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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, which require 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 practical implementation of the system.

Keywords	Knowledge Mining; Crowd Simulation; Ontology; Evacuation Design; Building Information Modelling (BIM); Industry Foundation Classes (IFC).

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Cardiff 29/11/2017

Dear Editor,

Please find attached a manuscript for a study entitled: "*Crowd simulation based knowledge mining supporting building evacuation design*" that we would like to be considered for publication in the Advanced Engineering Informatics Journal, for the EG-ICE2017 special issue.

Our research presents a framework on how crowd simulation linking with digital building models, which allows for an intelligent system capable to represent and interpret stored building and simulation data. The developed system prototype is presented to prove this methodology. The system is able to process IFC model data and other linked ontology models to create scenarios for fire evacuation. The system is then able to link building data with analysis data and provide new knowledge about its performance. This study brings significant insight on the essential concepts behind the crowd simulation and BIM interoperability, the interactions between the different models and to what degree knowledge about the design can be retrieved under performance design analysis.

I would like to inform you that this manuscript is an extended study for similar work already published in the EG-ICE 2017 conference proceedings, including however significant changes and more details. I would also like to confirm that for the submission of this paper we have no conflicts of interest to declare.

Sincerely,

C Boje

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Crowd simulation based knowledge mining supporting building evacuation design

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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, which require 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 practical implementation of the system.

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1. Introduction

The building design process has advanced significantly since the adoption of 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, these developments are more focused on validation of BIM models (Zhong et al. 2012) for various analyses and often apply prescriptive design rules (Eastman et al. 2009) 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 (Leite et al. 2016).

In the field of fire safety, Crowd Simulation (CS) analysis tools are used to estimate building performance in terms of human movement behaviour (Duives et al. 2013). This process requires several iterations in different scenarios, which can be a very time-consuming process and can often lead to wrong estimations of the building performance (Sagun et al. 2011). There are currently no practical ways of leveraging building information and designer knowledge to enhance and speed 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 invariance caused by human behaviour (Lovreglio et al. 2014).

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.

Moving towards a BIM level 3 way of working, model data and information need to be linked and stored in knowledge databases, which can be leveraged to provide advanced and speedy design support for various AEC applications. Succar 2009 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. 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. The system also describes a conceptual knowledge mining process, for creating valid simulation scenarios and return results in accordance to design objectives. A case study outlines the process of using the system points out advantages and limitations, followed by a discussion on the practical use of this approach and 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 degree to BIM processes. The overall research aims to bridge interoperability and perform knowledge mining using 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 (Gwynne et al. 1999) (Kuligowski 2005), application domains (Kuligowski 2005), scale (Zhou et al. 2010), degree of realism (Duives et al. 2013) and high-rise buildings focused (Ronchi and Nilsson 2013). 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 2005 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 2013 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. 2010 and Duives et al. 2013 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 trend is concerned with the emergency egress of a building scenario.

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, according to Hopfe and Hensen 2011, it is not always clear how relevant the simulation output is, as it is dependent on a large number of parameters. To compensate for this limitation, it is often required to conduct several simulations using different assumptions and scenarios. 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. Studies focused on automation of fire performance design systems are identified from reviewing the literature.

A number of studies are focused on integrating crowd simulation tools into various systems: Jalali et al. 2011 integrate 3 different domain tools together for fire evacuation management scenarios; Wang et al. 2015 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 2015; Additionally, the studies forget to mention that geometric information is insufficient for CS purposes, and that valid simulation models require input from various other sources.

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. 2016. 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 scalable or collaborative enough for more holistic design views or across the BIM lifecycle stages. These limitations are also mentioned by the same authors in another study (Dimyadi et al. 2015), where they recommend using ontology formats to express regulatory knowledge, due to higher expressivity and interoperability.

Malsane et al. 2015 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 sub-systems that require audit and their inter-dependencies. The authors furthers 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.

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 is less likely to meet the needs for inter-disciplinary design processes, when in the context of performance assessment. In addition to that, 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 et al. 2011 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 2011, which describes a framework for using ontologies as a means of integration on the project level, which can include multiple models and processes. Such approaches enable the rule checking process to go beyond the schema scope, thus allowing for more flexible model view definitions, which is crucial in including non-traditional design analysis under the BIM umbrella. Long before these developments, Rűppel et al. 2006 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 (Beetz et al. 2009) (OpenBIMstandards 2017b) 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, as concluded by

Venugopal et al. 2015. 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. 2017 investigate the optimisation issues around its representation in terms of geometry retrieval of the data. Farias et al. 2015 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 2015 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 (BuildingSMART 2017), which would open the gates towards web-languages oriented BIMs.

Abanda et al. 2013 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. 2012 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 human due to the focus on representing 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. 2014 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. 2015 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 and checking. The study was applied in the context of BREAM assessment, which is a good example of multi-disciplinary and multi-domain design decision making. The authors mention that when the SWRL 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). The users also have to complement missing data with input in many situations. A step further from this, Zhou and El-Gohary 2017 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.

3. Methodology and system design

Knowledge Mining is defined as "a derivation of human-like knowledge from data and prior knowledge" (Kaufman and Michalski 2005), which includes Databases, Knoweldge bases and Operators,as outlined in Table 1.

Table 1 - The main components for Knowledge Mining concept as described by (Kaufman and Michalski 2005), 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	ontology 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

Following the concept of Kaufman and Michalski 2005, this research aims to improve the evaluation of building design evacuation evaluation by proposing a conceptual framework which focuses on the knowledge mining of crowd simulation data. The framework aims to formalise the design knowledge using ontologies and to retrieve new knowledge back to the design loop in a BIM-oriented manner. There are several steps required, as listed below (see Figure 1), and which are presented in 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. Rules construction – the operators required to define the creation of new knowledge from the existing resources;
4. Integration of the system – requirement to achieve collaboration of system components.

