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Development of a personalized thermal comfort driven controller for HVAC systems

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ABSTRACT

Increasing thermal comfort and reducing energy consumption are two main objectives of advanced HVAC control systems. In this study, a thermal comfort driven control (PTC-DC) algorithm was developed to improve HVAC control systems with no need of retrofitting HVAC system components. A case building located in Izmir Institute of Technology Campus-Izmir-Turkey was selected to test the developed system. First, wireless sensors were installed to the building and a mobile application was developed to monitor/collect temperature, relative humidity and thermal comfort data of an occupant. Then, the PTC-DC algorithm was developed to meet the highest occupant thermal comfort as well as saving energy. The prototypes of the controller were tested on the case building from July 3rd, 2017 to November 1st, 2018 and compared with a conventional PID controller. The results showed that the developed control algorithm and conventional controller satisfy neutral thermal comfort for 92 % and 6 % of total measurement days, respectively. From energy consumption point of view, the PTC-DC decreased energy consumption by 13.2 % compared to the conventional controller. Consequently, the PTC-DC differs from other works in the literature that the prototype of PTC-DC can be easily deployed in real environments. Moreover, the PTC-DC is low-cost and user-friendly.

1. Introduction

Building sector constitutes 40 % and 32 % of total energy consumption of EU and Turkey, respectively [1,2]. In residential buildings, final energy consumption was decreased by 9 % in EU while a 48 % increase was encountered in Turkey between 2001 and 2015 [3]. Although Heating, Ventilating and Air-Conditioning (HVAC) systems consume 30–50 % of the building's energy share in Europe [4,5], 40 % of energy consumption can be saved by applying energy-efficient HVAC control systems [6]. HVAC control systems traditionally use thermostats, controlling on/off operation, to maintain given set point temperatures. Even though programmable thermostats are smarter and allow occupants to set a desired indoor air temperature for different time and date periods, none of these control systems are aware of occupant thermal comfort; they focus, instead, merely on controlling room temperature.

Thermal comfort is a subjective sensation in which satisfaction is expressed with the thermal environment and dependent upon whole body sensation which is the function of six parameters: indoor air temperature (T_i), relative humidity (RH_i), air velocity (v_a), clothing insulation (clo), metabolic rate (met) and mean radiant temperature (MRT) [7]. The reason to obtain thermal comfort is to satisfy occupant's desire to feel thermally comfortable human performance. Being the most renowned researcher on thermal comfort, Fanger [8] developed two thermal comfort indices, Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD), which were standardized in ISO 7730 [9] and ASHRAE 55 [10]. PMV uses a seven-point thermal scale from −3, refers to cold, to +3, refers to hot. PMV value of ±0.5 indicates that 10 % of the occupants feel thermally dissatisfied (PPD) (Table 1). In a

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Nomenclature

AI	Artificial intelligence
ANN	Artificial neural network
AMV	Actual mean vote
APD	Actual percentage of dissatisfied (%)
clo	Clothing insulation
FL	Fuzzy logic
met	Metabolic rate
MRT	Mean radiant temperature (°C)
N	Number
PID	Proportional-integral-derivative
PMV	Predicted mean vote
PPD	Predicted percentage of dissatisfied (%)
PPV	Predicted personal vote
R^2	Determination of multiple coefficient
RH	Relative humidity (%)
T	Air temperature (°C)
v	Velocity (m/s)
$\hat{y}$	Fuzzy logic estimation model results
y	Standart deviation
y_i	Measurement results

Subscripts

a	Air
i	Indoor
o	Outdoor

Table 1
Thermal sensation scale [10].

Thermal sensations	PMV	PPD (%)
Hot	+3	90
Warm	+2	75
Slightly warm	+1	25
Neutral	0	5
Slightly cool	−1	25
Cool	−2	75
Cold	−3	90

conditioned environment, PMV = 0 0.5 is the target to be achieved by an HVAC system [8,10].

The PMV/PPD method is reliable in air-conditioned buildings, however, several researchers [11–13] showed that the acceptance range of PMV of the occupants in naturally ventilated buildings in warmer climates is much wider than the standard PMV model based on objective (T_i, RH_i, MRT and v_a) and subjective measurements. Subjective measurements, are surveys that aim to collect the occupants' actual thermal sensation (AMV) and clothing information [11,13,14]. When AMV is used, Actual Percentage of Dissatisfied (APD) gives the percentage of dissatisfied occupants from indoor environment. Considering all parameters, to obtain personalized thermal comfort with energy efficiency becomes a challenge for HVAC system control.

In 1998, an adaptive thermal comfort model [11] was adopted in ASHRAE 55 [10] for naturally ventilated buildings, alongside the PMV method for buildings using HVAC equipment. The main effect of such model was to increase the range of conditions that designers can consider as comfortable, especially in naturally ventilated buildings where the occupants have a greater degree of control over their thermal environment. The model added a little more human behaviour to the thermal sensation models assuming that if changes occur in the thermal environment to produce discomfort, the occupants generally change their behaviour and act in a way to restore their comfort [12].

The HVAC systems, are typical nonlinear time-dependent multivariable systems with inter-related variables like T_i and v_a, T_o and RH_o as well as disturbances like occupants' behaviour [15], mostly use standard control systems like on/off and Proportional-Integral-Derivative (PID)-type controllers. Advanced HVAC control systems which are mainly based on Model Predictive Controllers (MPCs), can detect thermal comfort. However, MPCs require complex model of HVAC systems along with thermal comfort model of each occupant. Furthermore, advanced HVAC controllers do not give any direct feedback to the occupants [16]. Individual differences or preferences can be accommodated with personalized thermal comfort driven controllers [17–19]. For this reason, in the last ten years, development of new generation building monitoring systems and personalized thermal comfort control tools has accelerated [5]. The revised Energy Performance of Buildings Directive (EPBD) [20] aims to increase the use of smart and energy-efficient technologies in the building sector across Europe. It introduces a “smartness indicator” which will measure the buildings' capacity to use new technologies and electronic systems to optimize their operation and interact with the grid. An increase of smart technologies has potential to decrease energy consumption as well as to improve occupant's thermal comfort via adjusting control parameters in the building according to the needs of the occupant.

