Modeling occupants' metabolic rate in office buildings by implementation of smart wearable sensors considering personal thermal comfort

Pivac, Nikolina

U N I V E R S I T Y O F S P L I T
FACULTY OF ELECTRICAL ENGINEERING, MECHANICAL ENGINEERING
AND NAVAL ARCHITECTURE

Nikolina Pivac

MODELING OCCUPANTS' METABOLIC RATE IN OFFICE BUILDINGS BY IMPLEMENTATION OF SMART WEARABLE SENSORS CONSIDERING PERSONAL THERMAL COMFORT

DOCTORAL THESIS

Split, 2024

U N I V E R S I T Y O F S P L I T
FACULTY OF ELECTRICAL ENGINEERING, MECHANICAL ENGINEERING
AND NAVAL ARCHITECTURE

Nikolina Pivac

Modeling occupants' metabolic rate in office buildings by implementation of smart wearable sensors considering personal thermal comfort

DOCTORAL THESIS

Split, 2024

The research reported in this thesis was carried out at Laboratory of Thermodynamics and Energy Efficiency (LTEF), Department of Mechanical Engineering and Naval Architecture, University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture (FESB). HEP ESCO d.o.o partially supported this research under the project "Korištenje biosenzora u svrhu istraživanja uvjeta toplinske ugodnosti u uredskim zgradama javne namjene s ciljem racionalizacije potrošnje energije, te integracije podataka u ESCO MONITOR®", Contract Number: UU 6/18.

Supervisor: Prof. Sandro Nižetić, Ph.D., FESB, University of Split, Croatia

Doctoral thesis number: 200

BIBLIOGRAPHIC INFORMATION

Keywords (ključne riječi): thermal comfort (toplinska ugodnost); occupants' satisfaction (zadovoljstvo korisnika); office buildings (uredske zgrade); metabolic rate (intenzitet metabolizma); multi-layer perceptron (višeslojni perceptron)

Scientific area (znanstveno područje): Technical sciences (tehničke znanosti)

Scientific field (znanstveno polje): Fundamental technical science (temeljne tehničke znanosti)

Scientific branch (znanstvena grana): Thermodynamics (termodinamika)

Institution of PhD completion: University of Split, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture

Supervisor of the thesis: Prof. Sandro Nižetić, Ph.D.

Number of pages: 145

Number of figures: 48

Number of tables: 64

Number of references: 93

Committee for assessment of doctoral thesis:

1. Prof. Branko Klarin, Ph.D., FESB, University of Split

2. Prof. Damir Sedlar, Ph.D., FESB, University of Split

3. Asocc. Prof. Igor Pehnec, Ph.D., FESB, University of Split

4. Asocc. Prof. Tamara Bajc, Ph.D., Faculty of Mechanical Engineering, University of Belgrade

5. Assist. Prof. Ivo Marinić-Kragić, Ph.D., FESB, University of Split

Committee for defence of doctoral thesis:

1. Prof. Branko Klarin, Ph.D., FESB, University of Split

2. Prof. Damir Sedlar, Ph.D., FESB, University of Split

3. Asocc. Prof. Igor Pehnec, Ph.D., FESB, University of Split

4. Asocc. Prof. Tamara Bajc, Ph.D., Faculty of Mechanical Engineering, University of Belgrade

5. Assist. Prof. Ivo Marinić-Kragić, Ph.D., FESB, University of Split

Doctoral thesis defended on: July 16, 2024

Modeling occupants' metabolic rate in office buildings by implementation of smart wearable sensors considering personal thermal comfort

Abstract:

This doctoral thesis examines and discusses the results of the thermal comfort assessment research in two office buildings located in different climate zones in Croatia. In addition to standard equipment for measuring thermal comfort, the study employed wearable sensors to monitor the activities of eight occupants in order to calculate their metabolic rates. Furthermore, a survey questionnaire is used to investigate the occupants' subjective thermal sensation. Collected information enabled the development of a model for predicting the dynimacly changes of metabolic rates of certain groups of people using artificial neural networks. The models were validated with a correlation coefficient of 90%. Implementing them could potentially increase occupant's satisfaction and enable energy savings in office spaces. Moreover, the results showed that the metabolic rate (MET) response typically ranged between 1.0 and 2.0 over the seasons, which is higher than the values for standard-based office activities, questioning the applicability of using static MET values in calculating the PMV index. Finally, the study analyzed the differences in thermal conditions between the two buildings and presented valuable insights regarding the age, gender and body mass index of the occupants in relation to their level of satisfaction with the comfort conditions.

Keywords:

Thermal comfort; occupants' satisfaction; office buildings; metabolic rate; multi-layer perceptron

Modeliranje intenziteta metabolizma korisnika uredskih prostora primjenom pametnih senzora u svrhu analize individualne toplinske ugodnosti

Sažetak:

Ovaj doktorski rad ispituje i raspravlja o rezultatima istraživanja procjene toplinske ugodnosti u dvije uredske zgrade smještene u različitim klimatskim zonama u Hrvatskoj. U istraživanju su uz standardnu opremu za mjerenje toplinske ugodnosti prostora, korišteni i prijenosni uređaji za praćenje aktivnosti osam korisnika zgrade kako bi se izračunao njihov intenziteta metabolizma. Također, korišten je i anketni upitnik za istraživanje subjektivnog osjećaja ugodnosti korisnika. Na taj način prikupljene su precizne informacije o dinamičkim promjenama u intenzitetu metabolizma korisnika zgrade tijekom radnog vremena. Ove informacije omogućile su razvoj modela za predviđanje stope intenziteta pojedinih skupina ljudi korištenjem umjetnih neuronskih mreža. Modeli su potvrđeni s koeficijentom korelacije od 90% što bi potencijalno moglo povećati zadovoljstvo korisnika i omogućiti uštedu energije u uredskim prostorima. Nadalje, rezultati su pokazali da se intenzitet metabolizma (MET) tipično kretao između 1,0 i 2,0 tijekom godišnjih doba, što je više od vrijednosti MET-a za uredske aktivnosti temeljene na standardima, dovodeći u pitanje primjenjivost korištenja statičkih MET vrijednosti u izračunavanju PMV indeksa. Naposljetku, provedena je analiza toplinskih uvjeta između dvije ispitane zgrade i predstavljeni su vrijedni uvidi u pogledu dobi, spola i indeksa tjelesne mase korisnika i odnosu s njihovom razinom zadovoljstva uvjetima ugodnosti.

Ključne riječi:

Toplinska ugodnost; zadovoljstvo korisnika; uredske zgrade; intenzitet metabolizma; višeslojni perceptron

Acknowledgments

Zahvaljujem se svom mentoru prof. dr. sc Sandru Nižetiću na neizmjernoj podršci, strpljenju i stručnom vodstvu kroz cijeli proces izrade ovog doktorata. Vaša mudrost i smjernice bile su neprocjenjive.

Posebno hvala mom dragom prijatelju Ivanu Peki na dragocjenim savjetima i podršci koji su mi ovaj put učinili lakšim.

Veliko hvala mom suprugu na beskrajnoj ljubavi, razumijevanju i podršci, kao i na svim žrtvama koje si morao podnijeti da bih mogla ostvariti svoj cilj. Bio si moj izvor inspiracije i motivacije da ustrajem kada je bilo najteže.

I na posljetku, posebno hvala mojim roditeljima i sestri na njihovoj brizi, podršci i bezuvjetnoj ljubavi, te životnim vrijednostima koje su me vodile kroz svaki korak ovog putovanja. Hvala vam na svakoj riječi ohrabrenja, te na pomoći pri čuvanju moja dva najveća blaga, Eme i Luke, bez kojih bi ovaj doktorat bio napisan prije tri godine, ali bez kojih ne bih bila osoba kakva sam danas...

Contents

List of Figures

List of Tables

Abbreviations

ANN	Artificial Neural Network
BMI	Body Mass Index
CNN	Convolutional Neural Network
EE	Energy Expenditure
HVAC	Heating, Ventilation, and Air-Conditioning
IAQ	Indoor Air Quality
MET	Metabolic rate
MLP	Multi-Layer Perceptron
PMV	Predictive Mean Vote
PPD	Predicted Percentage of Dissatisfied
RH	Relative Humidity
SPSS	Statistical Package for Social Sciences
TSV	Thermal Sensation Vote

1. INTRODUCTION

1.1. Motivation

Even with notable enhancements in the energy efficiency of buildings, in most older buildings, built before the 2000s, there is a deviation of 18% between actual and designed building energy use [1]. Figure 1.1 shows a comparison between simulated (predicted) energy consumption modeled during the design phase and measured energy consumption in certified buildings in the USA. The created difference consequently affects the increase in electricity consumption in terms of heating and cooling, depending on the preferences of the building users, i.e. occupants [2].

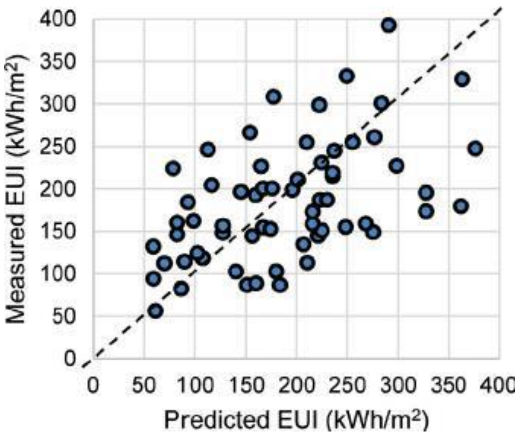

Figure 1.1. Difference between the designed and the actual building energy use intensity [1]

Due to the significant role that occupants play in managing the building in terms of improving the building’s energy efficiency, assessing and achieving their comfort is very important. A pleasant atmosphere has a positive impact on health performance and satisfaction of the occupants. Inadequate thermal environments, on the other hand, increase energy consumption as the occupants strive to bring their building occupancy into a state of their own comfort [2].

Moreover, occupant behavior in terms of the use of additional heaters and ventilators or simply window opening is generally recognized as an important factor which contributes to the uncertainty of building's energy performance [3] [4], because of its impact on the installed energy systems in the buildings [5] [6].

Once it became possible to regulate indoor environments such as temperature, ventilation, and humidity through Heating, Ventilation, and Air-Conditioning (HVAC) systems, the demand for better indoor comfort conditions was raised [3]. Efficient thermal comfort regulation by HVAC systems is substantial for healthy indoor conditions and other facts like artwork preservation [4]. Still, on the downside, such systems receive feedback from the single point temperature measurement provided by a thermostat in order to switch on or off the heating/cooling [6] and thermal comfort can rarely be achieved in this way.

Thermal comfort is the state of satisfaction with the thermal environment, which is influenced by thermal sensation. The thermal sensation vote (TSV) is thermal perception, defined as a conscious feeling commonly graded into the categories' cold, cool, slightly cool, neutral, slightly warm, warm and hot' [7] and is often the first step before estimating thermal comfort in practice [8]. By measuring and analyzing thermal sensation data through surveys or questionnaires, insights can be gained into how occupants perceive the thermal environment and whether it aligns with their comfort expectations. The connection between thermal sensation and thermal comfort lies in the fact that the perception of thermal sensation directly influences an individual's evaluation of thermal comfort.

If thermal sensation is considered as a critical aspect of thermal comfort assessment, environments that promote well-being, productivity, and satisfaction for the occupants can be created. It helps ensure that indoor spaces are conducive to the needs and preferences of the people using them, leading to enhanced comfort and an overall quality of life.

1.2. Standards regarding thermal comfort

International standard ISO 7730:2008 [8] determines the "methods for predicting thermal sensations and degree of discomfort of people exposed to moderate thermal environments." The range encompasses well individuals, both men and women, exposed to optimal thermal comfort but allowing for potential mild deviations. ASHRAE standard 55 [7] defines the thermal environmental conditions for human occupancy.

Standard HRN EN 16798-1:2019 (EN 16798-1:2019) [9] specifies requirements for indoor environmental parameters for the thermal environment, indoor air quality (IAQ), lighting and acoustics. It specifies establishing these parameters for building system design and energy performance calculations. The *thermal criteria* used within EN 16798 are based on the predefined Predictive Mean Vote (PMV), a heat balance model to determine the level of thermal comfort in air-conditioned buildings found in the ASHRAE 55 and ISO 7730 standards.

The PMV model is a mathematical expression of the occupant's thermal sensation based on the body's thermal balance. It represents the difference between thermal energy in the human body and the amount of heat exchanged with the environment. When the heat departing from the occupant surpasses the heat entering, the thermal perception is characterized as "cold." Conversely, if the heat entering the occupant outweighs the heat leaving, thermal perception is described as "warm" or "hot." In order for the occupants to feel comfortable, the PMV must be within the recommended limits (-0.5 < PMV < +0.5) for an interior.

The initial data was gathered by exposing a significant number of individuals (reportedly many thousands of Israeli soldiers) to various conditions within a climate chamber. They were then asked to indicate their comfort level by choosing a position on a scale that best described their sensation of comfort. The result relates the size thermal comfort factors to each other through heat balance principles and produces the following sensation scale presented in Table 1.1.

Table 1.1. Thermal sensation of the subject within a moderate indoor environment, in a 7-point scale reduced to 5-point questionnaire scale

PMV	TSV	Questionairre values
< -3.5	Very cold	5
-3.5 to -2.5	Cold	
-2.5 to -1.5	Cool	4
-1.5 to -0.5	Slightly cool	
-0.5 to 0.5	Comfortable / Neutral	3
0.5 to 1.5	Slightly warm	2
1.5 to 2.5	Warm	
2.5 to 3.5	Hot	1
> 3.5	Very hot	

The PMV index is obtained based on measured parameters, i.e. four environmental variables (air temperature, humidity, mean radiation temperature and air flow speed) and two personal variables (metabolic rate and level of clothing) described in Table 1.2.

Table 1.2. Parameters of PMV

Name	Symbol	Unit	Description
Air temperature	t_{a}	°C	Temperature of the air surrounding the occupant.
Radiant temperature	t_{r}	°C	The weighted average of all the temperatures from surfaces surrounding an occupant.
Air velocity	v_{a}	m/s	Rate of air movement given distance over time. The airflow is represented by the average wind speed.
Relative humidity (RH)	RH	%	Percentage of water vapor in the air.
Clothing insulation	I_{cl}	clo (clo = 0.155 ($\mathrm{m^2}$ K)/W)	Thermal resistance value of clothes.
Metabolic rate (MET)	M	$\mathrm{W/m^2}$ or met (metabolic equivalent of task) 1 met is dimensionless unit equivalent to the energy expended per unit surface area of an average person seated at rest (58.2 $\mathrm{W/m^2}$)	The energy expended from the human body during the specific activity (intensity of specific activity based on the amount of oxygen consumed during the activity). The energy expenditure of specific activity in relation to an individual's resting metabolic rate.

In general, the PMV can be expressed as a function 1.1:

$$PMV = f\ (t_{\mathrm{a}}, t_{\mathrm{r}}, RH, v_{\mathrm{a}}, I_{\mathrm{cl}}, M) \tag{1.1}$$

PMV is arguably the most widely used thermal comfort index today. It is used as an explicit definition of the comfort zone. It can be calculated using the following equation [8]:

$$\begin{aligned} PMV = {} & [0.303 \cdot e^{-0.036 \cdot M} + 0.028]\,\{(M - W) - 3.05 \cdot 10^{-3} \cdot \\ & \cdot [5733 - 6.99 \cdot (M - W) - p_{\mathrm{a}}] - 0.42 \cdot [(M - W) - 58.15] - 1.7 \cdot 10^{-5} \cdot \\ & \cdot M \cdot (5867 - p_{\mathrm{a}}) - 0.0014 \cdot M \cdot (34 - t_{\mathrm{a}}) - 3.96 \cdot 10^{-8} \cdot f_{\mathrm{cl}} \cdot \\ & \cdot [(t_{\mathrm{cl}} + 273)^4 - (\overline{t_{\mathrm{r}}} + 273)^4] - f_{\mathrm{cl}} \cdot h_{\mathrm{c}} \cdot (t_{\mathrm{cl}} - t_{\mathrm{a}})\} \end{aligned} \tag{1.2}$$

where:

M is metabolic rate of specific activity, i.e. energy expended from the human body [W/m^2],

W is the effective mechanical power [W/m^2],

p_{a} is the water vapour partial pressure [Pa],

t_{a} is the air temperature [°C],

f_{cl} is the clothing surface factor, described as:

$$f_{\mathrm{cl}} = \begin{cases} 1.00 + 1.29 \cdot I_{\mathrm{cl}}, & I_{\mathrm{cl}} \leq 0.078\ \ (\mathrm{m^2\ K})/\mathrm{W} \\ 1.05 + 0.645 \cdot I_{\mathrm{cl}}, & I_{\mathrm{cl}} > 0.078\ \ (\mathrm{m^2\ K})/\mathrm{W} \end{cases} \tag{1.3}$$

I_{cl} is the clothing insulation [(m^2 K)/W],

t_{cl} is the clothing surface temperature [°C], described as:

$$\begin{aligned} t_{\mathrm{cl}} = {} & 35.7 - 0.028 \cdot (M - W) - I_{\mathrm{cl}} \cdot \\ & \cdot \{3.96 \cdot 10^{-8} \cdot f_{\mathrm{cl}} \cdot [(t_{\mathrm{cl}} + 273)^4 - (\overline{t_{\mathrm{r}}} + 273)^4] + f_{\mathrm{cl}} \cdot h_{\mathrm{c}} \cdot (t_{\mathrm{cl}} - t_{\mathrm{a}})\} \end{aligned} \tag{1.4}$$

$\overline{t_{\mathrm{r}}}$ is the radiant temperature [°C],

h_{c} is convective heat transfer coefficient [W/(m^2 K)], described as:

$$h_{\mathrm{c}} = \begin{cases} 2.38 \cdot |t_{\mathrm{cl}} - t_{\mathrm{a}}|^{0.25}, & 2.38 \cdot |t_{\mathrm{cl}} - t_{\mathrm{a}}|^{0.25} > 12.1 \cdot \sqrt{v_{\mathrm{ar}}} \\ 12.1 \cdot \sqrt{v_{\mathrm{ar}}}, & 2.38 \cdot |t_{\mathrm{cl}} - t_{\mathrm{a}}|^{0.25} < 12.1 \cdot \sqrt{v_{\mathrm{ar}}} \end{cases} \tag{1.5}$$

v_{ar} is the relative air velocity [m/s].

Predicted Percentage of Dissatisfied (PPD) by the ISO is "an index that establishes a quantitative prediction of the percentage of thermally dissatisfied people who feel too cool or too warm". It is dependent on PMV, as an increase in PMV, indicating departure from the neutral point (0), leads to an escalation in PPD as illustrated in Figure 1.2. The maximum level of dissatisfaction with comfort conditions occurs when PPD reaches 100% and, as you can never please all of the people all of the time, the recommended acceptable PPD range is 20% occupants dissatisfied with an interior space. Since PPD is the function of PMV, it can be defined as function 1.6 [8]:

$$PPD = 100 - 95 \cdot e^{-0.3353 \cdot \mathrm{PMV}^4 - 0.2179 \cdot \mathrm{PMV}^2} \tag{1.6}$$

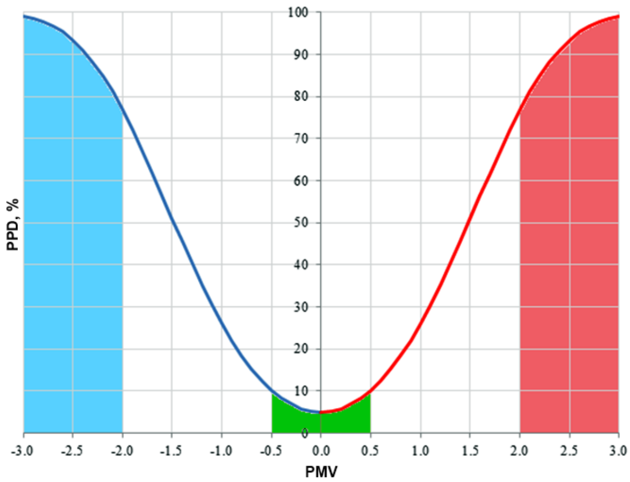

Figure 1.2. Relationship between PMV and PPD based on [8]

The global applicability of the PMV model has been discussed for a long time. It is argued that the controlled environmental parameters such as air temperature, air quality, velocity and relative humidity in laboratory experiments are unlike those in real buildings. Therefore, adaptations of the human body play a key role in determining subjective thermal sensation and perception.

In practice, indoor temperatures are often regulated within narrower ranges than what the standards permit. An examination of 100 US office buildings revealed that during summer, temperatures tended to fall below the comfort zone, and, on average, were even cooler than temperatures observed in winter [10]. Overcooling appears to be a problem that is growing worldwide [11].

Furthermore, it has been claimed that the ISO 7730 [8], overestimates the occupant responses on the ASHRAE scale at high temperatures and underestimates them at low temperatures [12] [13] which may lead to the use of more air conditioning than is necessary. Humphreys and Nicol [14] confirmed that the biases in PMV exceeds 0.25 scale frequently and reaches as much as one scale through meta-analysis. ignificant biases of this magnitude suggest that Predicted Mean Vote (PMV) might be inadequate in predicting thermal sensation [15]. The shortcomings of PMV in air-conditioned buildings are primarily attributed to errors in its input parameter [16]. One of the most common reasons PMV fails to estimate thermal sensation correctly is an inaccurate metabolic rate assessment.

1.3. Metabolic rate – the factor of the individual difference

Of the six basic parameters in the mentioned PMV model of thermal comfort, the metabolic rate (MET) is probably the most important yet underestimated in research and practice. The net heat production of a person must be continuously distributed and regulated to maintain a normal body temperature. An adult person produces about 100 W of heat in a state of rest [14]. As most of the heat is transferred to the environment through the skin, for practical reasons, metabolic activity is characterized as heat production per unit skin area. A person at rest has 58 W/m^2, or a metabolic intensity of 1 met [14]. A higher MET is expressed in relation to the state of rest. For example, a person walking will have 3 feet more than a person at rest (3 met). People have different metabolic rates that can fluctuate due to activity level and environmental conditions [17].

It has been experimentally confirmed that accurate input of MET can effectively improve PMV for thermal sensation prediction [18][19]. Conversely, misestimation of MET can also lead to an error in predicting the occupant's thermal comfort. A change of 0.1 met will cause a change in the occupant's thermal sensation equivalent to a change in air temperature of 1 °C, and a change in MET of 0.4 met will cause a change of at least 2.5 °C [20][21]. Luo et al. [22] concluded that an increase in MET from 0.9 MET to 1.5 MET corresponds to more than a 2°C variation in predicted neutral temperature and approximately a 1.5 unit difference on the PMV scale.

Figure 1.3 shows how MET affects PMV when the clothing level is 1 clo. A change in MET from 0.9 met to 1.5 met results in a variation of approximately 1.5-unit difference in PMV at the thermally neutral temperature (the temperature when comfort is achieved and PMV is equal to 0).

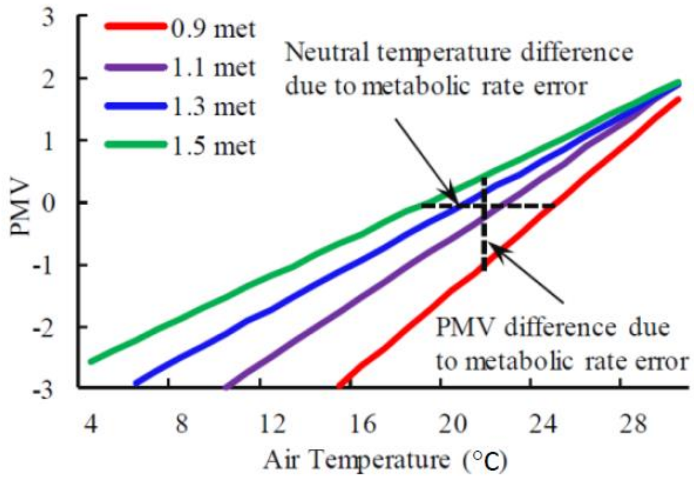

Figure 1.3. Metabolic rate effect on PMV [21]

The variability in MET among occupants is influenced by individual differences, such as race, gender, age, weight, and other personal factors. [20]. An illustrative instance of analyzing individual differences is presented by Kingma and Marken Lichtenbelt [23], who observed a metabolic distinction between genders. Their findings suggested that men exhibited a higher MET, implying that the global practice of overcooling buildings may prioritize the comfort of men at the expense of women's comfort. Another study byand Arens [24], utilizing data from the US Army, revealed that females typically experienced 10-30% lower metabolic rates compared to males with the same heart rate. The reduced metabolic rates observed in females can be linked to variations in the percentage of fat-free mass. Heat production per unit in fat-free mass tends to be higher compared to that in the body's fat tissue, contributing to this difference in metabolic rates. [25]. Typically, females tend to possess a higher fat percentage and lower muscle mass compared to males at an equivalent body mass index (BMI) [26]. As fat-free mass is considered the primary determinant of basal MET [27], noticeable variations between the sexes might be observed across all activity levels except walking at a speed of 4.0 km/h. However, the MET for walking at this speed showed no significant difference between the sexes due to considerable variability in the measurements [28].

Body shape is another contributing factor impacting differences in MET. As mentioned earlier, heat dissipation is contingent on the body's surface area. A taller and slender individual, possessing a larger surface-to-volume ratio, can disperse heat more effectively, enabling them to endure higher temperatures compared to someone with a more rounded body shape.[29]. An examination based on BMI indicated that MET tends to increase with higher BMI. In general, there is a positive correlation, meaning that as BMI increases, so does the MET value. However, when it comes to sitting and eating activities, according to Na and Kim [30] the higher the BMI, the lower the MET.

Regarding the race factor, Qi et al. [31] compared the respiratory CO_2 production between Chinese and Western, and reported that respiratory CO_2 production in 44 Chinese subjects was observed to be 15% lower than the values predicted by the empirical formula established for Western populations.

Furthermore, some studies [28] indicate that the existing international standards tend to slightly overestimate the MET for young and older adults performing office activities. Studies [21] [32] [33] found discrepancies in the heat balance or preferences for higher or lower temperatures between the young people and the old ones. There is an effect related to personal parameters (i.e. they show a lower activity level, and thus MET, than younger). The traditional thermostat lacks the capability to measure and control HVAC systems based on the actual thermal sensation of the end-user. Consequently, the resulting HVAC control may not accurately reflect the real thermal comfort experienced by individuals, potentially leading to increased energy consumption for climate control or the creation of unsuitable indoor environments.

In their research, Zhai et al. [34] claimed that ISO and ASHRAE standards overestimate MET for sitting and standing activities by 10-20%, and underestimate MET for walking activities by 5-9% in ISO, and by more than 20% in ASHRAE. The study results of Gauthier and Shipworth [35] indicate that current standards overestimate winter clothing insulation by 22% but underestimate residential metabolic activity by 9%.

Interestingly, both the ISO and ASHRAE standards primarily rely on data from the 1967 Passmore and Durnin review [36] on energy expenditure, which involved European and North American subjects. The MET tables in these standards have not been revisited or revised since then. Moreover, the sedentary rate of 58 W/m^2 (1 MET) is based on an average male European with a skin surface area of about $1.8m^2$. Given that metabolic rates can be influenced by ethnic and geographical factors [37], utilizing the same MET values for diverse genders, ages, ethnicities, geographical backgrounds, and body compositions might lead to potential systematic errors. Therefore, it's essential to validate the MET specifications in current standards through human subject tests conducted in various geographical locations and among different groups of people.

Moreover, these standards are suitable for static, uniformly thermal conditions and are based on the hypothesis that regardless of their individuality, human beings are thought to feel comfortable in a narrow, well-defined range of thermal conditions [38].

The reviewed field studies confirm that this personal variable is often estimated with a great degree of error. Considering that this variable is the most influential one, this high level of error will undoubtedly reduce both the accuracy and precision of the results of the predictive models [35]. To overcome this, methodological modifications must be made concerning MET. Thus, the next chapter is about the standard which presents the methodology for MET determination.

