the validation of the ontologies developed used in the system, along with a case study on a live building in different scenarios to test the capabilities and limitations of this approach and assess to what degree new knowledge can be retrieved using rules. Additionally, based on discussions presented above, an analysis into the performance of the reasoning processes involved in the knowledge mining will be carried out in order to determine the scalability of the proposed approach.

References

[1] F.H. Abanda, et al., Trends in built environment semantic Web applications: Where are we today? Expert Syst. with Appl. 40(14) (2013) pp. 5563–5577. 10.1016/j.eswa.2013.04.027.
[2] T.H. Beach, et al., A rule-based semantic approach for automated regulatory compliance in the construction sector, Available at: Expert Syst. with Appl. 42 (12) (2015) 5219–5231 http://linkinghub.elsevier.com/retrieve/pii/S0957417415001360.
[3] J. Beetz, et al., IfcOWL: A case of transforming EXPRESS schemas into ontologies, Available at: Artif. Intell. Eng. Des. Anal. Manuf. 23 (1) (2009) 89 http://www.journals.cambridge.org/abstract_S0890060409000122.
[4] BuildingSMAR, BuildingSMART Linked Data Working Group, 2017 http://www.buildingsmart-tech.org/future/linked-data.
[5] V. Cassol, et al., Analyzing egress accuracy through the study of virtual and real crowds, in: Virtual Humans and Crowds for Immersive Environments (VHCIE), IEEE, IEEE, 2016, pp. 1–6.
[6] J. Dimyadi, et al., Querying a regulatory model for compliant building design audit, in: Proc. of the 32nd CIB W78 Conference 2015, 27th-29th October 2015, Eindhoven, The Netherlands, 2015, pp. 139–148 10.13140/RG.2.1.4022.6003.
[7] J. Dimyadi, et al., Computerizing regulatory knowledge for building engineering design, Available at: J. Comput. Civil Eng. 30 (5) (2016) C4016001 http://ascelibrary.org/doi/10.1061/%28ASCE%29CP.1943-5487.0000572.
[8] D.C. Duives, et al., State-of-the-art crowd motion simulation models, Transport. Res. Part C: Emerg. Technol. 37 (2013), pp. 193–209. 10.1016/j.trc.2013.02.005.
[9] C. Eastman, et al., Automatic rule-based checking of building designs, Automation Constr. 18(8) (2009) pp. 1011–1033. 10.1016/j.autcon.2009.07.002.
[10] T.M. De Farias, et al., IfcWoD, Semantically Adapting IFC Model Relations into OWL Properties, in: Proc. of the 32nd CIB W78 Conference 2015, 27th-29th October 2015, Eindhoven, The Netherlands, 2015, pp. 175–185.
[11] J. Fruin, Designing for Pedestrians, Public Transportation United States, 1992.
[12] N. Gibbins, N. Shadbolt, Resource Description Framework (RDF), 2009.
[13] S. Gwynne, et al., A review of the methodologies used in the computer simulation of evacuation from the built environment, Available at: Build. Environ. 34 (6) (1999) 741–749 http://linkinghub.elsevier.com/retrieve/pii/S0360132398000572.
[14] HM Government, Digital Built Britain Level 3 Building Information Modelling - Strategic Plan, 2015 https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/410096/bis-15-155-digital-built-britain-level-3-strategy.pdf.
[15] C.J. Hopfe, J.L.M. Hensen, Uncertainty analysis in building performance simulation for design support, Energy Build. 43(10) (2011), pp. 2798–2805. 10.1016/j.enbuild.2011.06.034.
[16] I. Horrocks, et al., A semantic web rule language combining OWL and RuleML. W3C submission, 2004.
[17] L. Jalali, et al., Interoperability of multiple autonomous simulators in integrated simulation environments, in: 2011 Spring Simulation Interoperability Workshop, 2011 http://www.ics.uci.edu/~dsm/pubs/SIW-final.pdf.

