Knowledge-Based Holistic Energy Management of Public Buildings

S.K. Howell[1], Y. Rezgui[1] and B. Yuce[1]

[1]BRE Institute of Sustainable Engineering, Cardiff University, Queen's Buildings, The Parade, Cardiff, CF24 3AA, Wales, UK

ABSTRACT

Much recent work has been conducted towards reducing the energy consumption of mixed mode buildings through rule-based automation. This paper presents a novel rule generation methodology, through the simultaneous use of historical sensor data and theoretical models. The theoretical rule generation methodology will be explained, encompassing the development of an energy model to the inclusion of rules within the building specific ontology. This will include the development of use-case scenarios, their refinement through a sensitivity analysis and the generation of rules through an artificial neural network embedded evolutionary optimisation algorithm. Following a review of relevant literature, the methodology will be contextualised within the architecture of the KnoholEM project and applied to the first demonstration object; a mixed use public building in the Netherlands. An example of a rule generated will then be presented and the system will be considered within the existing solution space before comments regarding future developments.

INTRODUCTION

Efforts are increasingly being made to promote sustainability in the built environment through the reduction of energy consumption in buildings. This paper will focus on the use of automation rules to reduce the energy consumption of public buildings. Current approaches typically utilise either an empirical or theoretical methodology towards rule generation, whilst literature supports their combined use. The hybrid methodology presented aims to produce accurate and contextualised rules for use within the knowledge base of the KnoholEM project.

The understanding and prediction of a building's complex behaviour involves many systems and sub-systems, and can only be approached by considering the building as a holistic entity (Dibley et al 2012). This underpins the KnoholEM project, whereby actuation and sensing systems within a building are integrated and improved so as to enable optimisations through the consideration of system interactions.

Following a review of the literature, this paper will present the KnoholEM system architecture and explain the role of both the empirical and theoretical rule-bases. This will be followed by a detailed description of the theoretical rule generation process; including the energy model and scenario development, sensitivity analysis and finally the use of an artificial neural network embedded evolutionary optimisation loop. The presented methodology will then be discussed within the current solution space and the potential for future work identified.

RELATED WORK

Much work has been conducted in recent years towards the purpose of adding intelligence to combined building automation systems (BAS) and energy management systems (EMS). This review will consider two approaches and argue the need for a third, hybrid approach. Much work an empirical standpoint by analysing historical data to determine optimisation rules. Other studies model a building but lack the contextualisation of historical data. The use of a hybrid approach aims to deliver more accurate and relevant navigation of the decision space.

Regarding the empirical approach, Kolokotsa et al (2002) utilised genetic algorithms to optimise a fuzzy controller. Doukas et al (2007) developed an "integrated decision support model" through rule sets generated from sensor data. More recently, Ferreira et al (2012) utilised an artificial neural network (ANN) to optimise thermal comfort and energy consumption based on sensor data. Also, a BAS has been utilised with a graphical interface and control scenarios to optimise energy consumption and sensor values (Marinakis et al 2013). Aspects from each of these approaches are incorporated into that which is presented here.

An alternative approach to those presented above is to generate optimisation rules from a theoretical model; either a computer based energy model or some form of mathematical model. This is not a new concept; Clark and Mehta (1997) utilised a mathematical model to optimise start-stop cycles in a building. However, recent approaches to modelling mixed mode buildings (Spindler and Norford 2009, Spindler and Norford 2009, May-Ostendorp et al 2011, Hu and Kavara 2014) are able to exhibit greater accuracy. Model-predictive control (MPC) has been used with EnergyPlus (May-Ostendorp et al 2011). Similar to the approach presented, an energy model has been embedded within a stochastic search method (Hu and Kavara 2014).

The approach presented herein attempts to utilise both the holistic, 'big data' nature of simulation models and the real-world applicability of historical data. This is supported by Foucquier et al (2013), who state that hybrid models offer the advantages of both approaches.