1.4. Research overview

ISO Standard 8996:2021 [39] specifies methods to determine MET as a function of ergonomics of the thermal environment in different working climates. The standard ascertains the MET estimation in the context of the task requirements from the following: the body segment involved in work, the workload from that part of the body, the body posture and the working speed. The overall MET for a work cycle can be calculated using equation 1.7:

$$M = \frac{1}{\tau}\sum_{i=1}^{n} M_i \, \tau_i \tag{1.7}$$

where:

M is the average metabolic rate for the work cycle [W/m^2],

M_i is the metabolic rate (MET) for activity i [W/m^2],

τ_i is the duration of i-activity [min],

τ is the duration of the work cycle and represents the sum of the partial durations τ_i [min].

The Standard ISO 8996 [39] can also be used for other applications, such as the energetic cost of specific jobs or the total energy cost of an activity. The standard provides guidance on the level of accuracy one could expect with each method described in Table 1.3 and data refer to standard persons male 70 kg, 1.70 m, 1.8 m^2 body surface area; female 60 kg, 1.60 m, 1.6 m^2). It provides fundamental support to ISO thermal comfort and other standards and sets four levels of increasing accuracy for estimating MET.

Table 1.3. Methods for determining metabolic rate [39]

Level	Method
1. Screening	simple categorization of workload
2. Observation	metabolic rate is estimated by a time and motion study
3. Analysis	metabolic rate is estimated from heart rate recordings or accelerometers measurements
4. Expertise	sophisticated techniques for measuring rate of oxygen consumption

Level 1 represents basic classification of tasks. These range from general descriptions (resting, low, moderate, high, very high) to specific descriptions of occupations which are described in tables of metabolic rates. However, this method today is rearly used for the great risk of error. Brighenti-Zogg et al [40] confirmed that the average is misrepresenting the actual physical work demands of specific occupational groups, and that it does not account for gender-related differences in relative workload.

Level 2 is another method with the use of tables, where estimates are provided based upon a description of activity. The examiner assesses the subject's activity (e.g. sitting, standing or walking) via a questionnaire and then looks at the table to obtain the corresponding metabolic rate value. ASHRAE Standard 55 [7] provides a table of MET rates for a variety of activities.

Table 1.4. Some common values of MET rates for a variety of activities [7]

MET	ACTIVITY
0.7	sleeping
1.0	a seated and quiet position
1.2-1.4	light activities standing
2.0	activities that involve movement
< 2	lifting heavy loads or operating machinery

This method is simple, suitable for implementation and does not require high financial expenses, so it is widely used in studies of thermal comfort.

However, when calculating the PMV value according to the activity diary, the metabolic rate obtained under a certain activity level is constant. On the contrary, occupants' metabolic rates change over time during the working day. Thus, the real-time changes in metabolic rate are caused by moving around, changing postures, engaging in different jobs, and exposing to different environments. Therefore, the method of assuming a constant value for the metabolic rate may not be sufficiently accurate to sustain precise thermal comfort modeling [41].

Liu et al. [42] researched occupant’s clothes type, activity type, skin temperature, and clothes temperature extracted by vision-based procedures. They used a thermal camera to track the subjects, their movement, and their level of clothing and then recorded the metabolic intensity values from the tables for a certain time. Based on these input data, they created a model using a convolutional neural network (CNN) that would determine MET values in the everyday life of the subjects.

However, Havenith [43] indicated that the Level 2 methods have an error of up to 20% in obtaining MET. Similarly, Broday et al. [18] compared MET tables with real-time measurements and concluded that there is a significant difference of up to 20 W/m^2 between the measurements and tables.

Level 3 has been investigated by most authors due to its practicality and high level of accuracy. Given the availability and commercial use of sensor devices for measuring heart rate and activity, many studies have used smart bracelets and smart watches to determine subjects' metabolic rates. In their work, Vhaduri and Poellabauer [44] tested the Fitbit device based on three criteria: (1) accuracy (2) access to raw data to support research and (3) practicality of Fitbit wearing 24 hours a day. The test results, in line with the work of Liu et al. [45], showed that the device does not measure parameters with acceptable accuracy for this kind of research. However, the practicality of wearing the device was satisfactory. In terms of data access, the device collects heart rate data only when it is actually worn, while on the other hand, it collects activity data all the time, even when it is not being worn. Therefore, before using activity data, the researchers must remove "invalid" periods of activity minutes that do not coincide with heart rate measurement.

Sugimoto [46] used a sensor system to measure biological and activity data in daily life. The system consists of a temperature sensor worn in the ear, a skin temperature sensor, an electrocardiography (ECG) sensor with a tri-axial accelerometer and thermo-hygrometers. Based on the obtained values, as well as the temperature and humidity values in the room, he developed a Markov model for determining the degree of the subjects' satisfaction. Although neural networks proved to be an excellent tool for modeling, in this particular research no questionnaires were used that would give the relevance of satisfaction with thermal conditions. Hence, it is not clear on what basis the subjects' comfort was estimated. In this direction of modeling the MET, Na et al. [47] built two models, a self-evaluation model of MET value using neural networks and a third-party evaluation model based on collected data. The authors did a pilot study on a smaller sample which they extended afterward [48] by investigating the influence of gender and BMI on MET values during various activities. The shortcoming of their research is the measuring equipment used, which consists of an aforementioned Fitbit device for heart rate measuring and a Kinect camera for movement tracking. The latter's disadvantage is the possibility of accurately assessing the activity when the subject is outside the recording angle or obscured by an object or person in the room.

The number of new research investigations using this methodology proves that the determination of the metabolic rates by Level 3 is still insufficiently investigated. For example, in 2020, Zhang et al. [41] experimented by measuring the subjects' metabolic rates during walking. Subjects walked around the hall at different speeds while their heart rates were measured with a 3XMSH05HM smart bracelet. However, the individual characteristics of the respondents were ignored during the research. Özbey et al.[49] went a step further. In 2021, they measured the heart rate in order to model the MET by multivariable nonlinear regression analysis (MNLR) in MATLAB on a large number of subjects, 21 men and 17 women, with different individual characteristics.

Although, the heart rate measurement can provide an accurate MET estimation, the need for continuous measurement has made this method inapplicable in real-world scenarios [50]. Also, there is a possibility of an error occurring during the measurement due to the inconsistent emotional/psychological state of the subject [47]. Furthermore, when measuring heart rate based on PPG (changes in heart volume), artifacts can appear in the signals, which are unusual occurrences in the measured data that distort the results of the study [51]. In order to minimize artifacts caused by human movements from the collected pulse signal, it is also necessary to remove noise during data analysis, which further complicates the data analysis [52].

An individual's heart rate is considered to be a composite of various components. Typically, it exhibits a linear relationship with metabolic heat production for heart rates surpassing 120 beats per minute. However, since this level of heart rate is uncommon in settings where comfort is commonly assessed (an average heart rate of 120 beats/min implies work levels beyond typical office work), it may be considered beyond the scope of this investigation.

A recently proposed approach to activity recognition, grounded in a novel learning scheme, significantly diminishes the need for extensive annotation. This strategy adeptly harnesses sparsely labeled data in conjunction with readily accessible unlabeled data to enhance effectiveness [53].

The energy expenditure (EE) measurement of the subjects for the MET assessment is attracting the most attention [54] considering that MET, as already stated, is defined as the ratio between the energy intensity of activity and the reference rate of MET in the state of rest. In the review of papers so far, EE was mainly researched for medical purposes.

In 2015 Mukhopadhyay [55] reviewed the systems for monitoring human activity using wearable sensors have been documented, along with identified challenges that need to be addressed to overcome the associated issues. Back then, devices were of low accuracy and very expensive. Regardless, he predicted an increase in interest and consequent usage of wearable motion devices, so the cost of the devices would fall, resulting in wide application in society.

Gauthier and Shipworth [35] utilized various methods to estimate metabolic rate and clothing insulation, including visual observations as well as environmental and wearable sensors. The specific wearable sensor they employed was the SenseCam, manufactured by Vicon Motion Systems (Microsoft, UK). This device consisted of a tri-axial piezoresistive accelerometer (Kionix KXP84), a light intensity sensor, and a temperature sensor. The sampling frame for their study was determined based on three physiological attributes outlined in Standard [39], namely gender, age, and weight. As the monitoring was carried out on the chest, they only measured the thermal insulation level of the upper body. The thermal insulation value for the lower body was considered constant at 0.3 clo. The study took place only in the period of 10 consecutive days during the winters of 2012 and 2013.

In their work, Zhu et al. [56] focused on the accurate estimation of EE for monitoring ambulatory activities (walking, standing, climbing up or down stairs) of subjects wearing portable sensors. They used CNNs to automatically detect important features from data collected by wearable sensory devices. Such a promising new approach could be applied to investigate changes in metabolic rates of the occupants in office buildings during working hours and its impact on their thermal comfort.

Level 4 includes direct and indirect calorimetry [57]. Direct calorimetry measures the total amount of directly released heat from the body to the environment with complex equipment and complicated operations [58]. Indirect calorimetry calculates the MET from inhaled oxygen and exhaled carbon dioxide. It requires an analysis of the person's expired air. For this purpose, this either needs to be collected throughout interest using a 'Douglas bag' and analyzed afterward or directly analyzed using portable equipment. The primary challenge lies in abstaining from disrupting the task being measured and mitigating issues related to leaks, experimenter variability, and calibration. The duration for collecting expired air depends on the context. In the case of light to medium work, the collection is typically done throughout a representative period of the activity, employing the partial method. For this method, the MET [W m^{-2}] is calculated from function 1.8 [43]:

$$M = E_{\mathrm{eq}} \cdot \dot{V}_{\mathrm{O_2}} \cdot \frac{1}{A_{\mathrm{D}}} \tag{1.8}$$

where:

E_{eq} is the energy equivalent [W h l^{-1} of oxygen], typically around 5.7 W h l^{-1} for light work,

$\dot{V}_{\mathrm{O_2}}$ is the oxygen consumption (l h^{-1}),

A_{D} is the Dubios, body surface area [m^2], described as:

$$A_{\mathrm{D}} = 0.202 \cdot \text{body weight}^{0.425} \cdot \text{height}^{0.725} \tag{1.9}$$

Luo et al. [22] sed the Vmax Encore metabolic cart (SensorMedics, USA) to measure oxygen consumption and carbon dioxide production in the human body. Then they developed equations to determine the intensity of the subject's metabolism while ignoring the subject's age, gender, and BMI. On the other hand, Nomoto et al. [28] developed a more accurate equation for determining metabolic intensity. They first conducted a 3D measurement of the human body surface area to determine the appropriate formula to estimate the subject's body surface area accurately. Metabolic intensity rates were then calculated by dividing the subject's heat production (measured by indirect calorimetry) by his/her body surface area. Since indirect calorimetry requires people to wear uncomfortable masks, it is also inconvenient for practical application.

Consequently, some researchers have attempted to develop methods of approximating MET values that do not involve expensive equipment and are complicated to use. For example, Ruiz et al. [59] presented a method of rough estimation of subjects' MET values by calculating CO_2 concentration and assessing IAQ. However, such a method of measuring CO_2 concentration is limited because the interior space needs to be entirely sealed. Nevertheless, these parameters proved important for occupants' satisfaction with thermal conditions and need further investigation.

In addition to the methods prescribed by the standards, some authors have developed empirical methods for determining the MET. Thus, Dimara et al. [60] created an algorithm that calculates MET based on the personal assessment of the subject's thermal sensation considering the current conditions in the environment through numerous survey questionnaires. In this case, the MET is a function of air temperature, relative humidity, and level of clothing, as well as the subject's thermal sensation. In this way, profiles were created for precisely determined respondents that do not apply to anyone below them, and the survey procedure must be repeated for every other respondent or space occupant. Also, Zhang et al. [15] proved the linear dependence of MET and environmental conditions and, in their work, went so far as to omit MET from the PMV model completely; that is, they replaced it with the sum of temperature and air velocity in the room corrected by three constant coefficients (M = a t_{r} + b v_{ar} + c) and included the PMV index calculation as such.

Kingma et al. [23] used a biophysical analysis to illustrate the effect of incorrect metabolic rate calculation of the thermal comfort of women. The approach fundamentally differs from current thermal comfort models and builds predictions based on physical and physiological constraints rather than statistical associations with thermal comfort. It is unclear from the paper how the MET values were collected, nor whether dynamic changes were monitored during the day.

From the literature review of previous research in this area, it can be concluded that the methods commonly used in comfort research to determine MET have some inaccuracies, partly due to a lack of detailed descriptions for tasks relevant to assessing comfort. The range of tasks and MET levels typically considered in comfort assessment is relatively limited compared to the wide range of possible activity levels. The existing culture surrounding the measurement of metabolic heat may not be suitable for evaluating thermal comfort.

In order to enhance the estimation of MET according to ISO 8996, it is necessary to gather more data and provide greater detail for activities with a metabolic rate below 2 met. A large amount of human biometric data is needed along with environmental data from an environment under different conditions in order to conduct a thorough investigation of thermal comfort parameter MET and to find out what affects changes in its rates.

Hence, it is necessary to develop a model using neural networks based on input data of the physical activities of users of office spaces. Namely, by monitoring the user's activity inside the building with special portable non-invasive sensors, MET can be calculated from the energy expenditure of the user, and its dynamic changes during a typical working day can be monitored. Additionally, by measuring the environmental conditions of office spaces and monitoring user satisfaction with a questionnaire, it is possible to more precisely determine the PMV index, which would improve the thermal comfort of building occupants with an installed HVAC system, and consequently influence the minimization of the building's energy needs.

1.5. Hypothesis

It is possible to analytically model the occupant's metabolic rate as a function of the measured thermal conditions in the office building (relative humidity, air temperature and amount of carbon dioxide) without the use of an additional activity monitoring device.

It is possible to determine the value of thermal comfort metabolic rate parameter by applying a specific model of occupant's metabolic rate depending on the individual (personal) characteristics, which statistically significantly affect (changes) metabolic rate values.

1.6. Content and thesis organization

Chapter 01 describes the motivation for this particular Ph.D. topic of thermal comfort and why it is interesting and important to be further investigated. The terms and standards currently in force concerning thermal comfort and MET assessment are explained. A research overview was given to see how other researchers approached this problem, in what way and by which devices and methods they assessed MET, how successful they were in their research, and how much they contributed to MET assessment in general. The conducted review clearly identified the present research gap. In Chapter 02 research methodology is described. A preliminary investigation was conducted in the form of questionnaires to determine which of the thermal comfort parameters of the working environment are statistically significant for office space occupants to reach the state of comfort. In light of the outcomes derived from the statistical analysis of the occupant votes, devices were selected for further (in-depth, year-round) research. Further (year-round) research was conducted in 2 office buildings of the same type, in 2 locations with different climatic conditions. The MET of each occupant was obtained using the sensor and the statistically significant parameters on which it depends were determined (by analyzing the measured data) in such a way that the change in the MET of each user during different thermal conditions was considered. Additionally, the survey analysis determined individual thermal comfort parameters that statistically influenced the change in MET. Based on the above, a model was developed for obtaining MET (without the need for its daily measurement using the sensory device). In Chapter 03 obtained results and discussion of this research investigation were given, while the obtained scientific contributions were given in Chapter 04. In Chapter 05 conclusions were made along with the plan for the future research work in this topic.

2. EXPERIMENTAL APPROACH AND RESEARCH METHODOLOGY

In order to confirm the first working hypothesis, an experimental measurement of thermal conditions on the premises was carried out during working hours throughout the year in two buildings of different geographical locations and climate zones.

The measuring equipment is selected according to the results of statistically significant parameters of thermal comfort gain by a preliminary study described in Chapter 3.1 of this thesis. Furthermore, in order to determine the statistically significant individual parameters that affect the MET values of building occupants, a survey questionnaire (Appendix) is conducted three times a day during the periods of measurement.

Additionally, the wearable device is used for monitoring the occupant's activity. The obtained data are used for calculating the MET through its software on a minute level. Their further comparison with the survey questionnaires' answers results in statistically significant individual characteristics of occupants that affect changes in the MET value. The above enabled the grouping of occupants with common characteristics and comfort preferences.

Ultimately, for each group of people, a mathematical model is created using neural networks based on the input parameters of thermal conditions that have been shown to have a statistically significant effect on occupants' MET. The models are created using the computer program package *MATLAB R2018*.

The difference between the actual output value and the predicted value obtained by the artificial neural network (ANN) model represents the evaluation of the prediction accuracy rate of the developed model. A satisfactory ANN model should have a correlation coefficient greater than 0.8 and a mean square error as close as possible to 0.

In this section, a detailed description and general concept of the research methodology (Figure 2.1) as well as experimental setup will be described in detail in continuation.

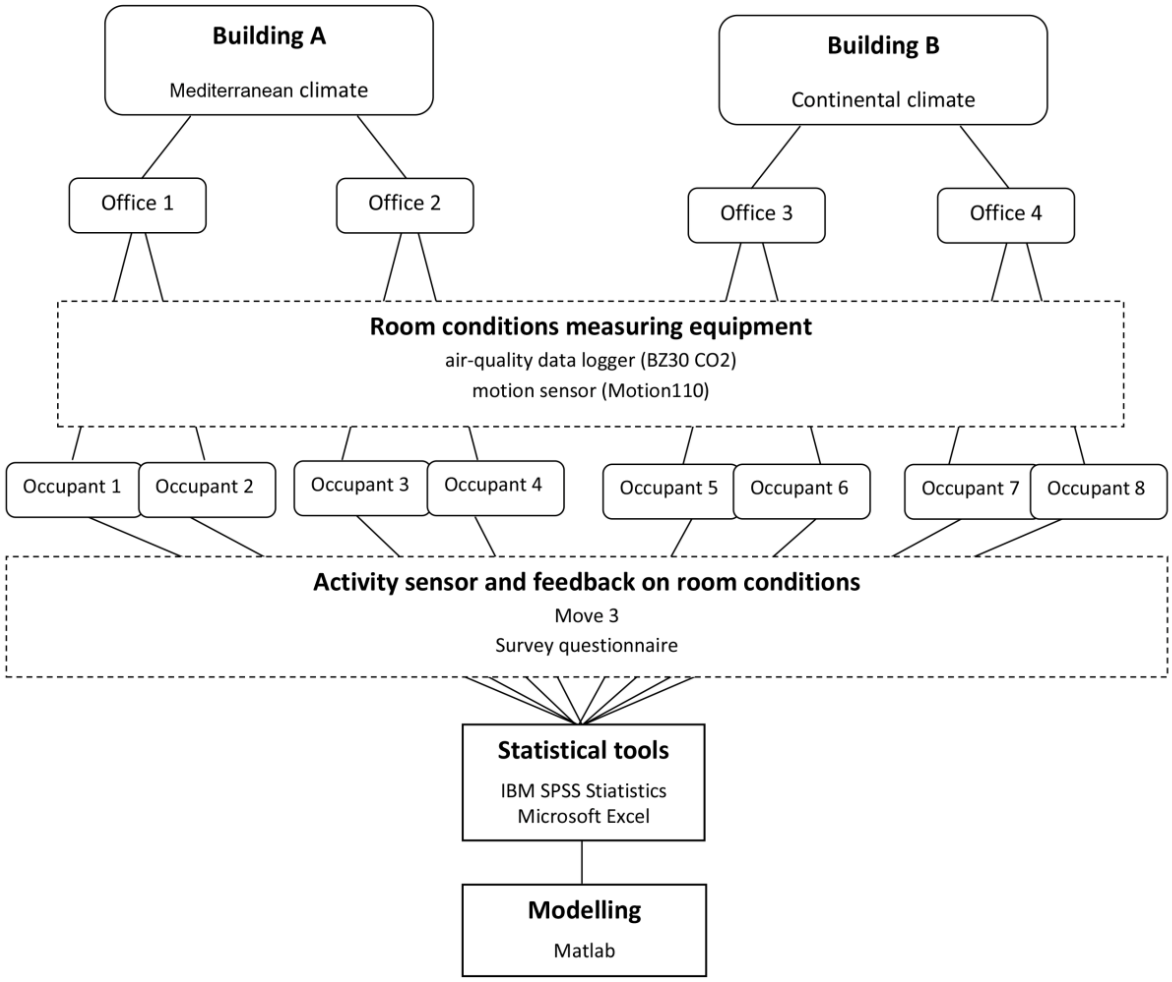

Figure 2.1. Research methodology

2.1. Climate conditions for geographical locations

The examined buildings are located in two different climatic zones. Distribution of climate types are given according to Köppen [61]. The climate of Building A (Split) is Mediterranean (Csa), with mild, rainy winters and hot, sunny summers (Table 2.1 and Figure 2.2). From December to February, the winter in this region is generally mild, marked by intervals of sunshine interspersed with episodes of inclement weather. However, occasional very cold days may occur when air masses from the interior of the Balkan Peninsula are ushered in by the Bora wind. During such periods, nighttime temperatures can drop to -6 °C or -7 °C, while daytime temperatures hover around freezing or slightly below. Light snowfall, usually not abundant, may also occur.

In contrast, the summer months of June to August bring hot and sunny weather, occasionally accompanied by afternoon thunderstorms, with a higher likelihood of rain in June. The impact of the nearby sea is somewhat diminished by islands that separate the city from the open sea. Consequently, the region may experience prolonged and intense heatwaves, with temperatures reaching highs of 34/35 °C and beyond. In Split, the average temperature in the coldest month (January) is 8.3 °C, while the warmest month (July) averages 26.9 °C. The highest relative humidity (RH) is in November (69%), the most rainfall month in Split (around 11 to 12 days). On the other hand, the month with the lowest RH is July (48%), with around 3 to 4 days of rainfall.

Table 2.1. Climate conditions in Split during the year [62]

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Avg. temp. [°C]	8.3	8.6	11.4	15.0	19.9	24.1	26.9	26.9	21.8	17.6	13.1	9.4
Min. temp. [°C]	5.9	5.9	8.4	11.7	16.2	20.2	22.8	22.8	18.3	14.7	10.7	7.0
Max. temp. [°C]	10.7	11.4	14.4	18.3	23.6	28.0	31.0	30.9	25.3	20.4	15.5	11.7
Avg. RH [%]	64	61	59	60	59	55	48	50	58	66	69	65

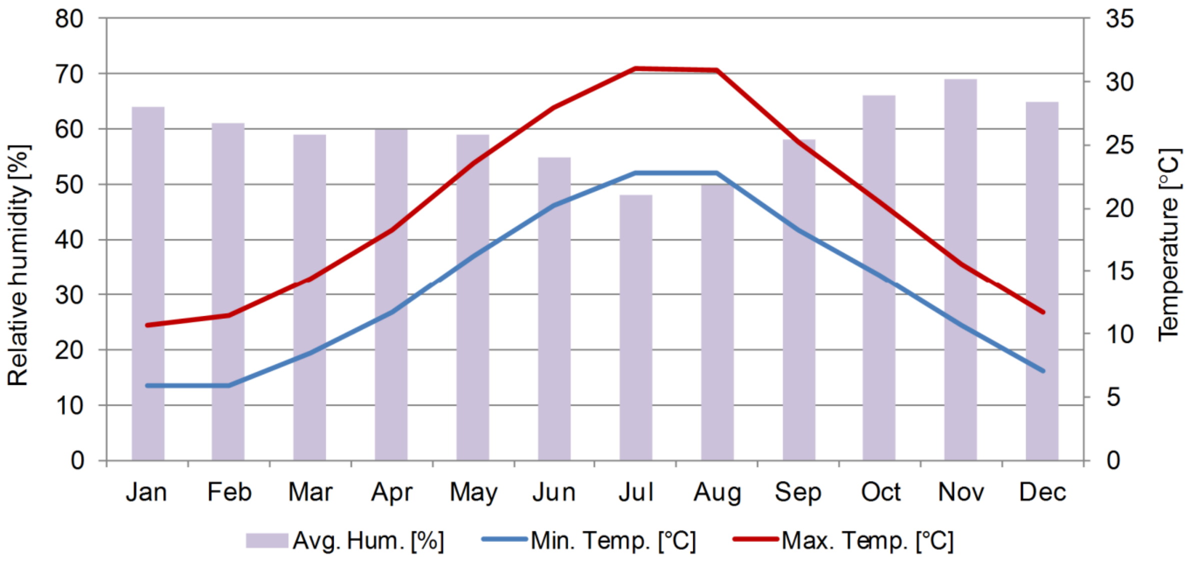

Figure 2.2. Climate chart, Split

The Building B (Zagreb) climate is classified as Ctb, warm and temperate (Table 2.2 and Figure 2.3). The rainfall in Zagreb is significant, with precipitation even during the driest month. The average annual temperature is 11.6 °C in Zagreb. Zagreb is located in the northern hemisphere. Summer begins in June and ends at the end of September. The temperatures are highest on average in July, at around 22.5 °C. At 0.5 °C on average, January is the coldest month of the year. The variation in annual temperature is around 22.0 °C. The month with the highest RH is December (84.04%). On the other hand, the month with the lowest RH is August (63.66%). The month which sees the most rainfall is May (8.47 days), while the driest month of the year is February (11.97 days) [61].

Table 2.2. Climate conditions in Zagreb during the year [63]

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Avg. temp. [°C]	0.5	2.0	6.6	11.8	16.2	20.4	22.5	22.2	16.9	12.0	6.9	1.8
Min. temp. [°C]	-2.8	-2.0	1.5	6.3	10.7	15.0	17.1	17.0	12.5	8.0	3.6	-1.2
Max. temp. [°C]	4.3	6.5	11.9	17.0	21.2	25.2	27.4	27.3	21.5	16.5	10.7	5.3
Avg. RH [%]	81	76	71	67	69	67	64	64	72	78	83	84

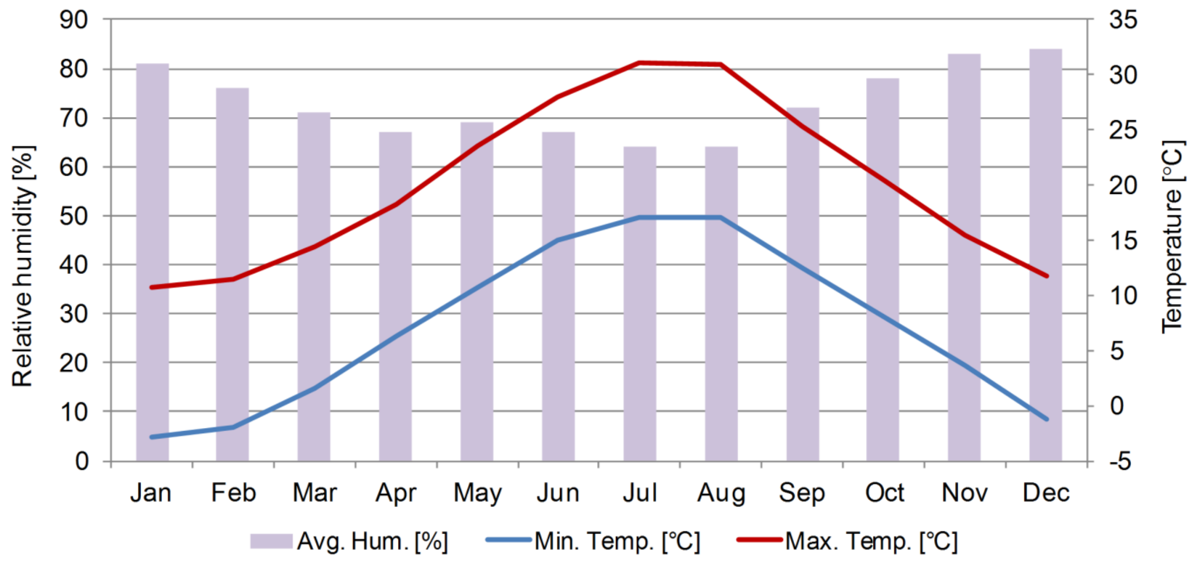

Figure 2.3. Climate chart, Zagreb

2.2. Technical description of buildings under field investigation

A study on occupant thermal comfort is carried out in two standard public office buildings in Croatia through field investigation. The first building (Building A) is the Faculty of Mechanical Engineering, Electrical Engineering and Naval Architecture (FESB), Figure 2.4, located in Split, Croatian coast. It is an educational and research building, housing on average 300 employees. It consists of two connected buildings, the old and the new one, which together cover an area of 29,477 m^2. While the old part of Building A has double-pane wooden windows, with inner and outer blinds, the new part of the building has double-pane aluminum windows with outer blinds.