[18] K.A. Kaufman, R.S. Michalski, From data mining to knowledge mining, Available at: Handbook Statist. (2005) 47–75 http://linkinghub.elsevier.com/retrieve/pii/S0169716104240020.
[19] E.D. Kuligowski, A review of building evacuation models, Gaithersburg, MD, 2005. http://nvlpubs.nist.gov/nistpubs/Legacy/TN/nbstechnicalnote1471.pdf.
[20] E.D. Kuligowski, Computer evacuation models for buildings, in: SFPE Handbook of Fire Protection Engineering, Springer, 2016, pp. 2152–2180.
[21] F. Leite, et al., Visualization, information modeling, and simulation: grand challenges in the construction industry, Available at: J. Comput. Civil Eng. 30 (6) (2016) 4016035 http://ascelibrary.org/doi/10.1061/(ASCE)CP.1943-5487.0000604.
[22] R. Lovreglio, et al., The validation of evacuation simulation models through the analysis of behavioural uncertainty, Reliab. Eng. Syst. Saf. 131 (2014) pp. 166–174. Available at: http://dx.doi.org/10.1016/j.ress.2014.07.007.
[23] S. Malsane, et al., Development of an object model for automated compliance checking, Automation Constr. 49(PA) (2015) pp. 51–58. Available at: http://dx.doi.org/10.1016/j.autcon.2014.10.004.
[24] NBS, R.E.L, Uniclass 2015, 2017 https://toolkit.thenbs.com/articles/classification/ (accessed 30.05.17).
[25] Oasys Limited, MassMotion, 2018 http://www.oasys-software.com/products/engineering/massmotion.html.
[26] T. Onorati, et al., Modeling an ontology on accessible evacuation routes for emergencies, Expert Syst. Appl. 41(16) (2014) pp. 7124–7134. Available at: http://dx.doi.org/10.1016/j.eswa.2014.05.039.
[27] OpenBIMstandards, How is IfcOwl generated? 2017a http://openbimstandards.org/standards/ifcowl/how-is-ifcowl-generated/.
[28] OpenBIMstandards, Web Ontology Language representation of the Industry Foundation Classes (IFC) schema, 2017b http://openbimstandards.org/standards/ifcowl/.
[29] P. Pauwels, D. Van Deursen, et al., A semantic rule checking environment for building performance checking, Automation Constr. 20(5) (2011) pp. 506–518. http://dx.doi.org/10.1016/j.autcon.2010.11.017.
[30] P. Pauwels, et al., Querying and reasoning over large scale building data sets, in: Proceedings of the International Workshop on Semantic Big Data - SBD '16. ACM Press, New York, New York, USA, 2016, pp. 1–6. Available at: http://dl.acm.org/citation.cfm?doid=2928294.2928303.
[31] P. Pauwels, et al., Enhancing the ifcOWL ontology with an alternative representation for geometric data, Automation Constr. 80 (2017) pp. 77–94. http://dx.doi.org/10.1016/j.autcon.2017.03.001.
[32] P. Pauwels, A. Roxin, SimpleBIM: From full ifcOWL graphs to simplified building graphs, 2016.
[33] P. Pauwels, W. Terkaj, EXPRESS to OWL for construction industry: Towards a recommendable and usable ifcOWL ontology, Automation Constr. 63 (2016) pp. 100–133. http://dx.doi.org/10.1016/j.autcon.2015.12.003.
[34] PD 7974, The application of fire safety engineering principles to fire safety design of buildings. Human factors. Life safety strategies. Occupant evacuation, behaviour and condition (Sub-system 6), British Standards Institution Group, London UK, 2004.
[35] E. Ronchi, D. Nilsson, Fire evacuation in high-rise buildings: a review of human behaviour and modelling research, Available at: Fire Sci. Rev. 2 (1) (2013) 7 http://firesciencereviews.springeropen.com/articles/10.1186/2193-0414-2-7.
[36] U. Rűppel, et al., Semantic integration of product model data in fire protection engineering, in: eWork and eBusiness in Architecture, Engineering and Construction. ECPPM 2006: European Conference on Product and Process Modelling 2006 (ECPPM 2006), Valencia, Spain, 13-15 September 2006, 2006, p. 115.
[37] A. Sagun, et al., Computer simulations vs. building guidance to enhance evacuation performance of buildings during emergency events. Simul. Modell. Practice Theory 19(3) (2011) pp. 1007–1019. http://dx.doi.org/10.1016/j.simpat.2010.12.001.
[38] R.J. Scherer, S.-E. Schapke, A distributed multi-model-based Management Information System for simulation and decision-making on construction projects, Adv. Eng. Inform. 25(4) (2011) pp. 582–599. Available at: http://linkinghub.elsevier.com/retrieve/pii/S1474034611000644 (accessed 19.10.140.
[39] Stardog Union, Stardog, 2018 http://stardog.com/.
[40] B. Succar, Building information modelling framework: A research and delivery foundation for industry stakeholders, Automation Constr. 18(3) (2009) pp. 357–375. http://dx.doi.org/10.1016/j.autcon.2008.10.003.
[41] W. Terkaj, A. Šojić, Ontology-based representation of IFC EXPRESS rules: An enhancement of the ifcOWL ontology, Available at: Autom. Constr. 57 (2015) 188–201 http://linkinghub.elsevier.com/retrieve/pii/S0926580515000886.
[42] A. Trento, et al., Building-use knowledge representation for architectural design, in: Proceedings of eCAADe 2012, 2012, pp. 683–690.
[43] M. Venugopal, et al. An ontology-based analysis of the industry foundation class schema for building information model exchanges, Adv. Eng. Inform. 29(4) (2015) pp. 940–957. Available at: http://dx.doi.org/10.1016/j.aei.2015.09.006.
[44] S.-H. Wang, et al., Applying building information modeling to support fire safety management, Available at: Autom. Constr. 59 (2015) 158–167 http://www.sciencedirect.com/science/article/pii/S0926580515000205%5Cnhttp://linkinghub.elsevier.com/retrieve/pii/S0926580515000205.
[45] S. Wang, G. Wainer, A simulation as a service methodology with application for crowd modeling, simulation and visualization, Available at: Simulation 91 (1) (2015) 71–95 http://sim.sagepub.com/cgi/doi/10.1177/0037549714562994.
[46] Wang Xiao Hang, et al., Ontology based context modeling and reasoning using OWL. In: IEEE Annual Conference on Pervasive Computing and Communications Workshops, 2004. Proceedings of the Second. IEEE, 2004, pp. 18–22. Available at: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1276898.
[47] B.T. Zhong, et al., Ontology-based semantic modeling of regulation constraint for automated construction quality compliance checking, Available at: Autom. Constr. 28 (2012) 58–70 http://linkinghub.elsevier.com/retrieve/pii/S0926580512001185.
[48] P. Zhou, N. El-Gohary, Ontology-based automated information extraction from building energy conservation codes, Automation Constr. 74 (2017) pp. 103–117. Available at: http://dx.doi.org/10.1016/j.autcon.2016.09.004.
[49] S. Zhou, et al., Crowd modeling and simulation technologies, Available at: ACM Trans. Model. Comput. Simul. 20 (4) (2010) 1–35 http://eprints.bournemouth.ac.uk/13285/1/licence.txt%5Cnhttp://portal.acm.org/citation.cfm?doid=1842722.1842725.