METHODOLOGY

The methodology presented here attempts to build on recent work in the field of EMS-BAS optimisation through a semi-empirical rule generation process. Figure 1 below outlines the overall workflow of the KnoholEM project.

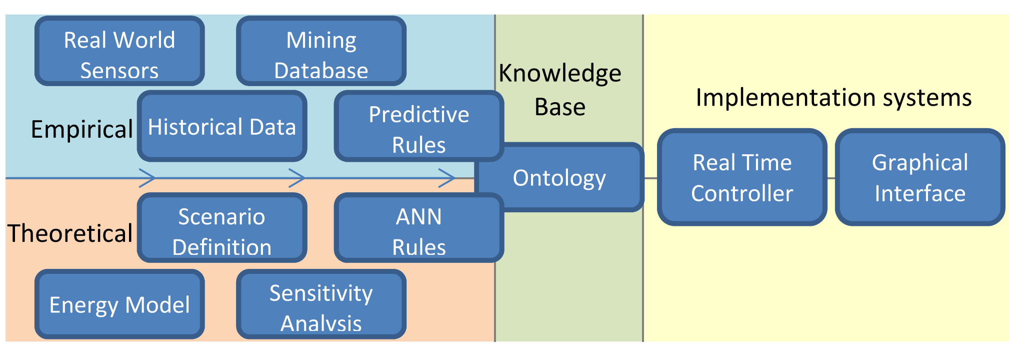

Figure 1. Flow of knowledge from generation to delivery to end user

Figure 1 shows 4 distinct sections; empirical and theoretical rule generation, an ontological knowledge base and implementation systems. The implementation systems include a fuzzy logic real time controller (RTC), a graphical user interface (GUI), a mapper and building-specific systems. Regular, automatic revisions of the rules allow the system to be dynamic. The system architecture is presented in figure 2 and shows information exchange between the various components, whereby the simulated and metered data are utilised together within the knowledge base.

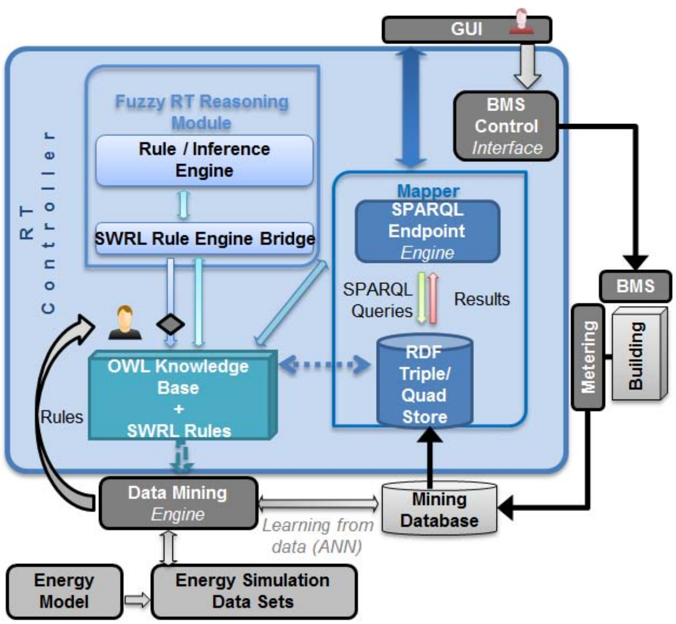

Figure 2. KnoholEM system architecture

ENERGY MODEL

An energy model of the building was developed in DesignBuilder. Starting with the geometry of the building, this was then enriched with data such as materials and occupancy schedules; these were described in detail for zones where questionnaires had been completed. This produced the model shown in figure 3 below, alongside a plan of the floor within the scope of the project; the main zone considered was the 3 storey atrium shown.

