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Development of a Smart Thermostat

Leonidas Zouloumis
Student Member ASHRAE

Giorgos Panaras, PhD
Member ASHRAE

ABSTRACT

Recently, understanding thermal comfort management enabled the scientific community to broaden its research towards smart device set-ups, in order to further reduce energy consumption and thermal comfort satisfaction. Thus, the need to minimize user interaction and implement prediction functions has arisen. In this work, the development of a smart thermostat is presented. The procedure is divided into three basic stages: calibration, development of energy saving and thermal comfort routines, and comparison with a conventional thermostat's operation. Calibration refers to the thermostat's ability to recognize the thermal characteristics of the thermal zone it is installed. For the needs of the calibration, as well as for the operation of the thermostat a simulation model is required; the degree-hour model, properly adjusted in order to cope with the requirements of the specific application, has been proven as the most convenient in terms of simplicity, reliability and effectiveness. Given the validity of the calibration process, a smart thermostat routine was developed, taking occupancy periods into account and attempting to save energy while ensuring satisfaction of thermal comfort. Operation of the smart thermostat is compared to that of the conventional analog thermostat. The results verify the potential of the developed thermostat in terms of thermal comfort satisfaction and energy savings. Future work includes the integration of more parameters into the operation of the thermostat, i.e. humidity and Indoor Air Quality ones, including CO_2 concentration for the controlling of fresh air adequacy through a complete air-conditioning system, as well as the testing of its operation under actual conditions.

INTRODUCTION

Nowadays, scientific community strives to improve personal interior thermal comfort management. According to ASHRAE 55 (ASHRAE, 2017), thermal comfort is defined as "that condition of mind that expresses satisfaction with the thermal environment". The relevant literature has investigated a wide range of aspects concerning thermal comfort, involving perception issues (Wang and Liu 2020; Ciuha et al. 2019; Kisilewicz 2019; Luo et al. 2018; Frontczak and Wargocki 2011; Wong et al. 2005), as well as its evaluation in buildings of various types and different climatic conditions (Aghniaey et al. 2019; Agüera et al. 2019; Liu et al. 2019; Papazoglou et al. 2019; Papadopoulos and Panaras 2019; Rajagopalan and Luther 2019; Fang et al. 2018; Antoniadou and Papadopoulos 2017; Roshan 2017; Zaki et al. 2017; Revel and Arnesano 2014; Corgnati 2007). Achieving thermal comfort in various indoor environments, through proper control devices is also an issue of emerging research interest, involving personalized assessment aspects (Du et al. 2019; Kim et al. 2019; Zhai et al. 2019; Ghahramani et al 2015), as well as Artificial Intelligence and Internet of Things ones (Ngarambe et al. 2020; Li et al. 2019; Valladares et al. 2019; Yoon and Moon 2019; Moon and Jung 2016). Concentrating on temperature, the most common device is the thermostat, a component that senses temperature levels and adjusts the heating/cooling systems, in order to maintain temperature at a desired setpoint. Over the course of time, employing PID controllers allowed thermostats to function continuously, controlling system energy usage through feedback loop (Nägele et al. 2017). Recently, technological improvement allowed programmable thermostats to replace conventional ones, promising better and more automated thermal comfort management (Schäuble et al. 2020; Wang et al. 2020; Adhikari et al. 2018; Nägele et al. 2017). However, according to Combe et al. (2012), most users have difficulty interacting with programmable thermostats that were set up in houses, resulting in increased domestic energy consumption. As a solution to this problem, smart thermostats are being developed (e.g. Nest, Ecobee), in order to minimize user interaction, while attaining desired thermal comfort in occupied rooms and saving energy. Additional energy save can be achieved, taking the variability of electricity cost into account, if it exists (Bin Zhou et al. 2016). The challenge of easy-to-operate products, achieving efficient energy use and acceptable thermal comfort conditions remains active (Nägele et al. 2017). Moreover, advancement in sensor communication allows smart thermostats to control other aspects of thermal comfort, such as air humidity or speed, Indoor Air Quality (IAQ), and lighting and acoustic levels, namely all factors involved in Indoor Environmental Quality (IEQ) (Dong et al 2019; Schieweck et al. 2018).

