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Usability Evaluation of a Web-based Tool for Supporting Holistic Building Energy Management

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Abstract

This paper presents the evaluation of the level of usability of an intelligent monitoring and control interface for energy efficient management of public buildings, called BuildVis, which forms part of a Building Energy Management System (BEMS.) The BEMS 'intelligence' is derived from an intelligent algorithm component which brings together ANN-GA rule generation, a fuzzy rule selection engine, and a semantic knowledge base. The knowledge base makes use of linked data and an integrated ontology to uplift heterogeneous data sources relevant to building energy consumption. The developed ontology is based upon the Industry Foundation Classes (IFC), which is a Building Information Modelling (BIM) standard and consists of two different types of rule model to control and manage the buildings adaptively. The populated rules are a mix of an intelligent rule generation approach using Artificial Neural Network (ANN) and Genetic Algorithms (GA), and also data mining rules using Decision Tree techniques on historical data. The resulting rules are triggered by the intelligent controller, which processes available sensor measurements in the building. This generates 'suggestions' which are presented to the Facility Manager (FM) on the BuildVis web-based interface. BuildVis uses HTML5 innovations to visualise a 3D interactive model of the building that is accessible over a wide range of desktop and mobile platforms. The suggestions are presented on a zone by zone basis, alerting them to potential energy saving actions. As the usability of the system is seen as a key determinate to success, the paper evaluates the level of usability for both a set of

technical users and also the FMs for five European buildings, providing analysis and lessons learned from the approach taken.

Keywords: Ontology; BEMS; Genetic Algorithm; Artificial Neural Network; Fuzzy Logic; Information Visualisation; IFC.

1. Introduction

Taking into account the whole Building Lifecycle (BLC), which includes the life stages of a building from design, through construction, operation, and on to eventual demolition/recycling [1][2], buildings are responsible for about 50% of total energy consumption in the EU [3]. The EU has established the Energy Performance of Buildings Directive (EPBD) [4], which by 2019 requires public buildings to consume zero energy. New strategies to reduce energy consumption during the operational phase of the BLC are a necessary step to achieving this goal. Energy use during operation is strongly influenced by the operation and utilisation of the different spaces [5] and the behaviours of occupants [6]. A large number of variables introduced through these interactions makes the task of reducing energy consumption challenging. Tools which monitor and analyse the different factors that contribute towards building energy consumption, so that actions may be taken (or enable to be taken) to improve energy efficiency, while also maintaining or improving user comfort, are required.

Within the commercial domain, tools already exist which provide methods for analysing energy consumption of devices and areas in a building [7] – [9]. These tools provide various platforms to visualise actuators status, historical data and device health status based on different time stamps and ranges. However, there are limitations to these traditional building energy management systems (BEMS). Firstly, there is a lack of flexible and user-friendly interfaces which provide integrated knowledge about the entire built environment in a manner which is accessible to the user, e.g. Facility Managers (FM). There is also a lack of intelligent control systems which go beyond the traditional approach of relying on the user's expert knowledge of the building, to enact energy saving changes to building configuration. To overcome the above weaknesses, a holistic and intelligent solution for FMs is required. This should be capable of running autonomously and provide knowledge about the entire built environment in near real time for enhanced decision support.

Within the research community, various systems and methodologies have been suggested to provide this kind of intelligent control to support energy management [10]. These systems bring together buildings sensory and actuation infrastructure, to measure and enact change in the environment, and the building control and automation systems [11]. For automated intelligent control, the sensitive nature of user comfort remains. This means, it is not always possible to adapt heating, cooling, and ventilation without consent from the responsible party (e.g. the FM), as the consequences of changing set points could be contrary to their responsibilities of providing adequate user comfort. The holistic knowledge-based intelligent system must, therefore, work with the FM, informing them

about energy saving strategies, but also leaving them with final control over implementation of new configurations.

This paper presents a holistic, flexible knowledge-based intelligent system, the evaluation of its level of usability and lessons learned from applying the approach taken. The proposed solution consists of a user-friendly web-interface (BuildVis) which interacts with the holistic intelligent decision support system, and enabling the FM to configure building environment optimisation. As it is the FM who must use the proposed solution (framework), the level of usability of the interface is a key indicator of success. The proposed framework presents suggestions, through the interface, which are designed to be simple to understand and execute. The suggestions are generated through analysis of building data using data mining techniques and theoretical rule generation based upon energy simulations. This hybrid approach of real and simulated rule generation is required due to the varying number of sensors available and the need to keep costs down by not introducing extra sensor installations into the building.

From this analysis, a rule base is developed which is triggered according to the changing values of the available building sensors and set points in near-real time. These are presented to the FM, who may then enact the changes. To support the integration of multiple data sources and improve interoperability, the solution makes use of building information modelling (BIM) principles and semantic web technologies in the form of a holistic knowledge base, into which the rules are integrated. The paper is structured as follows: the following section discusses relevant existing work. Next, the requirements and implementation of the tool are presented. Finally, the BEMS GUI interface is discussed before its evaluation and a discussion of the results are given.

2. Background

This section presents the background and related studies for the existing building energy management systems (BEMS) and their subsystems. It is divided into six parts; an overview for the BEMs, sensing and activation infrastructure in the built environment, simulation to supplement sensor data, data modelling and data management, data monitoring and control and finally social and behavioural considerations in energy efficient buildings.

2.1. Building energy managements systems

Building Energy Management System' (BEMS) is a term used to encapsulate a number of systems developed to improve the energy efficiency of operational buildings. BEMS collect data about the current state of the building, analyses this data and then, either a/ provides analysis and feedback to an appropriate stakeholder, who must enact some change or reconfiguration of the building's systems, or b/ an automated control system acts upon the available data to reconfigure the building automatically. Conceptually, a BEMS architecture can be categorised into different layers,

for example; the sensor layer, computational layer, and application layer. Collectively, these monitor environment states, perform statistical and algorithmic analysis, and provide feedback and control mechanism to users [12].

As an alternative architecture in the smart home domain, BEMS can be divided into four components; the sensor and actuation infrastructure, middleware, processing engine, and user interaction interface [10]. In this architecture, the sensor and actuation infrastructure handles all interaction between the digital infrastructure and the physical environment. The middleware integrates the infrastructure through a common interface. The processing engine conducts some ‘processing’ on the collected data to learn about the environment and building user activities so as to improve the buildings energy consumption. Data on the environment includes measurements relating to temperature, CO₂, humidity etc. (see section 2.2). User activities include scheduled activities (office work, meeting, lunch, etc.) and interrupt activities (toilet break, drink, exercise) [49]. The user interaction interface then supports interaction with end users; sending them notifications to stimulate behaviour, gather feedback and commands from them. Other architectural configurations for buildings and smart homes can be found in [13], [14] which define the similarities and differences in the sensing, data management and reasoning and human interaction layers. These separations of concern form the basis of the framework defined in this paper.

2.2. BEMS sensing and actuation infrastructures

To monitor the built environment, BEMS require a sensing infrastructure to measure phenomena such as temperature, humidity, lux levels, CO₂, and occupancy. This is achieved through the use of sensing technologies like PIR (passive infrared), thermostats, CO₂, ultrasound, cameras, and/or tag based system, like RFID, Bluetooth and Ultra-Wide Band [15], [16]. Based on these measured data, BEMS can adapt device behaviour to reduce energy consumption whilst also maintaining comfort levels, for example, by adjusting HVAC to a desired temperature. A common issue for commercial BEMS is the limitation of the sensing infrastructure. For example, occupancy detection is central to many BEMS systems [6], [15], [17], but existing sensor installations like PIR can only detect movement, and so, calculating numbers of occupants is difficult [6]. Reasoning and sensor fusion can be used to make inferences about more complex behaviours, but, these systems are not commercially available yet [16].