Personalized thermal comfort controllers deal with individual thermal sensation instead of taking average of a large group of occupants. These controllers generally use mathematical model of the HVAC plant, different types of cost functions and constraints besides thermal comfort model of occupants [17,21,22]. Moreover, these systems only regulate indoor air temperature. For instance, Lin et al. [17] developed a personalized thermal comfort control model by using multi-sensors for HVAC systems. The study addressed a single-actuator control problem which was solved by a computer program and optimization techniques. In the study, each room was equipped with multi-sensors and a sensor network and, the controller was operated only on the temperature reading from the room sensors utilizing the HVAC plant model. As a conclusion, the authors demonstrated that the energy-optimal strategy reduced energy consumption by 17 % while reducing PDD from 30 % to 24 %. Similarly, Feldmeir [18] created a novel air-conditioning control system which aimed personalized environments. The author developed an extremely low power, light weight, wireless sensor which can measure temperature, humidity, activity and light level directly on the occupant's body. The measured data were then used to immediately infer occupant's thermal comfort, and to control HVAC system in order to minimize both cost and thermal discomfort. The proposed controller decreased energy consumption by 3 % which were the direct result on improving occupant's thermal comfort. Another study by Ghahramani et al. [19] was used infrared thermography to maintain personalized thermal comfort with the help of sensors which was installed on eyeglass frame. The authors proposed a learning model in order to capture dynamic thermal comfort of occupants. Surveys were conducted for four days simultaneously with measurements and the proposed learning algorithm predicted uncomfortable conditions with an accuracy of 82.8 %. The authors concluded that real-time measurements of personalized thermal comfort decreases energy consumption while maximizing occupant's thermal comfort. However, for every occupant, wearing eyeglass frame with sensors in real environments is impractical. A personalized thermal comfort system, which uses Microsoft Kinect [23] as an occupancy sensor, was developed by Gao and Keshav [21,22]. The proposed system is based on sensor measurements and control over the operation of a small personal radiant heater/fan. The controller detects the parameters underlying the Predicted Personal Vote (PPV) model via Microsoft Kinect [23], then controls heating and cooling elements to dynamically adjust indoor air temperature to maintain thermal comfort. Besides indoor air temperature, thermal comfort is a function of other objective parameters of the indoor environment such as relative humidity, air velocity and mean radiant temperature. Considering these parameters along with indoor air temperature improves thermal comfort of the occupants.

Thermal comfort depends not only on physiological (such as environmental and personal) parameters but also psychological parameters like psychological adaptation, mood of the occupant and culture [11,24]. Thus, expressing the feeling of thermal comfort is almost impossible in mathematical models since the process in thermal perception is still too complex to comprehend [25]. Due to the nature of thermal comfort and thermal sensation, Fuzzy Logic (FL) provides a powerful approach for reasoning of uncertain and imprecise information. Moreover, using a “free-model” such as FL which is not bounded to any dynamic mathematical model of the system, provides quite a simple structure and easy implementation.

Personalized thermal comfort controllers are still expensive and complicated for occupants. Easy-to-understand wireless sensor networks and simple controller interfaces are needed. Furthermore, controllers should be easy to adopt to real environments. Developed personalized thermal comfort systems in the literature generally control only indoor air temperature, furthermore, the prototypes of the controllers are tested for limited days. However, seasonal variations are significant on the accuracy of the controller. On the other hand, wearable personalized thermal comfort controllers are impractical, i.e. requiring to wear a special glasses for each occupant, and intrusive, i.e. adding fans for all desks. The purpose of this study is to develop an easy employed, non-intrusive, non-wearable personalized thermal comfort driven controller (PTC-DC) using FL model to increase thermal comfort without any human interaction controlling both indoor air temperature and fan speed of an air-conditioning system.

2. Materials and methods

The PTC-DC is developed to maintain a particular comfort level based on objective sensor measurements, subjective occupant data and its control over the operation of an air-conditioner. Fig. 1 depicts the overall process of the study.

The PTC-DC consists of three main components: mobile application, control algorithm, and a box where the measurement system is located [26]. For the training phase of the PTC-DC, the mobile application is developed to collect subjective data such as Actual Mean Vote (AMV), thermal preferences and clothing information of the occupants. The AMV is obtained by using ASHRAE seven-point scale as given in Table 1 [10]. The occupant is requested to enter 1) name and garment once a day, 2) thermal preferences and whether the occupant is satisfied or not with the fan speed and set point temperature when the occupant feels any discomfort with the environment. Otherwise, the AMV value is taken as zero.

The control algorithm uses Fuzzy Logic (FL) Estimation Model, written in C programming language, and operates an HVAC system automatically based on the model which is trained by objective data taken by sensors and occupant's thermal sensation data

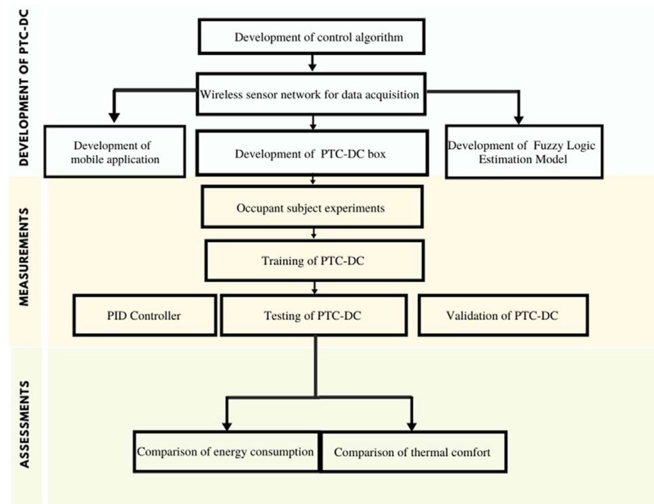


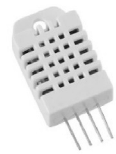
Fig. 1. Flow chart of the study.

gathered by mobile application.

FL model describes the parameters in a descriptive manner like humans by using simple rules developed from qualitative descriptions [26]. The FL relies on fuzzy rules which is constructed linguistically by the experts and observed human behaviour while the database consists of the membership function used in fuzzy rules. On the other hand, a training process is required to understand individual thermal preferences of the occupants. There is no need to cover whole range of objective and subjective data during the training period since the model can predict the output data with lost, missing or previously untrained data. Moreover, the model is mainly based on membership functions and rules instead of numerical values of environmental conditions [27–29]. The rules are constructed according to the thermal preferences of the occupant. Therefore, one-day training was enough in order to understand thermal preferences of the occupant. During the training period, objective and subjective data are transferred to the FL model. Then, the model starts to predict occupants' thermal preferences using objective and subjective data and controls HVAC system without any input or intervention by the occupants (testing period). In testing period, the PTC-DC operates the HVAC system according to the occupant's thermal preferences, automatically. In the study, FL model is used for a decomposition of a complicated nonlinear system in order to predict desired outputs. The advantage of selecting FL approach for the PTC-DC is simplicity. The model does not require complex mathematical systems and big data sets. Moreover, there is no need to re-train the model when a new data or rule is added to the system. The objective of the control algorithm is to maximize personalized thermal comfort of the occupant. The algorithm may not guarantee a decrease in energy consumption. Moreover, the FL model is not bound to a mathematical dynamic model unlike the conventional control systems.

A measurement campaign is designed to demonstrate the applicability of PTC-DC to an HVAC system of an office building at Izmir Institute of Technology, Izmir/Turkey. A wireless sensor network is deployed to the case building to collect objective data which include T_i, T_o, RH_o, RH_i and passive-infrared sensors (PIR). The images and specifications of sensors are given in Table 2. DHT22 [30] is used to measure indoor air temperature and relative humidity while HC-SR501 [31] detects the motion in order to understand absence/presence of the occupant. ESP8266 type Wi-Fi module [32] is added to the system for communication among PTC-DC, server and mobile application. IR receiver and transmitter

Table 2
Specifications of all components used for PTC-DC hardware.