Leonidas Zouloumis is a PhD student in the Department of Mechanical Engineering, University of Western Macedonia, Kozani, Greece. **Giorgos Panaras** is an Assistant Professor in the Department of Mechanical Engineering, University of Western Macedonia, Kozani, Greece.

In this paper, the development of a smart thermostat, functioning autonomously and taking personal user preferences into account will be presented. The thermostat would be able to identify room characteristics using calibration functions, predict indoor temperature behaviour and achieve thermal comfort during room occupancy periods, while minimizing energy consumption.

2 MATERIALS AND METHODS

2.1 Simulation Models

The operation of the thermostat, namely prediction of the indoor air temperature, requires integration of a simulation model; this is also the case for testing the thermostat, as for the needs of the specific analysis, a simulation model was used in order to provide the actual operation conditions of the building through the thermostat operation.

The simple hourly method, provided by EN ISO13790 (ELOT 2008) has been adopted in order to represent the actual indoor conditions of the building. It is a Resistance-Capacitance (RC) thermal model, calculating, on hourly basis, the temperature in the respective thermal nodes; these refer to ventilated air, indoor room air, internal and external wall surface and ambient air, while heat transfer coefficients of the building elements as well as internal (due to human occupancy or appliances) and external heat gains constitute the parameters of the energy balance model. The solving of the energy balance set of equations, through Crank-Nicolson iteration method, allows the calculation of indoor air temperature.

Moreover, a Degree-hour based model (ASHRAE 2017; Treur 2014; Guntermann, 1982) has been adopted as the simulation component of the thermostat. This model is based on a simplified heat balance equation of a controlled room; more specifically, it is supposed that inner temperature depends on two types of energy demands, temperature increase energy demand and temperature maintenance energy demand. As it will be discussed later on, this model has been proven to be the most suitable for the thermostat operation, due to its simplicity and reliability.

2.2 Thermostat calibration

Calibration of the thermostat refers to the determination of specific coefficients related with the thermal characteristics of the space to be controlled, thus, allowing the thermostat simulation model to predict indoor air temperature with regard to operation conditions.

According to the calibration procedure, as implemented by the calibration program, indoor air temperature data, as well as climatic ones, are collected by period(s) of deactivated heating/cooling systems. The integrated simulation model of the thermostat attempts to estimate the indoor temperature, through the use of building thermal characteristics within a defined range of values, called calibration coefficients. Using the least Sum of Squared Errors (SSE, equation (1)) criterion (error is defined as the difference between actual and estimated inside temperature during a time step), calibration program saves the best calibration coefficients, of a single day, as it will be explained in section 3.1.

$$SSE = \sum_{i=1}^{n}\left(y_{est,i} - y_{act,i}\right)^2 \qquad (1)$$

For the needs of calibration procedure both simulation methods, ISO EN 13790 (ELOT 2008) and Degree-hour model (Guntermann, 1982) were tested. The ISO EN 13790 model had too many variables to consider, when finding the best ones, leading to high calibration time; on the other hand, degree hour method was proven to be simpler and faster, but lacked in accuracy. The latter can be attributed to the fact that it is treating solar gains on a rather indirect manner. In order for its accuracy to be improved, an additional variable was added, representing solar gains throughout the day. Thus, the equation used by the calibration program is the following:

$$\Delta T_{id(t,t+\Delta t)} = \frac{1}{C} \cdot \left[ed_t - \sigma \cdot \varepsilon \cdot \left(T_{id,t} - T_{od,t}\right) \cdot \Delta t + k \cdot h_{sol,t} \cdot \Delta t\right] \qquad (2)$$

where ΔT temperature change (K), *id* refers to internal conditions, *od* to outdoor ones, *t* to time, and Δt to time step (h), *ed* to energy demand (kWh), σ to seasonal correction factor (-), ε to the average heat loss coefficient of the studied space (kW/K), C to thermal capacity of studied space (kWh/K), k to solar gains coefficient (kW) and h_{sol} to normalized daily solar radiation (-).

Concludingly, the calibration program aims to determine the ε, C, k values, whose daily estimated room temperature behaviour converges to the actual one.