Figure 2.4. Building A

Heating for the old part of the building is accomplished through a 1,400 kW oil-fired boiler, with an average yearly consumption of 342 tons of oil. This part of the building is not sufficiently insulated according to Croatian National Legislation on Rational Use of Energy and Heating Protection in Buildings [1]. In contrast, the new part of the building is sufficiently insulated according to the current standards. The building has a central heating and cooling (HVAC) system installed. The maximum simultaneous cooling load is 1,400 kW, while the daily energy consumption is 11,938 kWh. To reduce the required cooling capacity and the amount of electrical energy involved, the cooled tanks are installed. The stored cooling energy of 3,333 kWh allows two heat pumps of 382 kW basic cooling capacity to cover the cooling needs completely. During the winter, the heat pumps have a single effect of 415 kW and are used only when the outdoor air temperature is above 5°C. Both parts of the building have a lot of natural light, but there are also fluorescent tubes installed in every room.

The office space was 5 m length x 3.4 m width x 3.4 m height (Figure 2.5). The inquiry was conducted in office spaces located in the old section of the building. The heating season for

Building A spans from October to the end of March. The cooling season begins in June and extends until the end of July, resuming from mid-August to the end of September, with a temporary hiatus during collective vacation.

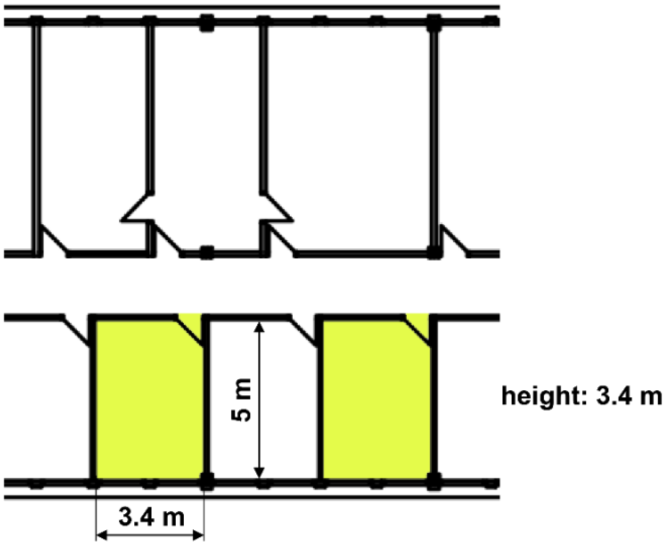

Figure 2.5. Floor plan of Building A with the offices and their basic dimensions marked

The second building facility (Building B) is located in Zagreb, inland Croatia. It is a HEP ESCO d.o.o. building housing around 30 occupants, (Figure 2.6). Constructed during the 1960s, the building was also built without adequate thermal insulation for its structure. Building B' office spaces are also of similar dimensions as in the Building A.

Figure 2.6. Building B

Building B utilizes the district heating system, employing radiators for heating needs. Additionally, each office is equipped with split heat pump units for cooling purposes. In Zagreb, the heating season spans from October to May, longer than in Split, while the cooling period lasts from June to September.

Both buildings share comparable constructional features and heating/cooling systems in their office units, facilitating an effective comparison of the results.

In Building B, the cooling season started on June 1 and ended in September. Split air conditioners are used to cool the building, which is installed in each office, and the users of the rooms use them according to their personal preferences. The heating season started on October and ended in May.

2.3. Period and conditions of measurement

The measurements were taken in four communal office spaces (two within Building A and two within Building B) over the course of a year, each conducted four times during a consecutive workweek (spanning five working days), Table 2.3. All operational cycles, encompassing the different seasons of the year (spring, summer, autumn, and winter), were taken into account. The measurements were obtained during a typical working day from 7:30 in the morning to 15:30 hours. The measurement of both buildings was carried out in the same period of the year with a gap of several days between the two buildings due to the use of the same measuring equipment.

As previously mentioned, motion (presence), air temperature, humidity, and CO_2 levels, along with data from wearable sensors, were recorded at one-minute intervals. Regarding adaptation strategies, occupants had the option to adjust the thermostat, open windows, and use additional heaters and fans in offices.

These adaptive strategies did not impact the measurements as the primary focus of this study was not to calculate precise energy consumption.

Table 2.3. Measurement period

Measurement	Building A	Building B
First	Apr 24 – Apr 30	May 22 – May 28
Second	Sept 04 – Sept 10	July 03 – July 09
Third	Nov 06 – Nov 12	Dec 04 – Dec 10
Fourth	Jan 29 – Feb 04	Jan 08 – Jan 14

2.4. Measuring equipment

2.4.1. Sensors for thermal conditions measuring

As preliminary research results showed (more detail about it in the Subchapter 3.1), the statistically significant parameters affecting occupants' personal thermal comfort are temperature and air quality. Hence, the measurement equipment was chosen accordingly.

Thermal comfort conditions were monitored using a motion sensor *Motion110* [64] (Figure 2.7a and Table 2.4) and air-quality datalogger *TROTEC BZ30* [65] (Figure 2.7b and Table 2.5). The precision of the utilized measurement equipment is outlined in Table 2.6, indicating that the measurement error is sufficiently minimal and has negligible impact on the results.

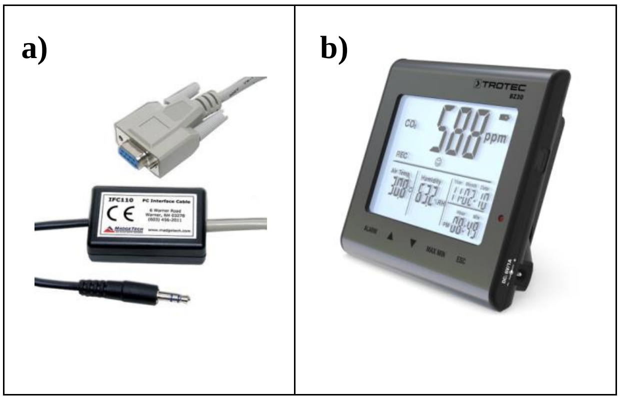

Figure 2.7. Research equipment:

a) Motion110 Data Logger, b) TROTEC BZ30 Data Logger

Table 2.4. Technical specification of motion sensor

Detection Distance	5 m
Detection Range	>80°
Time Resolution	1 second (reading rate dependent)
Memory	13,107
LED Indicator	Red
Required Interface Package	IFC110 or IFC200
Typical Battery Life	5 years typical at 25 °C
Baud Rate	57,600
Operating Environment	20 °C to +60 °C, 0 to 95% RH non-condensing

Table 2.5. Technical specification of air-quality datalogger

Sensor	NDIR (nondispersive infrared) CO_2-sensor
Measuring range	0 – 9,999 ppm CO_2
Resolution	1 ppm
CO_2 accuracy	±75 ppm or ±5% of the measured value
Temperature range	23 °F – 122 °F (-5 °C – 50 °C)
Resolution	0.1 °C/°F
Temperature accuracy	±1 °C
Relative humidity (RH)	0.1 to 99.9%
Resolution	0.1% RH
Accuracy of the RH	±5 %
Display	date and time, RH, temperature, Max/Min, CO_2 value

Table 2.6. Experimental equipment accuracy

Sensor type	Measurement error
Temperature (air)	±1.0 °C
CO_2 level	±75 ppm
Air humidity	±5%

2.4.2. Wearable devices for metabolic rate assessment

In addition to monitoring overall thermal comfort conditions, the measurements from wearable sensors gather data related to individual (personal) comfort, taking into account occupant activity.

The sensors were selected based on three criteria [45]: 1) accuracy; 2) raw data access for research support; 3) convenience to wear 24/7.

Wearable devices for sensing activity come in a wide range with different approaches to processing the raw acceleration data. Unfortunately, there is no standard for data processing, leading to a lack of standardized output variables. Consequently, data processing varies by company, making it nearly impossible to compare devices from different companies. Therefore, capturing and storing data in a unique storage format is recommended before processing it to obtain information. Raw data as output variable; the unprocessed/unfiltered raw acceleration signal of each axis (direction: x, y, z; unit: mg) are favored [66] [67] [68]. Hence, there is the possibility to recompute parameters, such as EE, at a future date using updated algorithms and methodologies. It is important because the MET may be presented as a MET value, corresponding to a linear relationship to energy expenditure. An activity with a metabolic rate of 2 met has twice the metabolic rate of a 1 met activity [69].

As per the estimation of EE, after filtering the raw data, many devices use linear regression models. Single regression models are recognized for their tendency to either overestimate or underestimate EE because of the non-linear correlation between activity and EE. For instance, the extra load on the body, such as pulling or pushing, remains challenging to accurately measure [66]. Consequently, there is no single regression model deemed suitable for estimating EE. Therefore, the appropriateness of employing linear regression models is questionable [70].

Demonstration revealed that an activity-based regression model is beneficial and provides increased accuracy [71].

Based on these suggestions, a sensor that records and saves the raw data from the triaxial acceleration signal movements *Move 3* sensors were chosen for the research. The sensors from *movisens* utilize a triaxial accelerometer for activity recognition. The acceleration data is categorized into pertinent activity classes before undergoing additional processing. Subsequently, a suitable algorithm for the respective activity class is chosen. This method offers advantages over other devices and yields a more precise estimation of EE compared to alternative devices [72] [73] [74].

To improve EE estimation, the *movisens Move 3* sensors incorporate a barometric sensor to evaluate variations in altitude. A notable limitation of many commonplace accelerometers is their lack of precision in estimating energy expenditure during incline ascent or descent, particularly on stairs. This challenge arises from the similarity in walking patterns between walking on an incline or stairs and walking on a flat surface [72] [71]. The inclusion of the barometric sensor substantially enhances the accuracy of EE estimation. *Movisens Move 3* sensors were evaluated with a mean classification rate of 98.2% [75]. The precise categorizations of activities result in an enhanced estimation of EE.

In comparison to questionnaires, activity sensors (accelerometers) offer the advantage of capturing movement in real-time as it occurs. Conversely, traditional forms entail a delay in documenting physical activity. Thus, a sensor-based system offers advantages in minimizing systematic errors when compared to traditionally timed forms. The *movisens Move 3* sensors are very small; thus, wearing them during everyday working hours does not hinder participants.

The algorithms integrated into the *movisens Move* sensors effectively address and resolve all previously identified issues related to energy expenditure (EE) estimation and activity recording in other devices. These improvements include features such as saving and displaying raw data in milligrams (mg) rather than Counts, utilizing an activity-based model instead of a linear regression model, and achieving more precise EE estimation through the incorporation of additional sensors like acceleration, barometric sensor, and skin temperature, as opposed to relying solely on one acceleration sensor. Thus, the *movisens* sensors are the most precise mobile sensors currently available on the market. *Move 3* (Figure 2.8) is designed and optimized for research applications to record the occupant's physical activity and other secondary parameters. The main technical characteristics are specified in Table 2.7. A person's physical activity is obtained by measuring a person's acceleration through three dimensions, as well as atmospheric air pressure and air temperature. The sensor can be configured via a computer using the *DataAnalyzer* software, which allows the calculation and analysis of the following parameters and the generation of desired reports:

- Acceleration in three dimensions
- Atmospheric pressure
- Temperature
- Acceleration of movement
- Acceleration along the axis of the body
- Axis body inclination
- Number of steps
- Activity classes
- Body position
- Height
- Activity (Energy expenditure)
- Total energy expenditure
- Metabolic rate
- Summary of energy expenditure
- Physical activity report
- Report on physical activity and energy expenditure

Figure 2.8. Wearable sensory device Move3

Table 2.7. Technical specification of wearable sensory device

Internal sensors	**3D acceleration sensor:** Measurement range: +/-16 g Noise: 4 mg Output rate: 64 Hz **Pressure sensor:** Measurement range: 300 – 1000 hPa Noise: 0.03 hPa Output rate: 8 Hz
Environmental conditions	Temperature: -20 °C to 60 °C 0 °C to 45 °C during charging Humidity: 0 to 75% RH Atmospheric pressure: 300 to1100 hPa absolute
Number of cycles	300 with 1C/1C > 80%
Maximum recording capacity	~ 2 months
Charging battery run time (recording)	~ 9 day

The calculation of energy expenditure and MET is done in two steps. In the first step, the activity class is estimated based on acceleration and barometric signals. The appropriate model for estimating energy expenditure is selected depending on the detected activity class. The model then takes the *MovementAcceleration* metric, elevation change extracted from barometric data, and personal parameters of age, gender, weight, and height to calculate energy expenditure. Energy expenditure values are internally calculated for 1 min intervals regardless of the configured output interval. The models were built by regression from a large database of indirect calorie measurements for each physical activity class and sensor location. The energy expenditure estimation quality depends on the sensor's location. The best results can be obtained for the hip and chest sensor positions. Therefore, occupants wore a *Move 3* sensor [76] on their belts for 8 hours each day throughout the measurement period.

2.5. Statistical research

Statistical research has been done in three phases:

1) statistical observation,
2) grouping (tabular and graphical presentation of statistical data),
3) statistical analysis and interpretation of the results of the analysis.

Subjective data were collected using a questionnaire developed according to ISO 10551:2019 [77], with additional questions concerning participants' basic information.

A survey questionnaire was employed to gather subjective responses from occupants three times a day (at 9:00, 12:00 and 15:00 hours) during the examination period. The initial series of questions pertained to personal information (including age, gender, height, weight, and educational level). The second set delved into the occupants' workload and productivity throughout the day. The third set assessed the occupants' attire, while the final set concentrated on the occupants' perception and contentment with room conditions concerning thermal comfort criteria in office settings.

Considering the characteristics of the target population, and logistical considerations, the direct access method was used to deliver the survey questionnaire, i.e. questionnaires were delivered to the users personally in order to ensure the timelines of the given answers. This way of delivering the survey enabled more control over the data collection process and ensured questionnaires were distributed and appropriately completed, reducing the risk of incomplete or inaccurate responses.

The survey was conducted anonymously so that the answers were honest and unimposed to get the most precise possible picture of the topic under consideration.

According to Goldman [78] the minimum subject in thermal comfort studies is at least 6 occupants. In this research, 8 occupants participated, four located in Building A and four in Building B. Two employees use the same office during working hours in both buildings.

Table 2.8 displays fundamental occupant details. BMI was computed based on participants' provided data, derived from their body mass or weight (in kilograms) divided by the square of their body height (in meters).

Table 2.8. Test subjects with respect to their age and gender

		Gender		Age		
	Total	**Men**	**Women**	**1. group 35-44**	**2. group 45-54**	**3. group 55+**
Building A	4	1	3	3	0	1
Building B	4	2	2	2	2	0

The tools that are used for data analysis are the *IBM SPSS Statistics* (*Statistical Package for Social Sciences*) software package and the *Microsoft Excel* programming language. In addition, *MS Excel* is used in all important phases of the statistical analysis process, from the formation of the database, sorting and grouping of data, graphical display of statistical series, calculation of basic statistical analyzes and procedures, as well as analysis of time series. *MS Excel* is compatible with SPSS, a software package used to investigate which measured indoor thermal parameters are statistically significant for further research. The results of all performed tests are considered statistically significant when the confidence (p) is $p \leq 0.05$. The interpretation of the results is as follows: $p \leq 0.001$ means highly significant, $0.001 < p \leq 0.01$ means significant, $0.01 < p \leq 0.05$ means weakly significant, and $p > 0.05$ means that the impact is not significant [79].

2.6. Mathematical modeling

Mathematical modeling was obtained in *MATLAB R2018* program package. Artificial Neural Networks (ANNs) are employed to establish a connection between influential environmental parameters affecting thermal comfort and occupant metabolic rates. ANN comprises artificial neurons interconnected through weighted connections, drawing inspiration from biological neural systems. The learning process in neural networks mirrors that of biological systems, involving training with input and output datasets. During this process, connection weights are iteratively adjusted to effectively address specific problems. The widely utilized feedforward ANN for supervised regression and classification tasks is the multi-layer perceptron (MLP), as depicted in Figure 2.9 [80]. The MLP includes an input layer, an output layer, and one or more hidden layers, each equipped with a weight matrix, w, and a bias vector, b.

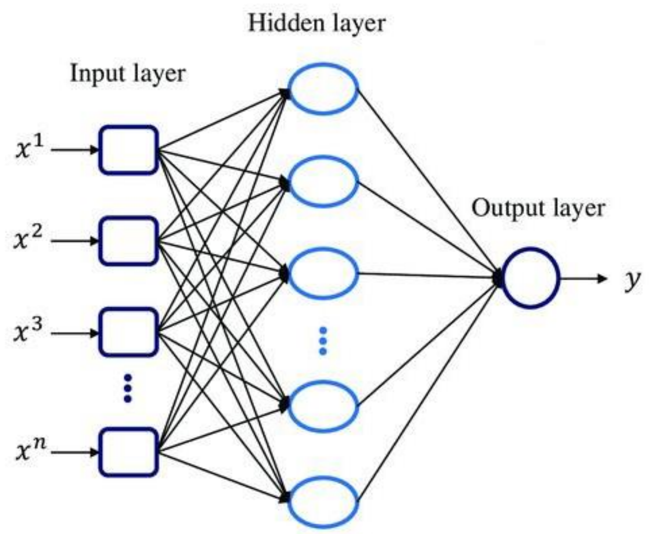

Figure 2.9. Multi-layer perceptron with one hidden layer

Every node in each layer of MLP, including the bias node, establishes a full connection with all nodes in the subsequent layer. The number of nodes in the input layer corresponds to the quantity of input parameters, while the output layer can accommodate more than one node, aligning with the number of predictions the network is tasked with generating. The hyperparameters, specifically the number of hidden layers and their nodes, are adjustable to ensure that the model meets the desired approximation and possesses suitable generalization capability. Hidden layers have the task of mapping complex relations between input factors and responses, i.e. between inputs and outputs of the ANN model. The number of hidden nodes impacts the network's capacity to learn and generalize from the training data.

With two or three hidden nodes, the network can potentially capture more intricate relationships between the input features, making it more capable of fitting a wider range of data distributions. Having more than one hidden node provides more opportunities for different feature combinations, which can improve the network's ability to capture non-linear relationships in the data. If the data is highly complex, using just one hidden node might result in underfitting, where the model cannot capture the underlying patterns effectively. However, it's essential to strike a balance and not add too many hidden nodes, as this can lead to overfitting. Overfitting occurs when the model becomes too specialized in the training data and fails to generalize well to new, unseen data. Selecting the optimal number of hidden nodes is often done through a process called hyperparameter tuning or cross-validation. This involves trying different configurations of the network, including various numbers of hidden nodes, and selecting the one that performs best on a validation dataset. Ultimately, the choice of the number of hidden nodes depends on the complexity of the problem, the amount of available data, and the network architecture as a whole. There is no one-size-fits-all answer, and it's essential to experiment with different configurations to find the best trade-off between model complexity and generalization performance.

MLPs are relatively easy to adjust. The primary reason is the availability of the backpropagation algorithm. Backpropagation is an efficient method to compute the gradients of the model's parameters (weights and biases) with respect to the loss function. This gradient information allows the model to update its parameters in the opposite direction of the gradient, effectively minimizing the loss function during training. This process is essential for adjusting the model to fit the data.

This method is selected because artificial neural networks seek correlations among non-linear data, amalgamating them into a unified and intricate input dataset. The statistical analysis results in this study show which of the measured indoor parameters are significant, so they can be taken as input parameters to develop a MET prediction model.

The artificial intelligence models employed in previous studies have demonstrated successful predictions of occupants' thermal comfort [49] [81]. The model's accuracy would be increased by applying similar strategies to the MET prediction.

3. RESULTS AND DISCUSSION

3.1. Preliminary study: Statistically significant parameters of thermal comfort in office buildings

In Building A, a preliminary study was conducted using surveys to determine the parameters that notably influence the thermal comfort of occupants in the office building. In definition, a preliminary study is a research activity carried out before a more extensive study to collect initial information about what occupants perceive as comfort parameters and information about the importance of specific comfort parameters. Another reason the preliminary study was used was to develop more focused and relevant research questions for the survey questionnaire that would be included in further investigation and to have a better understanding of the potential challenges involved in carrying out the research.

Furthermore, surveys are important tools in preliminary studies for gathering data, measuring attitudes and sensations, identifying needs and preferences, comparing groups, and providing evidence for decision-making. By using surveys to collect information in a structured and systematic way, valuable insights were gained that helped create a more precise survey question that would be used in later research and identify exact parameters that should be measured. The statistical sample providing insights about occupant's thermal comfort preferences in office building consisted of 35 randomly selected building users of different age, gender and years of working experience. Therefore, the overall quantity of completed questionnaires amounted to 35, with two not being filled entirely.

Overall, the preliminary study played a vital role in the research process by providing initial information and insights that informed the development of more focused and relevant research questions, refined the study design, and ensured the feasibility of the proposed comfort research.

The concluded analysis showed that among all the parameters taken into consideration to have an impact on occupant indoor sensation, indoor air temperature and air quality proved to be statistically significant.

Table 3.1 outlines the parameters identified as influential factors impacting occupants' thermal comfort within their work environment. Specifically, it details the linear relationships among numerical variables like window view, air temperature, and air quality.

Table 3.1. Linear correlation of parameters affecting the occupant satisfaction with the environment

Correlation		*Window view*	*Indoor air temperature*	*Indoor air quality*	*Occupant satisfaction*
Window view	Pearson Correlation, *r* Sig. (2-tailed), α N	1 35	0.127 0.467 35	0.331 0.052 35	0.280 0.104 35
Indoor air temperature	Pearson Correlation, *r* Sig. (2-tailed), α N	0.127 0.467 35	1 35	0.510* 0.002 35	**0.650*** 0.000 35
Indoor air quality	Pearson Correlation, r Sig. (2-tailed), α N	0.331 0.052 35	0.510* 0.002 35	1 35	**0.639*** 0.000 35
Occupant satisfaction	Pearson Correlation, *r* Sig. (2-tailed), α N	0.280 0.104 35	0.650* 0.000 35	0.639* 0.000 35	1 35

*Correlation is significant at the 0.01 level (2-tailed).

The linear correlation test utilizes the Pearson coefficient (*r*) [10]. Based on the magnitude of this coefficient, one can infer the direction and strength of the linear correlation between the observed variables. With *r* being 0.65 which represents the mean strong correlation, it can be concluded that occupant satisfaction with the room conditions i.e. environment is influenced by the indoor air temperature. Furthermore, with *r* being 0.639, representing the mean strong correlation, it can be concluded that occupant satisfaction is also influenced by air quality. In essence, the perception of thermal comfort tends to improve as the values of the discussed variables increase. Since the empirical significance of the coefficient of correlation (α) is approximately 0, the correlation coefficient between satisfaction and the mentioned variable in the observed building is statistically significant with a test significance of 95%.

Figure 3.1 and Figure 3.2 are denoting that an increase in occupants' satisfaction regarding indoor air temperature and air quality leads to an increase in the overall occupants' comfort sensation. These parameters are statistically significant, with a confidentiality interval of 99%.

Furthermore, the identical conclusion regarding the significance of the coefficient may also arise with a test significance level of 99%. In addition, test results showed that occupant satisfaction with the environment does not depend on window view.

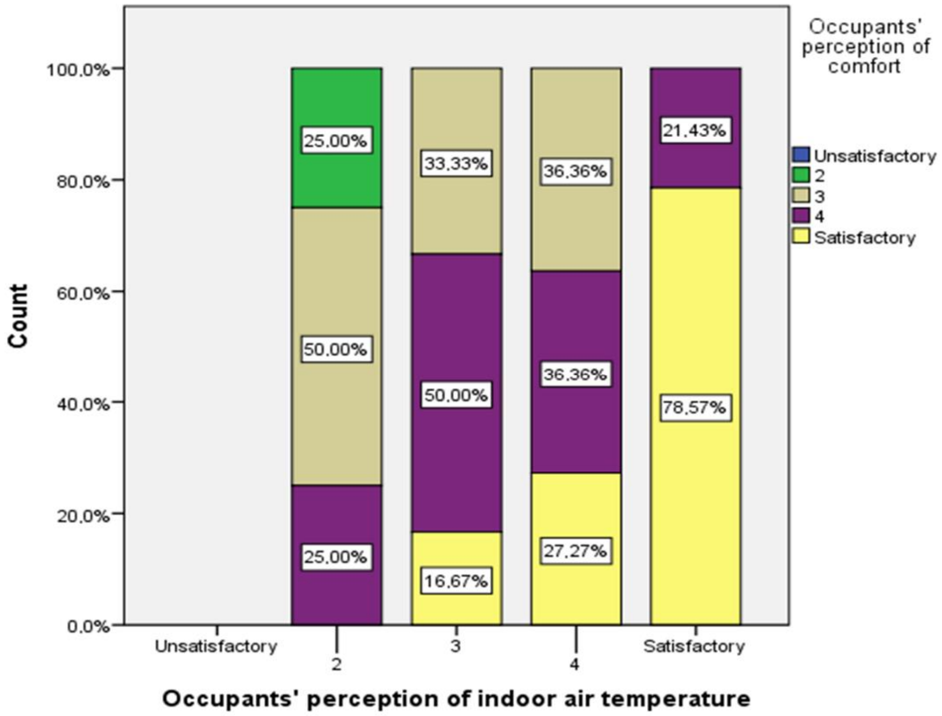

Figure 3.1. Correlation between occupants' perception of comfort satisfaction and occupants' perception of indoor air temperature

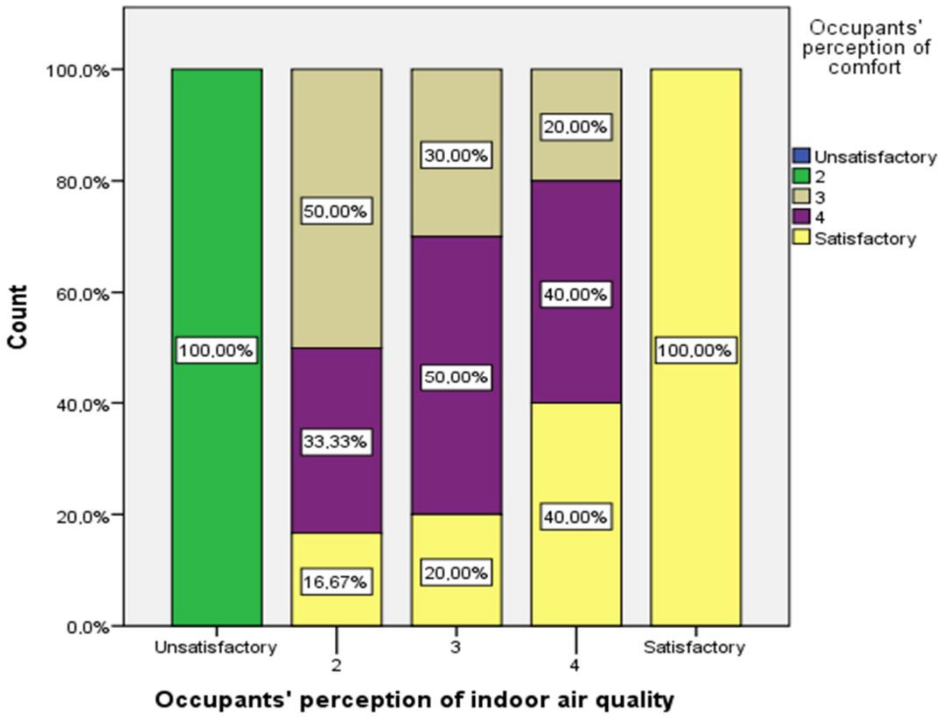

Figure 3.2. Correlation between occupants' perception of comfort satisfaction and occupants' perception of indoor air quality

Table 3.2 illustrates the correlation among numerical variables, including gender, smoking habits, age, duration of employment, office sharing, and occupant satisfaction. It displays the relationships among these occurrences with modalities linked to the ordinal scale. The rank correlation measurement test employes Spearman's rank correlation coefficient (r_s) or Spearman's rho. The coefficient can assume values within the range of -1 to 1. A value closer to the extremes of this interval indicates a stronger correlation in the ranking of observed variables [10].