2.3. Energy simulation and surrogate models

There is a general lack of sensing infrastructure in existing buildings. Further, the investment cost of a comprehensive sensing network is often prohibitive due to a long return on investment period. This leads to the role of simulation being pivotal in predicting building behaviour [18-19] for retrofit BEMS installations. Physical building simulation tools such as EnergyPlus [20] are able to supplement the directly sensed observations with comprehensive predicted knowledge about the

building's response to potential control scenarios. In order to mitigate the time per simulation, for use in optimization algorithms, surrogate models can be used [21]. This use of simulated data to train machine learning software, which can then approximate the simulation outcome within a narrower decision space, in far less time. However, integrating data within a BEMS from such software, simulation tools, physical sensors, and occupants, requires a comprehensive and robust approach to interoperability across these heterogeneous resources.

2.4. Data management in BEMS and linked data

BEMS data integration requires consideration of the underlying data models and their representation. Building Information Modelling (BIM) describes an integrated approach to structuring all information relevant to the BLC. Within the Architecture, Engineering and Construction (AEC) community the leading standard developed around the concept of BIM is Industry Foundation Classes (IFC). IFC is an open, freely available, non-proprietary data model which can be used to exchange and share BIM data for describing buildings regarding the semantics of constituent building elements. Modelling all this data remains a challenge, particularly for older buildings where the issue of fragmented and hard to access building data increases [22]. Linked Data (LD) refers to the recommended best practices for exposing, sharing, and connecting data on the Web [23]. LD builds, in particular, on the Resource Description Framework (RDF) as a data model for representing structured content. RDF is based essentially on triples of the form (subject, predicate, object), constituting a structured graph that can be queried over HTTP via the SPARQL query language. By integrating BIM into the wider web of data, building information can be queried alongside all other Linked Open Data (LOD) sources, e.g. data on materials and building systems, profiles of occupants, and information about weather patterns, etc. Together this information can make for more meaningful analysis of energy consumption and its relation to the localised costs of materials, systems, and personnel in existing and future buildings.

2.5. Data monitoring and control tools

The upmost layer of a BEMS system is the application layer which offers both presentations of data to the relevant stakeholders and building control capabilities. Several commercial energy monitoring tools exist for public and commercial buildings, which provide functionality to monitor the energy consumption of a building, for example, PlugWise [7] and MonaVisa [8]. They collect data, e.g. temperature, energy consumption, occupancy through sensors, calculate energy-related Key Performance Indicators (KPIs), and present the calculation results in different graphics, for instances, coloured charts, 2D floor image, etc. The drawback of these tools is that the FM has to be active in finding problems. The tools do not set out to help identify unwanted behaviour, like energy wastage, beyond simple thresholds that a variable should fall within. Methods which actively suggest

configuration settings to improve energy efficiency can potentially support FMs in the difficult tasks of monitoring and managing the energy consumption of the building.

2.6. Social and behavioural considerations in energy efficiency

Approaches to the factors influencing user behaviour and consumer choice, especially in relation to the energy efficiency, savings, and comfort, can be categorized into four groups: a) Social factors that largely relate to the family ties, social status, and reference groups; b) Cultural factors that are influenced by subcultures, social class, socio-cultural environment, and contemporary trends; c) Personal factors that refer to the users' gender, age, lifestyle, and purchasing power; and d) Psychological factors which can be related to the users' perception with reference to selective attention, distortion and retention, levels of motivation and learning, as well as attitudes and beliefs. Based on these influencing factors, two functional links in behavioural theories and models can be identified [24]. First, the heuristic functions to elucidate behavioural factors and the interrelations between these factors. Second, the empirical functions to interpret relationships between these factors and the relevant interventions in order to help envisage the behaviour patterns.

The contribution of ICT-based solutions to the energy efficiency, savings and behavioural change can, therefore, be looked at from the perspectives of 'individual', social or 'interpersonal', and 'community' or network levels. Relational choice theory offers an economic logic based on costs and benefits of an individual action in relation to the available choices to maximise personal welfare and comfort. Power (2008) highlighted the correlation between the economic logic and CO₂ emission which is stated in Stern Review that increased global awareness for reducing CO₂ emissions [25]. Theory of Planned Behaviour in this respect emphasizes the perceived individual benefits, constraints and social pressures in relation to behavioural choices, with intention as a proximal predictor of behavioural change and attitude [26]. Social or interpersonal level gives considerations to social relations, environment, support, cultural constraints and the role of social mentoring [27]. The diffusion of innovations theory explains the manner of how new ideas, products or social practices spread among the members of society or from one society to another. Social innovation refers to the interconnected individual, social and community-based actions that emerge as a result of social needs of people, promote social relations among individuals and groups of peoples, and empower them [28].

Social acceptance approach in this respect provides tools for socio-political, community and market acceptance through social and behavioural interventions [29]. These may include a mix of measures to influence consumer behaviour in favour of sustainable energy consumption, using social networks, community leadership, encouraging positive emotional responses and regulations restricting consumer choice to the sustainable alternatives [30]. Longer term change occurs when a new behaviour is easy to perform, people have the right skills and resources, and that social circle is part of the drive [31]. This can come through the antecedent measures (information and advice on energy

saving), consequence measures (feedbacks, rewards and incentives), and social influence techniques (eco-volunteering and goal setting) [32], such as rewards, incentives and social marketing efforts by the energy value-chain including producers, distributors, suppliers and the government by means of quantified indicators and targets [33].

3. Requirements, Design, and Implementation

The proposed BEMS solution is built upon requirements resulting from state of the art presented in the background section and analysis conducted over five pilot public buildings in Europe (Netherlands and Spain). The five buildings are: a home for the elderly called the Forum in Eersel, a technical institution for students called the Haagse Hogeschool in Hague (HHS), an office block called the Media-TIC in Barcelona and, the BlueNET and PICA buildings, both in Seville. These buildings have a range of different users, architectural layouts, seasonal energy demands, and building control/building automation systems (BCS/BAS). Site visits were conducted which included interviews with each building's FM. This revealed information regarding how involved with energy management the FMs were. All FMs had a policy of checking and analysing meter readings on either a monthly, or bi-monthly basis. The Forum building FM had a much larger range of responsibility, having to monitor and manage energy consumption in 15 buildings, with the other FMs only monitoring one building. From a usability perspective, the time that these different types of users could be expected to invest in analysing a building, places different requirements on the developed solution.

The range of tools currently available to the FMs also varied for control and monitoring. Priva [34] was popular in the Netherlands (2 buildings used it) and EUGENE [9] in Spain (2 Spanish buildings). Other tools being used were the Regin Climate control [35], Colt Caloris [36], PlugWise [7] and Monovisa [8]. Each of these tools had differing capabilities and user interfaces. The proposed solution should, therefore, support similar capabilities without drastically changing the types of interactions the FMs are skilled in. When developing new energy efficient strategies, all of these tools required the FM to analyse the available data presented by the tool. They did not provide any intelligent analysis to identify energy waste. This resulted in the FMs relying mostly on using schedules to control building set points, based on best practices. Another issue uncovered was the level of sensing infrastructure across the buildings. In the pilot buildings, several sensors have been installed, for example, CO₂ sensors (e.g. in the HHS building) alerted the HVAC units that a room is occupied using a threshold for CO₂ levels, but could not provide any accurate indication of numbers of persons in an area/zone. The available motion detectors for turning on and off lighting (HHS, Media-TIC and Forum buildings) also provide little information on actual occupancy. Other sensor installations included temperature, humidity, and energy metering, but in some cases these only covered small areas of the building, for example, the PlugWise [7] installation in the Forum only

covered a couple of rooms. BlueNet, on the other hand, only measured energy consumption for each entire floor. The types of the sensed data, therefore, put limits on what can be achieved through data mining alone. To minimise the required investment in additional sensing infrastructure, a combination of data mining and theoretical rule generation based on the use of energy simulation was therefore explored. Bringing these different elements together requires integration of multiple heterogeneous data sources.