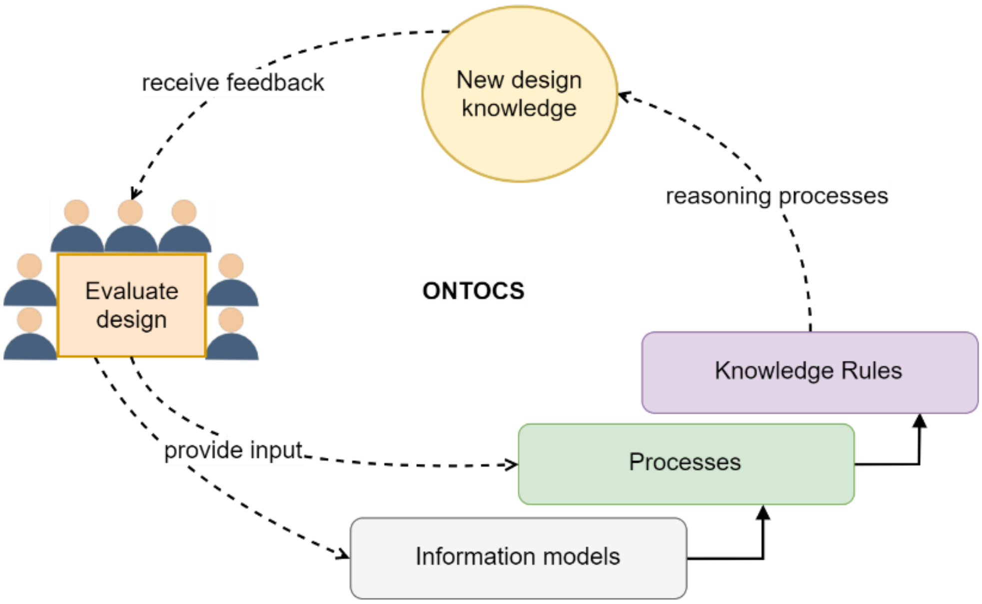


Figure 1 – The knowledge mining concept implemented in ONTOCS.

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:

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 definitions and information in RDF format. It includes the representations of various information models, the processes (described in section 3.4), 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 3.4). 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 manage the server-side databases;
5) Interfaces - the interfaces which are used for providing a user-friendly experience; they can be present at every application level, or as a web-service.

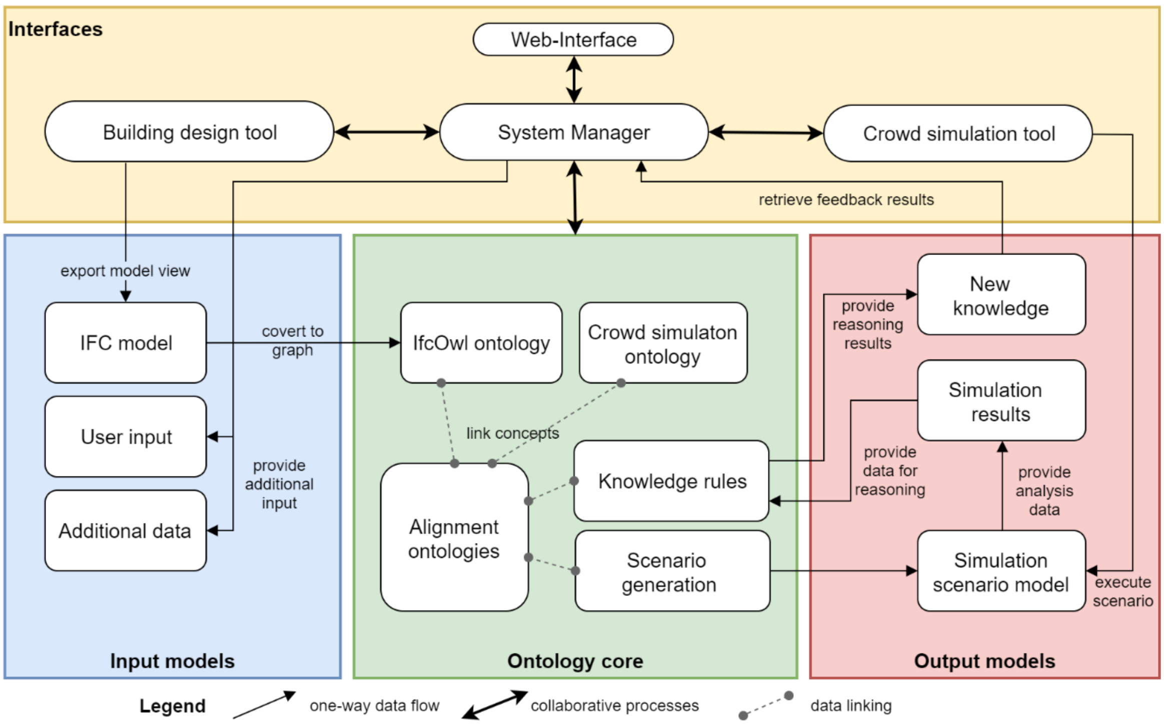


Figure 2 – ONTOCS system components interaction, categorised by their functionality.

The interaction of the system components is shown in Figure 2 above. 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 RDF format for ontology processing. The ontology core is hosted on Stardog graph databases (Stardog Union 2017) and the ontologies shown reflect the process from Figure 1. The information models act as resources for the process stages. The automation stage ontology 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 manager program coordinates this process and outputs a file for the MassMotion (Oasys Limited 2017) 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 presented for further decision-making to the users. 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. 2015. These are mapped using several *alignment ontologies* as can be seen in Figure 2.

4. ONTOCS framework development & implementation

4.1. Representation of information models

In its current state, the framework 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.

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

The BIM model is seen here as the central provider of information. The IfcOwl ontology (BuildingSMART 2017) 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, the developed knowledge base includes 4 distinct categories (Figure 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 imply 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.

Figure 3 outlines some of the links between the developed crowd 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 Figure 3 below, 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 *sameAs* axiom is not correct. 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 the research, this is especially true when referring to the geometry data. This issue is identified and addressed by Pauwels et al. 2017.

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 the IFC schema.