Table 3.2. Rank correlation of parameters to determine ones that affect the occupant satisfaction

Spearman's rho		*Gender*	*Smoker*	*Age*	*Years of employment*	*Office sharing*	*Occupant satisfaction*
Gender	Correlation Coef., r_s	1.000	0.053	-0.023	0.067	-0.293	**0.397**
	Sig. (2-tailed), α		0.761	0.895	0.703	0.088	0.018
	N	35	35	35	35	35	35
Smoker	Correlation Coef., r_s	0.053	1.000	-0.156	-0.107	0.000	-0.107
	Sig. (2-tailed), α	0.761		0.371	0.539	1.000	0.541
	N	35	35	35	35	35	35
Age	Correlation Coef., r_s	-0.023	-0.156	1.000	0.919*	-0.114	-0.047
	Sig. (2-tailed), α	0.895	0.371		0.000	0.516	0.788
	N	35	35	35	35	35	35
Years of employment	Correlation Coef., r_s	0.067	-0.107	0.919	1.000	-0.243	0.041
	Sig. (2-tailed), α	0.703	0.539	0.000		0.159	0.814
	N	35	35	35	35	35	35
Office sharing	Correlation Coef., r_s	-0.293	0.000	-0.114	-0.243	1.000	**-0.383**
	Sig. (2-tailed), α	0.088	1.000	0.516	0.159		0.023
	N	35	35	35	35	35	35
Occupant satisfaction	Correlation Coef., r_s	0.397	-0.107	-0.047	0.041	-0.383	1.000
	Sig. (2-tailed), α	0.018	0.541	0.788	0.814	0.023	
	N	35	35	35	35	35	35

*Correlation is significant at the 0.05 level (2-tailed).

In this scenario, with a test significance of 95%, the Spearman's rank correlation coefficient indicates a positive relationship between *Occupant satisfaction* and *Gender*, measuring at 0.397. Given that the gender variable holds a value of 1 for men and 2 for women, the analysis results suggest that women tend to feel more comfortable in their office space compared to men. Additionally, the Spearman's rank correlation coefficient demonstrates a negative relationship between the variability in *Occupant satisfaction* and *Office sharing*. This implies that both male and female occupants express higher satisfaction when they do not share the office space with anyone else. On the other hand, a qualitative assessment of the occupant's perception of the indoor environment showed no statistical difference in behavior between smokers and nonsmokers, and people of different age and years of employment in the office with a test significance of 95%.

3.2. Analysis of data obtained by measuring equipment and occupants' sensation according to survey questionnaire results

According to the methodology described in Chapter 02, an investigation was carried out in public office buildings in real working circumstances with devices for measuring the internal thermal conditions (motion level, air temperature in the office rooms, relative humidity, and level of CO_2) and wearable sensory devices (metabolic rate).

An internal sensor *TROTEC BZ30 Data Logger* was placed centrally at the desk level in the room. Once installed, sensors were fully automated and zero-maintenance, which allow reporting on air quality efficiently and effectively.

The total number of collected data was 53,760 values for air temperature, relative humidity and CO_2 singularly and 26,880 values for motion frequency. Data were retrieved each minute over a 7-day period and for the analysis were averaged per season. Two occupants were in the office at desks each working day between the hours of 8:00 and 16:00. The maximum occupancy was generally between 9:00 and 15:30.

On the other hand, survey questionnaires were used for gathering information about occupants' sensation in a given moment. They provided a wealth of information that was analyzed to identify patterns, trends, and relationships between variables of measured data and occupants' sensation. By asking occupants to rate their agreement or disagreement with a specific statement or question about comfort in a given time, insights into the views, needs and preferences of a particular population are gained to make the analysis more comprehensive.

A total of 670 questionnaires were completed for the study. Participant responses were averaged for each season, and the reported data were then compared with a set of measured data, leading to conclusions based on the analysis.

3.2.1. Motion level

For the conducted study, it was necessary to understand the movement of the occupants in a room to accurately determine how much time they spend in that space and what time is relevant for the measurements to take place. In Figure 3.3 the frequency of movement in the offices is shown. Straight lines represent periods of movement of any activities, and blank spaces represent periods without movement. The latter means either there were no occupants in the office during the time of the measurement or the sensor captured no movements at that time.

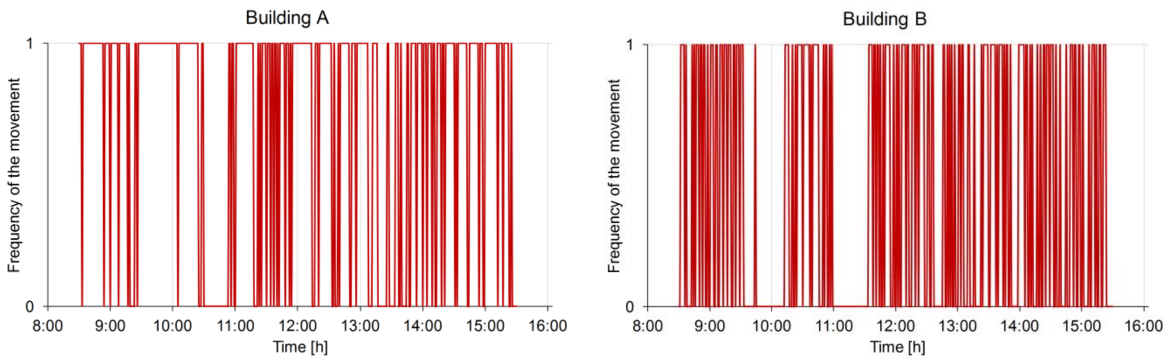

Figure 3.3. Frequency of movement in the offices

According to the results, occupants spend their working hours in the offices, except for a half-hour break, most often between 10:30 and 11:00 in Building A and between 11:00 and 11:30 in Building B.

Although, occupants were mainly engaged in predominantly sedentary activities like writing, typing, calculating, etc., it is evident from Figure 3.3 that the occupants are in movement the entire time they spend in their workplace.

The downside of this monitoring was that quiet activities could only be captured partially because of the office equipment like computer monitors, regardless of the sensor sensitivity. Furthermore, the sensor also captured the movement of curtains and plants. Thus, these results can only speak tentatively about the movements in the room and cannot be considered as general conclusions. However, the purpose of this investigation was to estimate how much time occupants spend in offices during their working hours.

3.2.2. Air temperature

Air temperature is the most known parameter affecting the thermal comfort sensation. Acceptable temperature for most types of work in office buildings are between 16 °C to 24 °C, with 20 °C optimal for an office [21].

The following tables (Table 3.3 to Table 3.6) show the temperature differences in the offices of Building A and Building B during different periods of the year, obtained by descriptive analysis in the SPSS software package. The results showed minimum and maximum value of the air temperature, as well as mean and standard deviation value for every season.

The mean value is a statistical measure that provides information about the central tendency of air temperature in the room during the periods of measurement. It represents an average air temperature value and is calculated by summing up all the temperature data points and dividing it by the number of days of measurement. It was used for comparing office temperature conditions between two buildings throughout the year.

On the other hand, standard deviation is a statistical measure that provides information about the dispersion or variability of air temperature. It measures the spread of the air temperature around the mean value and is calculated by taking the square root of the variance.

Table 3.3. Indoor air temperature in the spring season

Descriptive Statistics

Building A	N	Minimum	Maximum	Mean	Std. Deviation
Office 1	421	25.05	28.32	26.8547	0.85363
Office 2	421	25.39	29.60	27.4911	1.09922
Valid N (listwise)	421				

Building B	N	Minimum	Maximum	Mean	Std. Deviation
Office 1	406	25.48	27.32	26.6095	0.42432
Office 2	421	25.52	26.52	26.0416	0.25344
Valid N (listwise)	406				

In the spring season the mean value of air temperature in Building A was 26.9 °C and 27.5 °C, while in Building B was 26.5 °C and 26 °C, which is considered rather high for office premises. A standard deviation of 0.85363 (in Building A) is generally considered low. This indicates that the temperatures in the data set are relatively close to the mean. In more technical terms, a standard deviation of 0.85363 means that, on average, each data value deviates from the mean by 0.85363 units.

On the other hand, the standard deviation of 1.099 could be classified as moderate. This indicates that the temperature in the data set is somewhat spread out around the mean with some variation between individual temperature measurements. It suggests that the temperature in this data set is fairly typical for a particular location or time period. However, there may be some variability due to external factors such as weather or changes in the environment.

A standard deviation of Building B indicates that the data values are clustered relatively close to the mean and have similar central temperature tendencies of offices in between.

Table 3.4. Indoor air temperature in the summer season

Descriptive Statistics

Building A	N	Minimum	Maximum	Mean	Std. Deviation
Office 1	421	29.19	30.66	29.6714	0.32676
Office 2	421	26.99	29.07	27.9496	0.79202
Valid N (listwise)	421				

Building B	N	Minimum	Maximum	Mean	Std. Deviation
Office 1	421	26.03	29.10	26.7810	0.36981
Office 2	420	25.16	27.05	26.1015	0.42173
Valid N (listwise)	420				

Mean temperature in the summer period were higher in Building A (~28 °C to 30 °C) than in Building B (~26 °C to 27 °C). The standard deviation in the summer period is generally low for both buildings, meaning there was no significant variation or dispersion of the air temperature values from their mean.

Table 3.5. Indoor air temperature in the autumn season

Descriptive Statistics

Building A	N	Minimum	Maximum	Mean	Std. Deviation
Office 1	421	21.70	26.00	24.6409	1.32352
Office 2	421	21.78	27.63	24.2866	1.48278
Valid N (listwise)	421				

Building B	N	Minimum	Maximum	Mean	Std. Deviation
Office 1	421	23.51	24.59	24.0420	0.21924
Office 2	421	22.68	24.83	24.0900	0.44067
Valid N (listwise)	421				

In the autumn period, it was noted that Building A has a higher standard deviation of air temperature values than Building B. It indicates that the temperature in the Building A data set is somewhat spread out around the mean temperature of 24 °C, with a noticeable degree of variation between individual temperature measurements. On the other hand, the standard deviation of temperature values in Building B was low to very low.

The mean temperature value for the autumn period is around 24 °C for both buildings, with a higher maximum temperature in Building A.

Table 3.6. Indoor air temperature in the winter season

Descriptive Statistics

Building A	N	Minimum	Maximum	Mean	Std. Deviation
Office 1	421	22.03	27.58	25.8726	1.19860
Office 2	421	28.17	32.57	31.2328	1.08048
Valid N (listwise)	421				

Building B	N	Minimum	Maximum	Mean	Std. Deviation
Office 1	421	23.00	24.62	23.9584	0.45294
Office 2	421	22.79	24.90	24.0229	0.58704
Valid N (listwise)	421				

In the winter period, mean temperatures are considerably higher in Building A with moderate standard deviation for both offices. On the contrary, Building B has a low standard deviation as the mean temperature values are not so divergent from one office to another.

The previous tables show that the average temperature in the room varies significantly between Building A and Building B. While the offices in Building B are within the limits recommended by the ASHRAE manual [7], two extremes were recorded in Building A. The first one in the summer, due to extremely high outside temperatures and inability of the HVAC system to reach lower temperatures, and the second one in the winter, due to the use of additional heaters to heat the premises to higher temperatures than the one conditioned by the HVAC system. While the temperature during working hours inside Building B varied from 1 °C to 2 °C, in Building A the temperature varied much more. The most considerable variation in temperature during working hours can be seen in the autumn measurement period. The temperature ranges from 21.8 °C to 27.6 °C. In the summer period there were the least deviations in air temperature during the measurement period. In general, higher temperatures (both indoor and outdoor) prevail in Building A with a higher standard deviation of temperature.

During the cooling period (spring/summer), lower temperatures were recorded in the offices where occupants of the second age group (according to Table 2.8) maintained the temperature at approximately 26 °C. Building occupants of different age groups that share an office kept their office temperatures slightly higher, namely 26.6 °C in Building B and 27.5 °C to 27.9 °C in Building A. The measurement results also showed that the third age group (according to Table 2.8) prefers lower temperatures in the warmer period of the year.

During the heating period (autumn/winter), higher temperatures were recorded in the offices where occupants of the second age group (according to Table 2.8) maintained the temperature at approximately 24 °C during the entire period. Building occupants of different age groups that share an office kept their office temperatures slightly lower, namely 24 °C in Building B and 24.6 °C to 25.8 °C in Building A. Hence, occupants of age 55+ prefer higher temperatures in the winter compared to those aged 35 to 44.

According to the [82], the difference between the outside and inside temperature must not exceed 7 °C during the cooling period, which was the case for the both examined buildings.

Figure 3.4 represents the average temperature sensation of all occupants during the year. The neutral temperature, which on the Likert scale in the range from 1 to 5 indicates the value 3, represents the state of comfort. Lower values represent warm to hot sensation, while higher temperatures represent cool to cold sensation.

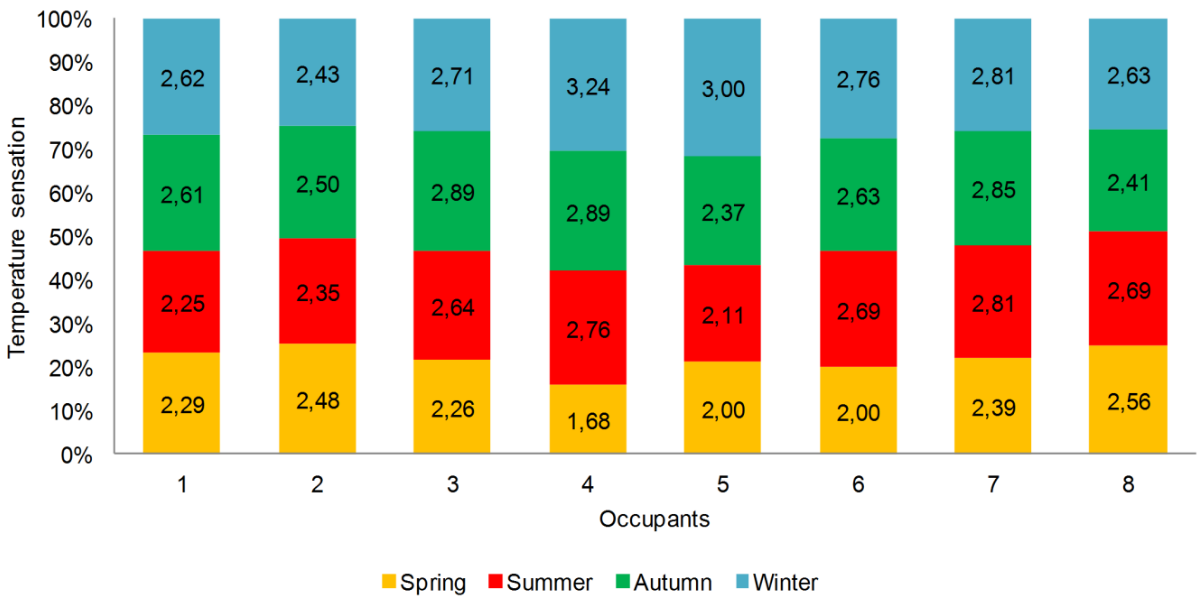

Figure 3.4. Occupants' temperature sensation during the year

It can be seen that occupants generally feel warm in their offices throughout all of the seasons. Moreover, the research results showed that women are more sensitive to temperature variations than men and are less satisfied with exposure to colder temperatures. In addition, by comparing temperature sensation with actual temperature values, it can be concluded that the neutral temperature for the occupants of Building B is 2 °C lower than for the occupants of Building A. Furthermore, occupants have adapted to the geographical location where they live and work. Hence, occupants of Building A are more satisfied with higher air temperatures than occupants of Building B. It can be concluded that one of the influences on satisfaction is an adaptation to the geographical location, i.e. general impact of specific geographical location.

The Friedman test in SPSS (Table 3.7) shows that occupants' satisfaction with room temperature depends on the season. A chi-square value of 9 with an asymptotic significance level of 0.029 suggests that there is a significant difference between the season’s temperature satisfaction being compared. This means that the null hypothesis, which states that there is no significant difference between the satisfactions, can be rejected at the chosen significance level of 95%. Based on the data, the air temperature in the offices in spring has the lowest average rank of satisfaction, which is 1.50. This result indicates that occupants are most dissatisfied with the office temperature in the spring season. Similar indicators are also valid for summer. Therefore, the office temperatures in the cooling season should be lower ones. On the other hand, in the heating season the office air temperature is mostly suitable for the building occupants.

Table 3.7. Friedman's test of occupants' satisfaction with the air temperature in the office

Ranks

	Mean Rank
temp_spring	1.50
temp_summer	2.25
temp_autumn	3.00
temp_winter	3.25

Test Statistics[a]

N	8
Chi-Square	9.000
Df	3
Asymp. Sig.	0.029

a. Friedman test

3.2.3. Air relative humidity

Monitoring humidity level was done for the purpose of investigation as a part of air quality, together with CO_2 level, as a parameter that is statistically significant for the occupants' comfort sensation. Besides comfort, maintaining an appropriate level of relative humidity in office buildings is important for the well-being and productivity of the occupants, as well as the maintenance of the building and its equipment. Generally, the recommended range of relative humidity in office buildings is between 30% and 60% [7].

High relative humidity can cause discomfort for building occupants by making the air feel sticky and oppressive, which can affect concentration. Additionally, elevated humidity can promote the growth of mold, mildew and other microorganisms, which can trigger allergies, asthma and other respiratory problems. Also, high humidity can make it more difficult for air conditioning systems to regulate the temperature, leading to higher energy bills.

On the other hand, the air is perceived as dry when the relative humidity is low which can cause dry skin, lips, and eyes, leading to discomfort and irritation. It can also exacerbate respiratory problems and increase the risk of catching colds and other illnesses which are often an indicator of the sick building [83]. Also, dry air can cause static electricity buildup, damaging sensitive electronic equipment. In addition to physical symptoms, some environmental cues can indicate low relative humidity. For example, static electricity buildup can indicate that the air is dry. This can cause clothes to cling to the body or produce sparks when touching metal objects. Another sign of low humidity is the cracking or shrinking of wooden objects or furniture, as the wood loses moisture and contracts in dry conditions. Paper can become brittle and static-sensitive electronic components can be damaged due to the lack of moisture in the air.

The relative humidity level inside a building is influenced by the temperature and humidity levels outside.

The following figures (Figure 3.5 to Figure 3.8) represent line graphs showing hourly averaged relative humidity level (%) for the offices of Building A and Building B during all four measurement periods.

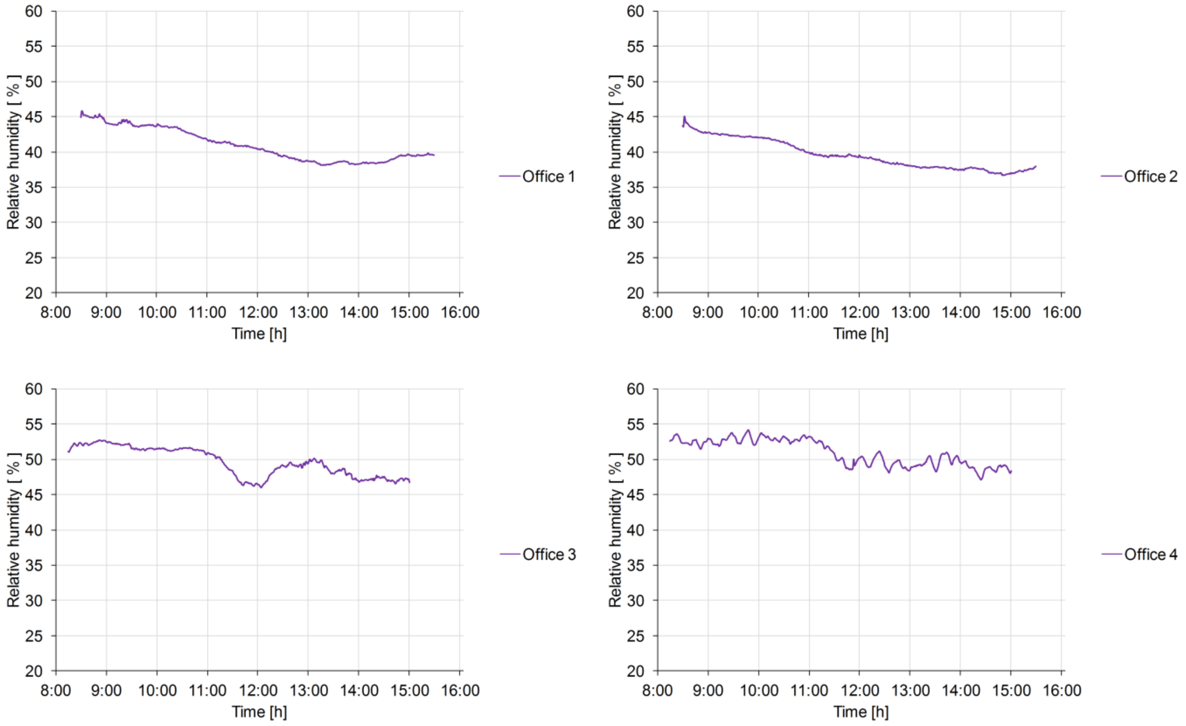

Figure 3.5. Variation of relative humidity in offices during the spring period

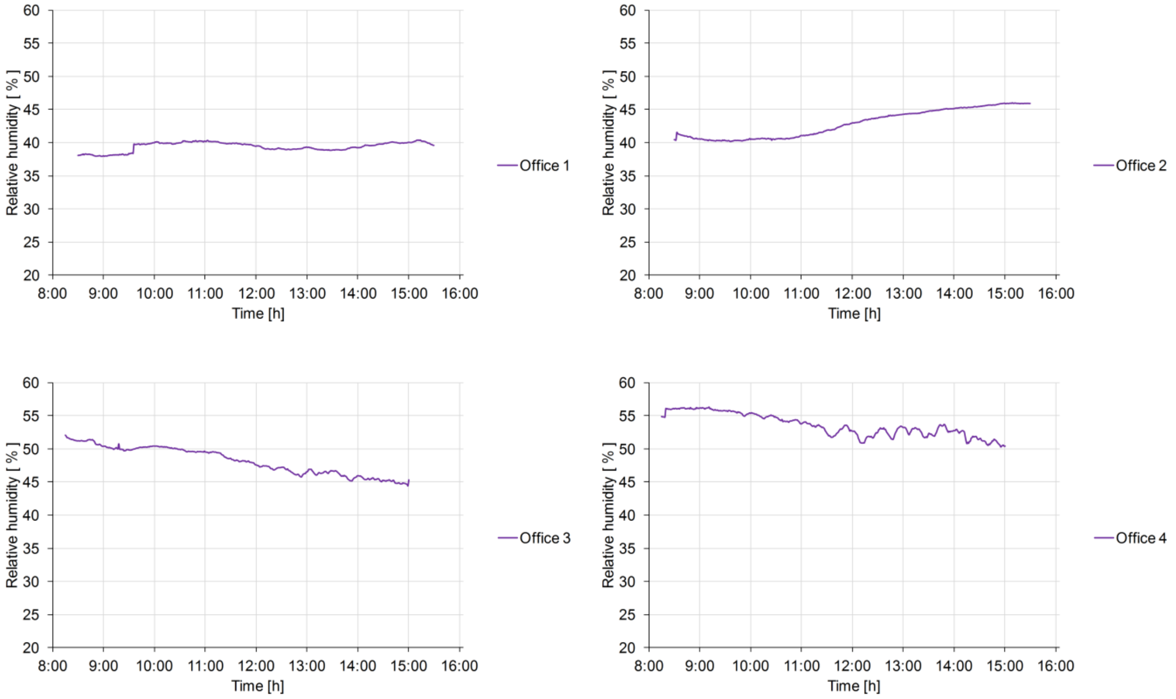

Figure 3.6. Variation of relative humidity in offices during the summer period

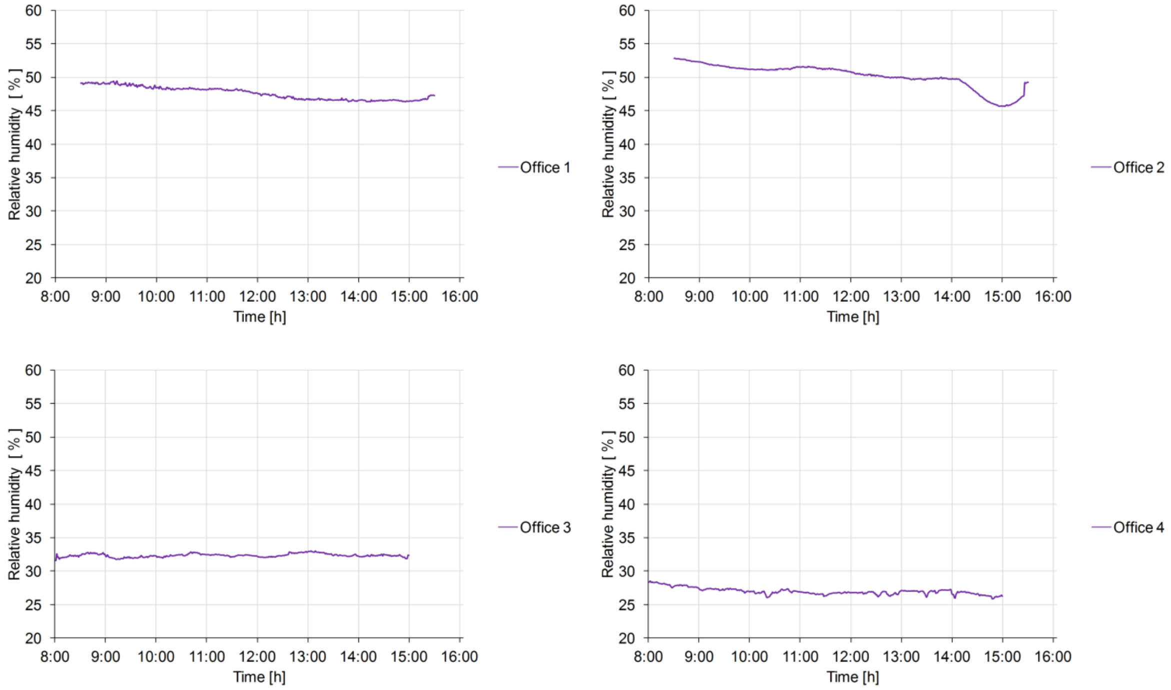

Figure 3.7. Variation of relative humidity in offices during the autumn period

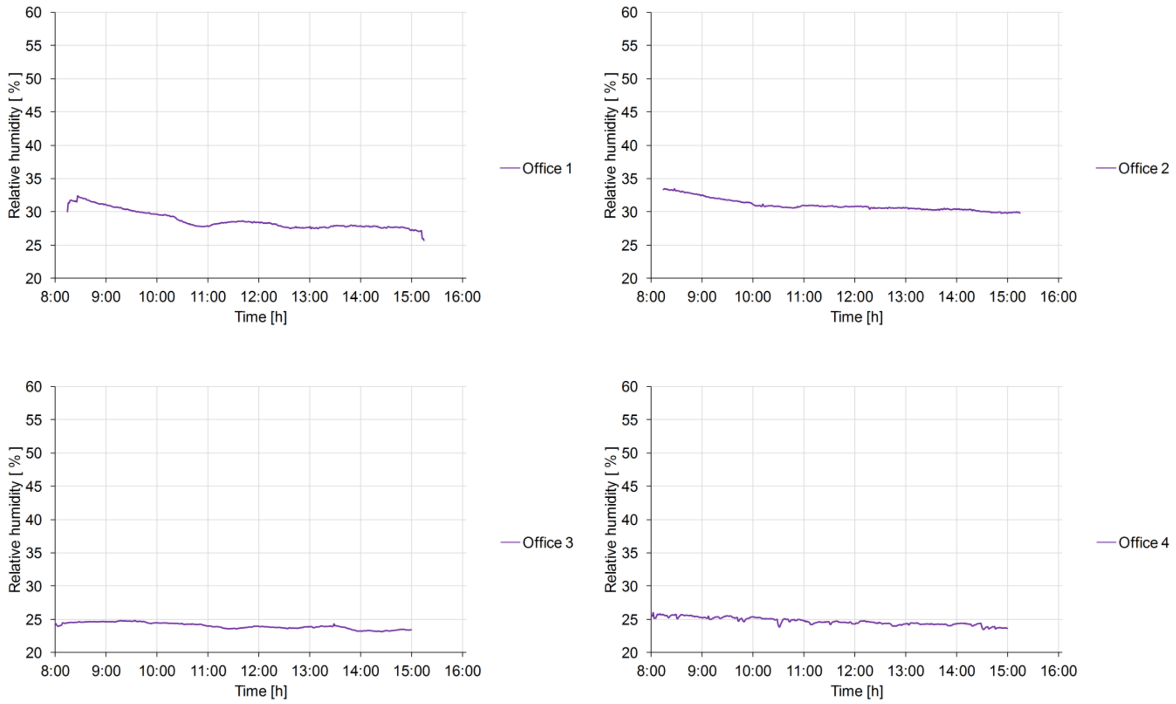

Figure 3.8. Variation of relative humidity in offices during the winter period

Throughout the study period, there was typically an anticipated inverse correlation between relative humidity and temperature, meaning that lower temperatures were frequently linked with higher humidity levels.