2.3 Reference building

As mentioned in section 2.1, given that the thermostat was not tested on an actual indoor space, the EN ISO 13790 (ELOT 2008) simple hourly method was used as a simulation model, predicting the tested space air temperature with regard to ambient conditions. The reference building is shown below (Figure 1). It has been assumed that it is located in Kozani, Greece, belonging to the coldest climatic zone of Greece; that is zone D (TEE 2010a). Building heat transfer characteristics and thermal comfort temperatures were obtained by the relevant technical Directive for the implementation of the Greek version of the European Performance Building Directive (EPBD) (TEE 2010a; EU 2018), while ambient temperature and local daily solar radiation levels by the respective Directive providing the respective climatic data (TEE 2010b).

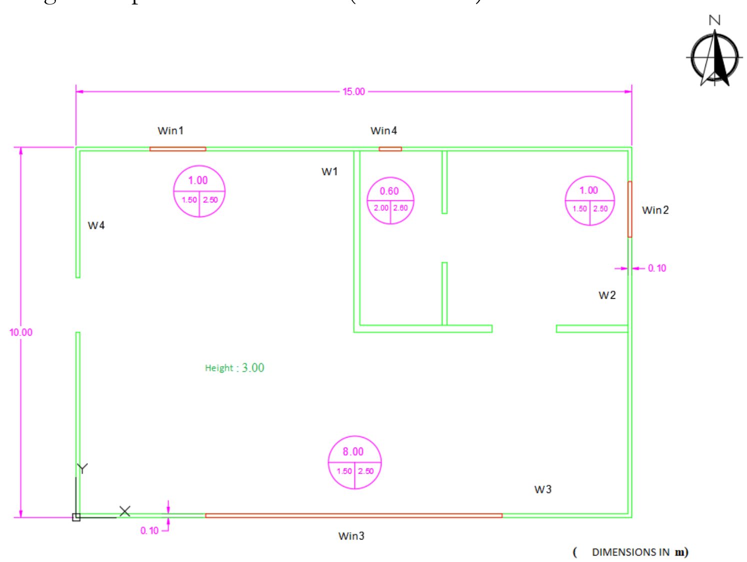

Figure 1. Reference building bottom view

Table 1. Building characteristics of the model

Calculated term	Value
H_{op} [W/K]	199.24
$H_{tr,w}$ [W/K]	42.32
A_{fl} [m2]	145.04
Cm [Wh/K]	6647.7

Where H_{op} refers to heat loss coefficient of opaque elements, H_w refers to heat loss coefficient of windows, A_{fl} to the floor surface and C the heat capacity of the building elements surrounding the studied space.

3 RESULTS

3.1 Calibration

Calibration periods of 24, 12, 8 and 4 hours have been tested; these refer to the implementation of the calibration procedure for the respective period and determination of the respective coefficients. As discussed in section 2.2, initially the calibration program calculates the respective calibration coefficients for each day of the year. Following the extraction of the coefficients for the respective day, it predicts daily temperature values of each day of this season and compares them to the actual ones.

The Root Mean Square Error (RMSE) indicator is used in order to evaluate the convergence of simulated and actual values; estimated, $y_{est,i}$, and actual, $y_{act,i}$, temperatures are calculated for each day of the year (equation 1).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_{est,i}-y_{act,i})^2}{N}} \qquad (1)$$

where N is the data size.

Then, the calibration program calculates the seasonal RMSE of this specific calibration day of the season. The term "season" refers to annual basis, if the same calibration coefficients are used for the complete year, semester if the coefficients are used for semester prediction, and seasonal if coefficients are used for seasonal prediction of indoor temperature. This procedure is repeated until RMSE of all calibration days of each calibration version is calculated. Results are shown below (Figures 2-5).