From this analysis, the following high-level requirements for the BEMS solution and interface were identified. These were to ensure that it be:

- **R1:** Usable by FMs to achieve energy savings in their building.
- **R2:** Built upon an integrated knowledge-base, so that the data can be accessed, reasoned over and presented to the FM to support energy management.
- **R3:** Scalable, so that it can be quickly deployed in new buildings with minimum costs associated (e.g. no new sensor installations).
- **R4:** Flexible and extensible, so as to support the types of functions of existing energy monitoring tools, but also support additional novel functionality.

Figure 1 gives an overview of the conceptual architecture of the BEMS solution. In the following sub-sections, each component is described briefly with reference to the numbers in the figure, before the user interface is discussed in detail.

3.1. Knowledge base and service integration

The knowledge base is the central integration component of the BEMS, integrating the heterogeneous data sources required and also providing the intelligence capabilities through reasoning over the rules and structures contained in the knowledge base. The Web Ontology Language (OWL) is used to represent the Semantic Model of the knowledge base to achieve a high degree of expressiveness. The ontology contains classes, relations among them, and definition of their properties, and is aligned to IFC to ensure interoperability beyond the solution. The alignment is done by defining explicit IFC-OWL mappings stored in the class annotations [37].

To apply the knowledge base to a specific building, the ontology is populated with instances corresponding to the objects in the building. It is considered essential for the energy management activities. Most current building layouts are drawn as two-dimensional sketches using CAD applications, such as AutoCAD, containing only geometrical primitives, such as lines, curves, points, etc. [38]. OntoCAD is an open source tool that extracts the semantic information of the sketch, populates an ontology with that information, and allows the user to validate the population [39]. The OWL model is then uploaded to a Fuseki RDF server [40]. Each building has its own instance of Fuseki. This data then becomes accessible to the other components using SPARQL queries. This

interaction is numbered 1 in Figure 1, which indicates that BuildVis can both query and update the knowledge base, either as a result of some action by a user, e.g. to query for a new suggestion, or periodically (at a minimum 5-minutes interval to reflect the data collection capabilities of the intelligent controller), to ensure that the interface reflects the changing state of the knowledge base.

The sensor and set points data are collected at a set time interval (minimum 5 minutes) to enable ‘near-real-time’ reasoning by the Intelligent Controller. The data is not stored in the Fuseki server, as RDF triples introduce performance overheads for large amounts of data. Instead, in the proposed implementation, it is stored in an SQL-database (interaction 8 in Figure 1), and referenced through the ID of the sensor which is found in the Semantic Model. Each sensor communicates with the Data Store via SQL updates. An application (e.g. the BuildVis interface) can then query the knowledge base to determine the ID of a sensor and other properties like its location. An application may then query the data store for the appropriate sensor values to enable monitoring (interaction 2 in Figure 1) or data mining (4 in Figure 1). In our implementation, this is done using SQL queries. SQL also provides some additional capabilities to run functions over data, such as returning the mean value over a set of data values for a particular time period. This supports BuildVis to display average measurements for a sensor in a particular zone, for a certain time period, configurable through the interface. The knowledge base also encompasses SWRL rules, generated automatically using data mining over the historical sensor data and simulated data. Each rule is equipped with a weight value in the range of 0 and 1 indicating the confidence of the rule. The Intelligent Controller may also reconfigure the sensors, BMS and actuators by adjusting setting in the data store, and through the use of listeners, which query the data store for these changes. This supports fileting of sensor data, adjusting the interval of sensor measurements, or adjusting set points.

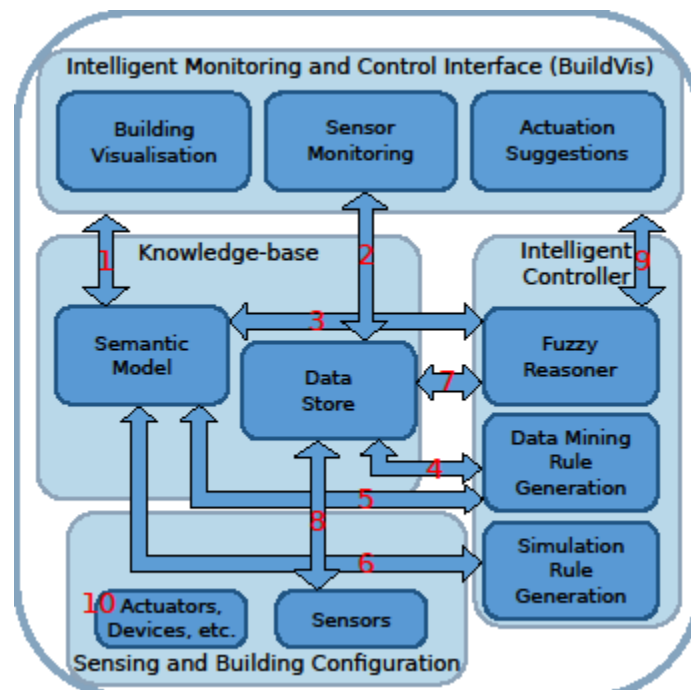


Figure 1. BEMS architecture highlighting the interactions between the different modules (numbers are references in text).

These rules are uploaded to the knowledge-base (via SPARQL updates) (Figure 1, interaction 5 and 6). The rules are then queried by the fuzzy reasoner together with the currently monitored state of the building to generate suggestions for the FM (interaction 3 and 4). The rules are activated depending on a request of the FM through BuildVis, e.g. provide me with suggestions for a particular zone based on a set of criteria, such as type of saving (energy, comfort improvement) and percentage of saving (10, 15, etc.). This is sent to the fuzzy reasoner, which selects the most appropriate and highest weighted rule (interaction 9). The weighting algorithm is necessary to filter a large number of rules generated by the data mining and theoretical rule generation engines. The selected rules are then visualised as a suggestion in BuildVis for the FM (interaction 9). Finally, the FM can then configure the buildings devices and systems based on the suggestion (interaction 10).

3.2. Data mining to generate rules from historical sensor data to support intelligent control

The rule generation process is highly complex and relies on either expert knowledge or using automated approaches to extract knowledge from datasets. Recent developments in the area of data mining provided promising opportunities to generate rules from datasets [41], [42]. Hence, in this study, data mining techniques have been used to extract rules from available historical data for the sensor based devices to determine correlations among them. The rules are then transformed into SWRL to integrate with the populated building specific ontology which in turn are then presented to the FM in an appealing manner. The extracted rules and equations set out to enable the following features to support energy management: (i) to predict the energy consumption of certain user activities, building zones (areas of the building defined in OntoCAD of particular relevance to energy efficiency), and appliances; (ii) to detect the energy consumption anomalies of user activities, zones, appliances, etc.; (iii) to detect user activities in building or zones based on gathered sensor data; (iv) to detect whether appliances still work properly by considering their energy consumption; (v) to identify building element states or configurations that meet certain comfort levels.

The necessary dataset to achieve the objectives is selected and stored in the data store. The dataset is an aggregation of sensor metering data, for instance, power consumption of building zones, inside and outside temperatures, light intensity, humidity, occupancy, and occupants' activities data. Those data were collected in five-minutes time interval for one year including all four seasons. Next, pre-processing steps are performed, such as cleaning, transformation, and discretisation. Only energy consumption data is discretised, in order to support classification and a rule generation which puts the energy consumption as the class attribute. Two data mining algorithms are implemented. The first generates linear functions for the energy consumption prediction using linear regression. These linear functions are then used to detect the energy consumption anomalies by considering the values from

sensor measurements. The algorithm only takes into account the numerical sensor values measured in a certain zone, i.e. temperature (x_1), humidity (x_2), and light intensity (x_3) as independent variables, and power consumption (y) as dependent variable, as shown in equation 1.

$$y = \beta_1 x_1 + \beta_2 x_2 + \beta_2 x_2 + \varepsilon \quad (1)$$

The second algorithm generates rules to predict energy consumption of appliances, zones, or buildings using a decision tree based classification algorithm by considering both numeric and nominal values, e.g. behaviour. The algorithm is based on M5 model tree developed by Quinland [43]. Equation 2 presents an example set of rules generated by the M5 model tree algorithm to predict the power consumption y , by splitting the tree node behaviour b .

$$y = \begin{cases} \beta_1 x_1 + \beta_2 x_2 + \varepsilon_1 & \text{if } b = 'office\ work' \\ \beta_1 x_1 + \beta_3 x_3 + \varepsilon_2 & \text{if } b = 'meeting' \\ \beta_3 x_3 + \beta_3 x_3 + \varepsilon_3 & \text{if } b = 'lunch' \end{cases} \quad (2)$$

In addition to the rules generated by this process, a second rule generation approach is also employed to generate simulation based rules which will be presented in the following section.