During the cooling period, the relative humidity in the premises of Building A and Building B is between 35% and 55%. During working hours in the offices of Building B, there are more frequent changes in humidity of the air. Also, the relative humidity in Building B is higher than in Building A.

During the heating season in both buildings, an issue with dry air was observed, attributed to indoor temperatures in winter that exceeded the recommended range specified by standards. During the heating period, extremely low relative humidity levels were recorded in the offices, partially conditioned by heating the air to higher temperatures, whereby it dries out.

Occupants identified a relative air humidity level of 50% as where they perceived the air as humid. Conversely, an air humidity level of approximately 40% was perceived by occupants as dry to satisfactory. Thus, results of occupants' range of relative humidity percievation are within the standard recommendation. Furthermore, occupants are generally satisfied with the humidity in the air.

3.2.4. Level of carbon dioxide

Carbon dioxide is a natural component of air. The amount of CO_2 in a given air sample is commonly expressed as parts per million (ppm). Normal outdoor CO_2 levels range between 350-450 ppm (parts per million) [84].

Since carbon dioxide is a natural product of human respiration, indoor occupants are its main contributors [34]. Meaning, where indoor concentrations are elevated (compared to the outside air), the source is usually due to the building's occupants. The exhaled breath of the average adult typically contains approximately 35,000 to 50,000 parts per million (ppm) of CO_2, which is about 100 times higher than outdoor air levels. Without proper ventilation to disperse and eliminate the continuously generated CO_2 by occupants, there is a risk of CO_2 accumulation. Chronic exposure to high levels of CO_2 can have a wide range of health effects such as inflammation, bones and kidney composition changes, respiratory acidosis as well as behavioral and physiological changes [85].

Indoor occupants may express discomfort with stuffiness and experience less comfortable breathing when indoor CO_2 levels range between 600-1,000 parts per million (ppm). General drowsiness can manifest when concentrations reach 1,000-2,500 ppm, and adverse health effects are more likely to occur when CO_2 concentrations surpass 2,500 ppm [86].

In a building with minimal ventilation, the CO_2 levels are prone to steadily rise during the day without reaching a stable concentration. Conversely, buildings equipped with robust ventilation and effective blending of outdoor air can hinder CO_2 buildup beyond outdoor levels, ensuring consistently low CO_2 concentrations throughout the day.

According to ASHRAE Standard 62.1 [87], offices should be provided with 20 ppm outside air per person. Using CO_2 as an indicator of ventilation, ASHRAE has recommended indoor CO_2 concentrations be maintained at/below 800 ppm in offices. Because indoor CO_2 levels are directly influenced by outdoor concentrations, it's crucial to evaluate outdoor CO_2 levels when assessing indoor air quality. ASHRAE suggests that indoor CO_2 concentrations ideally shouldn't surpass the outdoor levels by approximately 600 parts per million (ppm).

The following figures (Figure 3.9 to Figure 3.12) represent line graphs showing hourly averaged CO_2 concentration (ppm) data for the offices of Building A and B during all four measurement periods.

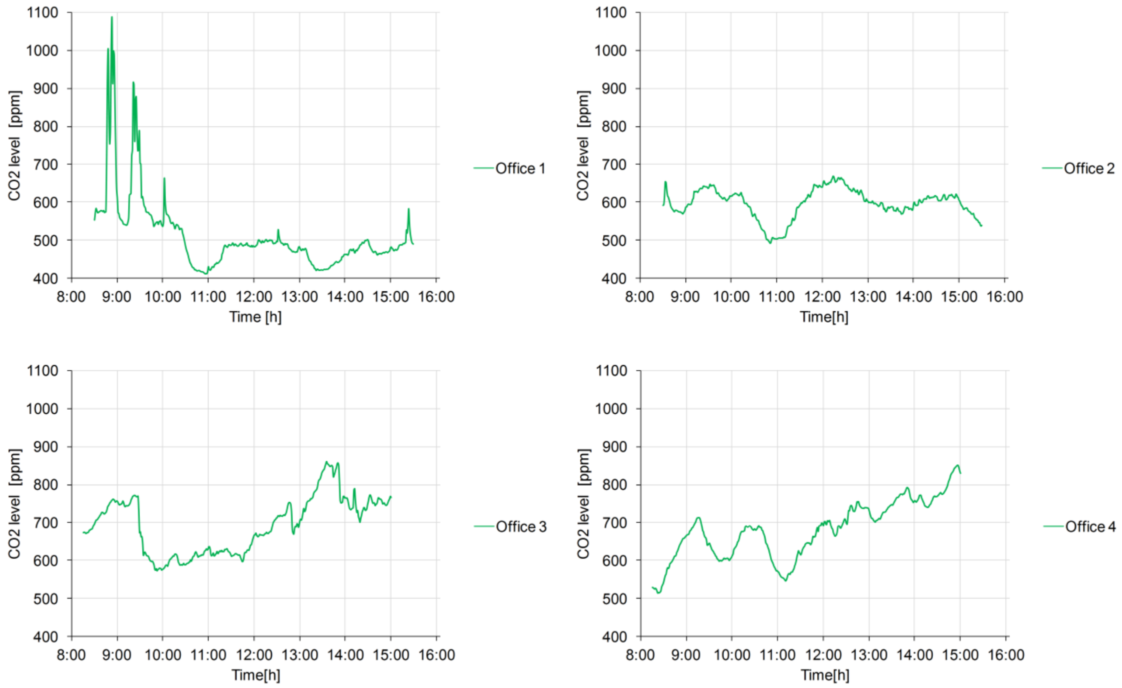

Figure 3.9. Level of CO_2 concentration during spring measurement period

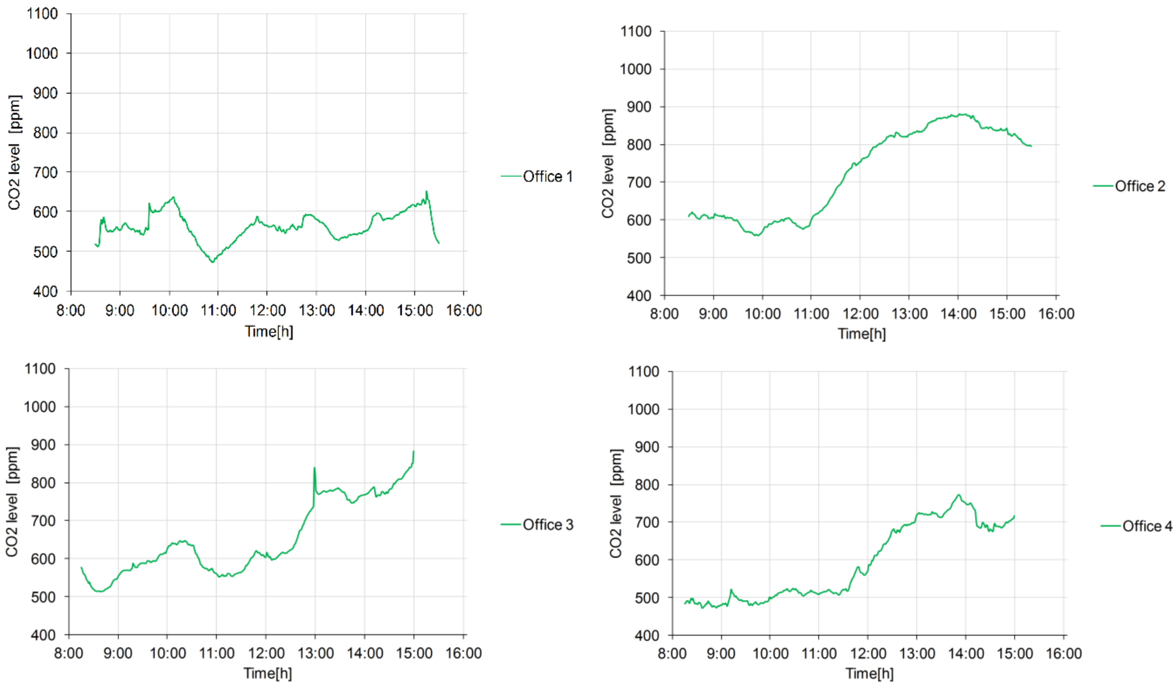

Figure 3.10. Level of CO_2 concentration during summer measurement period

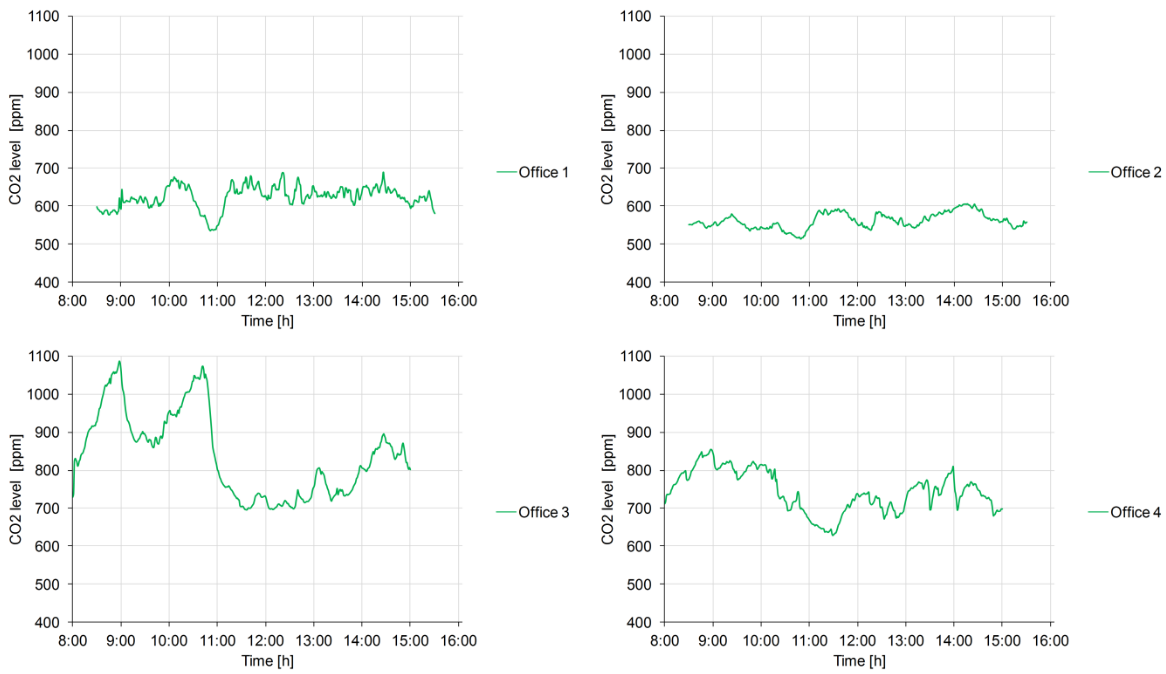

Figure 3.11. Level of CO_2 concentration during autumn measurement period

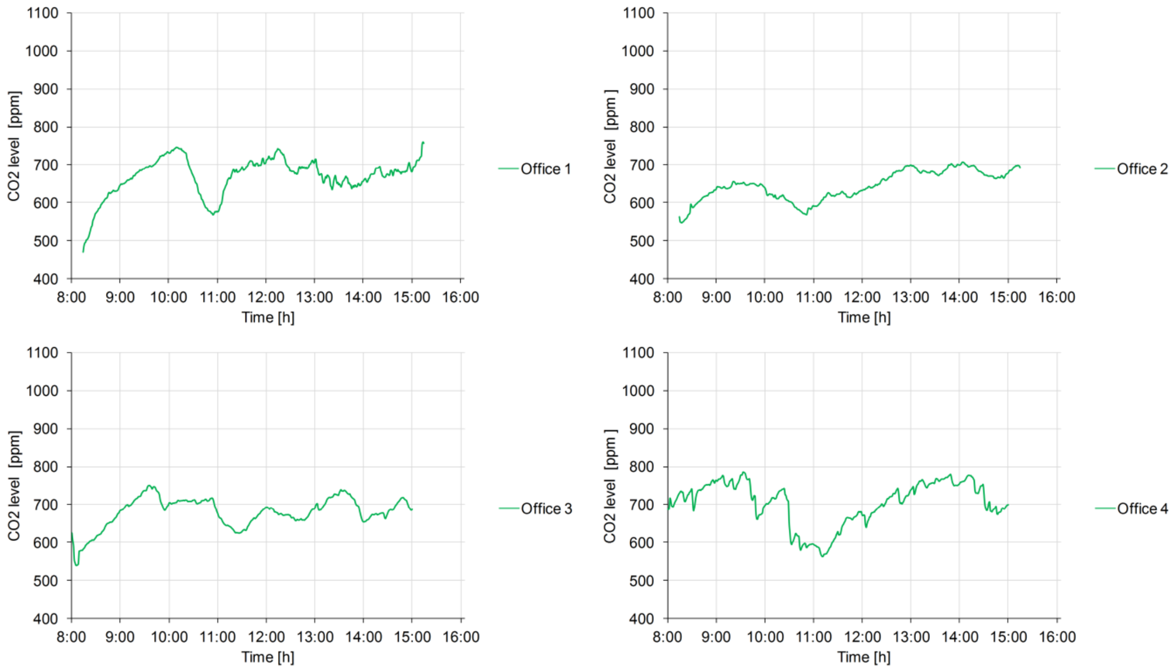

Figure 3.12. Level of CO_2 concentration during winter measurement period

Hourly averaged CO_2 data was analyzed. Generally, CO_2 levels peaked at around the end of a working day as the office was in full occupancy. Nevertheless, occupancy fluctuated in the afternoons due to work patterns, leading to a gradual decrease in CO_2 levels to a median value of 550 ppm during a daily break. Peaks exceeding 1,000 ppm occurred in the mornings when occupants did not start a day with a window opening.

During the cooling period, carbon dioxide levels in the premises of Buildings A and B ranged in average values between 500 ppm and 700 ppm. At the end of working hours, an increase in values is visible, which indicates a lack of adequate fresh air in the afternoon.

During the heating period, the carbon dioxide levels in the premises of Building A ranged in average values between 560 ppm and 650 ppm, while those values in Building B were 100 ppm higher. Hence, a decrease in the ventilation rate in Building B in the winter period compared to the summer period was observed. Therefore, increased frequency of air exchanges in space are required during the winter period. This can be attributed to the tendency of office windows to be open more frequently than they are closed.

This research reveals how temporal patterns of CO_2 change throughout the day in a small, two-person office environment. The data shows that, despite only having a few occupants in the office, CO_2 levels can rapidly rise during the initial hours of occupancy, surpassing the recommended comfortable threshold.

Clearly, occupants were aware of the reduced air quality, complaining of ‘stuffiness’ and the need to open a window. Occupants also felt that the ‘uncomfortable’ air impacted their concentration. The CO_2 level was observed to be significant for occupants, prompting them to routinely manage openings for intermittent natural ventilation within the room.

In general, occupants were satisfied with ventilation in the buildings. Dissatisfaction arises solely when the CO_2 concentration in the air nears the threshold of 700 ppm.

3.2.5. Metabolic rate

Sensors in this research were used to measure the occupant's MET as an interaction between a person's internal and external environment that considers individual differences and metabolic changes of the occupant in their daily activities.

According to Yang et al. [88] the critical temperature influencing MET changes is 24 °C. Below this threshold, ranging from 18-24 °C, the MET fluctuation is relatively gradual. However, beyond 24-33 °C, the rate of MET changes becomes significant, underscoring the importance of this research.

Activity is a complex feature that is closely intertwined with bodily movements, gestures, and the surrounding environment in which it occurs. Occupants' engagements can be classified into various dimensions, including movement, time, and location. Examples of typical activities include working in a designated workspace, walking to attend a meeting, and ascending stairs. Additionally, activities can be distinguished by whether they involve remaining stationary or involve movement within a building.

The eight occupants wore sensors for activity capturing and MET calculating as described in Chapter 02. The analysis of wearable sensor data involved several steps, including data sampling, filtering, segmentation, feature extraction, and ultimately classification and interpretation. The total number of collected data was 107,520 which was averaged to 419 seasonally for further calculation and analysis.

The following figures (Figure 3.13 to Figure 3.20) show the parameters measured by sensors, specifically the MET and energy expenditure measured in watts. Energy expenditure refers to the total amount of energy that an individual expends to sustain their body’s functions and physical activities. Total energy expenditure was obtained by summing the basic energy expenditure of metabolism and the energy expenditure of the sampled activity. Activity-related expenditure was calculated for each activity class separately, taking altitude into account. The value of MET was obtained by a regression model and is equal to the quotient of total energy expenditure and energy expenditure at rest.