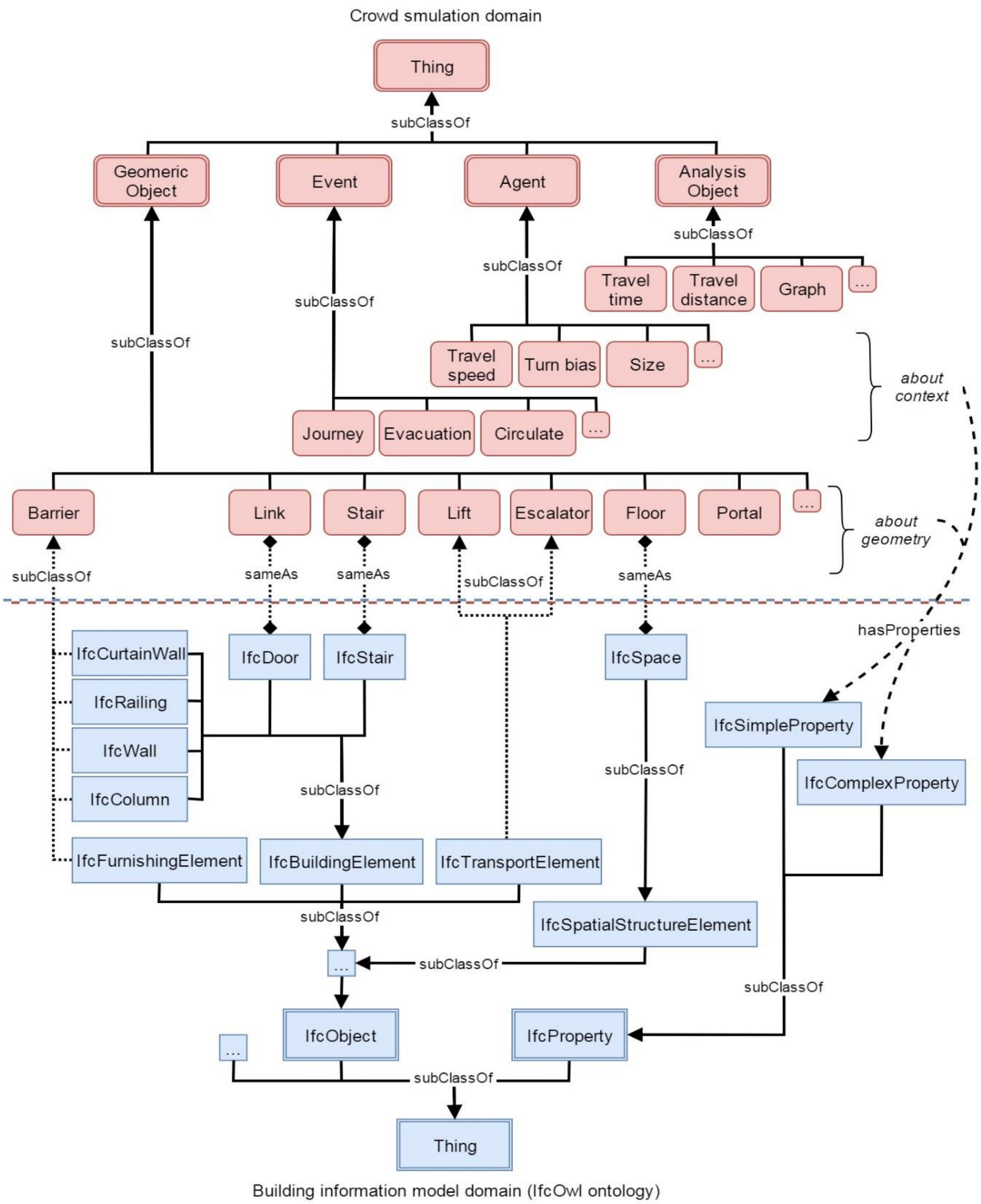


Figure 3 – Showing the difference in hierarchies between building ontology (IfcOwl) and crowd simulation ontology with common concepts and their alignment.

In addition to that, the IFC schema expresses geometry in a compressed way to save memory. Because of this, the geometry extracted from the IfcOwl needs to be reconstructed in the crowd simulation ontology. A low level of detail for geometric objects is often more than sufficient to achieve this. However, even so, the SWRL rules for such a procedure were considered too complex and have opted instead to convert the geometry via software code, which is then put into the crowd ontology resources explicitly. This process is more time efficient and a rule approach would not benefit the knowledge processes.

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 or 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 Figure 4.a, two main categories of information input were identified which are required for valid scenarios:

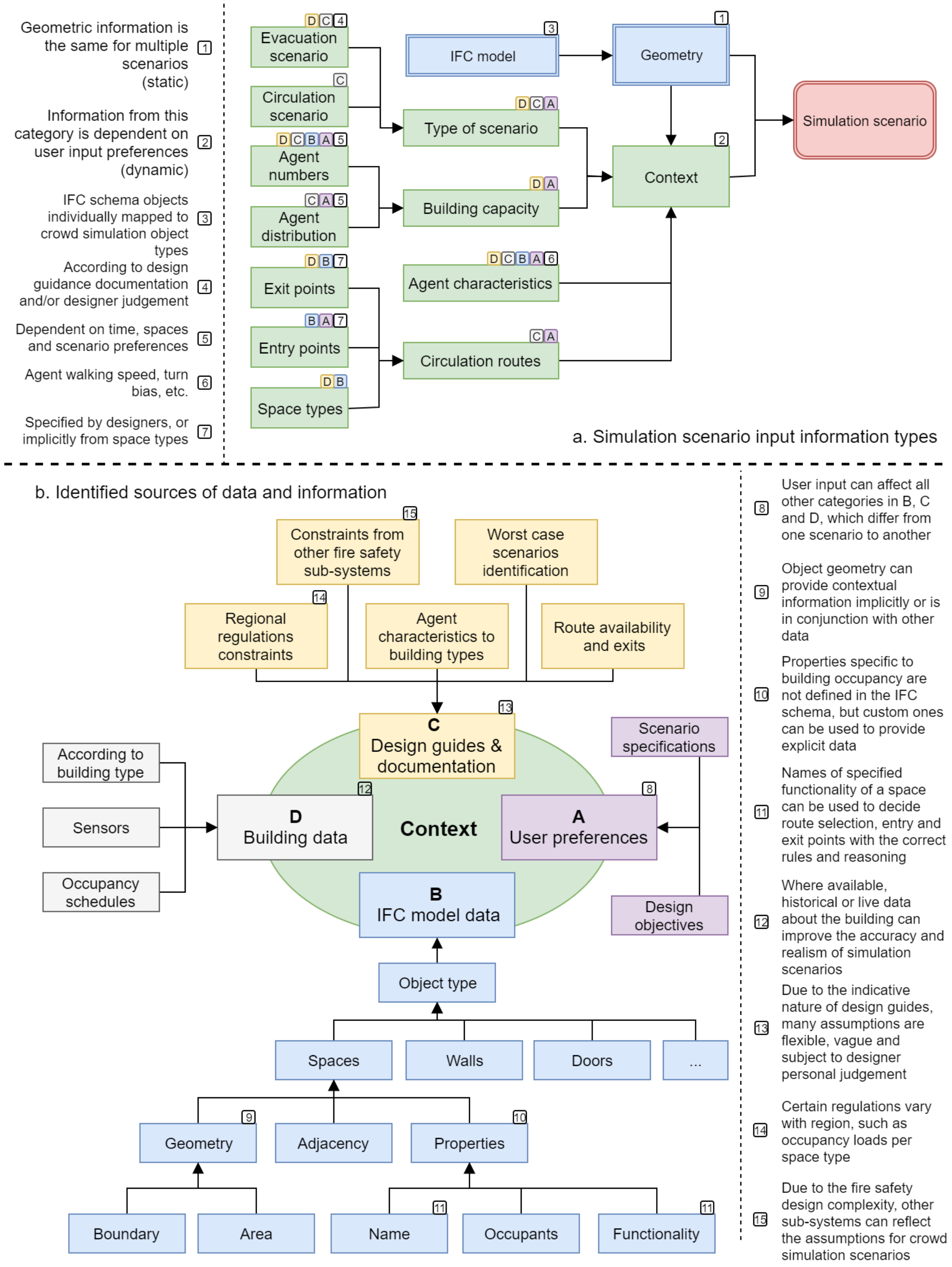


Figure 4 – a. shows the concepts which provide the relevant information for a fully functioning scenario with emphasis on contextual data types which are influenced by other information domains shown below; b. shows the four domains which influence the concepts in a. and their identified relevant factors.