Sensor		Brand/Model	Specifications	
			Measurement range	Sensitivity
Indoor air temperature (T_i) and relative humidity (RH_i)		Adafruit Industries/DHT 22 [30]	T: -40 ÷ 80 °C RH: 0–100 %	RH: ±3% (max. 5%) T: < ±1 °C
Infrared motion		OEM/HC-SR501 [31]	3–5 m	Angle: 140°
IR receiver, communication		Dasheng/DP1838 [33]	10 m	Wave lenght: 940 nm
IR transmitter, communication		5 mm LED [34]	10 m	Wave lenght: 940 nm
Wi-Fi module, communication		Espressif/ESP8266 [32]	2 ms	Power consumption<1.0 mW
Outdoor temperature (T_o) and relative humidity (RH_o)		HOBO/U12-012 [35]	T: 0–50 °C RH: 10–90 %	±0.35 °C ±2.5 %

[33,34] are included to de-modulate air-conditioner remote controller codes and re-send the codes according to occupant's thermal preferences. The sensors are collected in a storage box. The volume of the box is enough to add more sensors for various purposes such as to collect indoor air quality data.

Two versions of PTC-DC are produced in the study. While PTC-DC (v.1) controls only set point temperature of HVAC system, PTC-DC (v.2) aims to improve thermal comfort of the occupants by controlling fan speed along with set point temperature. It is worth to note that the PTC-DC (v.2) controls real fan speed of the HVAC system as control output. Hence, the real fan speed data is collected for the PTC-DC (v.2). The specifications of PTC-DC versions are given in Table 3. The versions are compared with each other and also with conventional controller (PID) in terms of thermal comfort and energy consumption.

3. Case building

An office building in Izmir Institute of Technology Campus, Izmir/Turkey, is used as case building for PTC-DC tests (Fig. 2). Izmir is located in Csa type climate zone under Köppen-Geiger climate classification [36] where heating and cooling seasons are from November to April and May to October, respectively.

The case building consists of two office rooms which have a total dimension of 6 m (width) x 6 m (depth) x 2.8 m (height) and faced outside with six windows and four external walls (Fig. 3). Two rooms are separated with a well-insulated internal wall. However, the internal door is kept open during the measurements.

The external walls of the case building consist of cement plastering, pumice concrete and cement screed. The building is constructed on a soil-filled ground. The innermost layers of the ground are cast concrete, floor screed and limestone.

The case building is occupied with an occupant during office hours (from 09:00 a.m. to 12:30 p.m. and from 13:30 p.m. to 17:00 p.m.). Indoor environment of the building is controlled by a split type air-conditioner and is maintained at 22 °C, to ensure optimal productivity and efficiency of occupants in office environments [37], from 09.00 a.m. to 12:30 p.m. and 13:30 p.m. to 17:00 p.m. during weekdays (Fig. 4). The air-conditioner has three (low, medium and high) fan speed levels and a PID-type conventional controller. PID controller is set to auto fan speed and the occupant is not allowed to change set point temperature and fan speed of PID controller. Heating and cooling capacities are 3.95 kW and 3.25 kW, respectively.

The case building is ventilated naturally twice a day for 15 min at 09:00–09:15 and 13:30–13:45. A personal computer (70 W) exists in the case building and two fluorescent lamps (50 W/each) are used for lighting. A three phase-power analyser was installed to the air-conditioner in order to measure electricity consumption in kWh. While air-conditioner is operated at a set point temperature of 22 °C and mostly constant fan speed at existing PID control, PTC-DC predicts and automatically adjusts set point temperature (v.1 and v.2) and fan speed (v.2) according to thermal preferences of the occupant. The test conditions of the PTC-DC are given in Table 4. Heating/cooling energy need of a building heavily depends on overall heat transfer coefficients (U) and thicknesses of the walls,

Table 3
Specifications of version 1 and 2 of PTC-DC.

	PTC-DC (v.1)	PTC-DC (v.2)
Temperature/RH sensor	✓	✓
PIR sensor	✓	✓
IR transmitter and receiver	✓	✓
Wi-Fi module	✓	✓
Interfaces in mobile application	*Name, garments, AMV*	*Name, garments, AMV, fan speed*
Control outputs	*Set point temperature*	*Set point temperature and fan speed*

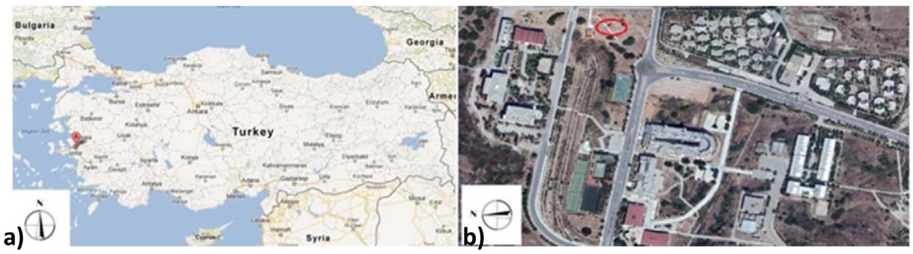


Fig. 2. Location of a) Izmir b) the case building.

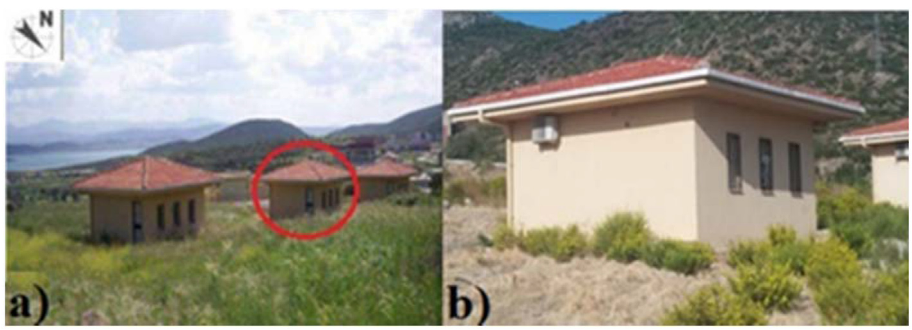


Fig. 3. a) Surrounding of the case building b) Selected case building.

Fig. 4. a) Inner view of the case building, b) Split type air-conditioner used in the case building.

floor, doors and windows. Thus, these parameters are also presented in Appendix A.

The test conditions of developed PTC-DC are limited with an adult-male occupant, a specific climate conditions, building materials and size. However, personalized thermal comfort varies greatly depending upon gender, age, behaviour and location while energy savings differ based on the climate, building materials and size. The FL model is a free-model which is not bounded to any dynamic mathematical model of the system. Therefore, any change in the abovementioned parameters that effect thermal comfort and energy savings, require further tests.

4. Results and discussions

4.1. Development of PTC-DC

A mobile application is developed to collect subjective data from the occupant (Fig. 5). The name of the occupant is first asked to detect which subjective data belong to which occupant. The occupant is then asked to give clothing information in order to calculate “clo value” by adding the garments according to ASHRAE 55 [10]. On another screen, the occupant is asked to select how he/she feels in the environment (AMV) using ASHRAE 7-point scale [10]. In addition, the mobile application asks the satisfaction of the

Table 4
Test conditions of the PTC-DC.

