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Evaluating the potential of Simulation Assisted Energy Management Systems : A Case for Electrical Heating Optimisation

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Abstract

Buildings consume a significant amount of energy worldwide in maintaining comfort for occupants. Building energy management systems (BEMS) are employed to ensure that the energy consumed is used efficiently. However these systems often do not adequately perform in minimising energy use. This is due to a number of reasons, including poor configuration or a lack of information such as being able to anticipate changes in weather conditions. We are now at the stage that building behaviour can be simulated, whereby computer programs can be used to predict building conditions, and therefore enable buildings to use energy more efficiently, when integrated with BEMS (i.e. simulation assisted control [1]). In this paper we demonstrate a low cost BEMS that uses building simulation to predict optimised electrical heating startup control points. Those that use electricity for heating in Scotland, where this study was based, tend to be fuel-poor, hence there is a strong case for optimisation, particularly when electricity costs nearly three times as much as the equivalent unit of gas for heating applications. The proposed system demonstrated a 50% energy saving in the reduced heating time compared to scheduling when retrospectively evaluated.

Keywords: Building Simulation, Energy Management, Fuel Poverty, Simulation Assisted Control

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1. Introduction

Buildings account for 40% of energy consumption worldwide and 30% of global carbon emissions [2]. As the population expands, this statistic is set to rise. A significant amount of the energy required in a building, is used to maintain a comfortable environment for the occupants. If the control of that energy is used inefficiently, it can lead to 'sick' buildings.

It is estimated that nearly 90% of buildings unfortunately have inapplicable or ineffective controls [3], but if they were to be rectified, there could be energy savings up to an additional 20% [4]. This is clearly a worrying statistic, and if it is addressed there is great potential to save significant amounts of energy worldwide.

Building controls have now evolved considerably into integrated building energy management systems (BEMS), which are dedicated systems installed to manage building services and energy consumption, whilst maximising comfort for occupants. Though BEMS are reserved for larger buildings, smart home systems for residential settings are now becoming common-place (e.g. Google Home). In this paper, the term *energy management system* is sometimes used interchangeably for BEMS and smart home systems.

Energy management systems are based on fixed rule sets which means they have to be adapted throughout the year, leading to a maintenance overhead. Furthermore, there are a multitude of factors to consider such as the time of day, the location of zones and occupancy profile which would contribute to internal heat gains [5]. Inappropriate selection of the parameters of the control strategies can cause both local and supervisory control loops to oscillate [5]. However building simulators and emulators can provide an efficient method of testing control strategies and software during the development and commissioning stages. For example, dynamic simulation tools can be used to test a control algorithm at difficult operating conditions (such as extreme thresholds) [5].

Taking this a step further, recent studies have been investigating the use of simulation assisted control (SAC), whereby simulation output is used directly in the control core of BEMS [6]. Consequently, such innovations are required more than ever, as fuel poverty is becoming an increasing problem, even for well developed countries such as Scotland.

1.1. Fuel Poverty

Fuel poverty is defined in Scotland if a household is required to spend more than 10% of its income in order to maintain a satisfactory heating regime. If a household is spending more than 20% of its income on heating it is in extreme fuel poverty [7]. At present, 54% of households in Scotland that use electricity for their heating are in fuel poverty [7]. Not only that, these homes are also in the lowest efficiency bands [8]. Furthermore a satisfactory heating regime is defined in [8] as 21°C in the living room and 18°C in all other rooms for 9 hours a day during the week and 16 hours a day during the weekend. This currently equates to a significant 74% of energy spend in an average household to satisfy this regime [8]. Much can be done therefore to improve this. The Scottish government have further recognised that energy saving technologies should be used in the development of the latest fuel poverty strategy - *'The new fuel poverty strategy should acknowledge and address a fourth driver of fuel poverty which is how people use energy in their homes'* [9]. In [9] it was also recognised that though most households in Scotland report actively using heating controls, other research had identified [10] that many people find heating controls hard to use, are confused about the different controls, and are uncertain over how to best use the timings and settings. With regards to timing and efficiency there is therefore scope to make use of technologies such as building simulation to help inform decisions for heat settings (such as optimum start setpoints).