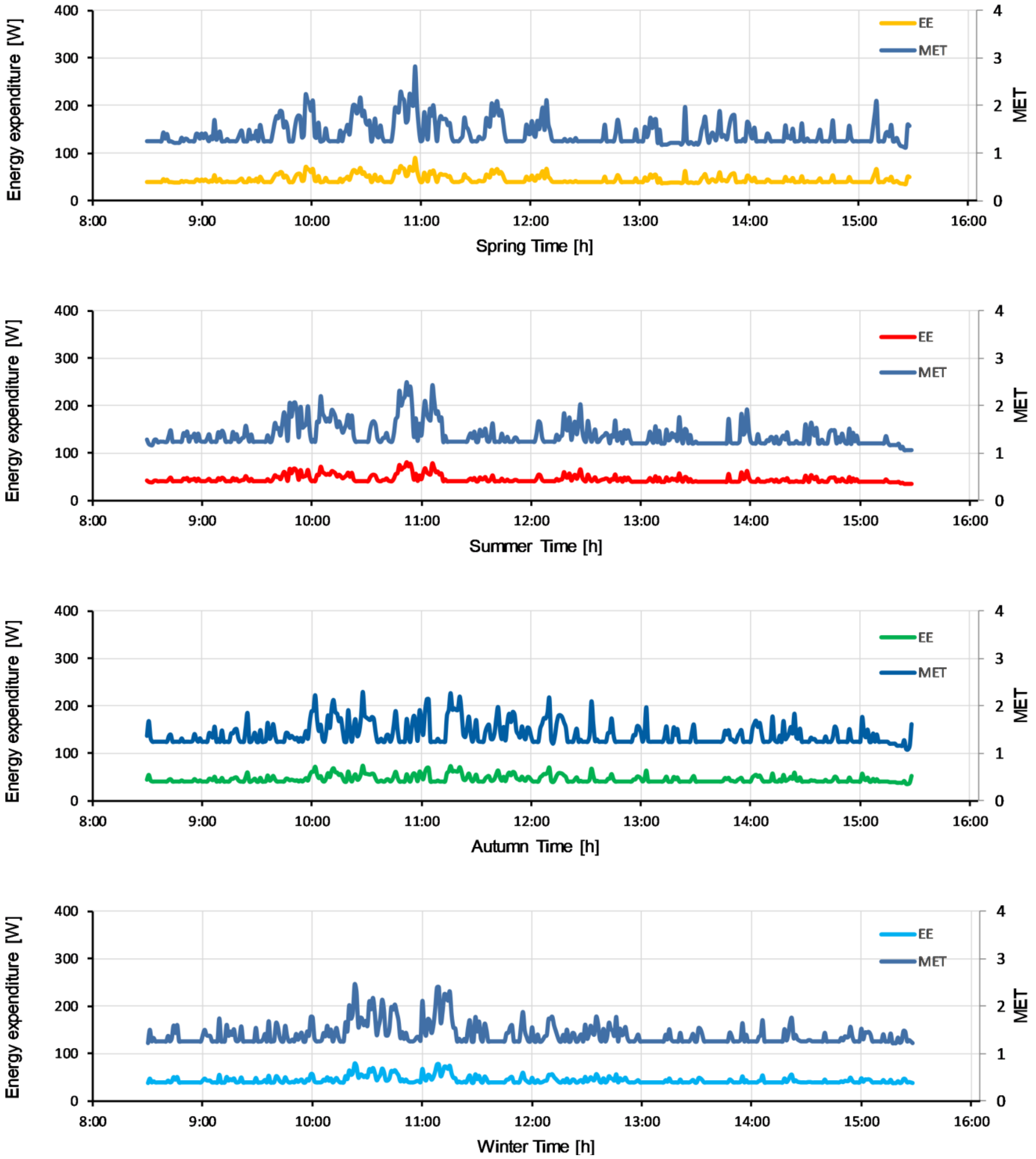

Figure 3.13. Energy expenditure and metabolic rate of Occupant 1

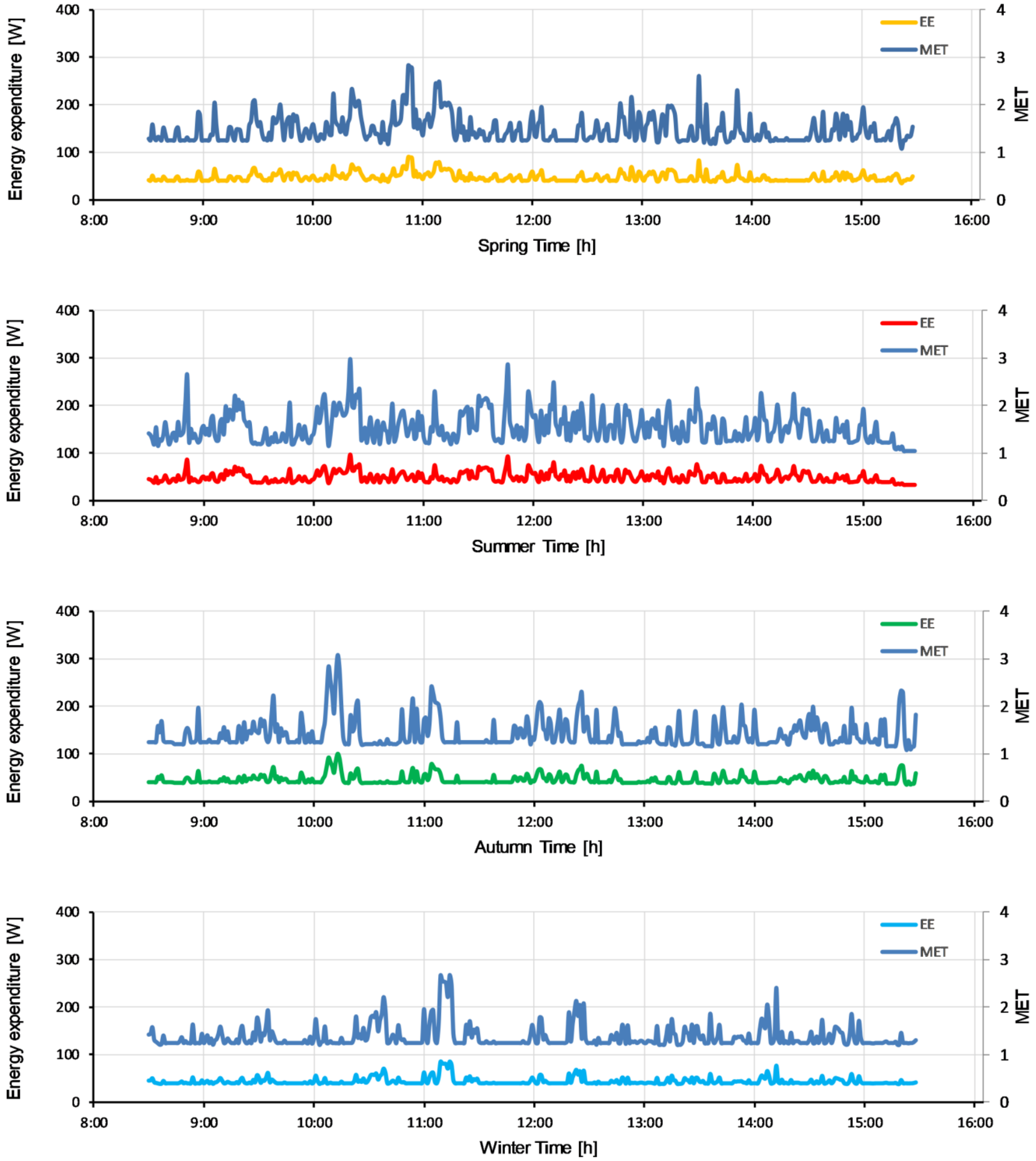

Figure 3.14. Energy expenditure and metabolic rate of Occupant 2

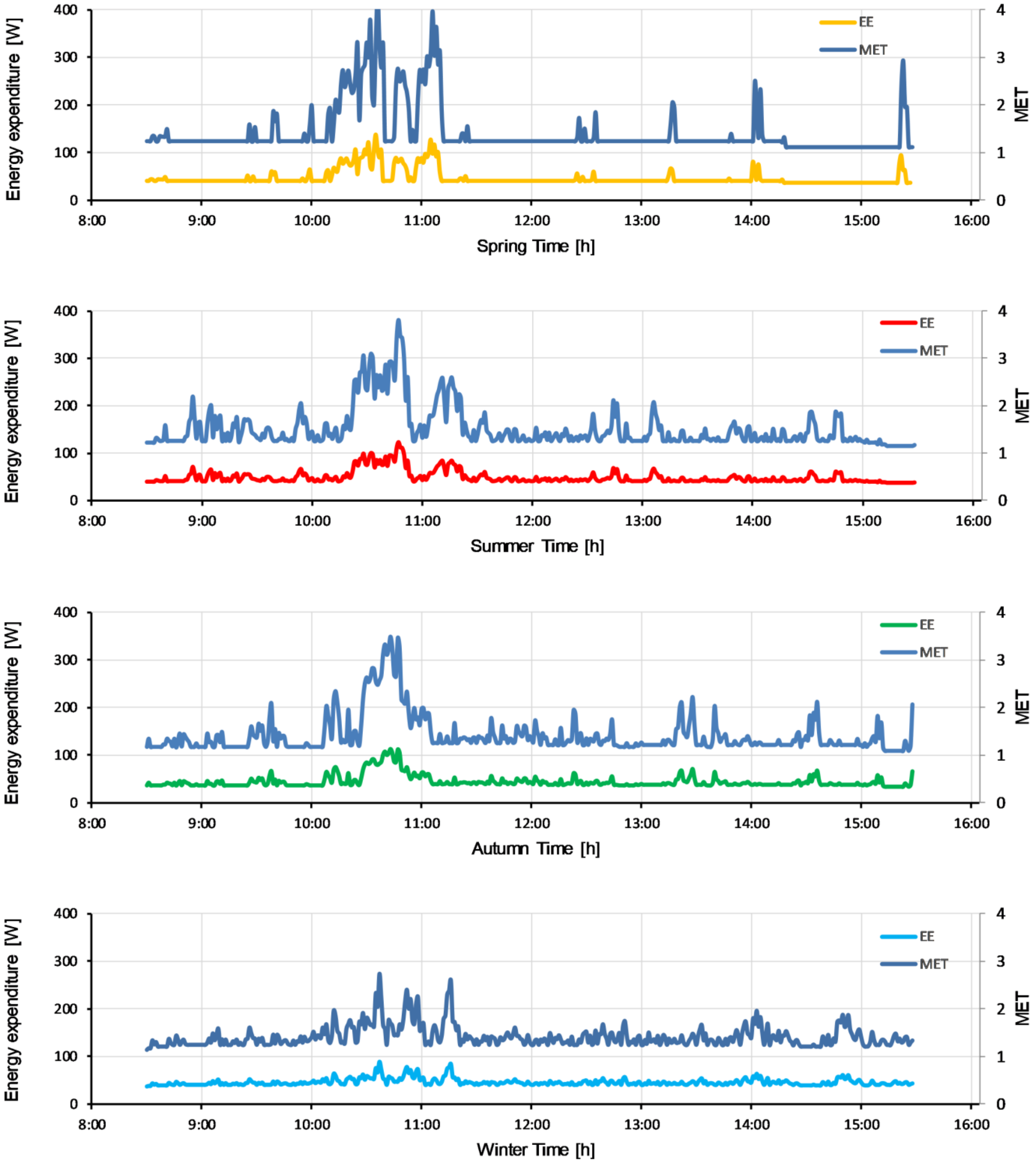

Figure 3.15. Energy expenditure and metabolic rate of Occupant 3

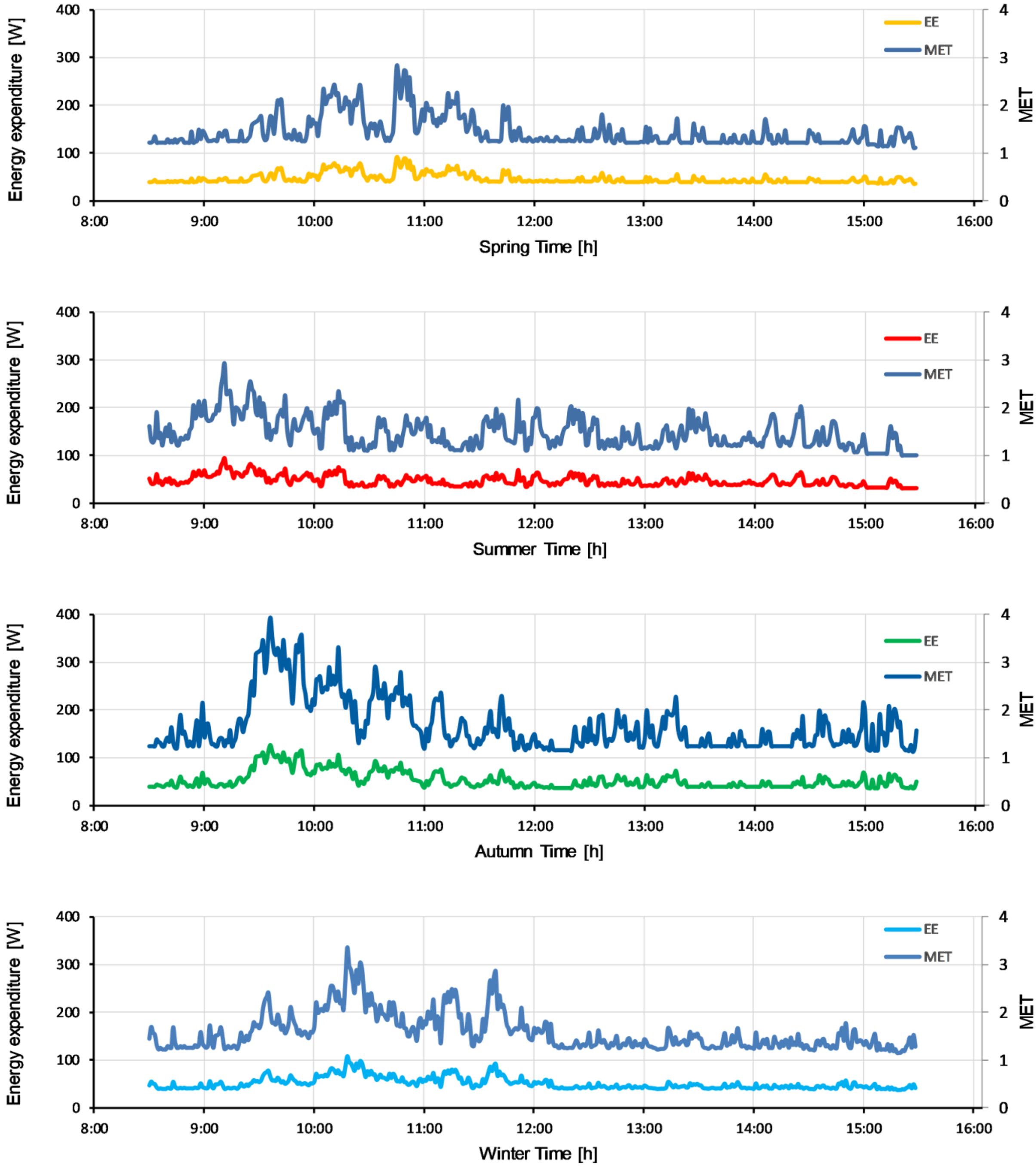

Figure 3.16. Energy expenditure and metabolic rate of Occupant 4

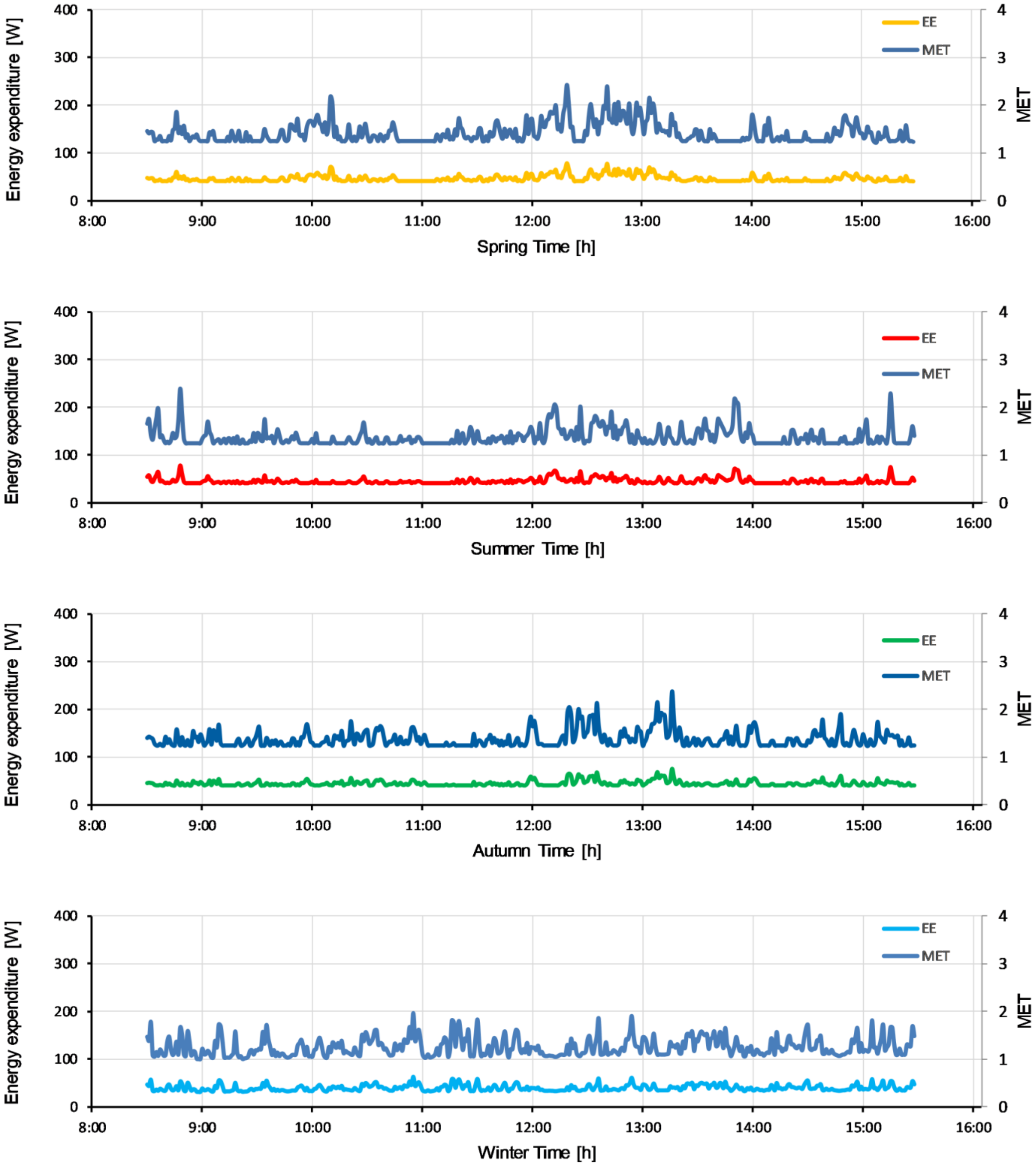

Figure 3.17. Energy expenditure and metabolic rate of Occupant 5

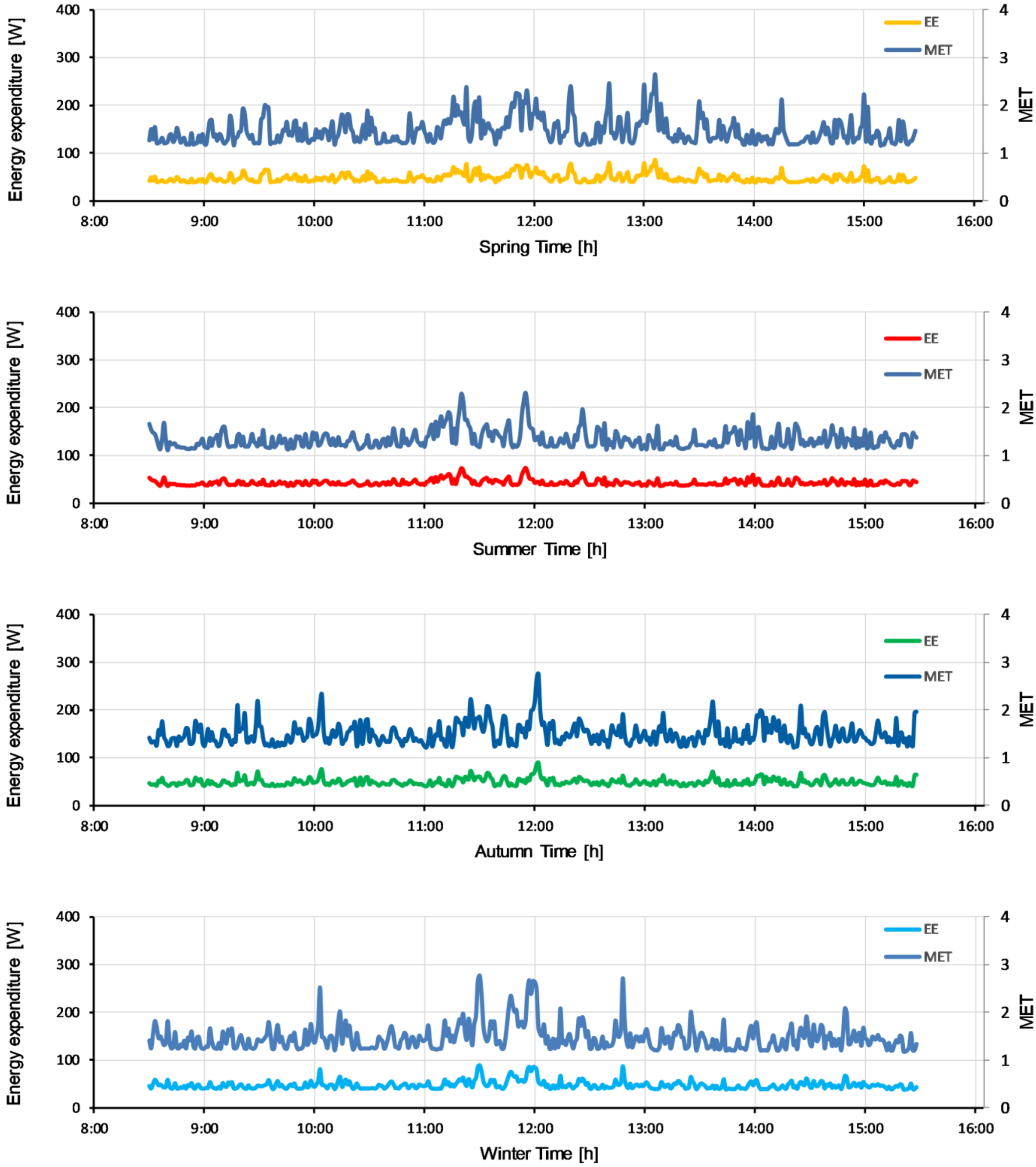

Figure 3.18. Energy expenditure and metabolic rate of Occupant 6

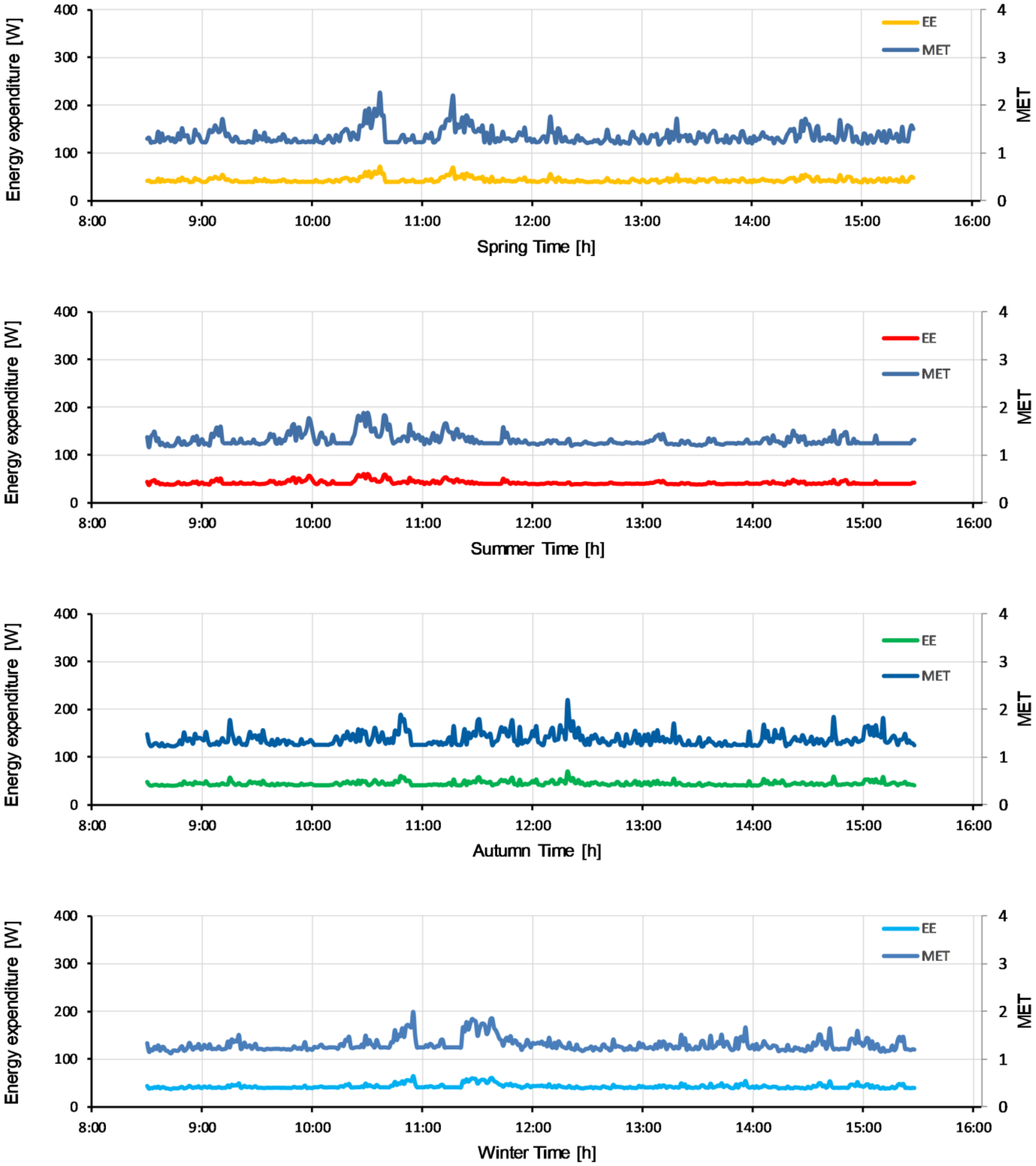

Figure 3.19. Energy expenditure and metabolic rate of Occupant 7

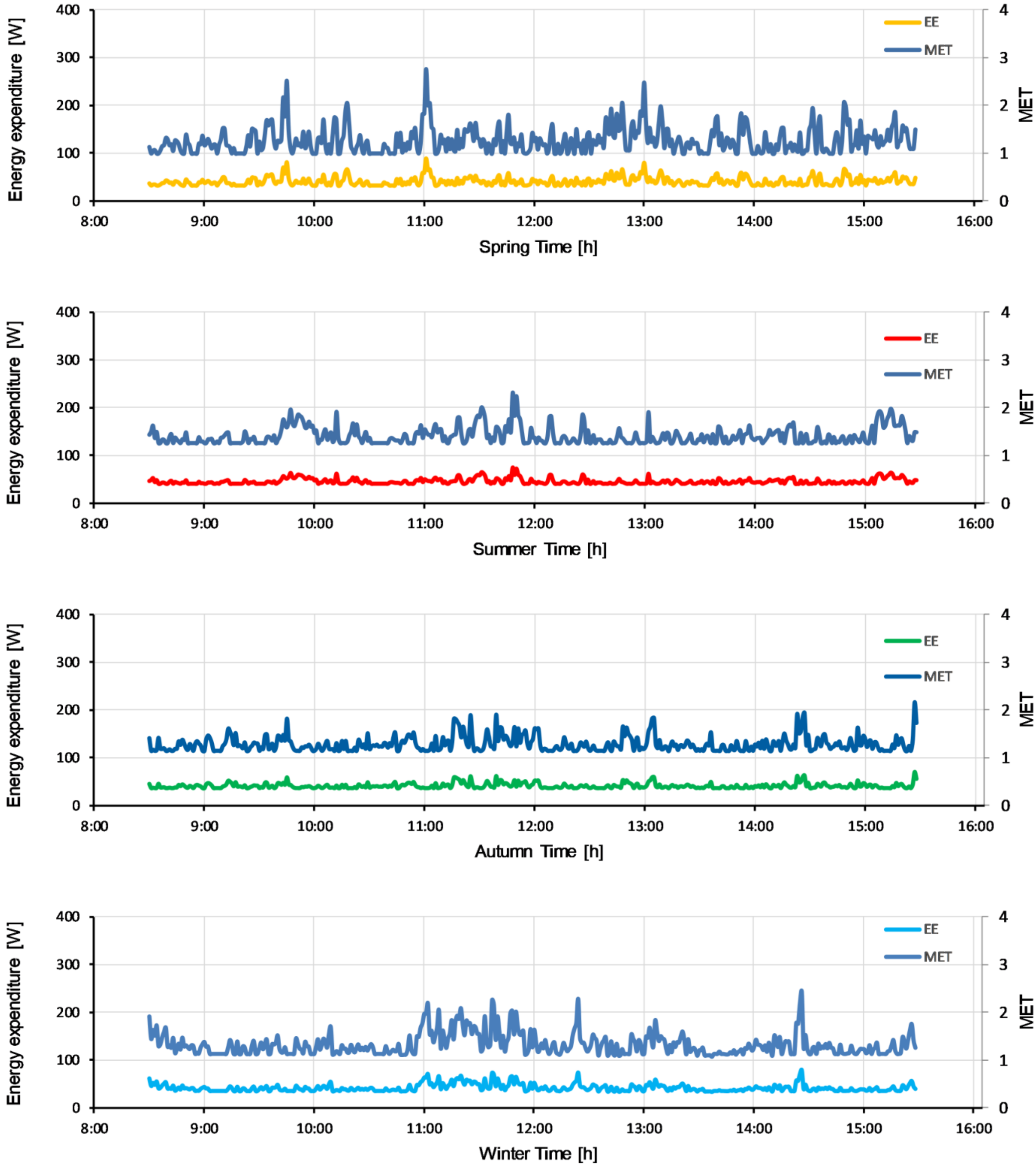

Figure 3.20. Energy expenditure and metabolic rate of Occupant 8

As it can be seen from the results presented in Figures 3.13 – 3.20, EE and MET are closely related as MET is a significant component of EE. MET refers to the rate at which the body consumes energy to maintain its essential functions and processes at rest. It includes energy required for breathing, circulating blood, maintaining body temperature and other vital functions.

The results obtained by sensors showed that Occupant 1 exhibits the highest average energy consumption between 10:00 and 10:30, with an energy expenditure ranging from 100 W to 200 W throughout the working day. On the other hand, Occupant 2 consistently has a significantly higher energy expenditure during the working day, ranging from 100 W to 250 W. Occupant 3 peaks in energy consumption between 10:30 and 11:30, with an average energy expenditure fluctuating between 150 W and 400 W. Finally, Occupant 4 consumes the most energy in the early part of the day, with an average energy expenditure ranging from 90 W to 210 W. Occupant 5 exhibits the highest energy consumption during midday hours, with an average energy usage between 120 W and 300 W. Occupant 6 similarly peaks in energy consumption around midday, averaging between 100 W and 200 W. On the other hand, Occupant 7 shows the highest energy usage during the winter, with an average energy expenditure ranging from 100 W to 210 W. Occupant 8 consumes between 100 W and 350 W on average. All occupants use the most energy during breaks due to increased activity.

Furthermore, the results showed that mental work, as well as simple standing and walking, increased the MET. Also, it has been proven that the value of the MET changes over time for the same occupant but also varies among people performing similar daily activities. In addition, it was observed that the MET is higher for men than women when performing the same type of work.

As for MET difference age-related, according to Table 2.8, the third age group has a lower activity level and, therefore, a lower MET. Therefore, a higher air temperature is needed as opposed to the first age group. Therefore, the third age group is less sensitive to alterations in the thermal environment but more susceptible to extreme temperature conditions. Their acceptable range of comfortable temperatures is narrower compared to younger individuals, likely due to a decline in the capacity to regulate body temperature as one ages.

Figure 3.21 shows imprecision of calculating MET by referencing tables of activities along with their corresponding MET values as outlined in guidebooks and standards. For clarity of comparison, only Building A' occupants are put through the analysis.

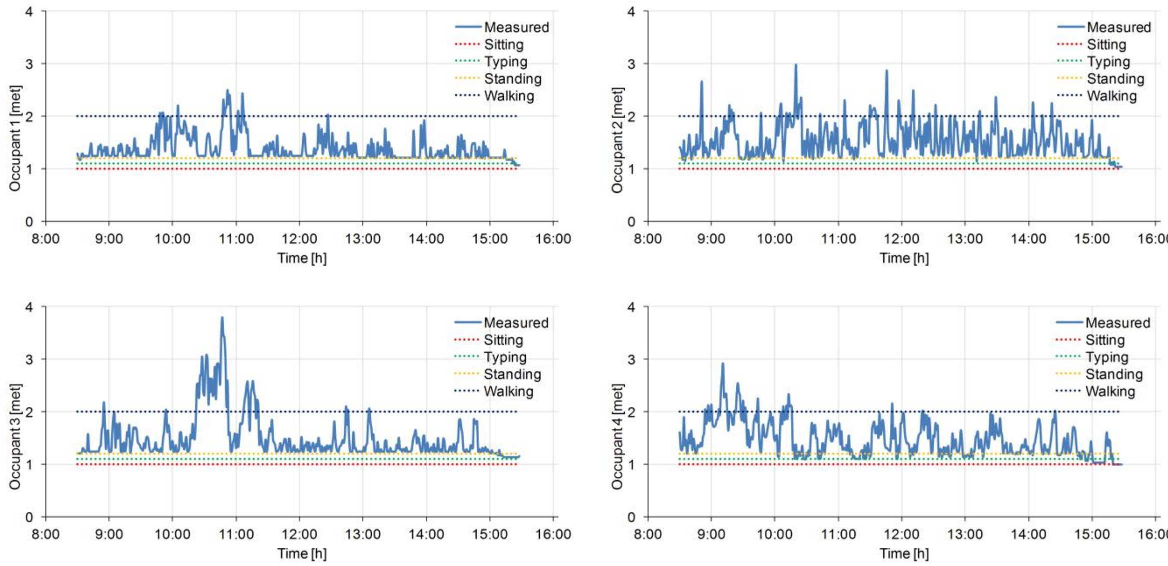

Figure 3.21. MET values of the occupants in Building A

Despite engaging in similar daily activities, there is a notable disparity in the MET among these occupants. Therefore, dynamic changes in MET gained by the sensor measurement suggest diary methods of MET assessment are inapplicable for accurate thermal comfort prediction.

3.2.6. Clothing insulation and occupant's sensation vote

For predicting and evaluating the thermal comfort in buildings, clothing insulation is also an important factor. There are cultural differences between men and women in choosing clothing for work. The standards recommend a clothing level in the cooling period of 0.5 clo, and in the heating period, a clothing level of 1 clo [7].

In addition to seasonal clothing insulation changes between the two buildings' occupants, differences were also observed during the same day. For the clothing insulation assessment, a survey questionnaire was used for occupants to mark the clothes they wear at different times during the day. The ASHRAE handbook [7] provides a compiled list of clothing insulation values for commonly worn individual garments.

Generally, higher clothing insulation was observed in the morning hours than in the middle and end of the working day. This is the result of lower morning temperatures. Based on the results of the analysis, it was concluded that women are more inclined to change the level of clothing than men during their working hours.

Figures 3.22 and 3.23 show the frequency of worn garments in clo during the year for Building A and Building B.

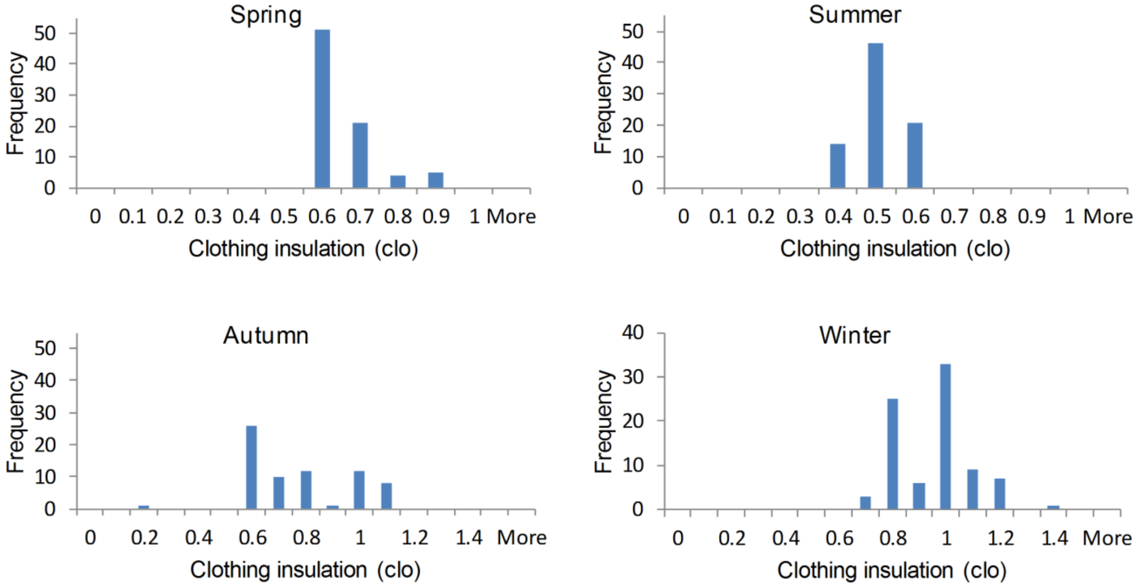

Figure 3.22. Clo frequency during the year in Building A

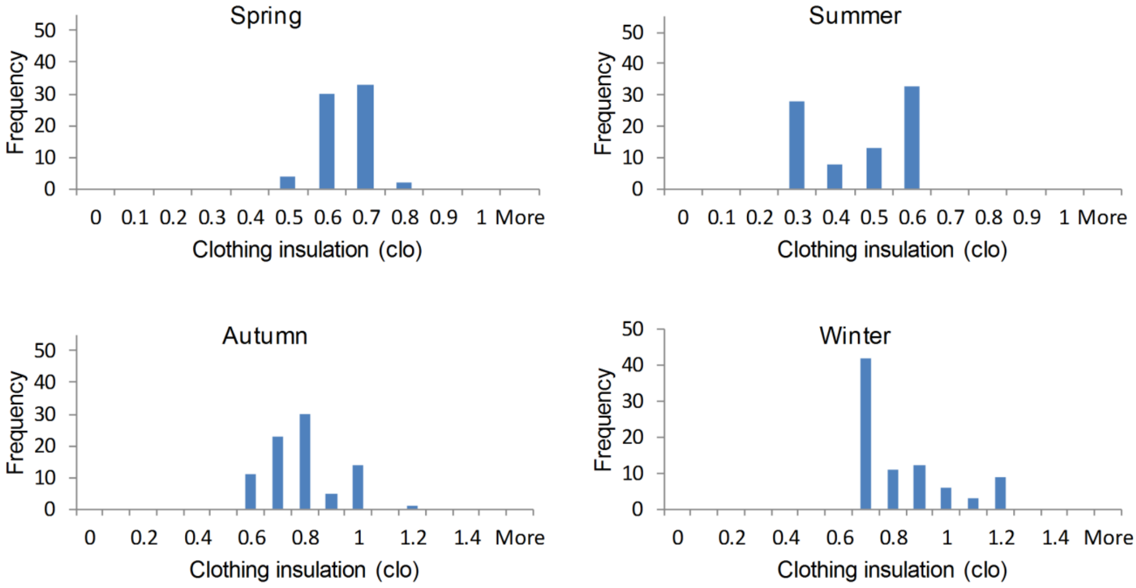

Figure 3.23. Clo frequency during the year in Building B

In the cooling period, lower clothing insulation is observed in Building A. In the warmer period, the most frequently worn garments were of 0.5 (summer) and 0.6 clo (spring). As for the cooling period, there is a big difference between autumn and winter. In the winter period, an increased frequency of clothing insulation of 0.8 clo was observed. However, the frequency of insulation greater than 1 clo was also noted. In the autumn period, the results are more dispersed, from 0.6 to 1.1.