3.3. Simulation-Based Theoretical Rule Generation

The simulation based rule generation is used primarily to supplement the data mining rules, due to the likely occurrence of poor historical data availability in existing buildings. The proposed approach uses pre-processing to produce usable simulation data and to identify sensitive variables, which are followed by generating the optimized theoretical rules from an Artificial Neural Network (ANN) - Genetic Algorithm (GA) based solution. The proposed process is illustrated in Figure 2. The pre-processing module shown has three sub-stages of holistic scenario definition, thermal simulation model development, and sensitivity analysis stages. The scenario defines the objectives of the optimisation and the available control variables, their ranges, actors, and sensors. Sensitivity analysis and variable mapping determines the most sensitive variables, and maps them with the building's artefacts, as expressed in the semantic model. Next, ANN based learning is employed to generate the link between inputs (actuators, sensors and actors' info) and outputs (objectives defined in scenario definitions) which mimics the human brain's learning process regarding highly nonlinear systems, [3, 44]. After ensuring the correct ANN topology, this well-trained ANN is utilised as a cost function in the GA-based optimisation process to generate the optimised theoretical rules. GA is one of the most popular stochastic optimisation algorithms to find a near global optimum solution for the complex nonlinear problem [3], [45], [46]. The proposed approach uses set points defined in the scenario definition stage and utilises the genetic operators; mutation and crossover, to determine the optimised objectives as a single objective problem. The fitness evaluation is based on the minimum distance between the initial objective value and the desired optimum value which has been set to 0.001 for

each objective. If this condition is not satisfied in the fixed set number of iteration (1000000 iterations), then the rule will not be generated for the selected particular conditions.

Once a rule is generated, the distance information will be utilised as a consistency value/weight value by normalising them in the range of 0 and 1. The primary stopping condition of the optimisation is the target improvement decided by the FM based on the desired reduction levels (negotiated reduction level). The generated rules are presented to the FM through the Actuation Interface of BuildVis and negotiate an acceptable set of actuations. Then, by observing the actuations required, FM can either accept these (and enact the changes) or adjust the target, shown in Figure 1; numbered as 9th operation. The final stage of the theoretical rule generation process is the rule evaluation stage, which evaluates the rule consistency and similarity among the generated rules with a certain level (10, 20 or 3 percent). The idea is to eliminate the overlapped and duplicated rules for similar conditions. If more than one rule exists for similar conditions, then the highest weighted rule will be kept, the others will be eliminated.

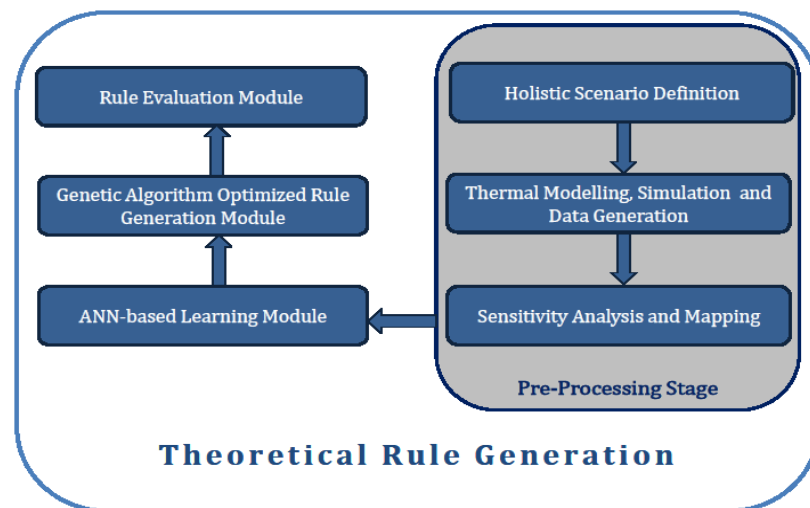


Figure 2. The proposed theoretical rule generation module.

3.4. Fuzzy Reasoner

The fuzzy reasoner module is one of the key modules in the architecture and it is the main interaction component between the knowledge base and the BuildVis interface. It selects the desired rules which are then displayed to the FM based on their configuration choices. Fuzzy logic is one of the most popular intelligent system techniques for dealing with the complex and uncertain problems using fuzzy sets theory, which mimics the reasoning process in the human brain [47], [48] and can work with incomplete data to find an appropriate solution in the proposed solution space. The fuzzy reasoner proposed consists of the following sub-modules: fuzzification module, rule engine, defuzzification module and rule selection module. The built environment consists of several uncertain variables which are mostly represented with the linguistic variables such as good thermal comfort

levels (in the range of -1 and 1), the temperature set point and humidity values (as low, normal or high). Further, there is no a straightforward way to demonstrate the relationship between the energy reduction level and the required set of rules at the BMS level due to the uncertain and complex relationship among the energy usage and the control variables. Further, usage of the linguistic variables between input and output variables provides a better understanding in the domain and generate a better reasoning among the variables. In the proposed fuzzy reasoning process, the optimised solution consists of thousands of rules for each energy reduction levels. It is not a straight forward process to choose rules for a certain level. A certain reduction level can be defined by the FM or the BuildVis user, however, the selection of an appropriate rule is an uncertain problem. Therefore, a fuzzy rule reasoning process is proposed to select the most convenient rule based on its weight. The weight is defined during the rule generation process as the accuracy of the optimisation process for the associated reduction level. Once a rule is selected by the fuzzy reasoner, it sends this selected rule as a recommendation to FM via BuildVis interface. The fuzzy reasoner is activated by the FM's request through BuildVis. When the FM's request is received, the fuzzy reasoner reads the last reading of sensors from the database. This input is then evaluated by fuzzification sub-module using the membership functions for each input to convert to fuzzy values. Each sensor input has three triangle membership functions to generate these fuzzy inputs according to the conversion given in equation 3, where μ_{V_k} is the membership value of the output variable and $\mu_{A_{mj}}$ is the membership value of the m .th input for the j .th membership function.

$$\mu_{V_k} = \min(\max(\mu_{A_{11}} \dots \mu_{A_{m1}}), \dots, \max(\mu_{A_{12}} \dots \mu_{A_{m2}})) \quad (3)$$

The next step is to use the fuzzy rule base to determine the rules to fire for the selected condition. These are selected according to the membership value for the fuzzified sensory information among the rules generated from ANN-GA based rule generation process, which is about 3000 rules. This rule-base consists of SWRL rules from the knowledge base; the antecedent part of these rules is the sensory information and the consequent part is the actuator set points. The last part of the fuzzy inference engine is the defuzzification process to determine the fittest control variable for the fired rules based on the weight of selected rules and equation 4.

$$V_{crisp} = \frac{\sum w_i \mu_V(Y) Y}{\sum w_i \mu_V(Y)} \quad (4)$$

In equation 2, w_i is the weight of i .th fired rule, $w_i \mu_V(Y)$ the membership value of the output Y .

3.5. BuildVis intelligent monitoring and control interface

BuildVis connects the ICT layers and FM interaction and therefore the interface must be user-friendly. Features that were identified early on during the development cycle of the tool were that it should provide:

- a. Visually and cognitively a means to identify and select different zones in the building,
- b. Energy usage feedback of zones,
- c. Suggestions to the FM on how to improve the efficiency of energy use of the zone.