1.2. Building Simulation

Using building simulation early in the building design process, can have a substantial impact on the building performance [11]. Building simulation software permit a wide range of physical attributes to be applied in a building model and analysed, such as thermal loads (e.g. TRNSYS) and lighting luminance (e.g. Radiance). They can take into account the full spectrum of building losses and gains, from the internal and external environment.

Generally losses are through the fabric of the building. However energy gains in a building can be from lighting, equipment, occupancy, windows (solar radiation) and heating. Losses are generally transmitted through windows, walls, ceilings, floors, roofs, doors, infiltration and ventilation. These are all parametric inputs in a building simulator.

Building simulators can be used to test out various occupancy profiles and usage scenarios that could occur in building, with respect to energy use and balances. For the case of efficient use of heating, there are opportunities to predict control strategies and integrate them into the control core of an energy management system. Consideration of the building form, via building simulation can further take into account internal and environmental factors, and thus aid in the decision making process of maintaining a stable energy efficient heating regime.

1.3. Objectives

This study explores the benefits of a low power computing implementation of a simulated assisted energy management system for houses that use electrical heating. Though electricity is not the dominant energy demand, the electrification of space and water heating has also recently started to gain traction as a strong option for achieving a low carbon buildings sector [12]. Note in Scotland, and in the rest of the UK, heating forms the major demand, where there is minimal cooling requirement for the domestic scenario. The exploration will evaluate the potential for savings in a test house developed for the purpose of energy efficiency optimisation through the use of smart technologies. The structure of the paper is as follows. Section 2 provides the background to the work. Section 3 discusses the experiment setup, Section 4 elaborates on the results and Section 5 concludes the paper.

2. Background

In the UK, much has been done to improve insulation characteristics of houses, with millions of homes having insulation upgraded (cavity walls and loft) as part of low carbon framework for significant reductions in energy by 2020 [13].

However there has been a lack of research to address heating systems, in terms of improving control strategies, that take into account environmental factors and conditions, though there has been a growing trend in internet connected ‘smart’ heating control devices that give occupants more options for control and ‘learn’ how they use it. These do little more than guess schedules such as the Nest learning thermostat [14], after a period of learning how occupants set temperatures throughout the day. Other examples of smart heating control devices, include the Tado [15], which guesses arrival times based on GPS coordinates, and the British Gas Hive system [16]. These systems rely on understanding human behaviour in an attempt to better control heating beyond predefined rules, which are commonly used to schedule heating. Energy management systems are often programmed with static rule based schedules, which are not optimised to react to changes in a building's use, which can often be dynamic (e.g. occupancy variation, change in climate).

A better method would be to employ a predictive control strategy that can supersede traditional rules based systems. There are two main techniques for predictive control in buildings that are currently being researched to improve control in building energy management systems. These are model predictive control (MPC) and simulation assisted control (SAC). Both techniques rely on being able to accurately forecast conditions based on various environmental factors, though can differ in their approaches, and some literature occasionally describe them as being essentially the same due to the fact they both use models for prediction. Mahdavi was one the first proponents of SAC identifying it as a separate method altogether, claiming *'This concept, which should not be confused with model-predictive control, involves the incorporation of explicit numeric performance simulation in the control core of buildings' environmental systems'* [17]. To further this point, MPC requires modelling of the building derived from first order principles or system identification. This requires model training; for example neural networks can be used for this purpose as black box models. Once the model is trained, it is a simplified, though highly focused, representation of the building control systems, rather than a representation of the complete building. The introduction of another parameter into the model, would require further retraining. On the other hand SAC utilises a full building model, allowing more diverse use cases to be applied and other control strategies to be explored, without having to go through a process of training and data collection for model verification. A lack of information in a building model may require model calibration to fit parameters, similarly to the MPC method, however this may lead to an incorrect physical model representation. For the case of smaller buildings, such as houses, the knowledge-based SAC approach can be viewed as more desirable, as they do not have complex HVAC systems that MPC data-driven methods often seek to optimise. Examples of approaches which are highly focused on optimum HVAC control, were performed by [18], [19] and [20]. There is as yet no studies for SAC in smaller buildings such as houses, which this paper addresses.

2.1. Simulation Assisted Control

Whereas MPC techniques use a black or grey box method to modelling, simulation assisted control takes the white box method or physical model approach and requires a full building model and a validated building simulator such as ESP-r.

