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A novel spatiotemporal home heating controller design: System emulation and field testing

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ABSTRACT

We have developed a spatiotemporal heating control algorithm for use in homes. This system utilises a combination of relatively low-tech hardware interfaced with electric heating systems and a smartphone interface to this hardware, and a central server that progressively learns users' room-specific presence profiles and thermal preferences. This paper describes the associated spatiotemporal heating control algorithm, its evaluation utilising the dynamic building performance simulation software EnergyPlus, and a longitudinal deployment of the algorithm controlling a quasi-autonomous spatiotemporal home heating system in three domestic homes. In this we focus on the prediction of occupants' presence and preferred set-point temperature as well as on the calculation of optimum start time and the utilisation of user-scheduled absences; this for two comfort strategies: to maximise comfort and to minimise discomfort. The former aims to deliver conditions equating to a 'neutral' thermal sensation, whereas the latter targets a 'slightly cool' sensation with corresponding heating energy savings. Simulation results confirmed that the algorithm functions as intended and that it is capable of reducing energy demand by a factor of seven compared with EnergyStar recommended settings for programmable thermostats. Field study results align with these findings and highlight the possibility to reduce energy under the minimise discomfort strategy without compromising on occupants' thermal comfort.

1. Introduction

This research is motivated by the IPCC's recommendation to achieve a 40–70% reduction in anthropogenic greenhouse gas emissions by 2050 and to fully decarbonise anthropogenic activities by 2100, to maintain global warming below 2 °C over the course of the 21st century [24]. With the Climate Change Act [29] the UK government has established legally binding targets to lower the UK's carbon dioxide emissions to 20% with respect to 1990 levels by 2050. In 2015, the domestic sector was the second-largest emitting sector (27%) in the UK, after transportation (38%) [3], with space heating contributing two-thirds of total domestic usage [26]. The UK housing stock is relatively poorly insulated and ageing, with between 85% and 97% of dwellings that will be in use in 2050 already having been built in 2006 [14]. But the expense of renovating an outdated housing stock suggests that more efficient ways of heating buildings need also to be examined. To this end, we develop and evaluate in this paper a new spatiotemporal heating control solution, which reduces the amount of energy used for heating whilst achieving occupant comfort aspirations.

Related prior studies on automated home heating control algorithms applied a neural network to predict occupancy probability that best matched observation using data from the past few hours, the previous three days, and for same weekday over the past four weeks, suggesting possible cost savings [22]. Others used GPS positioning data from occupants' phones as a trigger for a set-back mode and their simulations demonstrated that savings up to 7% could be obtained by integrating drive-home time as a trigger for re-heating the house to user-selected settings [11]. Subsequent work highlighted that a probabilistic presence schedule derived from GPS data outperformed user-reported presence schedules and driving home duration alone [17], indicating that an automated system could deliver better results for limiting heater switch-on time than a human-programmed thermostat. However, none of these studies applied these schedules to a simulated or situated heating system, thus not reflecting the complexities of managing a thermal environment to match users' expectations; nor did they adapt set-points according to users' preferences or exercise spatial discrimination in their control.

In a first response to this shortfall, Gao and Whitehouse [7] demonstrated, utilising a control algorithm that acted reactively after presence was detected, rather than proactively predicting presence and

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catering for future occupancy, that occupants' ability to forgive the algorithm's delays in this “miss time” could be utilised to reduce heating and cooling durations, resulting in potential heating and cooling demands up to 15% lower than those achieved using the US recommended EnergyStar setback schedule (8 a.m.–6 p.m.). This model applied a user-selected set-point temperature based on their presence. While an interesting approach, the energy saving was achieved at the cost of occupants' comfort, a trade-off that would not be acceptable to all users. Another control algorithm used motion sensor and magnetic door sensor data to (1) monitor occupants' presence to switch the HVAC system off during night-time and absences, (2) utilised previous presence data to predict presence and choose between a proactive and reactive approach to heating, and (3) utilised a ‘deep setback’ in which the temperature was allowed to decay to 10 °C or grow to 40 °C, (further change was limited to prevent damage to the building) [20]. A static set-point of 70 °F (21 °C) was used and the authors concluded that an energy use reduction of up to 28% was possible, highlighting that deeper set-backs (allowing temperature to decay or grow more) have a larger impact on energy saving than longer (limited decay or growth allowed for a longer period) setbacks [20]. Others have included weather and building characteristics in a controller utilising a combination of a proactive and reactive heating strategy, demonstrating that occupancy prediction can reduce energy spent by 9% [15]. A different approach utilised occupant discomfort history and occupancy prediction to constrain the expected discomfort to deliver energy savings in an office setting [21]. Whilst interesting, it would perhaps be more suitable to understand the occupants' experience of discomfort and avoid it, rather than exploit it.