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 our 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 ontology 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 Figure 3b. Four principal domains which can provide information input emerge:

A. **User input** – refers to the choices that the designer is using to 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. 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 PD 7974 2004 part 6 is one of 7 documents published in the UK which were used to gather knowledge for our ontology representations of the process. However, information concerning occupant densities was vague, so local official regulation documents were required.

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.

4.2.2. Analysis feedback

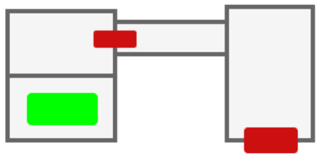
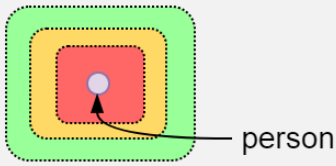
The second part in representing the knowledge processes looks at the act of evaluating simulation model data. This resembles the act of knowledge mining whereby gathered simulation data is analysed by the ontology rules and returned to designers. The feedback is highly dependent on the inputs provided 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 (Figure 4.b) 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.

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

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.

One building design is usually tested in several performance scenarios. When considering such large numbers of scenarios under evaluation, data can accumulate very quickly and it needs to gain 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 Figure 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.

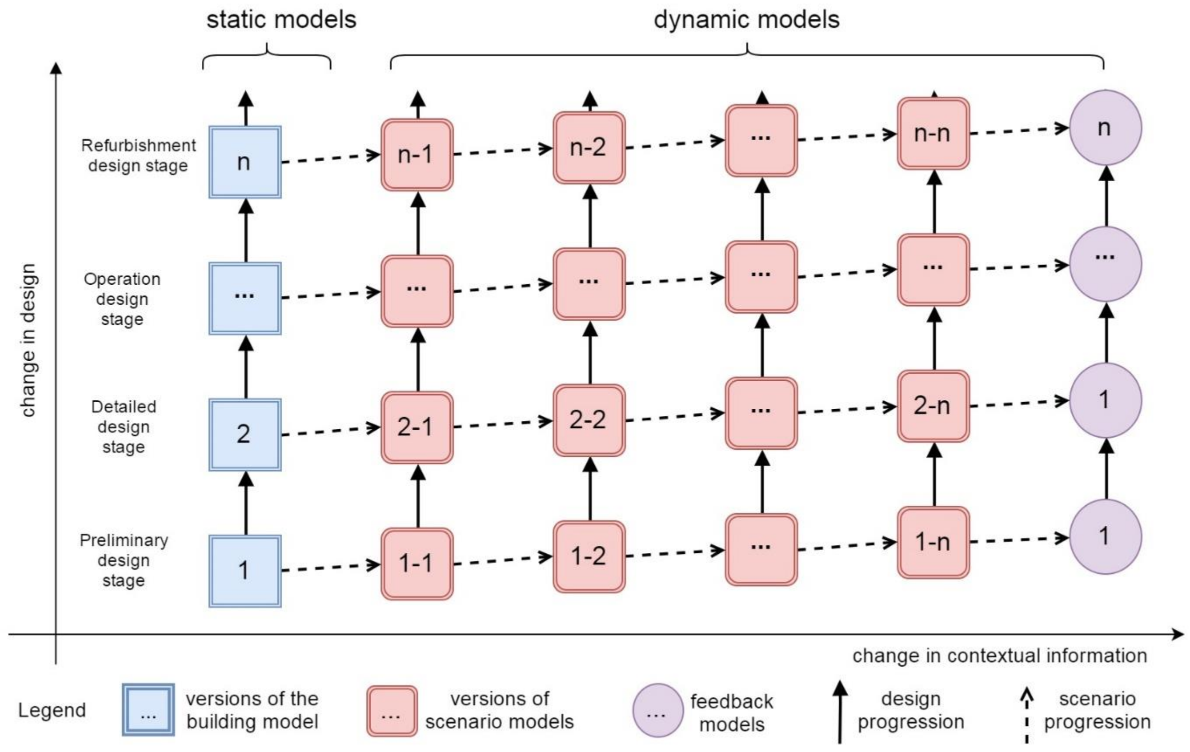


Figure 5 - Static and dynamic information model's progression with design change.

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. 2004, 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 are "true". Figure 6 below 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.