In Building B, during the cooling period, there are frequent repetitions of clothing insulation between 0.7 clo, while in the summer occupants dress much lighter, so often their clothes have insulation of 0.3 clo. This is significantly lower than in Building A. In autumn, in Building A, there is the largest dispersion of results, which vary between 0.6 and 1 clo, while in winter the clothing insulation of the occupants was usually 0.7 clo. Therefore, in winter the occupants of Building B dress much lighter than the occupants of Building A.

The correlation between occupant's BMI and the average level of clothing is shown in Table 3.8.

Table 3.8. Correlation between the occupant's BMI average clo level

Building A	Woman BMI=20.8	Woman BMI=23.6	Man BMI=23.8	Woman BMI=22.7
Season	clo	clo	clo	clo
Spring	0.56	0.55	0.62	0.63
Summer	0.44	0.43	0.51	0.46
Autumn	0.77	0.59	0.59	0.93
Winter	1.04	0.80	0.93	0.92

Building B	Man BMI=29.5	Woman BMI=23.9	Woman BMI=32.8	Man BMI=27.5
Season	clo	clo	clo	clo
Spring	0.64	0.62	0.53	0.64
Summer	0.49	0.41	0.33	0.53
Autumn	0.68	0.93	0.65	0.74
Winter	0.85	0.97	0.69	0.70

It can be seen that women have a higher average clothing insulation than men during the same season. As per the BMI, occupants with a higher index have a lower clothing insulation.

People with higher BMI might feel more comfortable wearing lighter and loose-fitting clothing as it allows better airflow and reduces the feeling of tightness. In addition, occupants with higher BMI may naturally generate more body heat due to their higher MET, making them feel warmer. Thus, with lighter clothing it is possible to avoid overheating.

3.2.7. Summary of analyzed results

Table 3.9 presents the average values concerning thermal comfort criteria for all periods of the year in both buildings.

In both buildings, occupants consider an average sensed air temperature of 26°C in offices as being on the higher side. The greatest dissatisfaction with air temperature is noted during the spring season. The transitions between seasons emerged as the most critical periods from the perspective of thermal comfort.

Table 3.9. Average values related to comfort conditions for both examined buildings

	Building A			Building B		
	Air temp. [°C]	CO_2 level [ppm]	RH level [%]	Air temp. [°C]	CO_2 level [ppm]	RH level [%]
Heating season value	26.7 ± 1.2	624.8 ± 25.3	39.4 ± 1.2	24 ± 0.4	742.2 ± 46.9	27 ± 0.3
Cooling season value	28 ± 0.4	599.4 ± 39.2	40.7 ± 0.6	26.4 ± 0.3	659.3 ± 81.1	50.5 ± 1.8

Satisfaction levels were assessed using the system of Likert scale [89], spanning from 1 to 5. A value of 3 denoted a neutral state (a state of comfort). Lower values indicated discomfort, such as warm to hot thermal conditions, dry air, etc. Conversely, higher values also indicated discomfort, but due to different factors, such as cool to cold thermal conditions, air humidity, and stifling air.

The survey showed that the occupants were most often dissatisfied with the thermal conditions of the office rooms. In the heating period (colder period of the year), Building B occupants were mostly cold, which means the space is not heated enough. On the other hand, Building A occupants generally feel too warm in winter.

However, during the cooling period (warmer months), Building B occupants were mostly satisfied. Nevertheless, this does not apply to Building A occupants, whose average TSV shows increased values. They feel warmer than what is considered a comfortable level of comfort.

Figures 3.24 and 3.25 provide a concise summary of TSV central tendency and variability throughout the year.

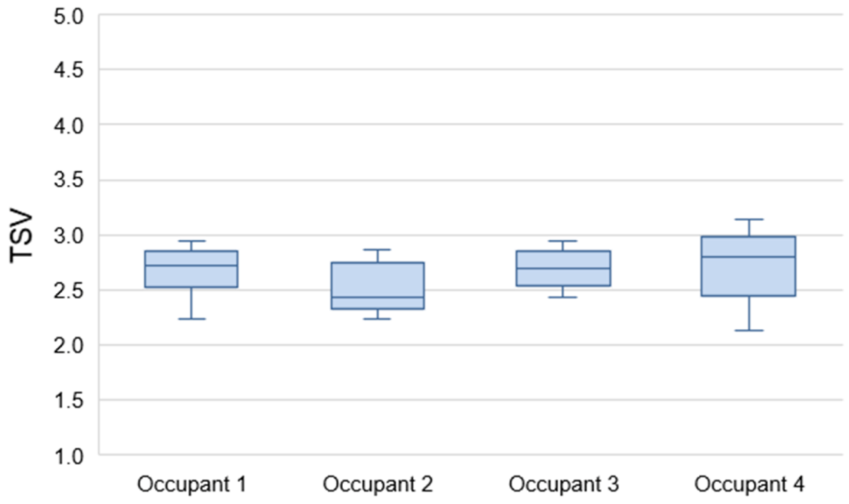

Figure 3.24. Building A occupants' TSV during the year

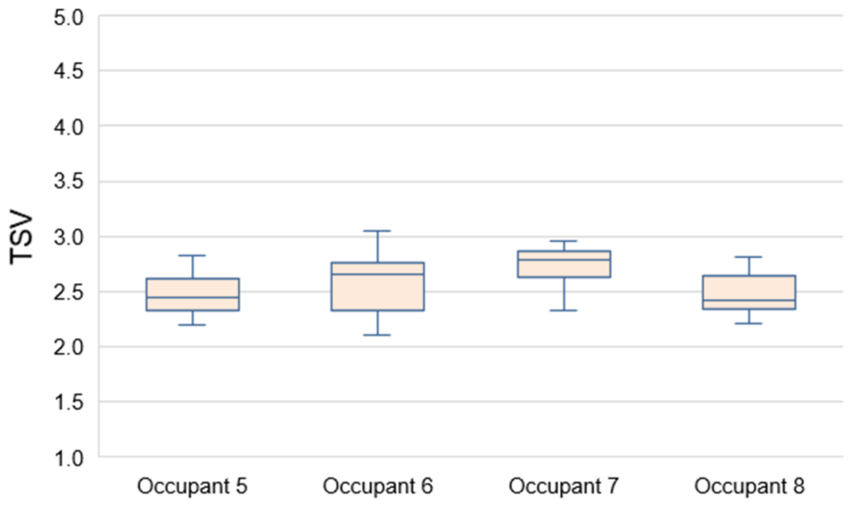

Figure 3.25. Building B occupants' TSV during the year

Overall thermal sensation that can be seen in Figures 3.24 and 3.25 denotes occupants from both buildings generally feel warmer than what is considered to be recommended thermal state during the year.

3.3. Predicting personal occupant's thermal comfort using PMV-PPD model

In order to assess the occupant's comfort with a measurable value, the PMV-PPD thermal balance model was applied. Its applicability was tested on the herein examined buildings. Using the PMV and PPD index calculation tool [90], the values presented in Table 3.10 and Table 3.11 were gained. The working temperature of the office room and MET were measured, while clothing insulation was obtained by daily observation of the occupants. Average values for each period were taken into consideration and an average of 0.1 m/s was taken for the speed of air flow. The PMV value was calculated in three parts of the working day for both buildings. Values that do not meet ASHRAE standard 55 are marked in red.

Table 3.10. The PMV and PPD values calculated for Building A occupants

1. measurement: Spring

9 h	PMV	PPD	12 h	PMV	PPD	15 h	PMV	PPD
Occupant 1	0.15	5	Occupant 1	0.49	10	Occupant 1	0.91	23
Occupant 2	0.15	5	Occupant 2	0.41	2	Occupant 2	0.84	20
Occupant 3	0.49	10	Occupant 3	0.55	11	Occupant 3	1.11	31
Occupant 4	0.28	7	Occupant 4	0.62	13	Occupant 4	1.16	33

2. measurement: Summer

9 h	PMV	PPD	12 h	PMV	PPD	15 h	PMV	PPD
Occupant 1	1.19	35	Occupant 1	1.13	32	Occupant 1	1.19	45
Occupant 2	1.19	35	Occupant 2	1.13	32	Occupant 2	1.19	45
Occupant 3	0.92	23	Occupant 3	0.71	15	Occupant 3	0.5	10
Occupant 4	0.92	23	Occupant 4	0.63	13	Occupant 4	0.42	9

3. measurement: Autumn

9 h	PMV	PPD	12 h	PMV	PPD	15 h	PMV	PPD
Occupant 1	-0.14	5	Occupant 1	0.47	10	Occupant 1	0.68	15
Occupant 2	-0.73	16	Occupant 2	0.15	5	Occupant 2	0.47	10
Occupant 3	-1.0	21.5	Occupant 3	-0.21	6	Occupant 3	0.84	20
Occupant 4	-0.27	7	Occupant 4	0.34	7	Occupant 4	1.12	31

4. measurement: Winter

9 h	PMV	PPD	12 h	PMV	PPD	15 h	PMV	PPD
Occupant 1	-0.01	5	Occupant 1	0.87	21	Occupant 1	0.91	22
Occupant 2	-0.3	7	Occupant 2	0.55	11	Occupant 2	0.65	14
Occupant 3	1.36	44	Occupant 3	2.05	79	Occupant 3	2.3	88
Occupant 4	1.33	42	Occupant 4	2.03	78	Occupant 4	2.29	88

Table 3.11. The PMV and PPD values calculated for Building B occupants

1. measurement: Spring

9 h	PMV	PPD	12 h	PMV	PPD	15 h	PMV	PPD
Occupant 5	0.27	6	Occupant 5	0.43	9	Occupant 5	0.75	17
Occupant 6	0.35	8	Occupant 6	0.43	9	Occupant 6	0.75	17
Occupant 7	0.08	5	Occupant 7	0.3	7	Occupant 7	0.22	6
Occupant 8	0.27	6	Occupant 8	0.47	10	Occupant 8	0.39	8

2. measurement: Summer

9 h	PMV	PPD	12 h	PMV	PPD	15 h	PMV	PPD
Occupant 5	0.24	6	Occupant 5	0.55	11	Occupant 5	0.52	11
Occupant 6	-0.05	5	Occupant 6	0.19	6	Occupant 6	0.17	6
Occupant 7	-0.47	10	Occupant 7	0.01	5	Occupant 7	-0.01	5
Occupant 8	0.08	5	Occupant 8	0.48	10	Occupant 8	0.46	9

3. measurement: Autumn

9 h	PMV	PPD	12 h	PMV	PPD	15 h	PMV	PPD
Occupant 5	-0.27	6	Occupant 5	-0.21	6	Occupant 5	-0.04	5
Occupant 6	0.12	5	Occupant 6	0.17	6	Occupant 6	0.25	6
Occupant 7	-0.5	10	Occupant 7	-0.23	6	Occupant 7	-0.09	5
Occupant 8	-0.32	7	Occupant 8	-0.05	5	Occupant 8	0.07	5

4. measurement: Winter

9 h	PMV	PPD	12 h	PMV	PPD	15 h	PMV	PPD
Occupant 5	-0.23	6	Occupant 5	0.04	5	Occupant 5	0.15	5
Occupant 6	-0.04	5	Occupant 6	0.19	6	Occupant 6	0.31	7
Occupant 7	-0.45	9	Occupant 7	-0.22	6	Occupant 7	0.02	5
Occupant 8	-0.41	8	Occupant 8	-0.24	6	Occupant 8	-0.02	5

Based on the calculations, it's evident that certain Predicted Mean Vote (PVM) values are notably high in this particular scenario, suggesting a need to address and improve the existing comfort conditions in the buildings. Furthermore, the computation of the Predicted Percentage Dissatisfied (PPD) indexes revealed that the proportion of dissatisfied occupants frequently exceeded 20% throughout the day, reaching up to 80% of the people in that environment would be predicted to feel dissatisfied with the thermal conditions, which indicates a significant level of discomfort.

In winter, occupants tend to have negative PMV values because there is a higher likelihood of drafts and air leakage in buildings. These cold air infiltrations can create localized discomfort for occupants, leading to negative PMV values. Differences in temperature between different body parts or between body and surrounding surfaces can influence the perception of thermal comfort. Cold surfaces or cold air in contact with the body can also cause discomfort and result in negative PMV values. In addition, inadequate heating systems or uneven heat distribution can result in temperature variations within a building.

On the other hand, in the warm period (such as summer), occupants tend to have positive PMV values higher than recommended because of the high temperatures and insufficient cooling. Summer often brings higher humidity levels, which can contribute to discomfort. High humidity reduces the evaporation of sweat from the skin, making it harder for the body to cool down. This can result in a sensation of stickiness and increased thermal discomfort, leading to positive PMV values.

The exceptions are summer mornings in Building B where the indoor environment is typically warmer than desired. Hence, air conditioning system might be set to temperatures lower than what is considered comfortable for some occupants, leading to a feeling of coldness, especially if they were sitting or standing in the airflow. Moreover, moving from hot outdoor environments to highly air-conditioned indoor spaces could cause discomfort leading to negative PMV values.

Occupants in Building B exhibit higher satisfaction levels based on the computed PVM indexes. In general, there are significantly fewer deviations from comfort in Building B than in Building A. There can be several possible reasons. Building B might have a more advanced or better-maintained HVAC system compared to Building A. An efficient HVAC system can better regulate temperature, humidity, and air quality, leading to a more comfortable indoor environment with fewer deviations as well as regular maintenance of HVAC systems. The orientation and design of Building B could be more favorable for maintaining thermal comfort. Factors such as the placement of windows, shading devices, and natural ventilation options can significantly affect the indoor temperature and reduce discomfort. Moreover, occupant behavior can also play a role. If occupants in Building B are more conscious of their comfort needs and utilize available controls effectively (e.g., adjusting thermostats), they contribute to a more comfortable environment with fewer deviations.

Figure 3.26 shows a visual representation of Table 3.10 in order to clearly present the deviation from what is considered a comfort level. The colored area between -0.5 and 0.5 represents *Neutral* thermal sensation i.e. state of comfort. Different lines indicate different Building A occupants.

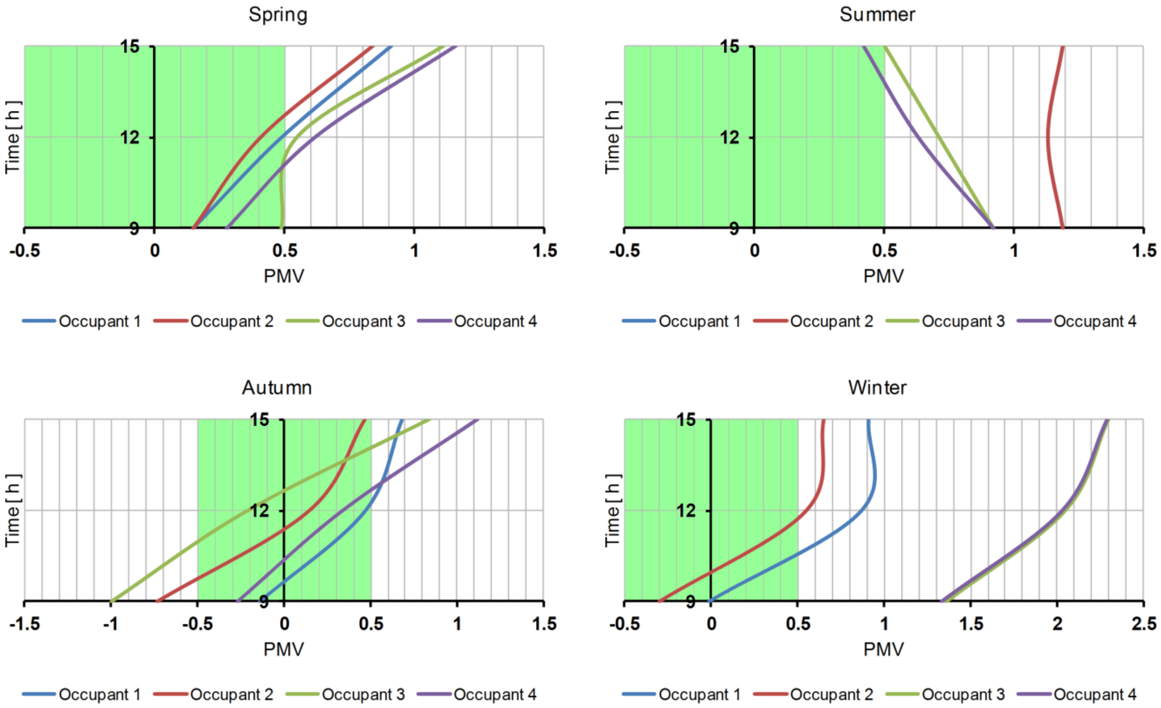

Figure 3.26. PMV values of the Building A occupants during the periods of measurement

Figures 3.27 and 3.28 provide a concise summary of PMV central tendency, variability and outliners throughout the year for both buildings.

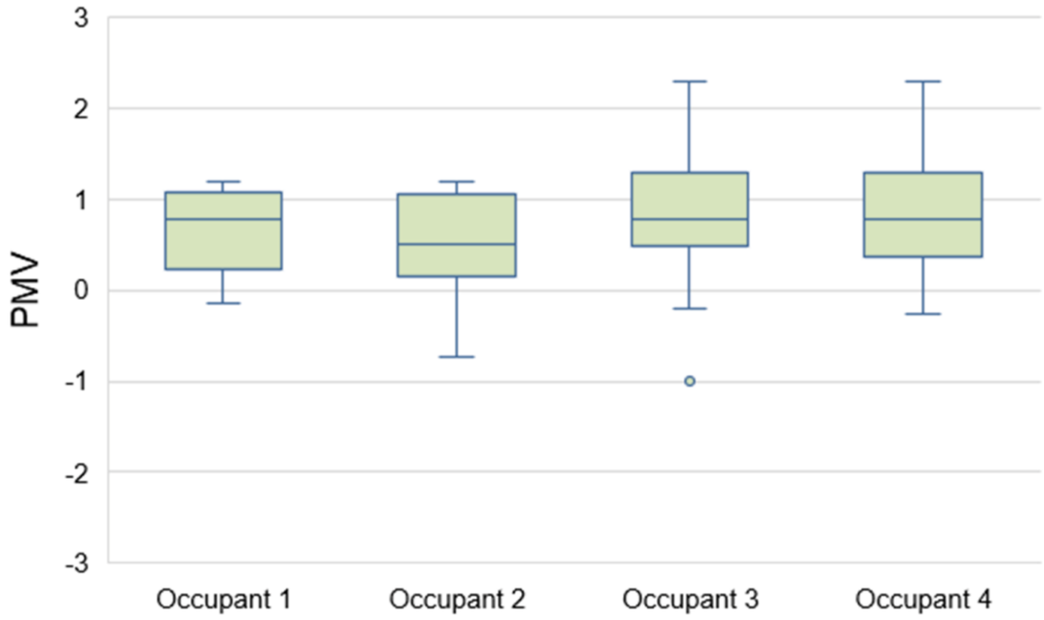

Figure 3.27. PMV values of the Building A occupants throughout the year

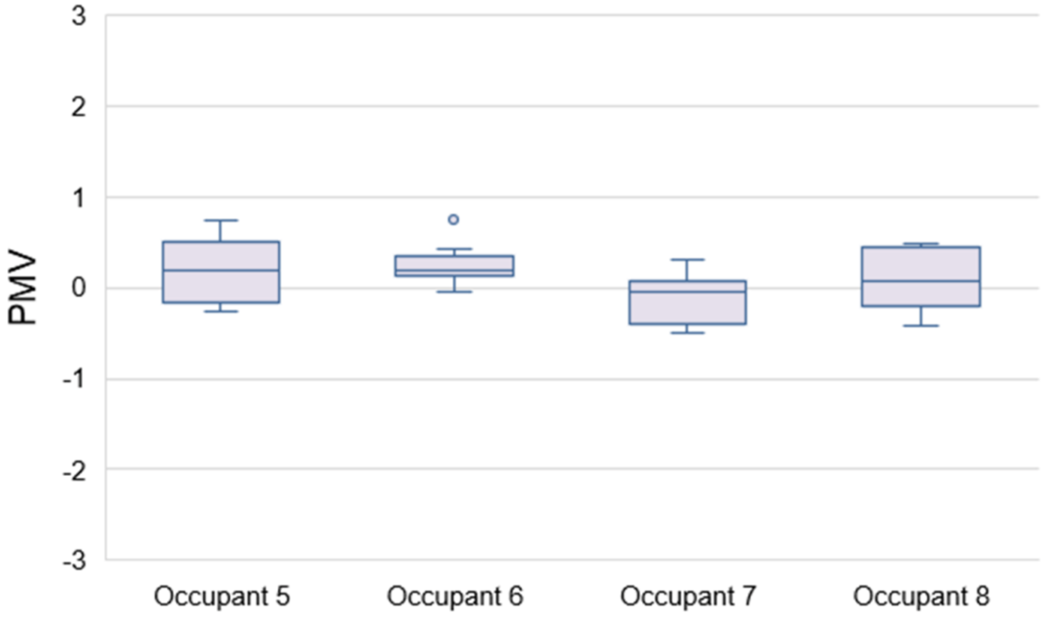

Figure 3.28. PMV values of the Building B occupants throughout the year

The minimum value is beyond the recommended for the Occupant 2 and the maximum is higher than recommended for all of the Building A occupants. Building B occupants' perennial PMV is narrower and in acceptable range, suggesting a higher degree of consistency than in case of Building A occupants' PMV.

In addition, in order to confirm the accuracy of the sensor, a comparison of the PMV index for Occupant 4 calculated using static MET value, against the PMV index calculated taking into consideration the dynamic MET value assessed by *Move 3* sensor was made. The sensor's accuracy was confirmed by Occupant 4 with the questionnaire answer. Other parameters of PMV are measured and computed in both scenarios, but they are presented specifically with regard to room air temperature.

Figure 3.29 illustrates the differences between the PMV index derived from the static MET value and the PMV index obtained using the MET value measured with *Move 3*.

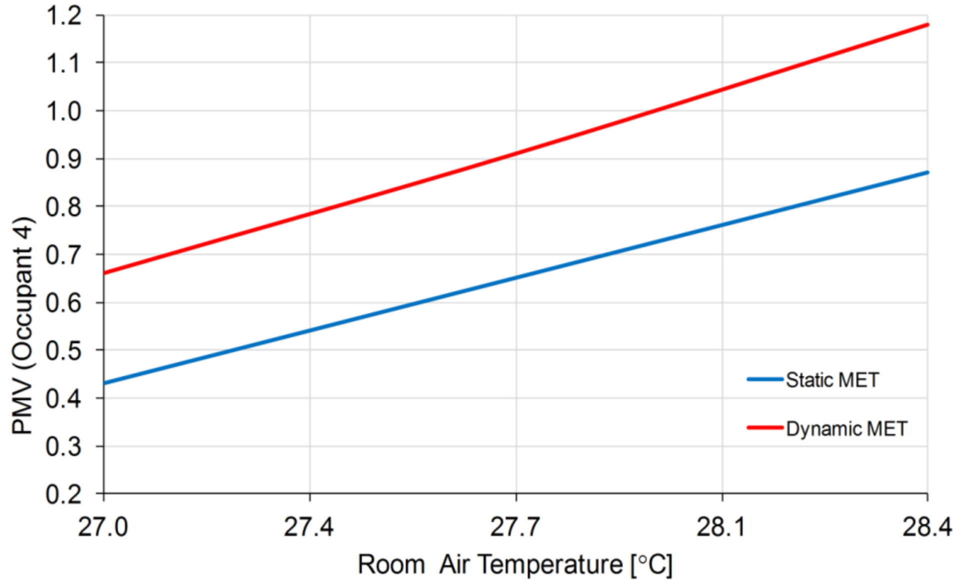

Figure 3.29. Comparison of PMV regarding standard and measured MET values

As Figure 3.29 indicates, the PMV determined using static MET values (as per the standard) does not accurately represent the actual state of occupant thermal sensation. For instance, at 15 hours, according to the acquired PMV indexes, the occupant should feel Neutral (N), indicating comfort. However, the measured value aligns with the response provided in the survey questionnaire (refer to Table 3.12), classifying the sensation as Slightly Warm (SW).

Table 3.12. Reported sensation of Occupant 4

	9 h	12 h	15 h
Static PMV	SW	SW	N
Dynamic PMV	SW	SW	SW
Questionnaire answer	SW	SW	SW

3.4. Mathematical modeling of metabolic rate

3.4.1. Significant parameters for model creation

The tests are conducted in order to investigate how internal working conditions impact occupants' metabolic rate and which of the occupants' individual parameters are significantly affecting it.

If a parameter has a proven relevance of 50%, it means that it has demonstrated a significant impact on the investigation or study at hand. While the relevance of 50% may not be considered very high, it still indicates a moderate level of importance. It allows for a comprehensive analysis of all potential factors that may contribute to developing a metabolic rate model for thermal comfort assessment. Even if this parameter alone has 50% relevance, it may have a more substantial influence when considered in conjunction with other relevant factors. Moreover, it reduces the risk of overlooking potentially significant aspects of the investigation.

First it was important to see whether the data has a normal distribution to decide which test should be used for testing. For test of normality, Shapiro-Wilk and Kolmogorov-Smirnov test were used [79].

The Shapiro-Wilk test calculates a test statistic (W) based on the discrepancies between the observed data and the expected values under a normal distribution. The test statistic is then compared to critical values to determine whether the data significantly deviates from normality. The null hypothesis for the test posits that the data follows a normal distribution, while the alternative hypothesis suggests that the data deviates from a normal distribution.

The Kolmogorov-Smirnov test is a statistical test applied to test whether the data follows a normal distribution. It compares the empirical distribution of the data to the cumulative distribution function of the normal distribution.

Normality test results for office temperatures and MET values of occupants in both buildings during the year are given in Table 3.13 and Table 3.14, respectively.