Simulator software such as ESP-r, allows exploration of the complex relationships between a building's parameters for form, fabric, airflow, plant and control [21]. ESP-r is based on a finite volume, conservation approach whereby problems are transformed into a set of conservation equations that are then solved at successive time-steps in response to climate, occupant and control system inputs. Other software take various approaches to solving building physics problems. ESP-r is notable in that it is an *integrated* solution, where it not only considers thermal domains, normally only considered by the aforementioned black and grey box methods, but also airflow. TRNSYS for example only performs thermal simulation. The coupling of the two domains, and the intricacies of inter and intra zone air flow are significant areas of research [22], and can enable the exploration of complex interactions. This would be difficult to achieve using black box or grey box methods, that often only represent a subset of the building knowledge, whereas BEPS white box models take a whole building approach. The key difference is that BEPS tools such as ESP-r have been extensively validated for numerous test cases [23].

2.2. Previous SAC implementations

In [1], a prototype control structure was developed and tested in an environmental test room operated by Honeywell at Newhouse in Scotland.

They successfully demonstrated predictive heating startup to reach a desired target temperature by a specified time, by integrating ESP-r building simulation software with a LabVIEW based BEMS. Though a successful demonstration, they concluded that further focus is required on a full-scale real building subject to external climate variation.

[24] also investigated SAC using ESP-r by developing a prototype BEMs (KOBRA) and new subroutines to link ESP-r into the BEMS. Experiments were carried out in a single zone purpose built test chamber. Data collection (monitoring) for temperature was performed by standalone HOBO dataloggers, and KOBRA was used for control. This study also did not consider the affects of external climate, or whole building simulation. Other examples of ESP-r integration include that with Matlab to replace the FORTRAN control system, using TCP/IP communication to link them [25]. The notable focus in this study was the use networking to run simulations on separate computer hosts (which could be geographically separated). Another example

of this integration was carried out by [26], who investigated cooling strategies using TRNSYS with Matlab, on a single computer host.

The integration of ESP-r with an energy management system, has mainly focused on heating control but Mahdavi who first proposed SAC has led the way in combined heating, lighting, shading and ventilation simulated assisted implementations [27], [28], [29].

In [28], simulation-assisted control of window positions in two reference buildings was investigated. The idea was to utilise the day-night difference in outdoor air temperature toward passive space cooling via optimized dynamic operation of windows.

[30] identified that optimising temperature schedules saves the most energy in an office building when applying simulation assisted control using DOE-2.2. They noted that this was a challenge because there is no available function in the DOE-2.2 software to simulate the energy management and control system. They investigated various temperature schedules that were closely aligned to thermal comfort in office buildings, and human work productivity, for example temperature set back when occupancy rates dropped, and reducing the temperature setpoint in the morning until occupancy body temperatures reached a certain comfort level. By applying these simulation assisted control strategies they demonstrated a 2.25% energy reduction, noting that though the gain was minor, the target building was modern and had good levels of insulation, glazing and an efficient HVAC system.

2.3. Research Gaps

This study intends to address previous issues not dealt with in the existing SAC literature. For example Clarke had not considered full scale building operation and external climate with ESP-r. This paper specifically looks at external climate variation with ESP-r. Mahdavi's previous studies are more focused on lighting, ventilation and cooling, whereas in this study the focus is predominantly on heating. Finally, Zhou's implementation of SAC did not use a full building model and used DOE-2.2 which does not simulate the energy management and control system, whereas ESP-r has this capability, and is used in this study. Furthermore there are no currently known studies that look at the comparison of measured and simulated temperatures in a residential house, with solar gains and electrical heating. This study will explore this.

3. Experimental Setup

To evaluate simulation assisted control requires several components.
(1) A building model (BIM).
(2) A building energy management system (BEMS).
(3) A building energy performance simulator (BEPS).
(4) A test building.

For (1) and (3), ESP-r has been used to create the model, and perform simulation for prediction. For (2), a BEMS has been designed, developed and integrated into the test building (4), with a focus on low cost. ESP-r has been chosen as it is well known as an integrated solution that covers both thermal and air-flow domains. Therefore climate files used also contain wind data[1] to aid the simulation of air flow. Furthermore, ESP-r's data files (model description files and simulation output) are based on clear text, making data extraction and manipulation straightforward using a text processing language (such as perl).

3.1. BEMS Components

The various layers to the system are as follows.