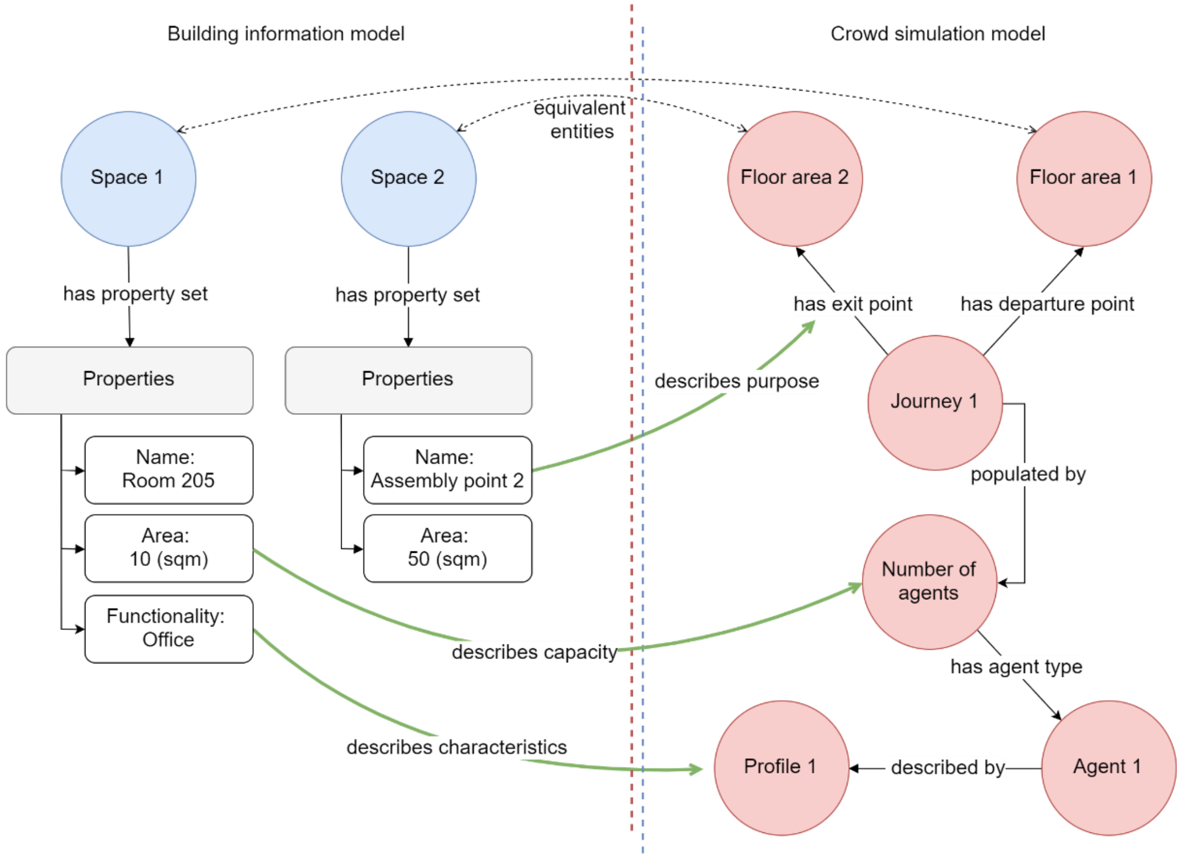


Figure 6 – Example of retrieving implicit information; the green heavy arrows indicate how certain BIM data can describe contextual data.

Explicit information is required to correctly extract the context from the above defined sources (Figure 4.b). 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 Figure 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.

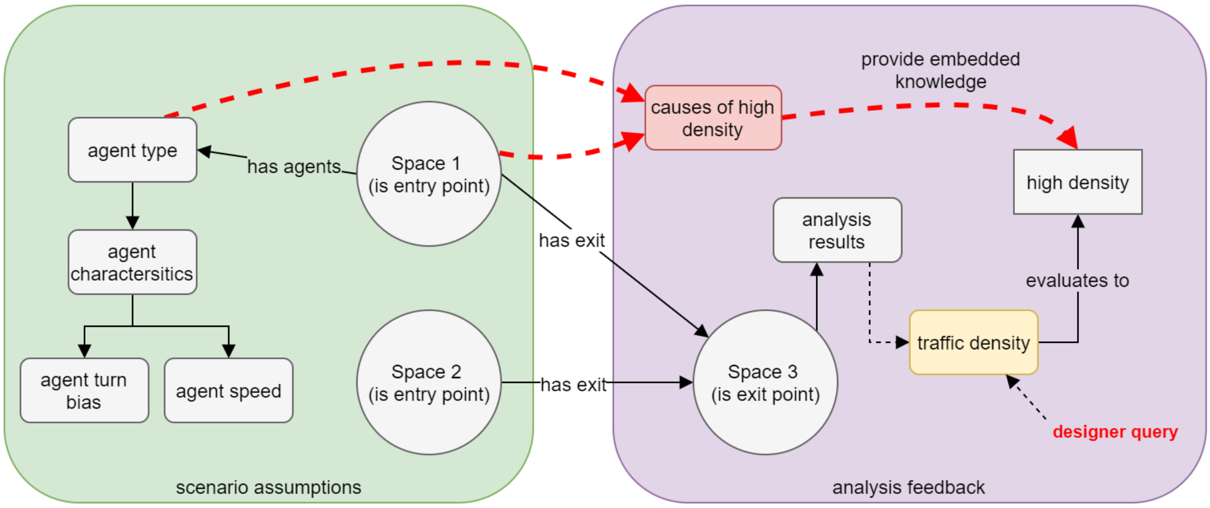


Figure 7 – Example of objects and properties (contextual and geometric) influencing the final analysis result. The red arrows indicate how certain knowledge rules can be embedded to provide more relevant feedback.

When considering such rules, careful consideration is required along with validation of the rules. The retrieval of such knowledge is complex, and it is limited by the reasoning types that ontologies and SWRL rules can provide. This is mainly due to the OWA which governs ontology reasoning, where evaluation of rules can not only be "true" and "false", but also "unknown".

This is also important when considering results across multiple platforms or other design domains in the context of iBIM, in similar terms as described by Hou et al. 2015.

5. Case study

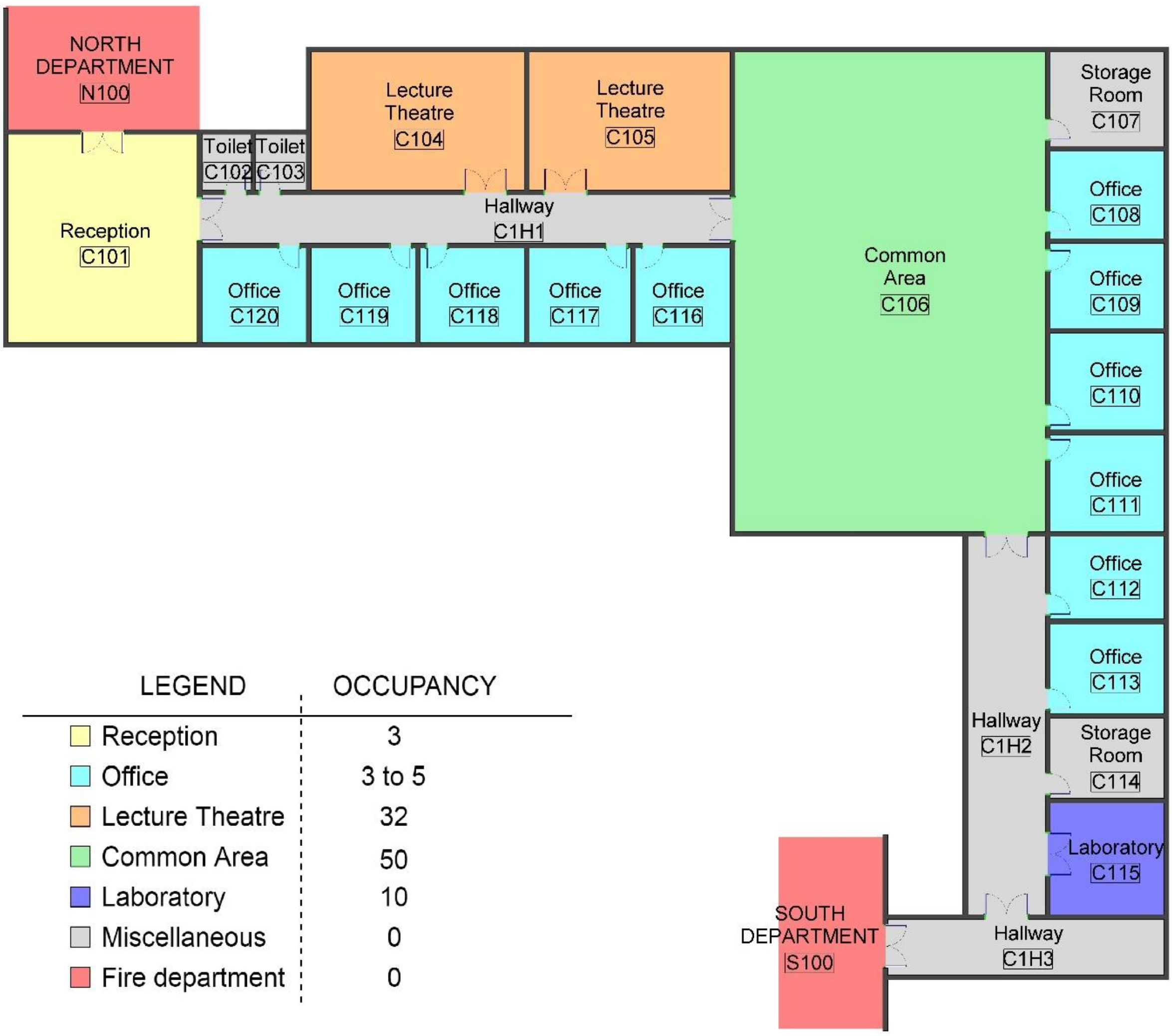
The purpose of this case study is to show the benefits of using the developed ONTOCS system which uses an ontology approach for aggregating simulation and BIM data in an automatic manner, while also providing insight about the building design performance in accordance to design objectives. To show this, 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 modelled using Autodesk Revit 2017 and exported to IFC. The IFC file was converted using a third party software (OpenBIMstandards 2017a) 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 Figure 8 below. 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.