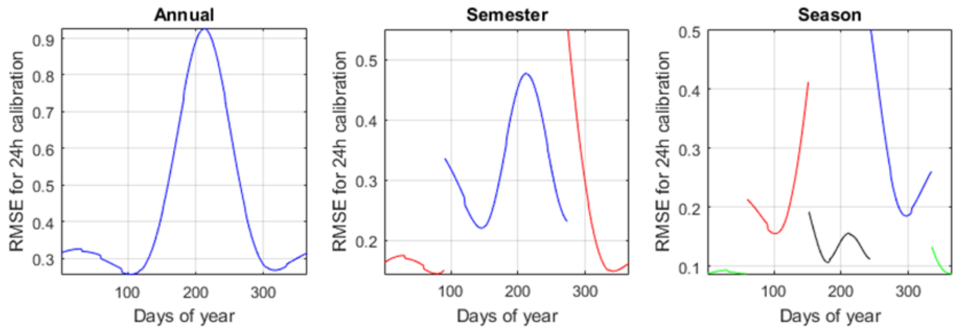

Figure 2. RMSE calculation results, 24-hour calibration (annual, semester and season versions)

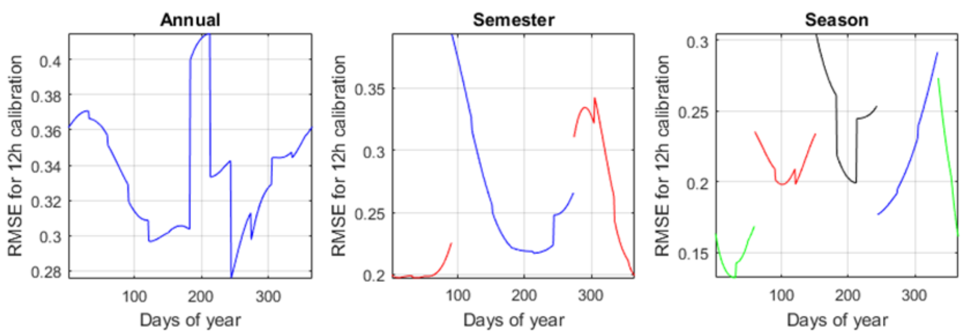

Figure 3. RMSE calculation results, 12-hour calibration (annual, semester and season versions)

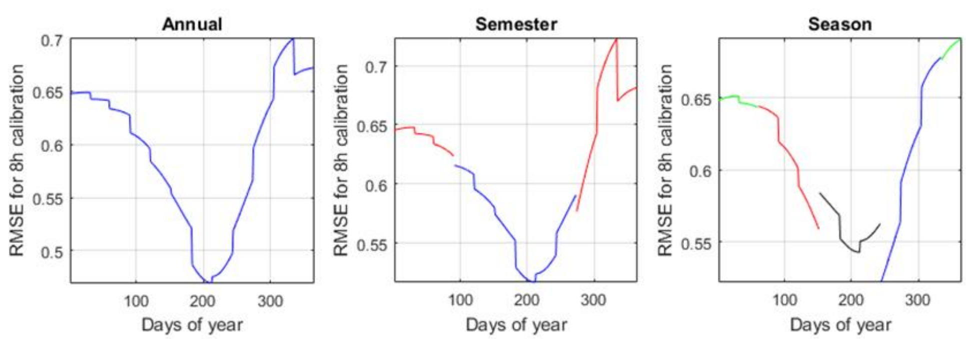

Figure 4. RMSE calculation results, 8-hour calibration (annual, semester and season versions)

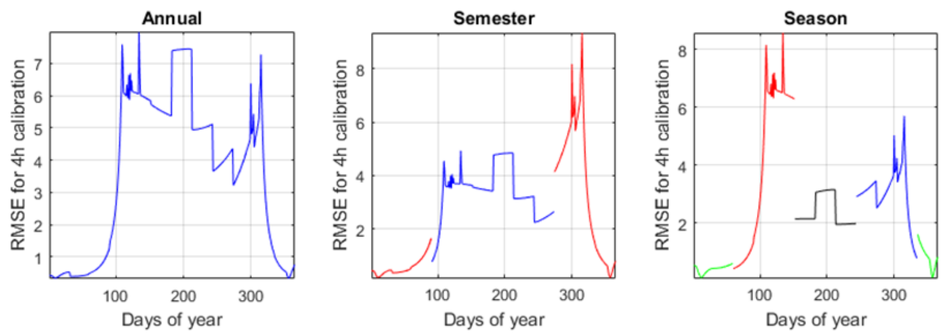

Figure 5. RMSE calculation results, 4-hour calibration (annual, semester and season versions)