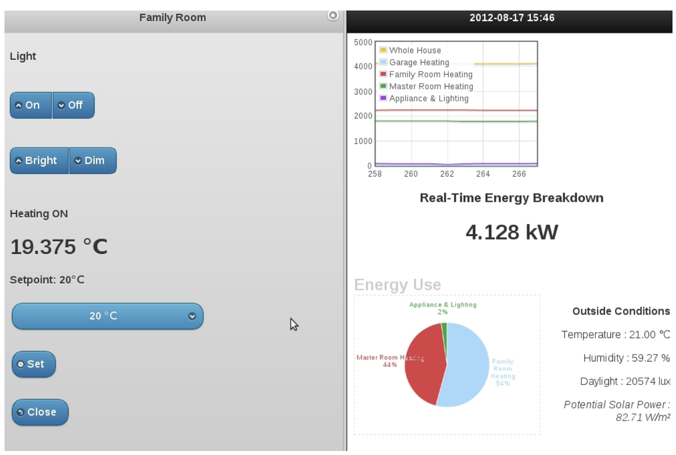

Figure 1: User Interface showing setpoint control and energy use

1. A monitoring layer which records sensor values from the environment, and measures and logs energy consumption.

[1]retrieved from Weather Underground (https://www.wunderground.com/)

2. A control layer which provides interfaces (HTML/jQuery) to allow user interaction (Figure 1) with heating control (e.g. changing temperature of a room using 'setpoints'). The control layer for the heating system is based on a simple 'on/off' algorithm, rather than a system based on a PID three term controller. This is due to the fact that the heaters can only be switched on and off from the wireless control network. The power output cannot be manipulated.
3. An automation layer which acts upon various user rules set in the system (e.g. heating schedules). By default the schedule is 6am to 5pm. This would actuate heating during this period. The heating system was provided by 2kW oil-filled or fan electric heaters in the Garage, Family Room and Master Bedroom.
4. A simulation layer which can forward predict control strategies to optimise the automation layer (e.g. optimum heat startup). Note for the purposes of this study, the simulation layer was only used to retrospectively evaluate potential to predict the control strategy and was not integrated with the control and automation layer. The integration is future work.

The management of layers 1 - 3 is performed by a BEMS controller, which was programmed to carry out the layer functions.

3.2. BEMS controller

An embedded plug computer (SheevaPlug) was chosen as the BEMS controller. Similar to a Raspberry Pi, it consumes less than 5W, with a hardware specification including a 1.2Ghz ARM processor and 512MB RAM. It was configured to run Linux and was interfaced to numerous sensor networks through USB, including a 1-Wire wired sensor network of carbon dioxide, luminance, temperature and humidity sensors (internal and external), a Z-Wave wireless control network (to control the heating and lighting) and a Current Cost wireless electricity network for energy monitoring. All sensor data for each main room in the house was logged to a USB hard drive every minute using a round robin database (RRD) and the BEMS software was written as set of perl language scripts. User interfaces to access the controls (Figure 2) for the heating and lighting were developed in HTML using jQuery libraries and an Apache web server.