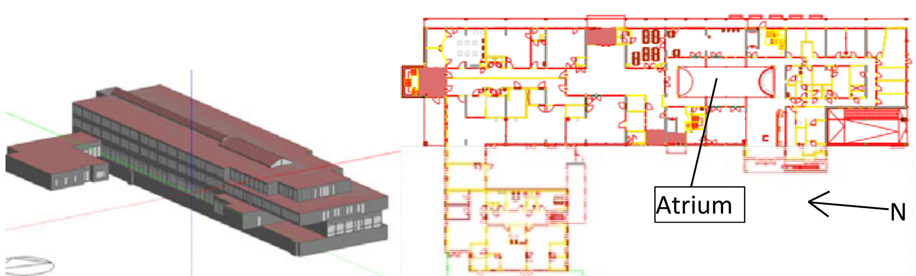

Figure 3. Energy model of demonstration building and floor plan

This model was then exported into EnergyPlus, which was the chosen simulation engine due primarily to its textual nature; this meant its inputs and outputs were machine readable, allowing automation of data generation and post-processing.

Before the completion of the energy model, it was necessary to ensure each of the intended actuation mechanisms was adequately represented. To this end, 4 variables were mapped from the scenario definitions; heating setpoint of the atrium zone, natural ventilation availability, actuation of the shading system and the activation of lights. Each of these variables was binary apart from the heating setpoint, which was limited to the range of 16°C - 26°C.

SCENARIO DESCRIPTION

In order to contextualise the theoretical rules, it was deemed necessary to utilise scenario-based optimisation of the building. A scenario was considered to be a formal definition of an identified mechanism by which energy consumption in the building might be reduced whilst maintaining occupant comfort. Scenarios are building specific and are dynamic; whilst they are proposed from expert knowledge, they are refined through the sensitivity analysis.

Four scenarios were defined within a template and were considered holistically. Firstly, it was recognised that cooling loads could be reduced through intelligent use of the roof windows in the atrium. Secondly, the existing shading system was integrated to a holistic EMS solution to account for the effects of solar gain as well as just luminance. Also, the implementation of presence based electric lighting and radiator actuation was considered in conjunction with other methods of lighting and heating the atrium zone. The 'presence based lighting' scenario is presented below in table 1.

Table 1. Presence based lighting scenario definition

Scenario	Scenario 3 – Presence based lighting
Scenario Description	Currently significant amounts of energy are wasted lighting unoccupied areas of the building. Through the introduction of presence sensors it would be possible to almost eliminate this energy wastage. By simultaneously considering lighting's effect on luminance and temperature, a holistic optimisation may be achieved.
Control Variables	Lighting state (on/off)
Variables	Occupancy Current light intensity Shading (on/off) Air temperature
Controls and Rules	Some areas must have a minimum luminance as is written in the Dutch building regulations.
Actors	BCS, occupancy sensors, temperature sensors, shading system, light automation system, facility manager and technician
When Applicable	Always, unless extended periods of vacancy are expected in a room. An override switch would be needed in this instance.

SENSITIVITY ANALYSIS

A sensitivity analysis was conducted in order to refine the scenario definitions. This utilised principal component and multivariate regression analyses to quantify the effect of each variable on the behaviour of the simulation model. This allowed a balance to be achieved between simplicity and accuracy, as indicated by Ferreira et al (2012).

Principal component analysis determined that 38 input variables was the minimum number required to explicitly predict the outcome of the simulation. Multivariate regression analysis was then used to quantify sensitivity to each of the input variables. The 38 most sensitive variables were used as the input variables for the ANN model. Figure 4 below shows the sensitivity of the model to the 8 inputs found to be most sensitive regarding each of the 4 performance indicators; heating energy, cooling energy, total electricity and occupant comfort (Fanger 1970).