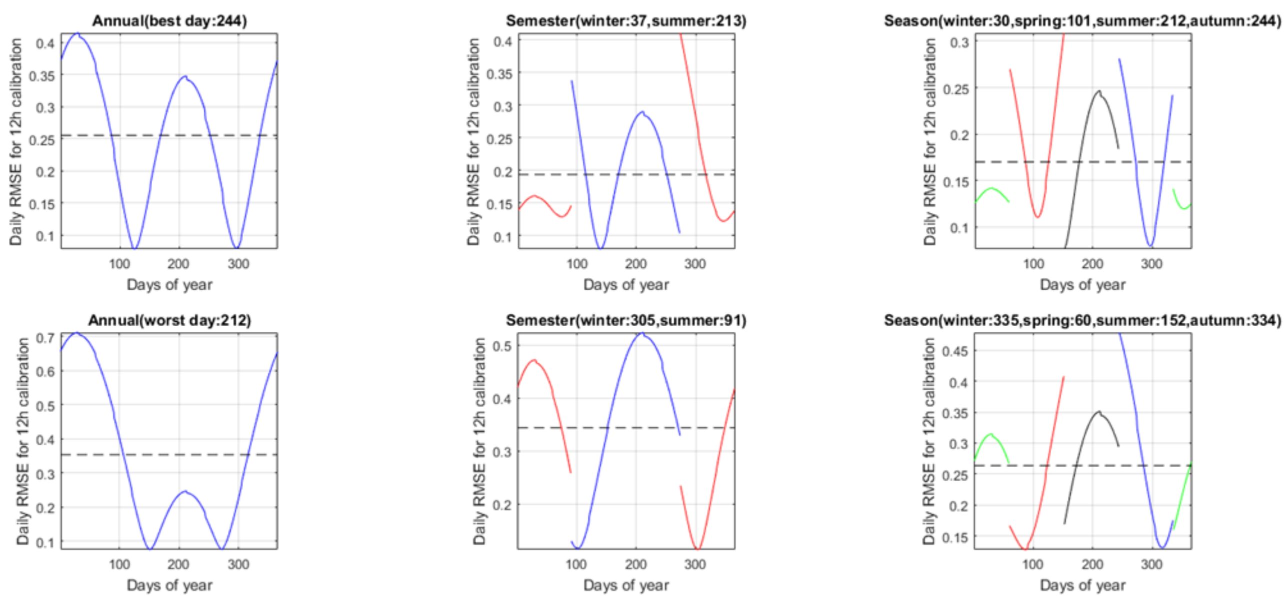

Figure 6. Daily RMSE calculation results, 12-hour calibration, of the best and the worst calibration days. Black dashed lines indicate the average RMSE of all days in a plot.

As observed in figures 2-5, 12-hour calibration is the most suitable one, because RMSE has the lowest values, compared to the other calibration set-ups; the 8-hour calibration is the second best. Dividing the calibration period in semesters and then seasons, proves to positively affect the minimization of RMSE, especially for the case of 12-hour calibration.

Of course, the user will not calibrate the thermostat by each day; for this reason, it would be interesting to investigate the effect of the best and worst calibration days on the final result, as expressed through RMSE, the worst day is the one that has the highest RMSE for the respective calibration period, while the best calibration day is the one with the lowest RMSE. In figure 6, the daily RMSE results, for the best and worst days, of annual, semester and seasonal calibration set-ups, 12-hour case, are presented. Even though the selection of the best day for seasonal version presents the minimum RMSE values, the differences between the studied cases are not so high. This can be positive, as it would not force the potential user to calibrate the thermostat in strictly prescribed periods of the year.

3.2 Development and evaluation of the smart thermostat

Following its calibration by periods the heating/cooling system is not operating, the thermostat is able to predict room temperature behaviour, throughout the complete year. During the heating or cooling system activation period, the thermostat can use the following equation:

$$Q_i = C * \left(T_{id,i} - T_{id,i-1}\right) + \sigma * \varepsilon * \left(T_{id,i-1} - T_{od,i-1}\right) * \Delta t - k * h_{sol,i} * \Delta t \qquad (4)$$

Where Q_i is the heating/cooling energy input of the energy system (kWh).