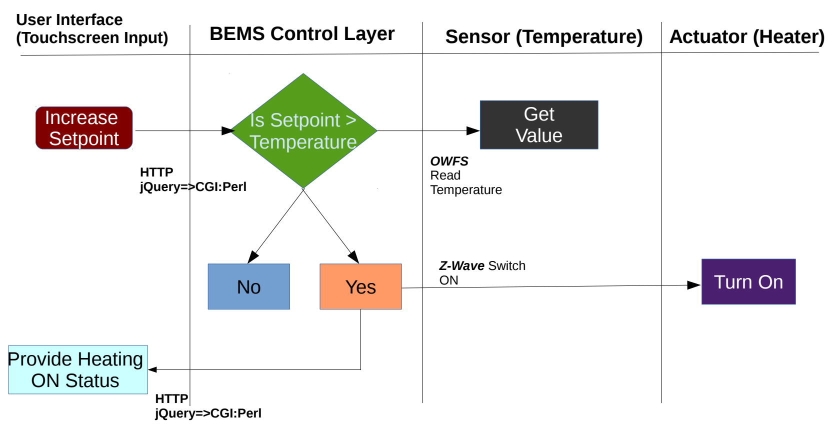

Figure 2: Flow of heating control actions in BEMS

3.2.1. 1-Wire sensor network

1-Wire sensors are the cheapest components used in the development. A typical 1-Wire sensor costs less than $1. The One Wire File System (OWFS)[2] library was used to interface to them. OWFS exposes all 1-Wire sensors as a set of unix style directories and files. For example a temperature value for a sensor can be retrieved by accessing the directory which represents the sensor's ID and within it, a the current sensor value would be contained within a file called temperature (e.g. /1wire/28.2B7554023400/temperature). A perl script was written to retrieve these values every minute and log the data to the database. The on/off control of the heating system was maintained using these sensors. 1-Wire temperature sensors are used extensively in the study to compare measured and simulated data during validation. These sensors are digital with 9 to 12-bit precision, and are operable from -55°C to 125°C (+/-0.5°C).

[2] `http://owfs.org/`

3.2.2. Z-Wave sensor network

A Z-Wave proof of concept perl script[3] was modified and integrated into the control and automation scripts of the system. The control scripts were used by the Apache web server to process HTML/CGI user interface setpoints to actuate the heating. Similarly the modified Z-Wave script was used to automate the scheduled heating.

3.2.3. Current Cost sensor network

The Current Cost monitors output XML strings [4] over a serial USB connection. A perl script was written to capture these XML strings and the provided data (total house consumption, and three appliance monitors for each heater) was decoded every six seconds. An average of this was then stored every minute in the database.

3.2.4. User interface (UI)

The user interface, developed in HTML permitted access by any web-enabled device to monitor and control the house (i.e. set temperature, monitor energy, dim a light (Figure 1 and 2)).

3.3. BEPS Layer

The BEPS layer consists of the ESP-r software, which has been compiled to run on the Sheevaplug and can be used to generate predictive control strategies for the heating, such as optimum heat startup. The simulator requires a building model of the test house, that has been appropriately validated so that it can make useful predictions. The validation study addresses the levels of uncertainty by assessing the prediction capabilities of the simulator. ASHRAE guidelines have been used for this purpose and are discussed in the next section.

3.4. Test House

The test house used in the study is a typical family-sized home based on an affordable Scottish house design, and built using modular construction. It consisted of two floors, and was composed of six prefabricated modules in a 3x2 configuration with a roof module. The house was situated on an off-site manufacturing facility. Individual modules were built and finished

[3] `https://www.bigsister.ch/zwave/zwave_s`

[4] `http://www.currentcost.com/cc128/xml.htm`

in the factory. The building exhibits some interesting features as it is a demonstration facility. The north, east and west facades have no external render finish, with only an exposed honeycomb layer, which is a fully vented and drainable panel made from aluminium.

3.5. BEPS Simulation Model

The building model was created from 2D floorplans, and detailed information about the construction of the walls was also gathered. Operating schedules for the heaters were derived from the BEMS.

In ESP-r the BEPS model requires a building to be divided into a number of zones. A zone is the primary reporting and descriptive unit in ESP-r and is used to represent a range of spaces which are a direct mapping from reality, e.g. a room, a portion of a room or a concatenation of several rooms. During a simulation, a zone is approximated to a node in a model that represents a number of variables such as temperature and pressure, which is calculated at each specified time-step. In this paper, temperature will be one of the variables under consideration when determining the goodness of fit, when comparing with monitored temperature data from the BEMS every hour to evaluate the potential for integrating a BEPS model in a BEMS for simulation assisted control. Other types of node include a specific load, such as casual gains or heating loads, that act on zones. High levels of goodness of fit across various data sets should indicate that the BEPS model can be used for the development of simulation assisted control strategies.

3.6. Predictive Control

An example of a predictive control strategy is to determine the optimum switch on for the heating system to reach setpoint at a particular time in the morning of the next day, when there is sufficient forecast data to do so and the predictive mode has been selected. This type of prediction is useful when there is a lookahead of several hours [1]. In order to have a lookahead for several hours, a weather forecast is required. Retrieving hourly forecast data for temperature, humidity and wind is relatively simple, with popular weather sites such as `weather.com` providing easy access however hourly solar radiation forecast data remains expensive (upwards of $2000 from specialist websites). Alternatively it is possible to estimate solar radiation data using solar tracking equations as in [31].