For identifying and selecting zones, the visualisation of the building geometry is required. Due to the availability of only 2D models for the majority of the five buildings, the solution would need to work within this constraint. The OntoCAD tool is then used to model zones by their perimeters, a unique ID and also a name (e.g. a room name, to support identification by the FM). To support monitoring of data, each sensor is described. The sensor description includes details about the position of the sensor, what zone it is in and a unique ID. All generated sensor data includes a property for identifying the sensor it originates from. Combined with the date and time it is generated, sensor measurements can be accessed for a given sensor in a given zone. It should be noted that a number of discoveries during the formative and summative evaluations of another related tool [49] were incorporated into the BuildVis design. For example, many details stored in the ontology are hidden from the user to reduce the cognitive load and allow them to focus on their specific task at hand, e.g. monitoring and reducing energy consumption in the building.

So, in the case of a zone only its symbolic name (i.e. the room number) is provided in the interface and details like its geometric properties and other relations are hidden. Sensors are also displayed by type rather than ID, so that where a zone contains many of the same types of sensor, this data is hidden and only information related to the entire zone is displayed. This was as a result of the decision to divide the building into zones which may contain many similar types of sensors. So, a zone which contains many energy metering devices will still only give information about the entire zone's energy consumption and not provide data on each sensor so as to reduce the amount of information being displayed. The suggestions that are generated are also given a property which relates it to a particular zone.

Given this information, it is possible to query a suggestion by selecting a zone through the appropriate relation. The suggestions interface was kept simple in terms of the amount of configuration the FM is required to conduct, using slide bars for selecting percentages of energy savings, a calendar entry system for selecting dates for historical monitoring and also a large chart area to display historical metered data. A traffic light system was also integrated to provide quick feedback about the current energy consumption of the zone against the mean energy consumption. Finally, the WebGL building visualisation was given large control buttons to navigate the 3D

representation of the building, features also designed to make the interface accessible to mobile applications with touch screens. In the next section, it will be described in more detail the implementation of the BuildVis Interface.

4. BEMS BuildVis GUI Implementation

This section describes the implementation and main features of the front end graphical interface, shown in Fig 3. The BEMS BuildVis interface is implemented using a combination of HTML5, CSS, JavaScript and JQuery. The page layout is controlled by an open source front-end framework called Bootstrap [50]. The interface contains three main windows which can be displayed as required using the bootstrap ‘accordion’ feature. Figure 3, shows the the WebGL Building Visualisation Interface, and Figure 4 and 5 visualise the sensor monitoring and actuation suggestions interfaces, respectively.

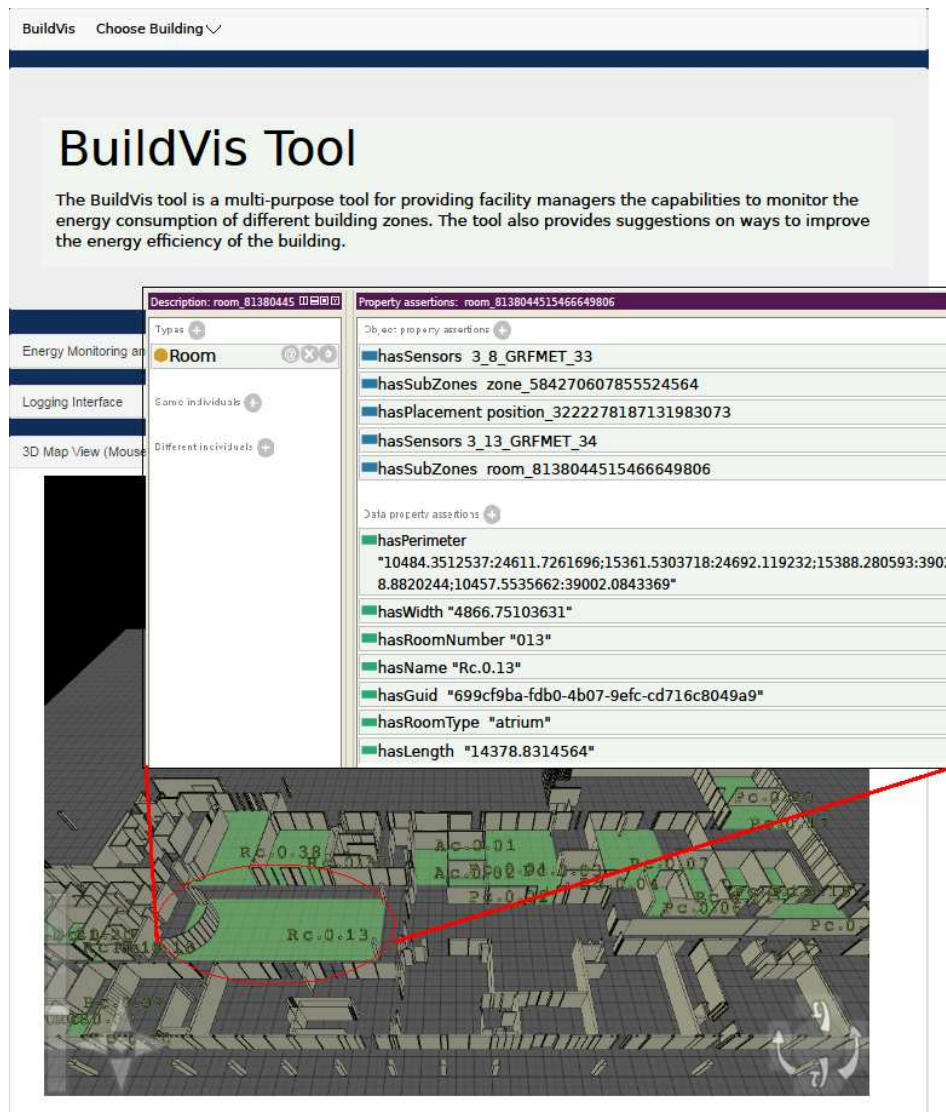


Figure 3. Overview of BEMS BuildVis interface.



Figure 4. Sensor monitoring interface.

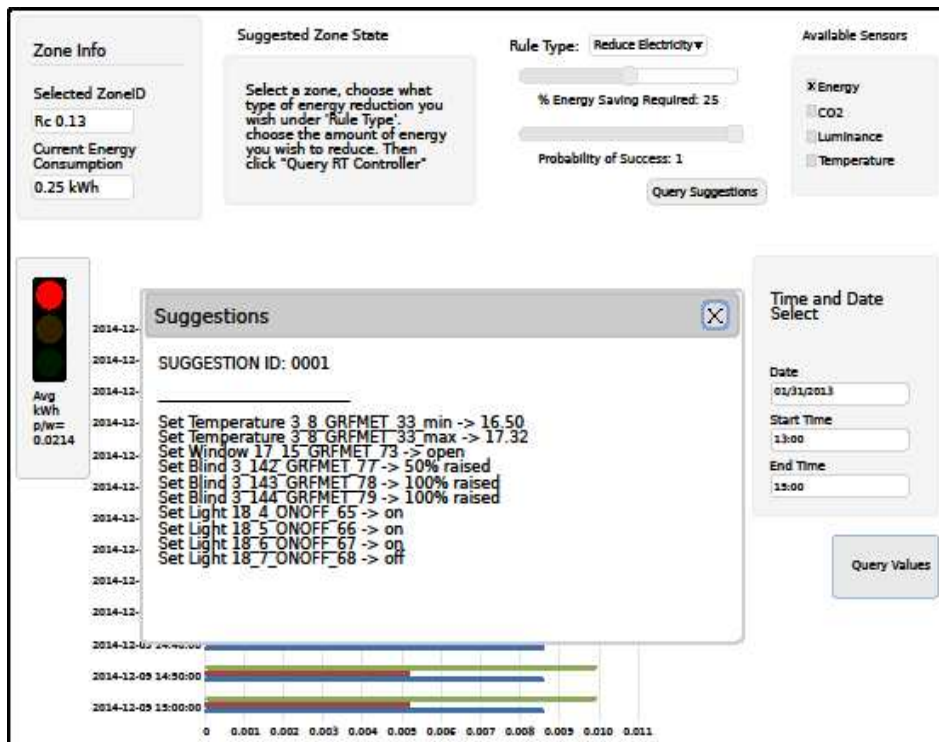


Figure 5. Actuation suggestions interface.