LEGEND	OCCUPANCY
Reception	3
Office	3 to 5
Lecture Theatre	32
Common Area	50
Laboratory	10
Miscellaneous	0
Fire department	0

Figure 8 – Plan view of the case study building being tested, split by space functionality. The areas in light grey are assumed to have no inhabitants, as per regulations.

The design problem is to assess the evacuation travel times of agents under various population capacity conditions. An initial design population was prescribed (Figure 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. Each scenario was given to simulate the environment for 5 minutes. The native MassMotion agent profile was chosen, along with other default settings. The assumptions can be seen in Figure 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 (NBS 2017) 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 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.

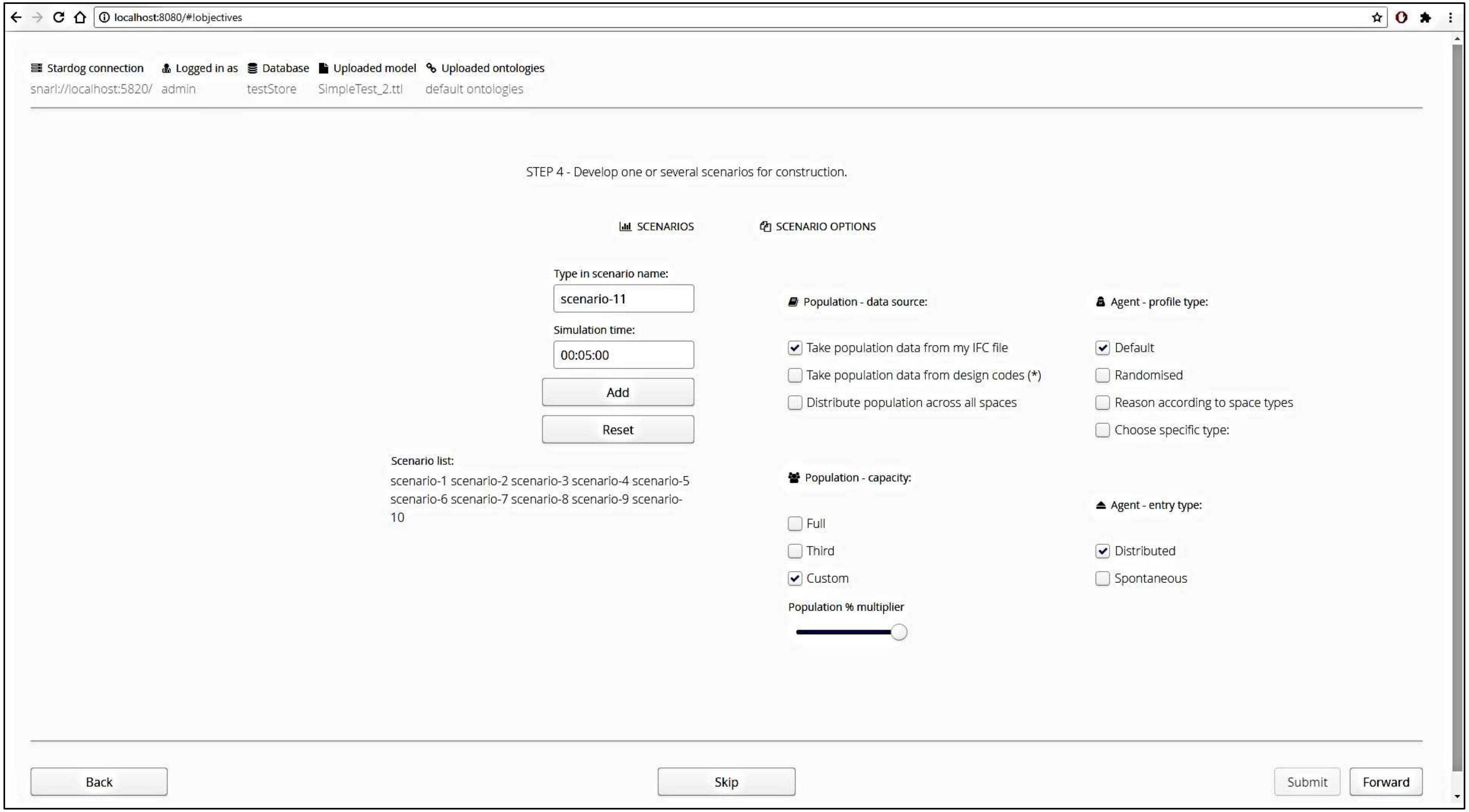


Figure 9 – ONTOCS system assumptions page. Each scenario can be set with different assumptions and added for generation and analysis.

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 below. 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?

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 to 9
2	90	75	45	1 to 5
3	120	75	60	1 to 10
4	120	95	90	1 to 13

By applying several rules, the system was able to provide answers for the sets of objectives chosen. After the simulations were executed, overall results are stored in various resources graphs and presented on the interface in a table, as can be seen in Figure 10. Below that, analysis objectives can be chosen by designers, which is submitted and evaluated using ontology reasoning.