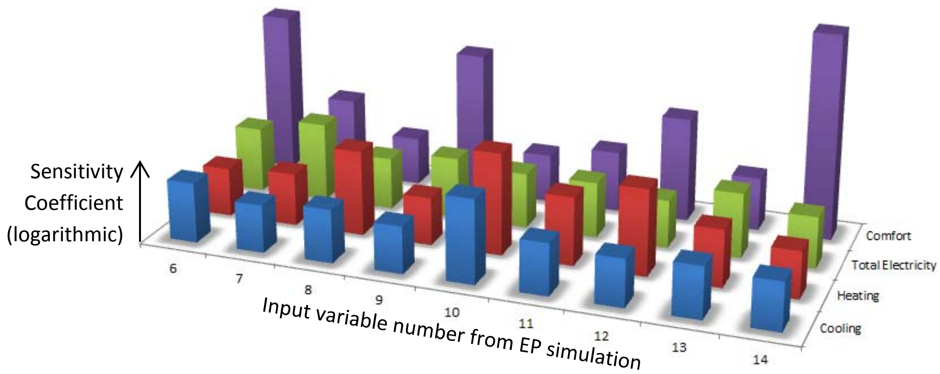

Figure 4. Sensitivity results regarding the most sensitive common variables

ARTIFICAL NEURAL NETWORK EMBEDDED OPTIMISATION

An ANN model was developed in MATLAB to replace the simulation model due to its speed as a prediction engine, and as the decision space was clearly defined. This allowed the ANN model to act as the cost function within an evolutionary optimisation method. A multilayer perception based ANN model was utilised with the Levenberg-Marquardt learning algorithm (Levenberg 1944, Marquardt 1963), using the topology presented in figure 5 below.

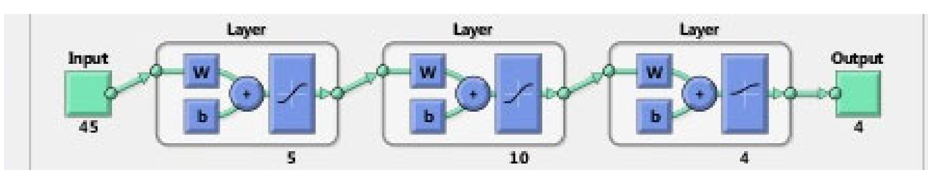

Figure 5. Topology of the proposed ANN

Genetic algorithms were utilised to provide a stochastic search method through the decision space. The termination condition of the GA loop was based on the input from the FM; the rules generated aimed to reduce the energy consumption by 5, 10, 20 or 30 percent. Logical 'if-then' rules were produced which dictated the actuations required to produce the desired change in building performance. An example of one of the large number of rules generated is presented below in figure 6.

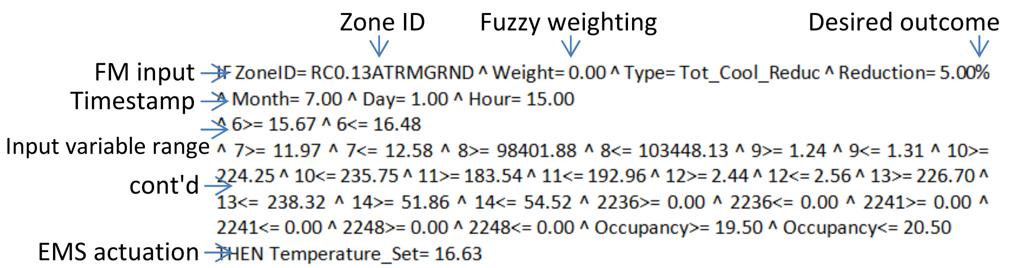

Figure 6. Example of rules generated from ANN-GA optimisation

ONTOLOGICAL KNOWLEDGE BASE

The ontological knowledge base was developed to contain all domain specific information for the KnoholEM project (Krahtova 2013), through building specific instances of a generic domain ontology. The population of the building specific ontology is represented in figure 7 below.