With an hourly forecast dataset in place, the simulator could be used to consider the differences between the predicted heat time to reach setpoint and optimum heat time. For example, if it took 1.25 hours to reach setpoint, this time could be subtracted from the arrival time of 9am to obtain an estimated start time at 7.45am. The process could then be iteratively repeated by instantiating simulation runs until the predicted time of reaching the setpoint is within the desired error of the algorithm. Once the prediction is complete, the BEMS control scheduler could then be appropriately modified with optimised start up time for the next morning.

4. Results and Discussion

Before evaluating the potential for simulation assisted optimisation, the BEMS datasets were validated with the BEPS simulated data. For validation, a number of metrics can be used for this purpose. In the early years of building simulation, simple per cent difference calculations were the primary means of comparing measured and simulated data [32]. Nowadays, the majority of literature for building simulation research make use of the CV (RMSE) (Coefficient of Variation of the Root Mean Squared Error) (Equations 1 and 2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (m_i - s_i)^2}{n}} \tag{1}$$

$$CV(RMSE) = \frac{RMSE}{\bar{m}}.100 \tag{2}$$

It measures the differences between simulated (s) and measured (m) values, at each timestep i, for a total number of timesteps, n. A lower value indicates less variance and hence higher quality model. CV(RMSE) aggregates time specific errors into a single dimensionless number. It is the most used metric in building simulation model research and a model has passed a threshold to be deemed useful, according to criteria set out in ASHRAE Guideline 14 [33] which uses CV(RMSE) to determine validation or calibration, specified under section 5.2.11.3 (Modelling Uncertainty). According to the criteria, a CV(RMSE) of 15% is acceptable for calibration models using monthly data and 30% for hourly models. Hourly data gives the most accurate results, though is the most difficult to capture; monthly data can also be acceptable depending on the application, but can mask inaccuracies that can appear at hourly or daily resolutions [34]. Another useful metric which can be used to determine goodness of fit is the Pearson correlation coefficient (Equation 3) which can determine how well measured and simulated values correlate in a particular period. It is also expressed as a percentage, whereby the higher the value the better the fit the simulated data is to the measured. For example 100% would yield a one to one match between the measured and simulated data.

$$r = \frac{\Sigma(m_i - \bar{m})(s_i - \bar{s})}{\sqrt{\Sigma(m_i - \bar{m})^2 \Sigma(s_i - \bar{s})^2}} \tag{3}$$

4.1. Validation of data sets for prediction

Validation periods need to have consistent data, which can therefore be replicated in the simulator, and also varied to consider different times of the year, to test seasonal validity of the BEPS model. The first validation period was 15th - 20th March 2012 and the second validation period was 10th - 17th September 2012. During these times the setpoint was kept constant in heated rooms.

4.1.1. Minor Calibration to determine density of glasswool in external wall

All building parameters and information were known, with the exception of the density of glasswool used for insulation. In order to determine this unknown parameter, the simulation is compared to measured data. One month of measurement results were used, and compared with matching simulations with various densities of glasswool. The density which gave the lowest whole house average CV(RMSE) for temperature and heating energy delivery was found to be 190kg/m^3.

4.2. Validation for goodness of fit

Table 1 shows the goodness of fit statistics for each zone in the model using the March dataset. The average CV(RMSE) for the whole house is computed to be 11.5% with the the individual CV(RMSE) for the Garage and all Bedrooms under 10%. The lowest individual CV(RMSE) is calculated to be for the Garage zone at 7.3%. The Master Bedroom has the highest Pearson correlation at 95%. Table 2 shows the goodness of fit statistics for each zone in the model using the September dataset. The average CV(RMSE) for the whole house is computed to be 8.6%, which is lower than March, with the the individual CV(RMSE) for all zones under 12%. However the Pearson correlations are lower than those computed for March,

Zone	CV(RMSE)(%)	Pearson (%)
Garage	7.3	93
Family Room	12.8	80
Kitchen	17.7	87
Bedroom 2	8.8	78
Bedroom 3	8.9	73
Master Bedroom	9.6	95

Table 1: CV(RMSE) & Pearson Correlation for Individual Zone Hourly Temperatures (March Dataset)

Zone	CV(RMSE)(%)	Pearson (%)
Garage	11	83
Family Room	8.88	56
Kitchen	7.52	85
Bedroom 2	5.85	70
Bedroom 3	11.6	63
Master Bedroom	8.09	69