Building dimension	6 m (width) x 6 m (depth) x 2.8 m (height)
Occupant number	1 adult male
Climate type	Csa [36]
Occupant position (assumption)	Seated
PTC-DC location	On the desk (close to the occupant)

Fig. 5. Screenshots of mobile application used by PTC-DC.

occupant with the set point temperature and fan speed for the training of the PTC-DC (v.2). All subjective data are transferred to the PTC-DC server via Wi-Fi module and then stored to be used in FL estimation model. The developed mobile application can be downloaded free from “Google Play Store”.

A control algorithm is developed using FL estimation model to predict occupant's thermal preferences and operate the air-conditioner automatically (Fig. 6).

The FL model is created in the MATLAB [38] environment (Appendix B) with two inputs (indoor air temperature and AMV) and two outputs (set point temperature and fan speed). Each data of input-output pairs is then used to generate an IF-THEN rule for the FL model. The number of fuzzy rules is decided by using “Mamdani” type fuzzy system according to input number and membership function following the Eqn. (1) [39].

$$N_{fuzzy\ rules} = \prod_{1}^{n} \left(N_{Membership\ Functions}\right)^{\left(N_{inputs/outputs}\right)} \tag{1}$$

N represents number while n shows total number of input and output pairs. The division of thermal perception index range into fuzzy sets membership function is given in Appendix B. The first (indoor air temperature) and second input (AMV) have 3 and 5 membership function numbers, respectively. The outputs (set point temperature and fan speed) include 3 membership function numbers. Hence, 135 FL rules ($3^1 \times 5^1$ x $3^1 \times 3^1$) are constructed.

In Mamdani type fuzzy system, the rules could be established from experts, computer databases, books and observed human behaviours [39]. In this study, the rules are established using objective measurements (indoor air temperature) and occupant feedbacks that collected by mobile application (AMV, set point temperature and fan speed). For instance, if indoor air temperature is measured as 21 °C, the rule is accepted as “low” according to the membership function and fuzzy sets in Appendix B. Simultaneously, the occupant assigns “too cold” for AMV via the mobile application. Then, the rule is formed as “too cold”. If the occupant votes “stronger” for fan speed while fan speed is medium, the rule is extracted as the fan speed is “high”. Similarly, the mobile application asks desired set point temperature to the occupant for the training phase. The desired set point temperature is set as “high, medium and low” in the fuzzy sets. For instance, if the desired set point temperature is 24 °C, the set point temperature is accepted as “high”. Each new vote and measurement create a new rule for the fuzzy rule base. The training period for the PTC-DC is only required for obtaining thermal preferences of the occupant. Following the training period, the rules are generated and used for operating the PTC-DC.

An example of a rule is given in Eqn.2 while a set of fuzzy rules is represented in Table 5.

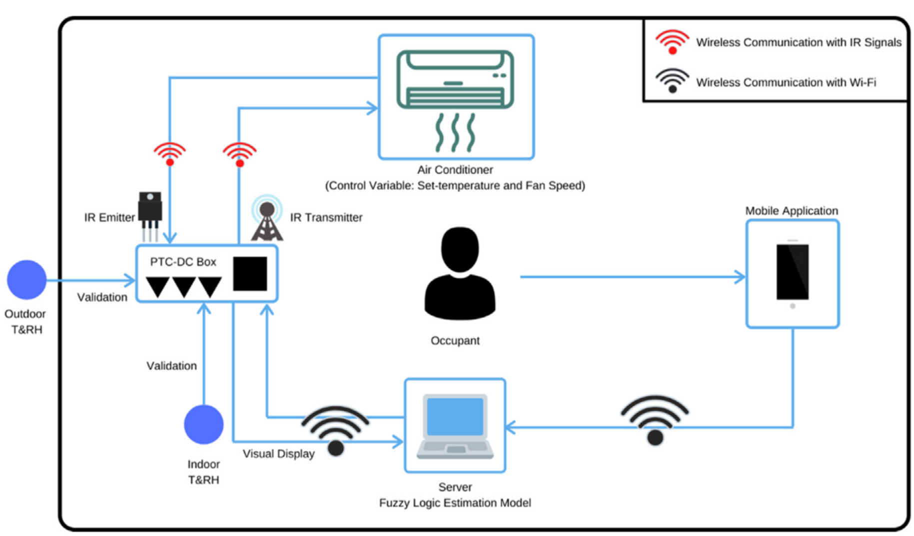


Fig. 6. The schema of PTC-DC.

Table 5
An example set of 135 fuzzy rules.

Indoor air temperature	AMV	Set point temperature	Fan speed
L	TC	H	H
M	C	H	M
M	N	M	M
H	H	M	L
M	TH	L	L
H	TH	L	L

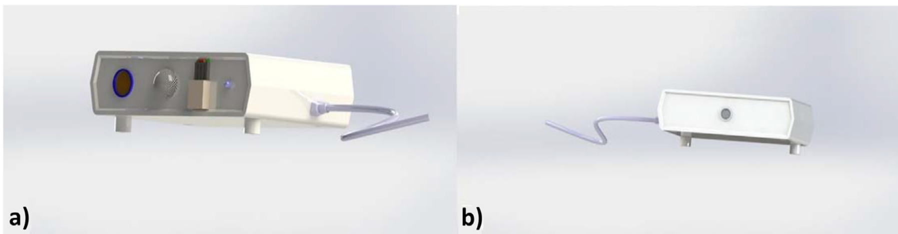


Fig. 7. Technical drawing of PTC-DC a) front b) back.

IF Indoor Air Temperature is *low*(L) and AMV is *too cold*(TC) THEN set − point temperature is *High*(H) and fan speed is *High*(H) (2)

The sensors are located in a box called “PTC-DC box” along with a Wi-Fi module, infrared (IR) transmitter and emitter and a micro-controller. PIR sensor is used to detect the absence/presence of the occupant. Wi-Fi module is used for communication between PTC-DC box and mobile application whilst communication of air-conditioner with PTC-DC is provided by IR transmitter and emitter. Arduino Mega [40] is used as micro-controller. In addition, resistances are used to prevent overvoltage burns and noise in the system. The PTC-DC box can be produced by any 3D printer easily (Fig. 7).

The FL model is trained for one day, then it predicts set point temperature and fan speed of air-conditioner according to thermal preferences of the occupant. However, the PTC-DC must be re-trained for seasonal changes. According to the outputs of the FL model, IR transmitter transmits signals that can change the set point temperature of air-conditioner.

The PTC-DC can be used for any air-conditioning system. First, the controller de-modulates IR codes of the air-conditioner via IR **e**mitter, then, uses these codes to send required signals to the air-conditioner with the help of IR transmitter (Fig. 5).

The produced PTC-DC box is 343 gr with a dimension of 170 mm × 130 mm x 45 mm (Fig. 8). T&RH and PIR sensors are placed on the box so that the sensors will not affected by internal heat. The legs are added to situate the box easily on a table where it can both detect the occupant and control the air-conditioner from maximum 10 m (Fig. 9).

The PTC-DC communicates with the occupant via main screen of the server (Fig. 10). In this main screen, occupant can follow the operation steps of PTC-DC, the objective data, presence/absence of the occupant in the building and display messages of the controller (for instance; PTC-DC is operating etc.).