This feature allows the FM to open and close relevant panels, reducing clutter on the screen and allowing the FM to focus on the particular task in hand. For example, navigating the building floor plan or monitoring the energy consumption of a zone. This approach also has the advantage of

being suitable for mobile applications where the screen space is at a premium. The interface also has a menu ‘Choose Building’, so that the FM can select different buildings, if they are responsible for more than one.

4.1. Communication between BuildVis and knowledge base

The knowledge base stores all the data about the building and its systems relevant to the BEMS. To enable visualisation of the building floor plan, an existing 2D DWG file is parsed and converted directly into RDF and stored on the Fuseki server [51]. The OntoCAD tool is used to identify zones in the building and add additional data regarding, for example, sensors. The BuildVis interface queries the ontology using a combination of AJAX (Asynchronous JavaScript + XML) and SPARQL (Protocol and RDF Query Language) [52].

On opening BuildVis in a browser, several SPARQL queries are made to the Fuseki server, one of which returns JSON objects which are then used to store a 2D array of JavaScript zone objects, which describe each zone in the building. The simplified query in Figure 4 is enough to display the zones graphically. The “hasPerimeter” property defines the position of each corner of a zone. In this case, four corners. As this is a string, it must be parsed client-side to extract points. These are used to display the zone graphically and also for point and click selection. The property “hasName” is used to tag the zone with a name the FM will recognize, to easily find it in the WebGL view. The zone also has other properties, such as “hasSensors”, which is required by the Monitoring Interface, described next.

4.2. Monitoring interface

In Figure 6, the Sensor Monitoring Interface is illustrated. It has the following features: On opening BuildVis in the browser, the ‘Available Sensors’ window displays all the available types of sensor in the building giving an overview of the different types available. No other information is displayed until a zone is selected, at which point only the sensor devices in that zone are displayed. On the top left of Figure 6, ‘Zone Info’ is displayed, and on the right, the sensor types related to this zone, i.e. ‘Energy’, ‘CO2’, ‘Luminance’ and ‘Temperature’, are displayed. The FM has the capability of selecting one or more of these by ticking the box to view its historical readings. These are displayed in the Chart at the bottom, and the time period is selected by the ‘Time and Date Select’ box on the bottom right to enable filtering. Here the energy data for the selected zone is presented. Likewise, Temperature and CO2 can be viewed either independently, or together if the FM wishes to compare the relationship between their values. The historical sensor data stored in the SQL database is queried using a combination of AJAX and PHP server-side scripting language. The PHP handles the query to the SQL database.

```

prefix kno:
<http://www.semanticweb.org/ontologies/2012/9/knoholem.owl#>
SELECT ?zone_name ?x_coord ?y_coord ?perimeter
WHERE
{?zone<http://www.w3.org/1999/02/22-rdf-syntax-ns#type>
<kno:Zone>;<#hasName> ?zone_name.
?zone <kno:hasPerimeter> ?perimeter.
?zone <kno:hasPlacement> ?sym.
?sym <kno:hasXCoord> ?x_coord.
?sym <kno:hasYCoord> ?y_coord.}

```

Figure 6. An example of a SPARQL query.

The ID of the JavaScript sensor object corresponds to a column heading in the SQL database for that sensor, along with other properties like date and time to enable queries. SQL was chosen for managing sensor data due to the speed at which it can handle queries for large amounts of historical data and as triples requires more storage capacity. It should be noted that where more than one sensor of a particular type exists for a zone, some post-processing is currently done and the arithmetic mean value is given for all the sensors of the same type (e.g. only an average temperature of a zone). This is to reduce the complexity of what is presented to the FM. On the top left under ‘Zone Info’ the current energy consumption of the zone is displayed. Together with the historical energy consumption of the zone, the traffic light on the left centre gives an indication if its energy consumption as higher, lower or the same as its mean energy consumption, highlighting, in a simple way, potential unwanted energy consumption. In Figure 4, the current energy consumption of 0.0029kWh is lower than the average of 0.0749kWh, and so, the traffic light displays red. SQL also supports the selection of all values greater than zero, and also returns the arithmetic mean value. This query is used to compare then with the current energy consumption to derive this comparison.

4.3. Action suggestion interface

The actuation suggestion interface brings together all the elements of the BEMS solution described in the previous sections to provide periodic suggestions regarding how the energy efficiency of the building may be improved. The suggestions are derived from the data mining and simulation rule generation. The generated suggestions can be filtered dependent on certain criteria. The FM configures these criteria using drop down menus and slider bars (Figure 5), generated by jQuery selectors. Once they have selected a zone, chosen the rule type (e.g. reduce electricity consumption) and moved the slider to the required energy saving (e.g. 20%), they press the ‘Query Suggestions’ button. This returns a suggestion which recommends a number of actuations, for example, adjusting the blinds, turning lights on and off, etc. This is achieved using AJAX and SPARQL queries to the knowledge-base. The suggestions can then be acted upon by the FM, or ignored. If the FM chooses to make the changes recommended, he/she must also log those changes through a simple logging interface. The FM simply types the suggestion ID into the ‘Log Data Entry Window’ and/or additional notes inclusion. This data can then be used to analyse the consequences of the actions taken. In the next section, the evaluation of the level of usability of the BuildVis solution is presented.

5. Evaluation of the Level of Usability of BEMS BuildVis

This section presents the usability evaluation of the BuildVis Interface of the BEMS solution. The methodology for the evaluation is based on the state of the art methods for assessing usability and has been applied in two previous usability assessments [49], [53]. This consists of both formative and summative evaluations. Formative evaluations are conducted during the development of a product; they are done to mould or improve the product. Outputs of formative evaluations may include participant comments (attitude's, sources of confusion, and reasons for actions) and other usability problems and suggested fixes determined through observation. In contrast, summative evaluations are carried out at the end of the development stage.

They set out to measure or validate the usability of the product. They look at comparing usable metrics and generating data to support claims about usability. Outputs of summative evaluations may include statistical measures of usability, for example success rate, the average time to complete tasks, the number of errors and/or number assists. The evaluations are structured upon Common Industry Format (CIF). A CIF usability report must include; a description of the product/model, the goals of the test, the test participants, their background and the tasks they are to perform, the method by which the test was conducted, the experimental design of the test, the usability measures and the numeric results and analysis [54].

The metrics of the evaluation are taken from Sauro and Kindlund [55], who have created a quantitative model of usability based on the ISO 9241 standard, resulting in four metrics [55]. These are time to complete tasks, a number of errors, whether a task is completed and the average satisfaction of users. User satisfaction is measured by using the System Usability Scale (SUS). SUS is a simple ten-item scale giving a global view of subjective assessment of usability. The statements in SUS are chosen to identify extreme expressions or attitudes. SUS also provides a point structure to assign to the answers of a particular test which rates overall satisfaction between 0 and 100. Bangor et al. [56] suggest that a score in the seventies should be deemed acceptable, and those below still have usability issues of concern. With respect to the number of participants required to find all potential problems, this may vary according to the users, the tasks, and the system under test. At least a range between five and fifteen is required to evaluate sensitive parameters as depicted in [57], [58].

The summative evaluation of the BuildVis tool is divided into two parts. The first part evaluated users with backgrounds in computer science, engineering, and related fields. This was purely to assess the usability of the tool for technically proficient users and to identify errors to determine if it was ready for use by the FMs. The second part looked at each of the FMs for the five buildings to assess usability for the targeted users of the tool.