Table 2: CV(RMSE) & Pearson Correlation for Individual Zone Hourly Temperatures (September Dataset)

suggesting the prediction capability is not as strong. For example, the lowest individual CV(RMSE) for temperature in this dataset is calculated to be for the Bedroom 2 at 5.85%, but the correlation is 70%. This comparatively low CV(RMSE) is interesting to note, as CV(RMSE) results in shorter time periods (such as March) are penalised more, when they have higher Pearson correlation. There are few building simulation calibration/validation studies that look at individual hourly temperature zone CV(RMSE) with the majority focusing on energy loads at monthly and hourly intervals, but these values are competitive against a study for a large office building presented in [35]. They attained a range between 12.4% - 28.7% for CV(RMSE) when comparing indoor zone temperatures of measured and simulated data. Similarly, a study of a historic building yielded RMSE results of 0.48 and 0.49 for interior air temperature [36]. Overall the results presented here show that the model is well within the ASHRAE guidelines when considering goodness of fit using hourly temperature comparisons, which requires a CV(RMSE) of less than 30% and compare well against similar studies.

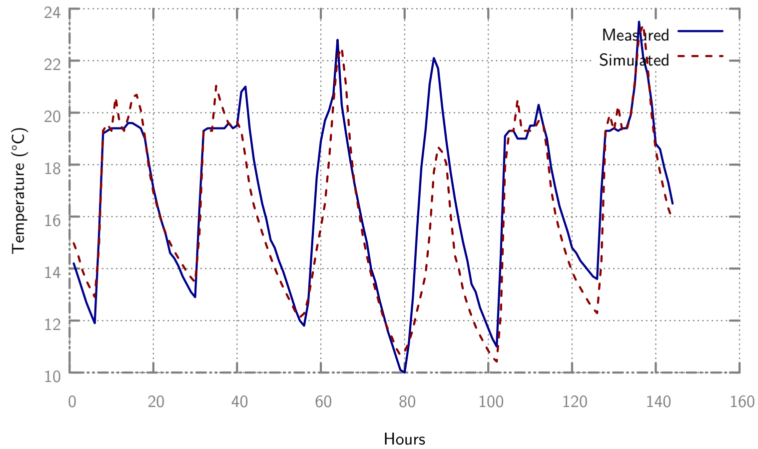

Figure 3: Temperature : March 15th - 20th 2012 : Garage, Setpoint 19.3°C.

4.3. Implementation of Optimum Heat Startup

We choose the March dataset for the evaluation. The implementation for the controller was designed to be scripted externally from ESP-r, to find the optimum start up time for the setpoint to be reached by 9am on the 19th March 2012, which was a Monday, following a weekend of no heating activity.

4.4. Results of retrospective evaluated Simulation Assisted Control

Figure 4 graphically shows the results of measured (blue line), simulated scheduled (purple line) and simulated optimum start (green line) for Monday 19th March 2012.

The measured downward curve shown in Figure 4, starting from 6pm on the 18th March is fairly well represented by the simulator response, and the measured and simulated start at 6am on the 19th March is in near perfect agreement, showing that the BEPS is representing the BEMS heating control system effectively, as shown by the (purple) simulated gradient tightly aligned with the (blue) measured data. These two features demonstrate that the simulator is responding well enough for this evaluation and highlights the problem with scheduled heating starting at 6am, in that the setpoint is reached at 7:48am, leaving over an hour of wasted energy in maintaining a setpoint with an arrival time of 9:00am. The results of the optimum start search have predicted the start up time should be at 7.30am rather than the scheduled time at 6am. This is represented by the green line in the figure, and demonstrates the effectiveness of employing predictive control using BEPS tools, and is an example of how simulation assisted control can enhance the control core of the BEMS to save energy — in this case by delaying the switch on time for the heating system as part of an optimum heat startup control strategy. This leads to a 50% saving compared to scheduling. Not only can savings be made by adapting scheduling times, but in some cases simulation can aid in predicting that no heat would be required leading to potential 100% savings. We can see this in Figure 3; if the heating was desired at a specific time on the third day (the third and fourth days being the weekend with no scheduled heating), the BEPS could predict (with forecast climate data and a lookahead of several hours) that in fact the space would be passively heated and heating would not be required.