The final stage considers transformation of the thermostat into a smart one; thus, enabling it with the potential to take decisions regarding the satisfaction of user's thermal comfort needs, while saving energy. In the presented work, a smart thermostat routine was developed, that accesses predicted temperature values, taking occupancy periods into account. Then, it calls two subroutines; the first one ("eco") attempts to save energy by turning off energy systems earlier than the time the user leaves the controlled space, while the second one ("preheat"), having the exact information for the time the user will come back, ensures that by that time, the room will have achieved the desired thermal comfort settings. For winter operation, which is the case studied following on, this is enabled through preheating the room.

In figure 7, the results of the operation of the "smart" thermostat are presented for a typical winter day; results are compared to the ones of a conventional device. Occupancy period is set from 10:00 to 20:00. Room is assumed to have wall insulation acceptable by the Greek version of the EPBD (TEE, 2010a). Table 2 presents the thermal comfort satisfaction percentage and energy saving for the complete day.

As can be seen in figure 7, both thermostats present the same behaviour, without the integration of the "smart" subroutines. The "eco" operation allows the thermostat to deactivate energy system (2 hours) earlier, without affecting thermal comfort, while the integration of "preheat" subroutine is responsible for activating the energy system (3.5 hours) earlier than the arrival of the user; as it will be demonstrated by the results of table 2, this has positive effect on thermal comfort, while slightly increasing energy consumption. The occupants' thermal comfort is expressed through the thermal comfort satisfaction ratio, namely the fraction of the time period in which the occupants are in state of thermal comfort to the total time period in which the indoor space is occupied.

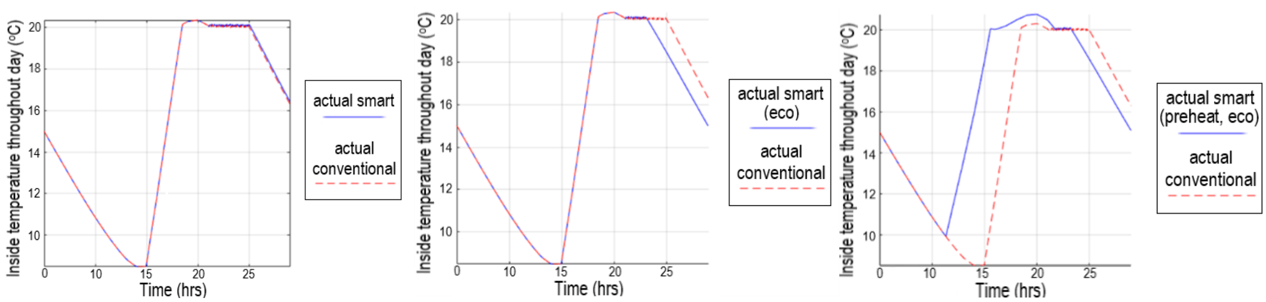

Figure 7. Smart vs conventional thermostat 24-h operation

Table 2. Conventional vs smart thermostat operation

	Conventional	Smart	Smart (energy save)	Smart (preheat, energy save)
Thermal comfort satisfaction (%)	72	72	72	100
Energy consumption (kWh)	61.5	62.2	54.2	62.2

Results indicate that the smart thermostat can achieve thermal comfort during the occupancy period, without consuming excess energy. As noticed from "eco" routine results, it can prioritize energy saving, if needed.

4. CONCLUSIONS

According to the analysis, the proposed thermostat can be installed on a space and calibrated for a specific period of 12-hours; within this period, energy systems have to be deactivated. Calibration allows the determination of the thermal characteristics of the controlled space; if it is repeated seasonally, results are improved. Through the integration of proper subroutines for the early deactivation and activation of energy systems, with regard to the occupants' scheduled presence, the smart thermostat has proven to be superior to the conventional one, both in terms of energy saving and thermal comfort satisfaction.

The calibration algorithm could be further improved, in order to help the smart thermostat to be more effective, in terms of temperature prediction and room behaviour understanding, while increasing the number of calibrations throughout a year tends to improve indoor temperature predictability.

Future work should include the testing of the thermostat, on an actual test cell, including its combination with energy systems operating on partial heating/cooling loads, and not only complete, as was the case in this work. Integrated thermal comfort concern, taking into account personalization of users' preferences, as well as consideration of indicators as the Personal Mean Vote (PMV), for evaluating thermal comfort, could also be the case.

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