5.1. BuildVis evaluation based on the background knowledge

5.1.1. Goal, participants, and backgrounds

The goal of this experiment is to assess the level of usability of the BuildVis tool for users with technical backgrounds when conducting typical tasks related to the BEMS. Nine participants took part in this experiment, all members of the Knowledge and Data Engineering group in Trinity College Dublin. The pre-questionnaire asked them to name their role within the group. This broke down as follows: six computer scientists (three of which also classed themselves as researchers, and one of those three also as an engineer), one educational technologist and two researchers (specific field not specified). The interface had already undergone iterative testing in previous experiments related to a specific feature of the tool (the activity modeller [49]) in which 45 participants took part over three evaluations (two formative and one summative). Therefore, the number was considered a sufficient number for initial testing of usability of the tools features, which were already considered robust at this stage. None of them had used any energy management software in the past. They were also asked about how comfortable they felt using their web browser with two agreeing and seven strongly agreeing. 8 of the participants used chrome with the remaining one using Firefox. They all used windows, with three using Windows 7, five using 8 and one not specifying the version.

5.1.2. Experimental description, tasks description, and technologies

The experiment set out to determine the level of usability of the BuildVis tool when used by technical users in order to identify usability issues related to the interface design. The evaluation was achieved by presenting the participants with four tasks (below) which relate to typical uses of the BuildVis interface:

1. Navigating the 3D building floor plan.
2. Selecting a zone in the building and monitoring sensors related to energy consumption metering.
3. Enacting suggestions from the real-time controller.
4. Logging information regarding changes made to the building configuration related to those suggestions.

The technologies employed are presented in the previous implementation section.

5.1.3. Findings

The average time to complete the tasks was 20.6 minutes with a standard deviation of 7.8 minutes (Figure 7). The SUS scored 73.9. Figure 8 gives a breakdown of the SUS questionnaire. The participants were also asked ‘Would you like to see additional features (give the features)?’ and to provide any ‘Further comments’. The following three suggestions for additional features were given: ‘Moving the 3D map back to the original position in one click.’, ‘3D Map views easy to navigate but I

would have preferred having both the map and the energy monitoring information in view at the same time (e.g. side by side).’, ‘In the 3D map, all zones were coloured in green (dark green for all and light green for the selected one). My interpretation of the green colour would be that all zones were ok and below average in energy consumption. It would be good to show ones that were above average in yellow/orange/red colour on the 3D map’. There were no significant errors during the course of the evaluation.

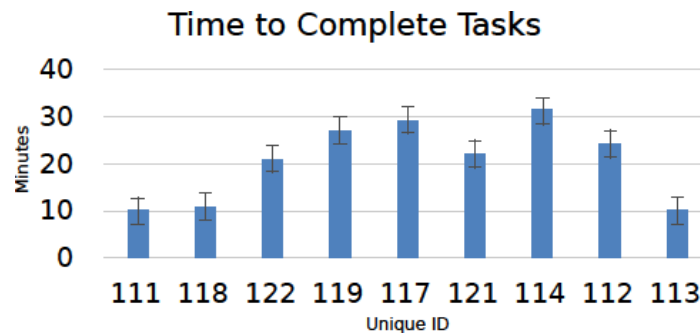


Figure 7. Time to complete tasks with error bars, average response to SUS questions.

5.1.4. Interpretation of Findings

The target participants were all in fields related to IT and so the majority felt confident using their web browser. None of the participants had experience with building or building energy management software. Therefore, their ability to judge the usefulness of the tool with respect to energy management was assessed based on the participant task completion time. According to the observation, all the participants completed the tasks in times ranging from 10 to 31 minutes, with the average time of 20.6 minutes and a standard deviation of 7.8 minutes. This time also included the answering of the post questionnaires, which we roughly estimate would take between 3 and 8 minutes. Nonetheless, it places the average time below twenty-five minutes. It was anticipated that this was an acceptable amount of time to expect an FM to use a BEMS tool for the first time, when examining energy consumption for a zone, and assuming that with time, their proficiency would improve, and they would require less time to complete these types of tasks.

The SUS score of 73.9 is positive for a first evaluation; giving it a ‘C’ grade. This may reflect the nature of the participants, who due to their backgrounds would be familiar with these types of interfaces. The majority of the SUS responses were indicative of positive experiences (with respect to the usability), with many being on the far ranges of responses e.g. four strongly agreed that they ‘felt very confident using the system’ and another two strongly agreed they ‘thought the system was easy to use’ (Figure 8). In the latter case, it should be noted that even though all responses were positive, the difference between even the positive responses (5 agreeing and two strongly agreeing) suggest a noteworthy difference in opinion and as such improvements can be made. Due to the complexity of the problem, though, it may always be the case that there will be some tasks which are less than easy.

This fact, perhaps, is reflected in the one disagreement and one neutral with that statement. The same distribution of responses can also be found in the statement ‘I would like to use this system frequently’ which is a key requirement of the energy management software, and so again, improvements are required. It should also be noted, though, that the neutral and disagreement with the statement ‘I thought the system was easy to use’ both spent only 10 minutes completing the tasks and post questionnaire, and so, we believe this may have influenced their perception of its ease of use.

The application specific questions revealed that while the navigation of the map was not challenging (3 strongly agreed and five agreed), the number of neutral responses which found that ‘selecting a zone was easy to do’ (6) is of concern and future implementation need to improve this score. The participants felt strongly that the use of the historical data for energy management was a useful feature (5 agreeing, three strongly) but due to their backgrounds, they may not be truly able to assess this functionality. 3 of the participants were neutral with the statement ‘The suggestion to improve the energy consumption of the zone was easy to understand’ and six agreed. 2 participants disagreed (1 neutral) that they would use the suggestion interface frequently. These findings are also of concern considering the importance of this feature. Specific feedback was also very helpful. The comment regarding the colouring of zones on the map is something to consider definitely for future implementations, as the green colour of the zone may give the false impression that the zone is functioning correctly. Also, the addition of more visualisations may aid analysis, and this is something we are already considering. A reset button for the 3D map is also a useful feature and will be added in future implementations. The usability of the BuildVis FM interface was considered a success. There were no serious issues which caused significant errors. The time to complete the tasks and the SUS score of ‘C’ grade is acceptable for the tools first evaluation. It was therefore decided that the tool could be deployed to the Facility Managers for each of the five buildings.

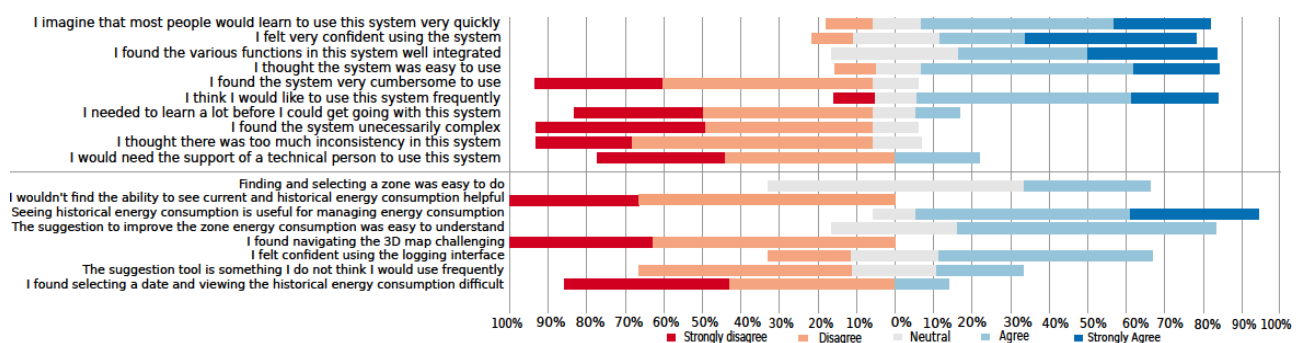


Figure8. Evaluation 1 SUS and specific tool responses as percentages.