Once the *Evaluate* button (Figure 10) is pressed, the application sends SPARQL queries to the RDF databases. The process time increases with the complexity of the rules in place, as well as with the number of tested scenarios. Figure 11 shows the two rules responsible for answering the two types of objectives (Table 4) under analysis. The rules work with classes and properties defined in a developed feedback ontology.

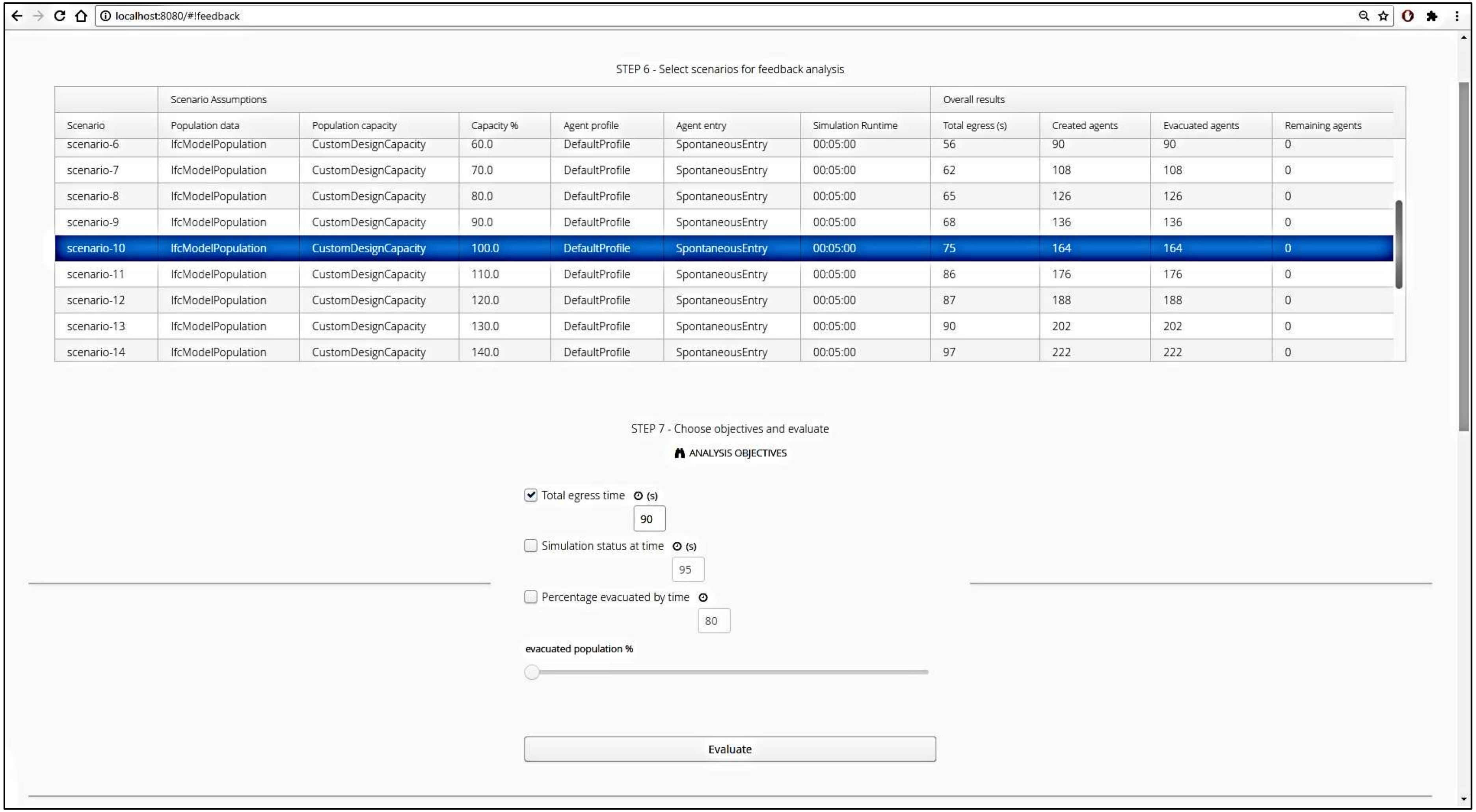


Figure 10 – ONTOCS initial results reporting & objectives page

```
Rule name: FB-01-B1-ValidTotalEgressScenario

Comment: 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 name: FB-03-A1-ValidCapacityEgressScenario

Comment: 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)
```

Figure 11 – Example feedback SWRL rules for assessing which scenarios have valid results. The 'fbo' prefix stands for the 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 Figure 12. The results are summarised in Table 4, showing which scenarios meet both objectives.

Reasoning results are then reported back and presented on page in Figure 12. The basic functionality here is to categorise the various scenarios in accordance to each rule. It appears that some scenarios are both valid and invalid under certain sections. 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 which checks that all objectives are met, categorising it as a "*FullyValidScenario*" class within the developed feedback ontology.