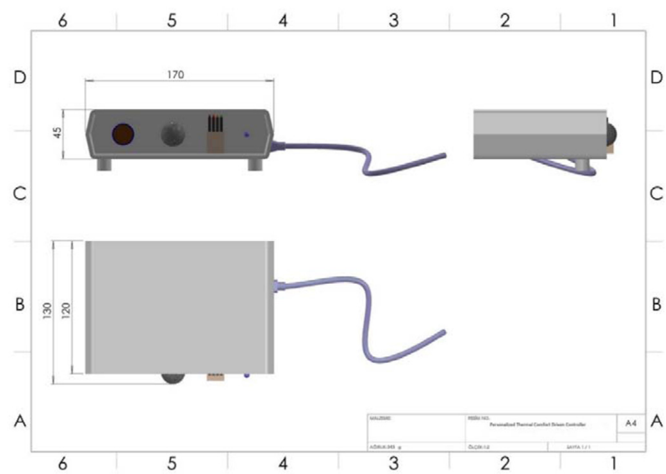


Fig. 8. Three-view drawing of PTC-DC.

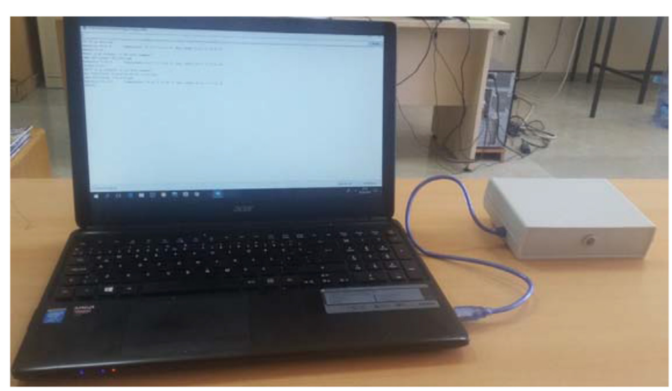


Fig. 9. The prototype of PTC-DC.

4.2. Testing of PTC-DC

The developed PTC-DC is operated from July 3rd, 2017 to March 7th, 2018 for PTC-DC (v.1) and between March 8th, 2018 and November 1st, 2018 for PTC-DC (v.2) (Fig. 11). It is worth to note that, for an ideal comparison, PTC-DC and PID controllers are operated alternately for one-day period in order to minimize environmental parameter changes that affect thermal comfort.

The training days of the FL model for each season are given in Fig. 11. Each version of the PTC-DC is trained twice for each season. During training days, the occupant is asked to use mobile application to give AMV and clothing information. Based on the collected data, clo value is calculated as 0.79 for heating season and 0.54 for cooling season. Furthermore, using AMV data, preferred temperatures of the occupant are determined (±0.5 AMV). Following the training period, the PTC-DC is operated automatically according to

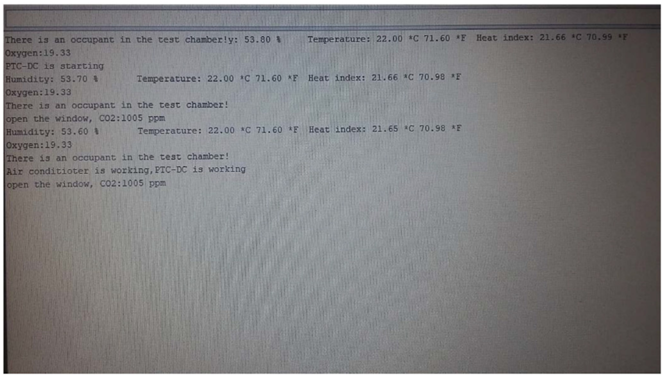


Fig. 10. The main screen of PTC-DC.

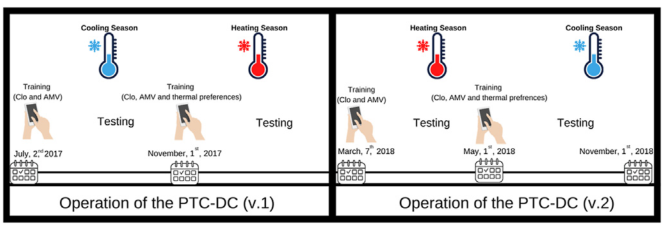


Fig. 11. Training and testing days for the PTC-DC versions.

thermal preferences of the occupant obtained during training period. Table 6 gives total measurement days, min., max. and mean T_o, set point temperature of PID controller and preferred temperature ranges of the PTC-DC for heating and cooling seasons.

4.3. Assessment of the testing period

The PTC-DC versions are compared with each other and PID controller based on thermal comfort and energy consumption.

Fig. 12 depicts the comparison of AMV values for both PID controller and PTC-DC (v.1) for the measurement period of 86 days in total. The range of ±0.5 AMV is accepted as comfortable zone (grey area). The purple line (secondary y-axis) shows T_o while black and red lines represent AMV values for PID controller and PTC-DC (v.1), respectively.

While PID controller remains in the comfort zone in 40 % of the total measurement period, it does not satisfy neutral thermal comfort (AMV = 0) for 95 % in the same period. However, AMV values of the occupant are generally zero in 88 % of total days during PTC-DC (v.1) operation. It is worth to note that outdoor temperatures of the days which PTC-DC (v.1) does not satisfy AMV = 0 value, are extremely higher or lower than the rest of the period (Fig. 12). The outdoor temperature varies in the range of 5–21 °C and 22–37 °C for heating and cooling seasons, respectively.

ISO 7730 [9] provides criteria for thermal comfort based on PMV and PPD indices. However, in the study, Actual Percentage of Dissatisfied (APD) is used instead of PPD since AMV is obtained as subjective data. Fig. 13 shows APD values of PID controller and PTC-DC (v.1). It can be seen that APD values of PTC-DC (v.1) are between 5 and 10 % for the total measurement period. However, APD values of PID controller reaches to 90 %. The PTC-DC (v.1) reduces the APD level by 88 %.

Fig. 14 exhibits AMV values of PID controller and PTC-DC (v.2). The PTC-DC (v.2) satisfies neutral thermal comfort in 92 % of the total measurement period whilst PID controller remains on the AMV = 0 value only for 6 % of the total days.

Fig. 15 compares APD values of PID controller and PTC-DC (v.2). APD values of the PTC-DC (v.2) are around 5 % which is the lowest bound of the APD values. However, APD values of PID controller reach nearly 40 %.

Table 7 shows APD values of PTC-DC and PID controllers for each version. The table indicates that APD values of both PTC-DC and PID are improved for v.2 over v.1 for both heating and cooling seasons. The simultaneous improvement of APD values of both controllers in heating season could be because of the higher outdoor temperatures of v.2 (16–22 °C) compared with v.1 (5–21 °C). Furthermore, the reason for higher outdoor temperature range for v.2 in this season would be the shorter measurement period (18 days) than v.1 (46 days).

The decrease in APD level is calculated for each version comparing with PTC-DC and PID measurements for the same version and also given in Table 7. While the decrease in APD level for v.2 in cooling season is higher than v.1, the situation is opposite for heating season. The reason could be the shorter test period (18 days) of v.2 than v.1 (46 days).

The developed PTC-DC versions also compared with each other and PID controller based on energy consumption.