5.2. BuildVis evaluation based on the target user

5.2.1. Goal, Participants, and Backgrounds

The goal of this experiment was the same as previous; the difference being that the participants were the five FMs for each respective building. It was essential to use only these five, as they each required knowledge about the building floor plans, the different areas, devices and their behaviours etc.

5.2.2. Findings

The average time to complete the task was 13 minutes with a standard deviation of 4.24 minutes. There was one significant error for participant 144 who had difficulty accessing the URL for the BuildVis tool which was made available after the completion of the pre-questionnaire. This also meant that we could not get an accurate time for completion of the tasks. The SUS score was 59.5. Figure 9 gives an overview of the responses. The participants were also asked the same follow-up question as the previous evaluation. The only following suggestion for additional features was given: ‘As an additional feature, it is useful to display system information (data) continuously in the time in order to see the evolution of the taken decisions during the time (or by indicating a starting point). Another useful feature is to show system alerts when an inefficient strategy (or anomaly) is appearing in a certain zone.

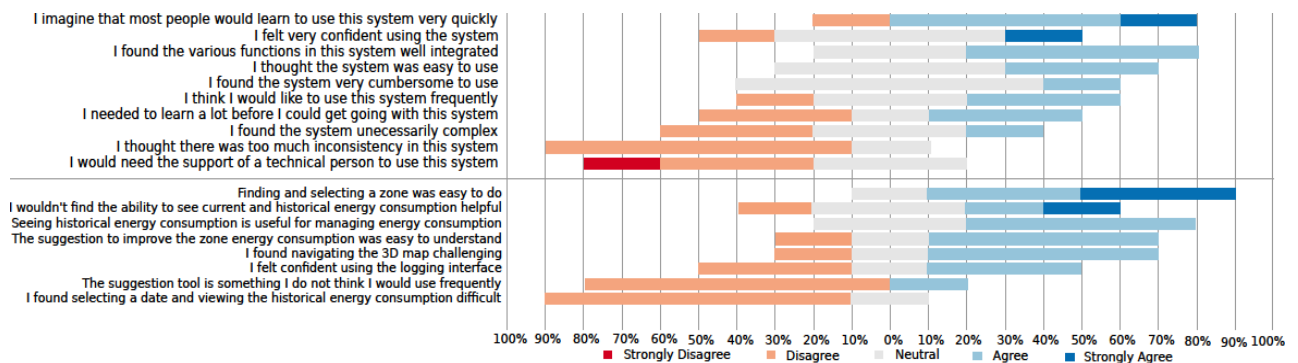


Figure9. Evaluation 2 SUS and specific tool responses as percentages.

5.2.3. Interpretation of Findings

The tasks themselves were completed by all FM's and no significant errors were reported in using the BuildVis Tool. The tasks were completed (taking into account the post questionnaire) in an average of 13 minutes, with a standard deviation of 4.24 minutes. This time is well within twenty-minutes time taken in the previous example, and this is a promising result, taking into consideration the constraints on time the FM's have to devote to energy management. The SUS score of 59.5 is

below an acceptable range, according to the scale by Bangor et al. [56]. This means that the tool still requires development to be considered usable for FMs. This being said, for a first live evaluation, there are many positives to be taken from the responses given to the SUS and specific tool features questionnaires. For example, the majority of answers to the question ‘I imagine that most people would learn to use this system very quickly’ (3 agree, 1 strongly agree) indicates that the FMs felt the tool was something over time they would be able to use. The majority also felt that the functions were well integrated (3 agreeing) and disagreed with the statement ‘I thought there was too much inconsistency in this system’ (4 disagreeing).

The majority also disagreed on whether one would ‘need the support of a technical person (2 disagree, 1 strongly disagreed). On other important questions though, for example ‘I thought the system was easy to use’ had too many in the neutral (3 neutral, 2 agreed). Also, with the statement ‘I needed to learn a lot of things before get going with this system’ (2 agree, 2 disagree, 1 neutral) and ‘I felt confident using this system’ (3 neutral, 1 disagree, 1 strongly agree) shows that the FMs may still feel that there are aspects of the system that they still do not fully understand.

6. Discussion and Conclusion

This paper presented a Building Energy Management Solution (BEMS) for addressing the issue of providing intelligent control suggestions to facility managers who must enact energy saving strategies in buildings whilst keeping the cost of installation of new equipment (e.g. sensors) down. The solution makes use of Building Information Modelling and Semantic Web technologies to integrate buildings, sensors and actuation infrastructure, and intelligent software components. These components encompass Artificial Neural Network (ANN) and Genetic Algorithms (GA) combined with simulation models, rules generated using Decision Tree techniques over historical data and an intelligent controller. The intelligent controller generates ‘suggestions’, based on the sensor measurements in the building. The suggestions are presented to the facility managers through a 3D interactive web interface called ‘BuildVis’. The BEMS solution does not require any additional installation of sensor deployments in a building and the use of a hybrid approach to rule generation eases its integration into a wide set of potential buildings. The data mining algorithms do require that access is made to the different sensor data and set points in the building. Overall, the solution is referred to as ‘intelligent’ as a reference to its artificial intelligence characteristics, wherein the software components demonstrate a human-like agency, within the bounded BEMS problem space, which are the ANN-GA rule generation, the fuzzy rule engine, and the semantic knowledge base, which each mimic aspects of human cognition, and the GUI then leverages towards business value. Here, the most crucial issues are related to the different protocols for building control systems.

The use of Semantic Web technology and machine learning technique allows a simple replication of this work in any projects utilising BEMS to help facility managers or building owners to monitor

and control the energy consumption in their buildings. The knowledge base contains a level abstraction model describing the BEMS that is independent of technologies or application model developed by the BEMS vendors. Therefore, it is not necessary to change the model to apply this work to other buildings that have different BEMS technologies. The machine learning algorithms generate suggestions based on the building condition learned from the historical data. Therefore, if this work is implemented on another building, the generated suggestions will always correspond to the context of the building. However, some efforts are still required to uplift data into the knowledge base, for example, to use OntoCAD and to input the user activities.

Ongoing research is, therefore, now required towards the iterative improvement of the system. As Web of data and Internet of Things technologies are making the integration of wider sets of data with the intelligent solutions a reality, new opportunities arise to generate new insights into energy efficient building behaviour. With these new open technologies, come new challenges, related to related to; standardisation, data interdependency, data access and security [1]. These issues must be explored over a range of building types.

Finally, the evaluation has demonstrated that while technical users had no difficulty using the tool, there are still issues related to the usability of the tool for its target users, FMs. Although the number of FM participants for the final evaluation was small (5), their background means that their results are of particular relevance to the system and are indicative of the types of challenges facing developers of BEMS. The SUS score of 59.5 demonstrates that BuildVis requires improvement. The main issues are related to the difficulty for FMs interacting with the tool.

A number of good suggestions have been made on how to improve this interaction, and these will be implemented and tested in future versions. For example, colouring zones according to their energy consumption levels in relation to their mean values to quickly alert them when energy wastage is occurring across the building. Also, the use of pop-up alerts to notify the FM when a new energy saving suggestion is made. This type of feature could also be integrated into a mobile application, such as a tablet or smartphone so that they can be alerted in the field. The user may then use this mobile app to analyse the suggestion and make adjustments and re-configuration as needed. Other features which are of interest for exploration are the use of a wizard or a walkthrough video to help and inform the FM with tasks. Also of importance is to begin the localisation effort, so that multiple languages are supported by the tool.

In conclusion, the lack of significant errors when interacting with BuildVis, shows that the developed BEMS is now robust. This combined with the low average time to complete tasks, can be taken as positive results from the usability evaluations and indicative that such a solution has the potential to provide FMs with much-needed support for identifying energy wastage scenarios. The experiences in developing this solution and evaluating its usability also provide much-needed insights

into the issues for those wishing to develop similar solutions and the challenge of engaging its target users.

7. Acknowledgment

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