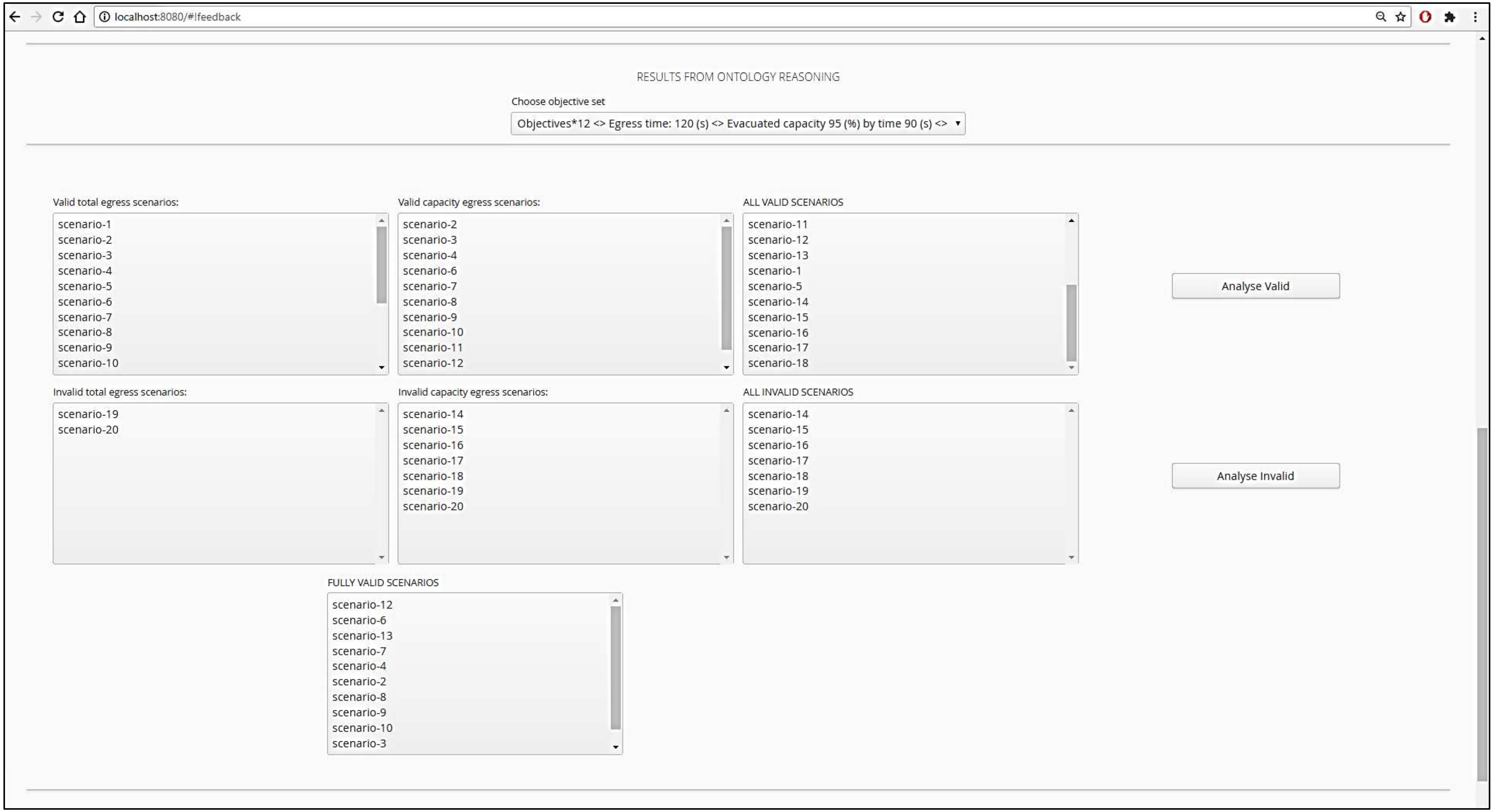


Figure 12 – ONTOCS reasoning results page.

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 progress of the evacuation procedure was plotted in Figure 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 light green dotted line and the light green shaded rectangle show the area 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.

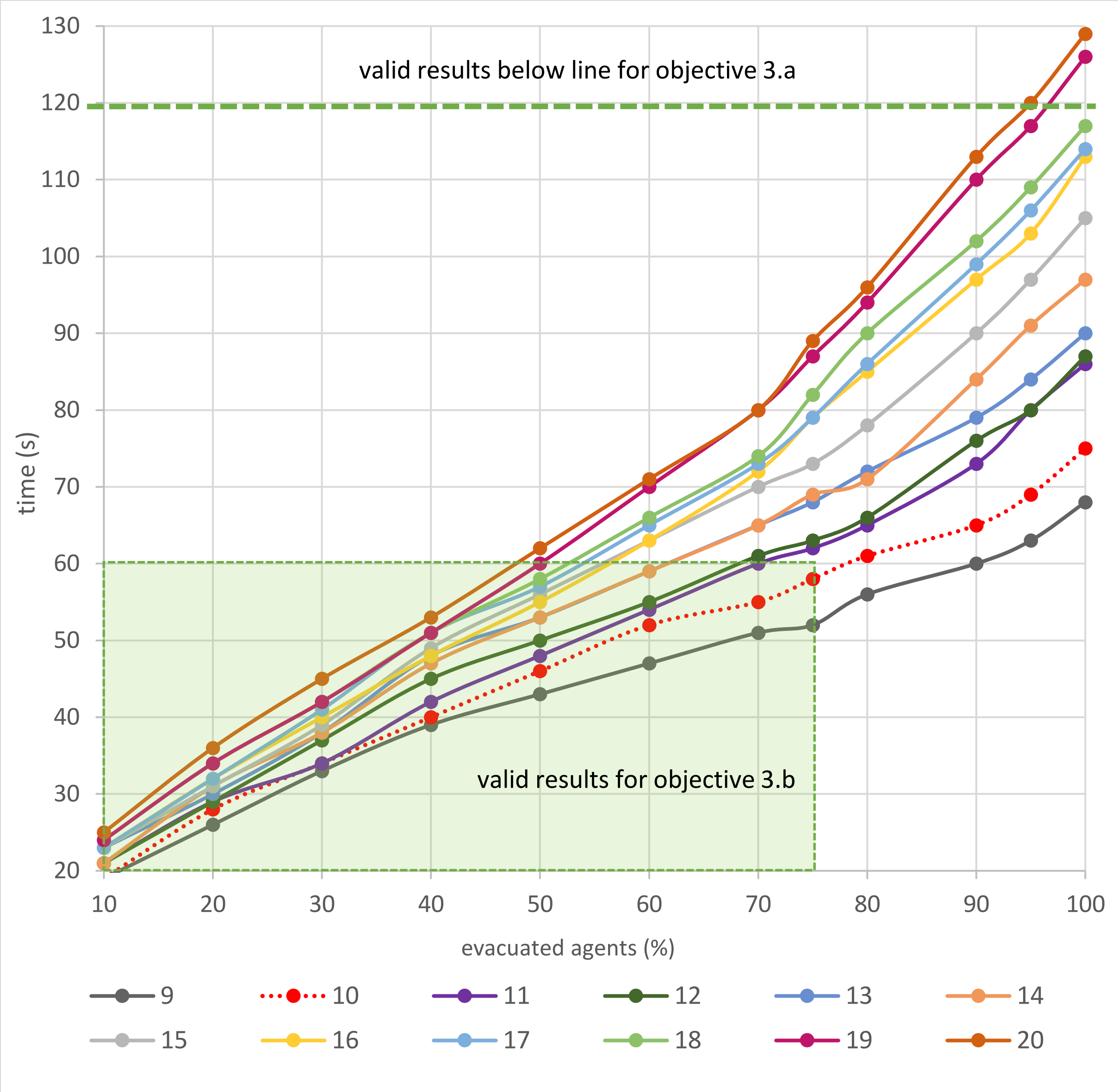


Figure 13 – Plotted results of the egress progression for each tested scenario. Scenario 10 is depicted by the red dotted line, which assumes 100% population capacity for the building.

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. 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 might export IFC defined differently. This presents a serious limitation to using ontologies 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 will always change, the extent of the available options can be narrowed down quite easily and is not expected to change. Design regulations and guides 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 values limited by objectives. This effectively provides knowledge by notifying the designers of which scenarios are performing in accordance to their performance standards 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 as a framework to achieve interoperability, representing information models, a design process for crowd simulation analysis and a way to perform knowledge mining using rules on top in section 4. 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 due to OWA, and the cost of reasoning increases with the number of rules applied in conjunction with each other, as well as with the number of scenarios evaluated.

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.

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