Fig. 16 demonstrates an example of comparison of set point temperature and fan speeds selected by both the controllers as a time series for a day (9th of March 2018 for PID, 10th of March 2018 for PTC-DC (v.2)). In the figure, it is worth to remind that 1, 2 and 3 refer low, medium and high fan speeds, respectively. The figure indicates that PID controller is generally operated at high fan speed since the controller is based on indoor air temperature. However, PTC-DC takes into account the thermal satisfaction of the occupant instead of indoor air temperature. Thus, the proposed controller

Table 6
Total measurement days and, outdoor, set point and preferred temperatures for measurement period.

			PTC-DC (v.1)		PTC-DC (v.2)	
			PID controller	PTC-DC	PID controller	PTC-DC
Total measurement period (day)	heating		46	46	18	18
	cooling		40	40	67	67
T_o (°C)	heating	min	5	5	17	16
		max	20	21	24	22
		mean	13	13	19	19
	cooling	min	22	22	21	20
		max	38	37	38	38
		mean	30	31	30	30
Set point temperature (°C)	heating		22	–	22	–
	cooling		22	–	22	–
Preferred temperature (°C)	heating		–	21.9–22.6	–	21.7–22.8
	cooling		–	22.2–23.8	–	22.1–23.6

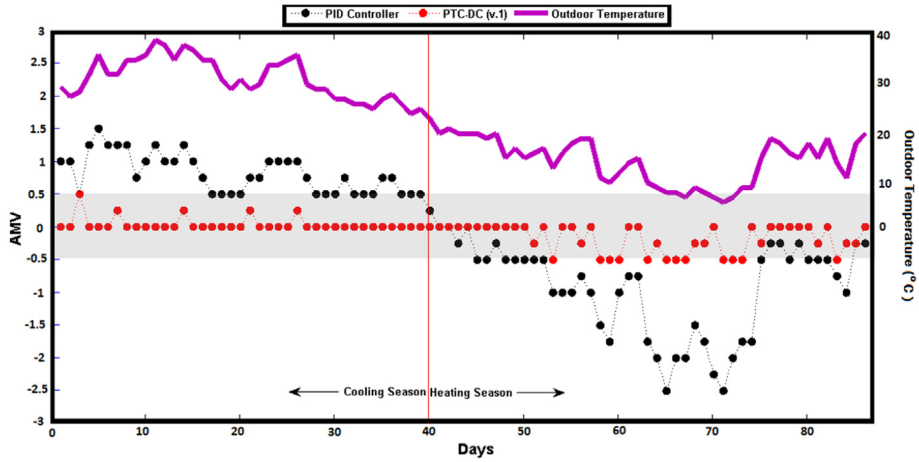


Fig. 12. AMV comparison for PID controller and PTC-DC (v.1).

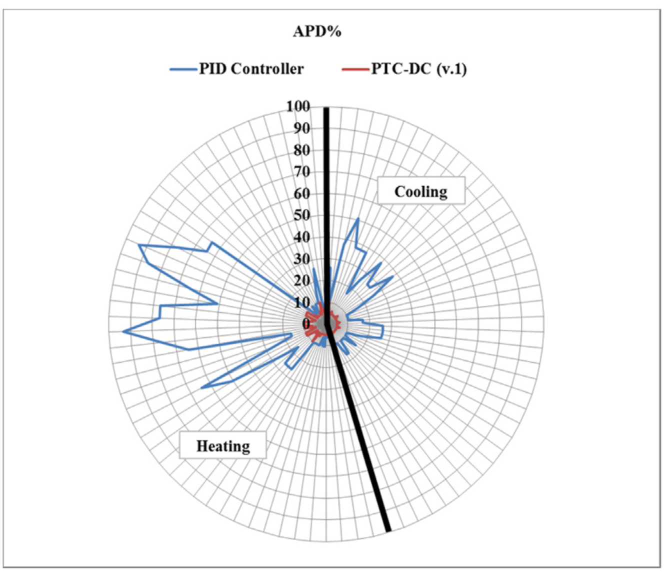


Fig. 13. APD levels for PID controller and PTC-DC (v.1) for the total measurement period.

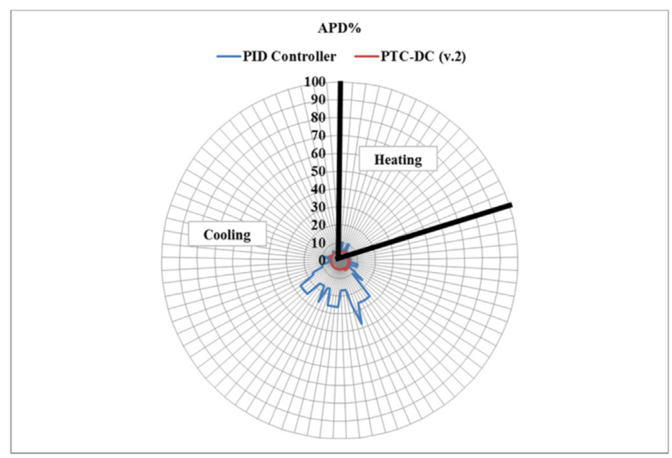


Fig. 15. APD comparison for PID controller and PTC-DC (v.2) for the total measurement period.

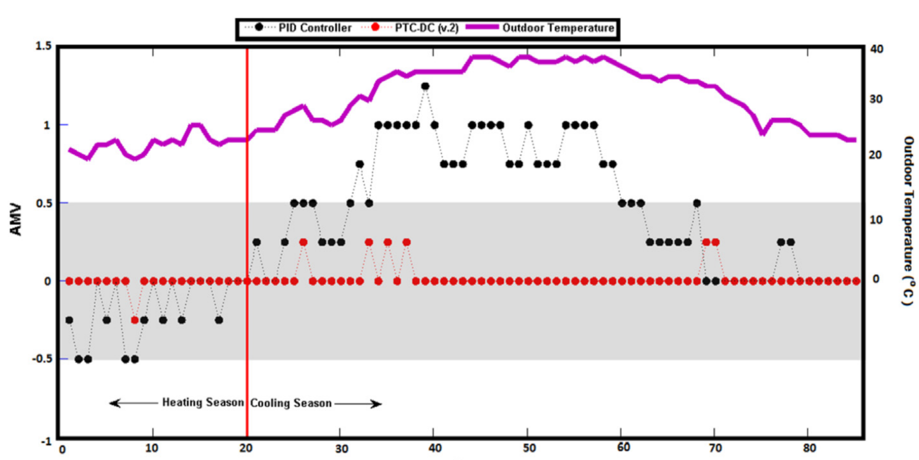


Fig. 14. AMV comparison for PID controller and PTC-DC (v.2).

Table 7
APD values and decrease in APD levels for each version.