5. Conclusion

In this paper we have presented a retrospective evaluation of simulation assisted energy management system for electrical heating systems to demonstrate the potential for a solution to the problem of fuel poverty reduction. The system has been developed using low cost components, such as 1-Wire sensors and also gives the ability to monitor energy consumption. With the recent introduction of cheap and affordable smart home technology (e.g. WiFi smart plugs and wireless temperature sensors) it can be seen that there is great potential to explore this further and future work should entail an actual implementation, to thoroughly evaluate simulation assisted control with forecast weather data. There is also scope to make this a cloud-based system, which is currently the trend home energy management systems are taking. In which case, the simulator could also be made a cloud application and linked to the cloud energy management system, whereby demand information could be further shared to a utility. This paper has also shown that external climate can have such an effect on passive solar heating, that in some cases heating can be predicted to be not required, or can be reduced. The system developed gives the necessary prediction capabilities to anticipate and manage heating regime requirements, and therefore aid in efficient use of space heating. Given that research has identified that one of the key problems is ineffective control of heating, a predictive system could alleviate this issue. This study is also one of the few that has looked at solar gains in a residential house, and the effect it has on indoor temperatures, particularly with an electrical heating system. Notably cooling has not been explored since there is largely no need in Scotland, where this study has been based however the

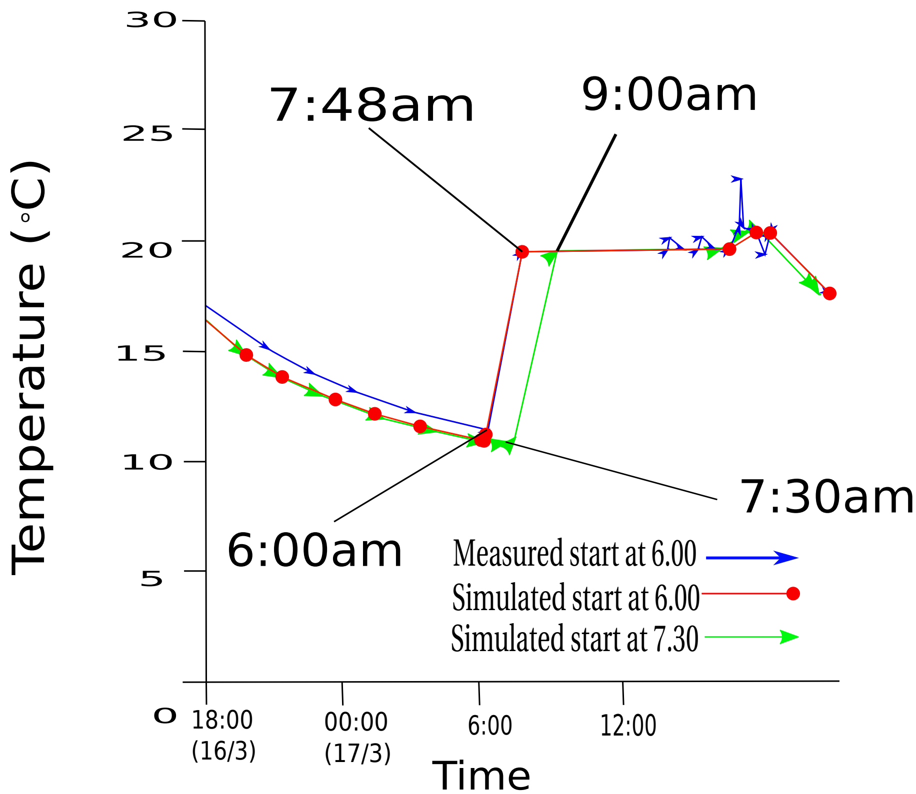

Figure 4: 19th March. Scheduled Heating showing that setpoint is reached at 7:48am, and optimum start up should be 7.30am to reach setpoint by 9am - revised figure -increase size and font

same principles should apply to a cooling system such as an air conditioning unit, whereby an optimum cool start time can be determined. It is expected that solar gains in such an application will be a dominant consideration, and the modelling of shading and actuation of blinds will feature heavily as part of the control system. Lastly this paper has considered an electrical heating system, using basic on/off control. A more complex system of modelling a boiler and simulating a wet central heating system, with zoned thermostatic radiator valve (TRV) control can be developed for a simulation assisted application for those that are fuel-poor with gas heating. TRVs can now be controlled wirelessly, and are available as Z-Wave enabled devices, which can be readily integrated into the prototype BEMS presented and described in this paper.

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