A more comprehensive approach by Scott et al. [28] gave their algorithm control over a gas-fired heating system in 5 households in the UK (2) and the US (3). One of the five participating households tested a spatiotemporal control algorithm, whilst the remaining four were controlled to provide a uniform thermal environment throughout the house; both responding to predicted occupancy. User presence was detected using RFID tags and the algorithm's performance was measured against a 7-day programmable thermostat schedule. Their algorithm pre-heated living spaces in expectation of future presence, applying a user-defined set-point when the space was occupied during the day and a sleep set-point during the night. When the space was unoccupied their algorithm predicted the next occupied period by representing space occupancy as a binary vector for each day, where each element represented occupancy in a 15- minute interval. A partial occupancy vector from midnight up to the current time was used to predict future occupancy by finding similar days from the past. The algorithm then computed the Hamming distance, which simply counts the corresponding number of unequal binary vector elements between the current partial day and the corresponding parts of all the past occupancy vectors, picked the 5 nearest past days and predicted presence as a mean of those five days [28]. Results from deployment demonstrated an 18% decrease in gas usage for individual room control and an 8% reduction for a uniform solution, showing that a spatiotemporal heating solution delivers greater energy savings. Koehler et al. [16] used a GPS-enabled smartphone application to provide location data to predict occupancy and give the smartphone control over one of ten domestic heating systems. Their algorithm used time periods of *Unnecessary Heating* (percentage of daytime periods when the user was away from home, but the temperature was above 15.5 °C) and *Lost Comfort* (percentage of daytime periods at home when the temperature was below the user's preferred temperature) periods to optimise heating times to occupant presence. The authors concluded that 44 min of unnecessary heating per day can be avoided and that their prediction model was up 6.3% more accurate than manual control, or Scott et al.'s controller [28]. While these proposed algorithms are a step in the right direction, they fail to close the thermal comfort feedback loop and dynamically account for users' thermal preferences. By that, we mean that they merely applied a user-defined set-point temperature and did not treat this set-point as a variable that can be part of a thermal comfort dialogue.

Jazizadeh et al. used fuzzy logic to compute weighted thermal preference profiles of multi-occupant spaces using occupants' thermal preference votes, to determine dynamic heating set-points [13]. The authors gave their algorithm control over a 2-zone office space and concluded that increased comfort was delivered. It has also been demonstrated that temperature set-point variations of ± 3 °C can lead to 7–37% savings in energy usage, depending on climate and building size [9], suggesting that additional energy savings are possible then including thermostat set-point in the control algorithm.

From this review of the key advances in advanced home heating control systems, we conclude that significant effort has been invested in strategies to predict occupancy, using a variety of data sources, to best match pre-heating and heating output with presence. Those studies that have incorporated real-life deployment have treated the thermal comfort feedback loop as closed, so that preferred heating set-point was not included as a control variable; and few of these have addressed the domestic setting. The work presented here aims to fill this gap. We propose that including thermal sensation feedback from users over time can lower the temperature set-point; and/or better match users' spatiotemporal thermal preferences. Furthermore, we suggest that by nudging this set-point towards the lower end of thermal neutrality, further energy savings could be realised.

We refer the interested reader to Kruusimägi (2017) for a more detailed review of advances in home heating control systems and of joint-cognitive systems approaches [12] to include human subjects in their design and subsequent deployment, with the aim of maximising the dual objectives of acceptance and performance gains.

1.1. Aims and objectives

The aim of this paper is to develop a heating control system that delivers thermal comfort and energy efficiency and to evaluate its fitness for purpose in real-life contexts. In this we consider thermal comfort to mean that the occupant experiences a sensation of (close to) thermal neutrality in the space they occupy, and energy efficiency to mean the delivery of these conditions at minimal energy usage. For a heating control system to achieve these objectives it needs to: (i) account for individual differences in occupants' thermal sensation, (ii) demonstrate an ability to adjust itself to its context, (iii) operate in relative autonomy to limit energy use in heating unoccupied spaces, and (iv) facilitate an appropriate degree of manual over-ride for occupants. The control algorithm of such a system would, therefore, need to: (**a**) capture and predict occupants' presence in the space, (**b**) include occupants' thermal feedback and adaptation in a heating set-point calculation, and (**c**) optimise heating system start time, to reflect the (potentially varying) thermodynamic characteristics of the space within which it operates, and (**d**) enable occupants to override the heating system operation and associated set-point. In addition, such an algorithm could be enhanced by a nudging mechanism (a variant of (**b**)), utilising occupants' thermal feedback to adjust the heating set-point to the lower boundary of their comfort range, thus limiting the amount of energy required without compromising on comfort.

Our interpretation of an algorithm and its underpinning technology that meets these criteria is presented in the following section. We then evaluate the fitness for purpose of the core elements of this algorithm, emulating its operation in a simulation environment, before deploying the combined system in the field - giving the algorithm control over heating regimes in three homes for a six month period. In this way, we were able to explore the user experiences of living with such a system in a highly ecologically valid[1] setting over extended periods.

[1] By ecological validity it is meant that a phenomenon observed in a hypothetical situation also proved true when applied in a real-world setting.