		APD ranges (%)			Decrease of APD (%)		
		Heating	Cooling	Total	Heating	Cooling	Total
v.1	**PTC-DC**	5–10	5–7	5–10	91.0	86.0	88.0
	PID	5–90	10–52	5–60			
v.2	**PTC-DC**	5–7	5–6	5–7	52.1	88.1	87.5
	PID	5–10	5–40	5–40			

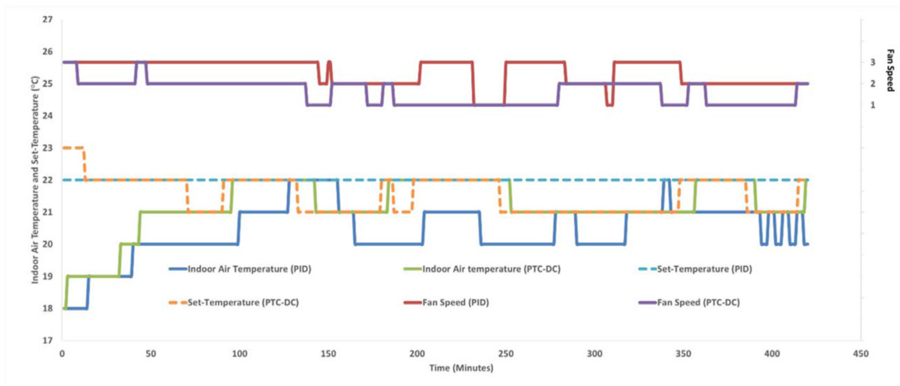


Fig. 16. Set point temperature and fan speed selection for PTC-DC (v.2) and PID controllers with respect to indoor air temperature.

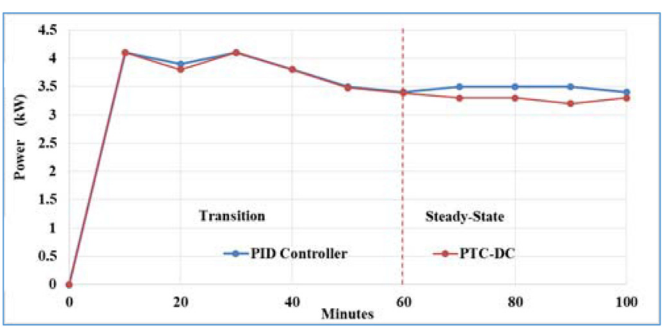


Fig. 17. Power requirement profile of transition and steady-state conditions.

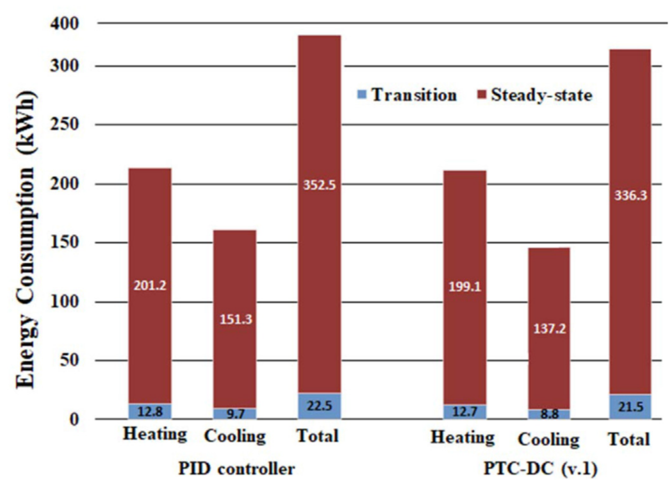


Fig. 18. Comparison of energy consumption for PID controller and PTC-DC (v.1).

selects the fan speed according to the thermal preferences.

Power requirement of air-conditioners changes at different periods of the operation. For instance, air-conditioner draws extra power each time it turns on. The reason for that is high current flow while turning the air-conditioner on and pressure of the gas in air-conditioner which is initially out of equilibrium. When a system reaches to steady-state condition, power consumption drops down [41]. To be able to determine the transition period, power requirements in the first 100 min of the operation are plotted for PTC-DC and PID controllers (Fig. 17).

Fig. 18 gives energy consumption of PTC-DC (v.1) and PID controllers with respect to heating, cooling and total measurement periods. The figure shows transition period and steady-state operation together. Total energy consumption was recorded as 375 kWh (22.5 kWh and 352.5 kWh for transition and steady-state conditions, respectively) for PID controller and 357.8 kWh (21.5 kWh and 336.3 kWh for transition and steady-state conditions, respectively) for PTC-DC (v.1) for more than one-year period. It is worth to note that total energy consumption was decreased almost 6 % by both PID controller and PTC-DC (v.1) when transition period was disregarded. The PTC-DC (v.1) decreased energy consumption by 4.6 % and 10.9 % for heating and cooling seasons, respectively. Moreover, PTC-DC (v.1) decreased total energy consumption by 7.4 % compared to PID controller.

Fig. 19 exhibits energy consumption of PTC-DC (v.2) with PID controller for heating, cooling and total measurement periods. Energy consumptions of transition and steady-state periods are also shown in the graph. The PID controller consumed 317.7 kWh (19 kWh and 298.7 kWh for transition and steady-state conditions, respectively) energy while PTC-DC (v.2) consumed 284.6 kWh (16.8 kWh and 267.8 kWh for transition and steady-state conditions, respectively). Compared to PID controller, PTC-DC (v.2) decreased energy consumption by 10.3 % and 13.7 % for heating and cooling seasons, respectively. However, decrease in total energy consumption by PTC-DC (v.2) was encountered as 13.2 % comparing with PID controller excluding transition period.

Fig.s 18 and 19 indicate that PTC-DC provides a considerable energy savings over PID controller of a single air-conditioner under

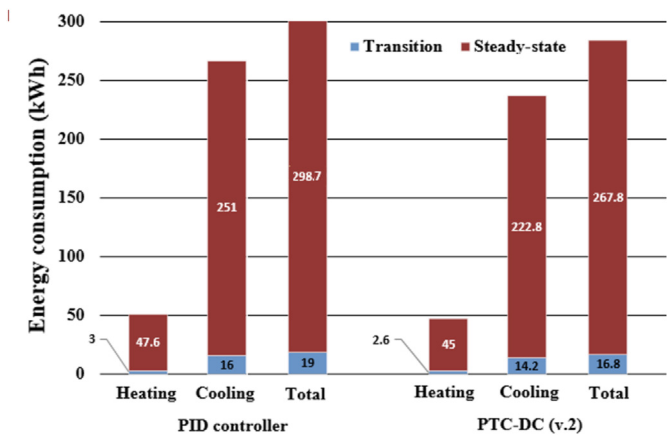


Fig. 19. Comparison of energy consumption for PID controller and PTC-DC (v.2).

Table 8
Summary of energy savings of PTC-DC versions compared to PID controller (excluding transition period-first 1 h).

PTC-DC	Energy saving (%)		
	Heating	Cooling	Total
(v.1)	4.6	10.9	7.4
(v.2)	10.3	13.7	13.2

given conditions and saving rates obtained at heating, cooling and total measurement periods are summarised in Table 8. Total energy consumption was decreased by 7.4 % and 13.2 % for PTC-DC (v.1) and PTC-DC (v.2), respectively. Considering the seasons, energy savings in the cooling season are higher than the heating season. Even though compressor power consumption is lower in heating season, energy consumption of PTC-DC is higher in the heating season than cooling season. One of the reason could be the sensor locations which are closer to the north facade. Another reason could be the occupant's thermal perception and the adaptation to the climate. The case building is located at temperate climate with hot and humid summers and mild winters. As given in Table 6, the occupant prefers higher temperatures at both heating/cooling seasons beyond ASHRAE 55 comfort scale [42–45]. Therefore, higher preferred temperatures than set point temperature caused an increase in energy consumption in winter while a decrease is encountered in summer.