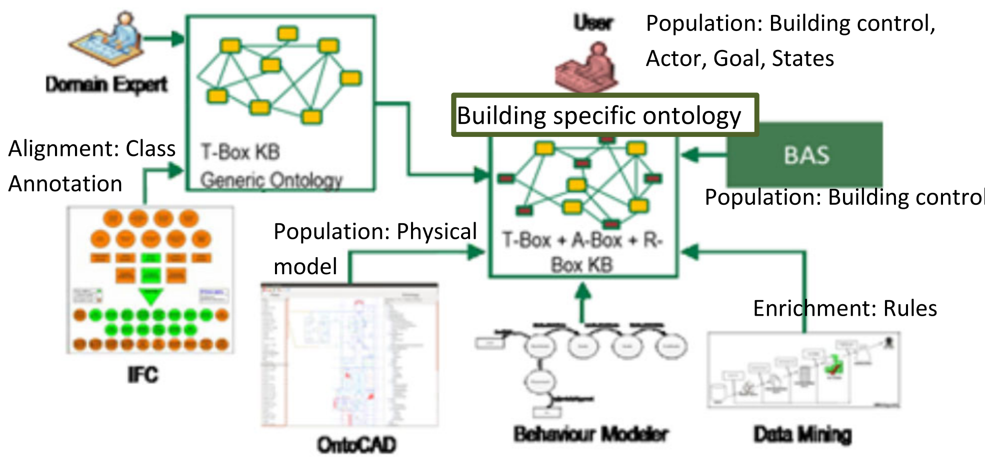

Figure 7. Specific building ontology development

The ontology is queried by the FM through the GUI by stating optimisation goals. The ontology utilises the rules available to achieve the desired goal and reports the rules to be implemented and their effect on relevant performance indicators.

DISCUSSION AND CONCLUSION

This methodology has detailed the production of energy optimisation rules using a theoretical approach. The rules generated via this methodology are embedded in an ontological representation of the building they are specific to and are routinely updated based on feedback via the installed sensors. An area of future development would be to embed the rule generation process itself into the ontology, such that rules could be generated for the specific conditions sensed within the building in real time. This would allow the system to be more dynamic than the current approach of matching the current conditions to the closest rule available which has previously been generated. This would however require significant computational power which is unlikely to be available on-site; the possibility of utilising cloud-computing could be explored.

The solution space established within the literature has typically only explored the use of each of the considered techniques independently. The proposed solution aims to build upon these approaches by intelligently combining their advantages in a holistic manner. For example, the use of an ANN model allows a great improvement in the prediction time of the energy consumption and PMV, whilst also providing accuracy in the role of interpolating within the required ranges of input values. The combined use of empirical and theoretical rules allows a consideration of a wider range of sensitive variables than those which can be directly measured, and allows the calibration of these rules through the available sensors. The observed benefits of the hybrid approach presented is summarised in table 2 below. It is critical to note here that the extent to which the theoretical rules can be calibrated by the historical data is determined by the number of sensors which can be mapped to sensitive variables within the theoretical data set. The more variables which are expressed in both domains, the more accurate the theoretical rules may be.

Table 2. Summary of hybrid approach presented

Theoretical Approach	Empirical Approach	Hybrid Approach
Wide range of input variables allows more holistic scenarios	Narrow selection of highly contextual variables	Sensitive variables chosen from wide selection
No requirement for sensor installation	Many sensors required	Available sensors improve accuracy of rules generated
Not contextualised through real-world readings	System interactions may be ignored if insufficient sensors	Rules calibrated through mapping between historic and theoretical variables
No feedback mechanism to allow dynamic rule refinement	Rules can be refined in real-time	Rules refined periodically with historical data

In addition to the benefits of the combined use of the theoretical and empirical approaches, the approach presented here utilises the key concept of negotiation between the FM and the energy optimisation engine. This process is achieved by varying the termination goal of the multi-objective optimisation process in an iterative manner. Through interaction with the GUI, the FM may experiment with the desired energy reduction in order to gauge its effect on the key performance indicators within the facility such as PMV, temperature or luminance. This recognises the importance of including an FM within the decision making process. This underpins another key concept; that the system does not aim to replace the FM as the decision making unit within a building, but to better inform the FM to enable more holistic and data-driven decisions to be made.

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