Compared to PTC-DC (v.1), PTC-DC (v.2) increases energy savings by 5.6 % and 2.8 % for heating and cooling seasons, respectively. For total measurement period, PTC-DC (v.2) increases energy savings by 5.8 %. The reason of higher energy savings for PTC-DC (v.2) is controlling fan speed along with set point temperature according to thermal preferences of the occupant.

The results showed that the PTC-DC achieved better thermal comfort and decreased total energy consumption compared to PID controller.

The PTC-DC is tested in a real office environment with a single occupant. If the number of occupant increases, average vote of the occupants could be taken into consideration or PMV method should be employed. Lam et al. [46] developed a set point optimization algorithm to obtain the optimal set point temperature for a group of occupants in a specific room by collecting their thermal preferences to ensure a certain percentage of occupants are in the comfort zone. The authors also conducted short term (maximum 10 days) real world experiments in Hong Kong and declared that they maintained thermal comfort while reducing energy consumption by 18 %. But these approaches cannot guarantee the thermal comfort conditions for each occupant and/or energy saving. To prevent comfort loss, Shin et al. [47] proposed a fairness index. Besides efforts to improve models, experimental confirmations of the reliability of the models in real environments are required. Thus, to be able to determine the performance of the developed PTC-DC controller for several occupants, it has to be re-tested and should be modified/improved based on the test results.

The PTC-DC uses FL model with two inputs (AMV and indoor air temperature) and two outputs (set point temperature and fan speed). If the occupant number and the size of the building are increased, more inputs are needed to feed the model. However, increasing input numbers in the FL model introduces significant complexity with little obvious merit as discussed in Ref. [48]. Therefore, FL model could be replaced with data-driven controllers such as Artificial Neural Network (ANN) or Model Predictive (MPC) based controllers.

The PTC-DC uses wireless communication protocol with IR signals. Since the system stores IR codes of the HVAC system in the server, one PTC-DC box can communicate with only one HVAC system. A new controller working with several HVAC systems should be considered as a future study. The tests are conducted with one occupant who is assumed as seated. Since office building is small, it is also assumed that the environmental conditions do not vary throughout the room. Thus, the movement of the occupant would not cause a considerable error. But, this may not be a valid assumption for a larger office room since thermal preference of the occupant could change with location. The proposed controller should be tested in a larger room where the influence of the environmental conditions is larger on the occupant. Thus, the sensor number should be increased. However, an increase in the number of sensors can result in larger hardware and computational heavy systems. As a result, the price of the system will increase.

PTC-DC uses a split type air-conditioner as an HVAC system. The controller should be tested with different HVAC systems which uses different communication protocols other than IR.

5. Conclusions

This rstudy presents development of two versions of a personalized thermal comfort driven controller (PTC-DC). The prototypes of two PTC-DC versions were tested in a case building for 15 months: 1) PTC-DC (v.1) controlled only set point temperature, 2) PTC-DC (v.2) controlled both set point temperature and fan speed of an air-conditioner. An assessment based on thermal comfort and energy consumption was conducted comparing PTC-DC versions with PID controller and also each other. The results showed that the PTC-DC decreased electricity consumption by 13.2 % compared to the PID controller. Moreover, neutral thermal comfort was satisfied as 92 % by PTC-DC comparing with 6 % by PID controller for the total measurement period. With enhancements in PTC-DC (v.2) decreases energy consumption by 5.8 % and achieves further improvement in thermal comfort compared to the PTC-DV (v.1).

A number of personalized thermal comfort systems are commercially available, but highly expensive and not easy-to-use by occupants. The developed PTC-DC uses cost-effective wireless sensors and simple FL rules to satisfy occupant's thermal comfort level.

The PTC-DC calculates clothing value of the occupant for heating and cooling seasons. However, the occupant has the flexibility to change his/her personal parameters in order to improve thermal comfort and can arrange his/her garments from the interface of mobile application to re-calculate clothing value but it is worth to mention that the processing of large data sets can become computationally heavy. Instead, image-processing which can directly calculates clothing value from the temperature of the clothes can be used for PTC-DC.

The test conditions of developed PTC-DC are limited with an adult-male occupant, a specific climate conditions, building materials and size. However, personalized thermal comfort varies greatly depending upon gender, age, behaviour and location while energy savings differ based on the climate, building materials and size. The FL model is a free-model which is not bounded to any dynamic mathematical model of the system. Therefore, any change in the abovementioned parameters that effect thermal comfort and energy savings, require further tests. In a future research study, the PTC-DC will be tested in larger office buildings in different climatic zones with a variety of occupants to explore its performance and further improvements.

The PTC-DC box would be improved such as decreasing the dimensions and adding image-processing sensors. On the other hand, the PTC-DC can be improved further with controllable windows by servo-motors. In this way, the system becomes occupant-free. Similarly, a Heat Recovery Ventilation (HRV) system can be integrated into the PTC-DC control system. For a heating season, HRV system takes fresh air from outside and gives pre-heated fresh air inside the building for better indoor air quality. Furthermore, HRV system increases energy savings by pre-heating and pre-cooling the outside air [49]. Wi-Fi module of PTC-DC can also be used to communicate between HRV system and the PTC-DC.

The PTC-DC offers a cost-effective and user-friendly controller to the occupants. Unlike the other personalized controllers, the PTC-DC has easy to understand wireless network and simple control interfaces while it can be easily adopted to the real environments.

Better thermal comfort and energy savings could be obtained without any retrofitting of HVAC system components using the PTC-DC.

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Credit author contribution statement

Cihan Turhan: Investigation, Data curation, Writing – original draft, Visualisation. Silvio Simani: Conceptualization, Methodology, Supervision. Gulden G. Akkurt: Formal analysis, Writing-reviewing & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

APPENDIX A

Overall heat transfer coefficients and thicknesses of the walls, floor, doors and windows of the case building.

Parameter	Thickness (m)	U value (W/m^{2}K)
External walls	0.25	0.84
Roof	0.36	2.93
Floor	0.19	2.07
Partition wall	0.25	0.84
Windows	–	1.924
Doors	–	1.9

Input variables	Linguistic terms	Membership function type	Fuzzy sets (a,b,c)
Indoor air temperature	Low (L)	Trapezoid	∞, 20, 22
	Medium (M)	Triangular	20, 22, 24
	High (H)	Trapezoid	22, 24, ∞
AMV	Too Cold (TC)	Trapezoid	∞, −1, −0.5
	Cold (C)	Triangular	−1, −0.5, 0
	Neutral (N)	Triangular	−0.5, 0, 0.5
	Hot (H)	Triangular	0, 0.5, 1
	Too Hot (TH)	Trapezoid	0.5, 1, ∞
Output variables	**Linguistic terms**	**Membership function type**	**Fuzzy sets (a,b,c)**
Set point temperature	Low (L)	Trapezoid	∞, 20, 22
	Medium (M)	Triangular	20, 22, 24
	High (H)	Trapezoid	22, 24, ∞
Fan speed	Low (L)	Trapezoid	∞, 1, 1.5
	Medium (M)	Triangular	1, 1.5, 2
	High (H)	Trapezoid	1.5, 2, ∞

APPENDIX B

The division of thermal perception index range into fuzzy sets membership function.

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