Table 3.13. Normality tests for office temperatures in both buildings during the year

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Office1_spring	0.164	406	0.000	0.932	406	0.000
Office2_spring	0.085	406	0.000	0.969	406	0.000
Office3_spring	0.096	406	0.000	0.951	406	0.000
Office4_spring	0.152	406	0.000	0.944	406	0.000
Office1_summer	0.135	406	0.000	0.933	406	0.000
Office2_summer	0.168	406	0.000	0.841	406	0.000
Office3_summer	0.261	406	0.000	0.771	406	0.000
Office4_summer	0.250	406	0.000	0.783	406	0.000
Office1_autumn	0.258	406	0.000	0.832	406	0.000
Office2_autumn	0.130	406	0.000	0.936	406	0.000
Office3_autumn	0.075	406	0.000	0.976	406	0.000
Office4_autumn	0.096	406	0.000	0.960	406	0.000
Office1_winter	0.235	406	0.000	0.725	406	0.000
Office2_winter	0.098	406	0.000	0.926	406	0.000
Office3_winter	0.156	406	0.000	0.912	406	0.000
Office4_winter	0.107	406	0.000	0.947	406	0.000

a. Lilliefors Significance Correction

Table 3.14. Normality tests for MET values of occupants in both buildings during the year

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
MET1_spring	0.222	419	0.000	0.767	419	0.000
MET2_spring	0.173	419	0.000	0.812	419	0.000
MET3_spring	0.388	419	0.000	0.630	419	0.000
MET4_spring	0.201	419	0.000	0.760	419	0.000
MET5_spring	0.201	419	0.000	0.803	419	0.000
MET6_spring	0.143	419	0.000	0.859	419	0.000
MET7_spring	0.154	419	0.000	0.799	419	0.000
MET8_spring	0.157	419	0.000	0.861	419	0.000
MET1_summer	0.195	419	0.000	0.775	419	0.000
MET2_summer	0.117	419	0.000	0.922	419	0.000
MET3_summer	0.216	419	0.000	0.691	419	0.000
MET4_summer	0.110	419	0.000	0.932	419	0.000
MET5_summer	0.231	419	0.000	0.745	419	0.000
MET6_summer	0.136	419	0.000	0.843	419	0.000
MET7_summer	0.191	419	0.000	0.751	419	0.000
MET8_summer	0.198	419	0.000	0.813	419	0.000
MET1_autumn	0.219	419	0.000	0.782	419	0.000
MET2_autumn	0.227	419	0.000	0.747	419	0.000
MET3_autumn	0.251	419	0.000	0.642	419	0.000
MET4_autumn	0.172	419	0.000	0.812	419	0.000
MET5_autumn	0.215	419	0.000	0.774	419	0.000
MET6_autumn	0.115	419	0.000	0.883	419	0.000
MET7_autumn	0.134	419	0.000	0.843	419	0.000
MET8_autumn	0.182	419	0.000	0.809	419	0.000
MET1_winter	0.243	419	0.000[a]	0.701	419	0.000
MET2_winter	0.243	419	0.000	0.634	419	0.000
MET3_winter	0.169	419	0.000	0.768	419	0.000
MET4_winter	0.159	419	0.000	0.824	419	0.000
MET5_winter	0.111	419	0.000	0.904	419	0.000
MET6_winter	0.158	419	0.000	0.797	419	0.000
MET7_winter	0.181	419	0.000	0.772	419	0.000
MET8_winter	0.157	419	0.000	0.821	419	0.000

a. Lilliefors Significance Correction

Considering that the level of significance (*Sig.* in Tables 3.13 and 3.14) is less than or equal to the chosen significance level for both tests, the null hypothesis should be rejected, indicating that the data significantly deviates from a normal distribution. Hence, non-parametric tests and correlations will be used in the next statistical investigation.

Including an excessive amount of data can make the analysis unnecessarily complex. Processing and analyzing excessive data are time-consuming and may strain the capabilities of the analysis. Furthermore, redundant variables provide similar information and can lead to inflated relationships or erroneous conclusions. It is important to strike a balance between having enough data to draw meaningful insights and avoiding the inclusion of excessive data that may complicate the analysis and obscure the main findings.

The following tables (Table 3.15 to Table 3.22) show whether occupants' metabolic rate varies due to office temperature for all four offices and eight occupants under the investigation in the different seasons of the year. Data is presented for summer and winter season.

Table 3.15. Correlation between office temperature and MET values of occupants 1 and 2 in the summer season

Correlations

			Office1_summer	MET1_summer	MET2_summer
Spearman's rho	Office1_summer	Correlation Coefficient	1.000	-0.485**	-0.232**
		Sig. (2-tailed)	.	0.000	0.000
		N	421	419	419
	MET1_summer	Correlation Coefficient	-0.485**	1.000	0.204**
		Sig. (2-tailed)	0.000	.	0.000
		N	419	419	419
	MET2_summer	Correlation Coefficient	-0.232**	0.204**	1.000
		Sig. (2-tailed)	0.000	0.000	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.16. Correlation between office temperature and MET values of occupants 3 and 4 in the summer season

Correlations

			Office2_ summer	MET3_ summer	MET4_ summer
Spearman's rho	Office2_summer	Correlation Coefficient	1.000	0.413**	0.400**
		Sig. (2-tailed)	.	0.000	0.000
		N	421	419	419
	MET3_summer	Correlation Coefficient	0.413**	1.000	0.094
		Sig. (2-tailed)	0.000	.	0.055
		N	419	419	419
	MET4_summer	Correlation Coefficient	0.400**	0.094	1.000
		Sig. (2-tailed)	0.000	0.055	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.17. Correlation between office temperature and MET values of occupants 5 and 6 in the summer season

Correlations

			Office1_ summer	MET5_ summer	MET6_ summer
Spearman's rho	Office2_summer	Correlation Coefficient	1.000	0.216**	0.135**
		Sig. (2-tailed)	.	0.000	0.006
		N	421	419	419
	MET5_summer	Correlation Coefficient	0.216**	1.000	0.002
		Sig. (2-tailed)	0.000	.	0.963
		N	419	419	419
	MET6_summer	Correlation Coefficient	0.135**	0.002	1.000
		Sig. (2-tailed)	0.006	0.963	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.18. Correlation between office temperature and MET values of occupants 7 and 8 in the summer season

Correlations

			Office4_summer	MET7_summer	MET8_summer
Spearman's rho	Office4_summer	Correlation Coefficient	1.000	-0.133**	0.043
		Sig. (2-tailed)	.	0.006	0.383
		N	420	419	419
	MET7_summer	Correlation Coefficient	-0.133**	1.000	0.091
		Sig. (2-tailed)	0.006	.	0.064
		N	419	419	419
	MET8_summer	Correlation Coefficient	0.043	0.091	1.000
		Sig. (2-tailed)	0.383	0.064	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.19. Correlation between office temperature and MET values of occupants 1 and 2 in the winter season

Correlations

			Office1_winter	MET1_winter	MET2_winter
Spearman's rho	Office1_winter	Correlation Coefficient	1.000	-0.136**	-0.086
		Sig. (2-tailed)	.	0.005	0.078
		N	421	419	419
	MET1_winter	Correlation Coefficient	-0.136**	1.000	0.203**
		Sig. (2-tailed)	0.005	.	0.000
		N	419	419	419
	MET2_winter	Correlation Coefficient	-0.086	0.203**	1.000
		Sig. (2-tailed)	0.078	0.000	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.20. Correlation between office temperature and MET values of occupants 3 and 4 in the winter season

Correlations

			Office_ winter	MET3_ winter	MET4_ winter
Spearman's rho	Office2_winter	Correlation Coefficient	1.000	0.024	-0.407**
		Sig. (2-tailed)	.	0.629	0.000
		N	421	419	419
	MET3_winter	Correlation Coefficient	0.024	1.000	0.343**
		Sig. (2-tailed)	0.629	.	0.000
		N	419	419	419
	MET4_winter	Correlation Coefficient	-0.407**	0.343**	1.000
		Sig. (2-tailed)	0.000	0.000	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.21. Correlation between office temperature and MET values of occupants 5 and 6 in the winter season

Correlations

			Office3_ winter	MET5_ winter	MET6_ winter
Spearman's rho	Office3_winter	Correlation Coefficient	1.000	0.207**	-0.036
		Sig. (2-tailed)	.	0.000	0.464
		N	421	419	419
	MET5_winter	Correlation Coefficient	0.207**	1.000	0.075
		Sig. (2-tailed)	0.000	.	0.124
		N	419	419	419
	MET6_winter	Correlation Coefficient	-0.036	0.075	1.000
		Sig. (2-tailed)	0.464	0.124	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.22. Correlation between office temperature and MET values of occupants 7 and 8 in the winter season

Correlations

			Office4_ winter	MET7_ winter	MET8_ winter
Spearman's rho	Office_winter	Correlation Coefficient	1.000	-0.052	-0.173**
		Sig. (2-tailed)	.	0.290	0.000
		N	421	419	419
	MET7_winter	Correlation Coefficient	-0.052	1.000	0.076
		Sig. (2-tailed)	0.290	.	0.121
		N	419	419	419
	MET8_winter	Correlation Coefficient	-0.173**	0.076	1.000
		Sig. (2-tailed)	0.000	0.121	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

According to the correlation, there is a statistically significant relationship between occupant's MET value and temperature in the summer with a test significance of 99%. As for the winter temperatures in the office, there is a 50% proven relationship between parameters. Hence, the overall relationship between MET and office temperature has been taken as significant.

Furthermore, relative humidity and variation of CO_2 level in the room proved to be in correlation with MET. The following tables (Table 3.23 to Table 3.30) show correlation between CO_2 level and MET values, and between RH and MET values (Table 3.31 to Table 3.38), which are given for all four offices and eight occupants under the investigation in the different seasons of the year (data is again presented for summer and winter season).

Table 3.23. Correlation between CO_2 level and MET values of occupants 1 and 2 in the summer season

Correlations

			CO2_B11_ summer	MET1_ summer	MET2_ summer
Spearman's rho	CO2_B11_summer	Correlation Coefficient	1.000	-0.063	-0.054
		Sig. (2-tailed)	.	0.197	0.272
		N	421	419	419
	MET1_summer	Correlation Coefficient	-0.063	1.000	0.204
		Sig. (2-tailed)	0.197	.	0.000
		N	419	419	419
	MET2_summer	Correlation Coefficient	-0.054	0.204	1.000
		Sig. (2-tailed)	0.272	0.000	.
		N	419	419	419

Table 3.24. Correlation between CO_2 level and MET values of occupants 3 and 4 in the summer season

Correlations

			CO2_B12_ summer	MET3_ summer	MET4_ summer
Spearman's rho	CO2_B12_summer	Correlation Coefficient	1.000	-0.329**	-0.335**
		Sig. (2-tailed)	.	0.000	0.000
		N	421	419	419
	MET3_summer	Correlation Coefficient	-0.329**	1.000	0.094
		Sig. (2-tailed)	0.000	.	0.055
		N	419	419	419
	MET4_summer	Correlation Coefficient	-0.335**	0.094	1.000
		Sig. (2-tailed)	0.000	0.055	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.25. Correlation between CO_2 level and MET values of occupants 5 and 6 in the summer season

Correlations

			CO2_B21_ summer	MET5_ summer	MET6_ summer
Spearman's rho	CO2_B21_summer	Correlation Coefficient	1.000	0.038	-0.101*
		Sig. (2-tailed)	.	0.447	0.043
		N	406	406	406
	MET5_summer	Correlation Coefficient	0.038	1.000	0.002
		Sig. (2-tailed)	0.447	.	0.963
		N	406	419	419
	MET6_summer	Correlation Coefficient	-0.101*	0.002	1.000
		Sig. (2-tailed)	0.043	0.963	.
		N	406	419	419

*. Correlation is significant at the 0.05 level (2-tailed).

Table 3.26. Correlation between CO_2 level and MET values of occupants 7 and 8 in the summer season

Correlations

			CO2_B22_ summer	MET7_ summer	MET8_ summer
Spearman's rho	CO2_B22_summer	Correlation Coefficient	1.000	-0.208**	-0.020
		Sig. (2-tailed)	.	0.000	0.686
		N	406	406	406
	MET7_summer	Correlation Coefficient	-0.208**	1.000	0.091
		Sig. (2-tailed)	0.000	.	0.064
		N	406	419	419
	MET8_summer	Correlation Coefficient	-0.020	0.091	1.000
		Sig. (2-tailed)	0.686	0.064	.
		N	406	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.27. Correlation between CO_2 level and MET values of occupants 1 and 2 in the winter season

Correlations

			CO2_B11_ winter	MET1_ winter	MET2_ winter
Spearman's rho	CO2_B11_winter	Correlation Coefficient	1.000	0.128**	-0.057
		Sig. (2-tailed)	.	0.009	0.244
		N	421	419	419
	MET1_winter	Correlation Coefficient	0.128**	1.000	0.203**
		Sig. (2-tailed)	0.009	.	0.000
		N	419	419	419
	MET2_winter	Correlation Coefficient	-0.057	0.203**	1.000
		Sig. (2-tailed)	0.244	0.000	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.28. Correlation between CO_2 level and MET values of occupants 3 and 4 in the winter season

Correlations

			CO2_B12_ winter	MET3_ winter	MET4_ winter
Spearman's rho	CO2_B12_winter	Correlation Coefficient	1.000	-0.101*	-0.431**
		Sig. (2-tailed)	.	0.038	0.000
		N	421	419	419
	MET3_winter	Correlation Coefficient	-0.101*	1.000	0.343**
		Sig. (2-tailed)	0.038	.	0.000
		N	419	419	419
	MET4_winter	Correlation Coefficient	-0.431**	0.343**	1.000
		Sig. (2-tailed)	0.000	0.000	.
		N	419	419	419

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.29. Correlation between CO_2 level and MET values of occupants 5 and 6 in the winter season

Correlations

			CO2_B21_ winter	MET5_ winter	MET6_ winter
Spearman's rho	CO2_B21_winter	Correlation Coefficient	1.000	0.095	-0.132**
		Sig. (2-tailed)	.	0.051	0.007
		N	421	419	419
	MET5_winter	Correlation Coefficient	0.095	1.000	0.075
		Sig. (2-tailed)	0.051	.	0.124
		N	419	419	419
	MET6_winter	Correlation Coefficient	-0.132**	0.075	1.000
		Sig. (2-tailed)	0.007	0.124	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.30. Correlation between CO_2 level and MET values of occupants 7 and 8 in the winter season

Correlations

			CO2_B22_ winter	MET7_ winter	MET8_ winter
Spearman's rho	CO2_B22_winter	Correlation Coefficient	1.000	-0.222**	-0.324**
		Sig. (2-tailed)	.	0.000	0.000
		N	421	419	419
	MET7_winter	Correlation Coefficient	-0.222**	1.000	0.076
		Sig. (2-tailed)	0.000	.	0.121
		N	419	419	419
	MET8_winter	Correlation Coefficient	-0.324**	0.076	1.000
		Sig. (2-tailed)	0.000	0.121	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.31. Correlation between relative humidity and MET values of occupants 1 and 2 in the summer season

Correlations

			RH_B11_ summer	MET1_ summer	MET2_ summer
Spearman's rho	RH_B11_summer	Correlation Coefficient	1.000	0.142**	-0.073
		Sig. (2-tailed)	.	0.004	0.134
		N	421	419	419
	MET1_summer	Correlation Coefficient	0.142**	1.000	0.204**
		Sig. (2-tailed)	.004	.	0.000
		N	419	419	419
	MET2_summer	Correlation Coefficient	-0.073	0.204**	1.000
		Sig. (2-tailed)	0.134	0.000	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.32. Correlation between relative humidity and MET values of occupants 3 and 4 in the summer season

Correlations

			RH_B12_ summer	MET3_ summer	MET4_ summer
Spearman's rho	RH_B12_summer	Correlation Coefficient	1.000	-0.415**	-0.469**
		Sig. (2-tailed)	.	0.000	0.000
		N	421	419	419
	MET3_summer	Correlation Coefficient	-0.415**	1.000	0.094
		Sig. (2-tailed)	0.000	.	0.055
		N	419	419	419
	MET4_summer	Correlation Coefficient	-0.469**	0.094	1.000
		Sig. (2-tailed)	0.000	0.055	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.33. Correlation between relative humidity and MET values of occupants 5 and 6 in the summer season

Correlations

			RH_B21_ summer	MET5_ summer	MET6_ summer
Spearman's rho	RH_B21_summer	Correlation Coefficient	1.000	-0.067	-0.022
		Sig. (2-tailed)	.	0.175	0.657
		N	406	406	406
	MET5_summer	Correlation Coefficient	-0.067	1.000	0.002
		Sig. (2-tailed)	0.175	.	0.963
		N	406	419	419
	MET6_summer	Correlation Coefficient	-0.022	0.002	1.000
		Sig. (2-tailed)	0.657	0.963	.
		N	406	419	419

Table 3.34. Correlation between relative humidity and MET values of occupants 7 and 8 in the summer season

Correlations

			RH_B22_ summer	MET7_ summer	MET8_ summer
Spearman's rho	RH_B22_summer	Correlation Coefficient	1.000	-0.094	0.204**
		Sig. (2-tailed)	.	0.058	0.000
		N	406	406	406
	MET6_summer	Correlation Coefficient	-0.094	1.000	0.049
		Sig. (2-tailed)	0.058	.	0.321
		N	406	419	419
	MET7_summer	Correlation Coefficient	0.204**	0.049	1.000
		Sig. (2-tailed)	0.000	0.321	.
		N	406	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.35. Correlation between relative humidity and MET values of occupants 1 and 2 in the winter season

Correlations

			RH_B11_ winter	MET1_ winter	MET2_ winter
Spearman's rho	RH_B11_winter	Correlation Coefficient	1.000	0.145**	0.009
		Sig. (2-tailed)	.	0.003	0.849
		N	421	419	419
	MET1_winter	Correlation Coefficient	0.145**	1.000	0.203**
		Sig. (2-tailed)	0.003	.	0.000
		N	419	419	419
	MET2_winter	Correlation Coefficient	0.009	0.203**	1.000
		Sig. (2-tailed)	0.849	0.000	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.36. Correlation between relative humidity and MET values of occupants 3 and 4 in the winter season

Correlations

			RH_B12_ winter	MET3_ winter	MET4_ winter
Spearman's rho	RH_B12_winter	Correlation Coefficient	1.000	-0.064	0.364**
		Sig. (2-tailed)	.	0.194	0.000
		N	421	419	419
	MET3_winter	Correlation Coefficient	-0.064	1.000	0.343**
		Sig. (2-tailed)	0.194	.	0.000
		N	419	419	419
	MET4_winter	Correlation Coefficient	0.364**	0.343**	1.000
		Sig. (2-tailed)	0.000	0.000	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3.37. Correlation between relative humidity and MET values of occupants 5 and 6 in the winter season

Correlations

			RH_B21_ winter	MET5_ winter	MET6_ winter
Spearman's rho	RH_B21_winter	Correlation Coefficient	1.000	-0.145**	-0.107*
		Sig. (2-tailed)	.	0.003	0.029
		N	421	419	419
	MET5_winter	Correlation Coefficient	-0.145**	1.000	0.075
		Sig. (2-tailed)	0.003	.	0.124
		N	419	419	419
	MET6_winter	Correlation Coefficient	-0.107*	0.075	1.000
		Sig. (2-tailed)	0.029	0.124	.
		N	419	419	419

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 3.38. Correlation between relative humidity and MET values of occupants 7 and 8 in the winter season

Correlations

			RH_B22_ winter	MET7_ winter	MET8_ winter
Spearman's rho	RH_B22_winter	Correlation Coefficient	1.000	-0.015	-0.023
		Sig. (2-tailed)	.	0.759	0.635
		N	421	419	419
	MET7_winter	Correlation Coefficient	-0.015	1.000	0.076
		Sig. (2-tailed)	0.759	.	0.121
		N	419	419	419
	MET8_winter	Correlation Coefficient	-0.023	0.076	1.000
		Sig. (2-tailed)	0.635	0.121	.
		N	419	419	419

Spearman's rank correlation coefficient assesses the strength and direction of the monotonic relationship between two variables, regardless of whether the relationship is linear. Monotonicity means that as the values of one variable increase, the values of the other variable either consistently increase or decrease. According to conducted correlation, the relationship between RH and MET as well as CO_2 and MET are mostly negative which means that as RH or CO_2 variable's ranks increase, the MET variable's ranks tend to decrease. Nevertheless, it can be concluded with test significance of 99% that those variables have significant relationship.

3.4.2. Characteristics of individual groups for model creation

The *Move 3* wearable sensory device was employed to monitor building occupants and measure their daily metabolic rates. The data collected was utilized to assess the influence and importance of individual factors such as age, gender, and BMI on changes in occupants' metabolic rates. This data was also employed to analyze the thermal preferences of the occupants and establish the foundation for creating a model (given at the end of the subsection, in Table 3.45). For this purpose, non-parametric tests were carried out first, Mann-Whitney Test (for two independent groups) and Kruskal-Wallis Test (for three or more independent groups).

Results of Mann-Whitney Test are presented according to cooling (Table 3.39) and heating season (Table 3.40) in order to explore is there a statistically significant difference between the average metabolic rate of users with regard to their gender.

Table 3.39. Comparison of MET medians between males and females during the cooling season

Ranks

Gender		N	Mean Rank	Sum of Ranks
MET_cooling	Female	2095	1561.60	3271548.00
	Male	1257	1868.00	2348080.00
	Total	3352		

Test Statistics[a]

	met_cooling
Mann-Whitney U	1075988.000
Wilcoxon W	3271548.000
Z	-8.917
Asymp. Sig. (2-tailed)	0.000

a. Grouping Variable: Gender

Table 3.40. Comparison of MET medians between males and females during the heating season

Ranks

Gender		N	Mean Rank	Sum of Ranks
MET_heating	Female	2095	1812.56	3797321.00
	Male	1257	1449.73	1822307.00
	Total	3352		

Test Statistics[a]

	MET_heating
Mann-Whitney U	1031654.000
Wilcoxon W	1822307.000
Z	-10.534
Asymp. Sig. (2-tailed)	0.000

a. Grouping Variable: Gender

Based on the Table 3.39 and Table 3.40, averaged MET among the female and male occupants is significantly different during the cooling and heating period.

As described in Chapter 02, Participants in the field study research are categorized into three groups based on age (Table 2.8) to assess the significance of age differences in the average daily metabolic rate.

Table 3.41 and Table 3.42 show the Kruskal-Wallis test results of the occupants' age difference, also presented according to cooling and heating season, respectively.

Table 3.41. Comparison of MET medians between groups of occupants with regard to their age during the cooling season

Ranks

Age		N	Mean Rank
MET_cooling	1st age group	2095	1693.65
	2st age group	838	1570.68
	3st age group	419	1802.37
	Total	3352	

Test Statistics[a,b]

	MET_cooling
Chi-Square	17.938
df	2
Asymp. Sig.	0.000

a. Kruskal Wallis Test

b. Grouping Variable: Age

Table 3.42. Comparison of MET medians between groups of occupants with regard to their age during the heating season

Ranks

Age		N	Mean Rank
MET_heating	1st age group	2095	1712.11
	2st age group	838	1326.34
	3st age group	419	2198.76
	Total	3352	

Test Statistics[a,b]

	MET_heating
Chi-Square	235.688
df	2
Asymp. Sig.	0.000

a. Kruskal Wallis Test

b. Grouping Variable: Age

The results of the Kruskal-Wallis test indicate a statistically significant difference in metabolic rates among building occupants of varying ages. Additionally, there is only a 0.1% probability that this difference is attributed to chance.

Further results of Kruskal-Wallis test are presented according to cooling (Table 3.43) and heating season (Table 3.44) in order to explore is there a statistically significant difference between the average metabolic rate of users with regard to BMI.

Table 3.43. Comparison of MET medians between groups of occupants with the different BMI during the cooling season

Ranks

BMI		N	Mean Rank
MET_cooling	normal	2095	1699.62
	overweight	838	1788.19
	obese	419	1337.51
	Total	3352	

Test Statistics[a,b]

	MET_cooling
Chi-Square	64.383
df	2
Asymp. Sig.	0.000

a. Kruskal Wallis Test

b. Grouping Variable: BMI

Table 3.44. Comparison of MET medians between groups of occupants with the different BMI during the heating season

Ranks

BMI		N	Mean Rank
MET_heating	normal	2095	1940.72
	overweight	838	1192.05
	obese	419	1324.29
	Total	3352	

Test Statistics[a,b]

	MET_heating
Chi-Square	423.652
df	2
Asymp. Sig.	0.000

a. Kruskal Wallis Test

b. Grouping Variable: BMI

Based on Table 3.43 and Table 3.44, averaged MET values among the three groups of people (of normal body mass, overweight and obese) are significantly different during the cooling and heating period.

Finally, according to the conducted tests of significant parameters relating MET values on the collected measurement data, Table 3.45 was created as the creation base for the further model, in which occupants are categorized into 3 groups conforming to similar metabolic rate trends and personal characteristics.

Table 3.45. Characteristics of individual groups

	Thermal comfort according to metabolic rates				Description
	Hot [met]	Warm [met]	Neutral [met]	Cold [met]	
Group 1	≥ 2.3	1.7 – 2.3	1.4 – 1.7	Not recorded	1st age group higher temperature acceptance range mostly females
Group 2	≥ 2	1.9 – 2	1.5 – 1.9	Not recorded	1st age group higher activity level mostly males
Group 3	≥ 1.8	1.5 – 1.8	1.3 – 1.5	≤ 1.3	2nd and 3rd age group narrow comfort range people with high BMI

Observations indicate that occupants with higher BMI tend to have a lower average metabolic rate. Consequently, they tend to experience a sensation of cold earlier than individuals in Group 1 and Group 2. Group 1 represents occupants with a broader acceptance range for temperatures. Conversely, Group 2 exhibits a wider neutral temperature range, meaning that activities exceeding 1.5 met do not induce a sensation of warmth due to their higher physical fitness and physiological adaptation. Group 3 represents the occupants which are mostly of higher BMI (compared to the other groups) and have a small range of environmental parameters within which they feel comfortable.

3.4.3. Neural network modeling of metabolic rate

As it was explained in previous chapter, the modeling approach employed artificial neural networks, with a specific focus on utilizing the multilayer perceptron [53] as a valuable tool for the intended purpose. The occupants were divided into three different groups (Table 3.45) which were developed according to the correlation of the experimentally obtained MET values, the environmental conditions and occupant's individual differences. For both the cooling season (spring and summer) and the heating season (autumn and winter), a distinct model was created for each group.

Consequently, a total of six simulation models were developed to establish the relationship between input parameters and analyzed outputs. These models specifically link MET values with specific thermal comfort conditions, including air temperature, air relative humidity, and CO_2 levels:

• Model 1: defines the relationship between the input factors of air temperature, relative air humidity and the level of carbon dioxide in the air (conditions in the working environment) and the metabolic effect of Group 1 for the cooling period;

• Model 2: defines the relationship between the input factors of air temperature, relative air humidity and the level of carbon dioxide in the air (conditions in the working environment) and the metabolic rate of Group 2 for the cooling period;

• Model 3: defines the relationship between the input factors of air temperature, relative air humidity and the level of carbon dioxide in the air conditions in the working environment) and the metabolic rate of Group 3 for the cooling period;

• Model 4: defines the relationship between the input factors of air temperature, relative air humidity and the level of carbon dioxide in the air (conditions in the working environment) and the metabolic rate of Group 1 for the heating period;

• Model 5: defines the relationship between the input factors of air temperature, relative air humidity and the level of carbon dioxide in the air (conditions in the working environment) and the metabolic rate of Group 2 for the heating period;

• Model 6: defines the relationship between the input factors of air temperature, relative air humidity and the level of carbon dioxide in the air (conditions in the working environment) and the metabolic rate of Group 3 for the heating period.

The total amount of data for analysis was reduced to 28, which is equal to a 15-minute sensor reading.

The experimental data underwent normalization using the provided expression to mitigate the influence of dominant functions and enhance convergence speed. The normalization was performed within the interval [a, b], which was specified as [-1, 1], respectively [91]:

$$x_{\mathrm{n}} = (b - a)\frac{x_0 - x_{\min}}{x_{\max} - x_{\min}} + a \tag{3.1}$$

where x_{n} and x_0 are normalized and original data, while $x_{\min}$ and $x_{\max}$ are minimal and maximal values.

After collecting, filtering and preparing the data, it was necessary to divide all collected data into a set for training the network, a set for testing and a set for validating the developed model. The generalization and robustness of the model was checked on randomly selected data from the testing and validation sets.

70% of experimentally collected data, chosen at random, were employed to train the multi-layer perceptron and develop the six specified mathematical models. 15% of randomly selected experimental data were designated for testing purposes, while another 15% were allocated for validating the created models.

The model was derived using a neural network featuring one hidden layer, given the assumption of a single output. The architecture of the multilayer perceptron is 3–3–1, i.e. three neurons in the input layer, three neurons in the hidden layer and one neuron in the output layer for each analyzed response (Figure 3.30).

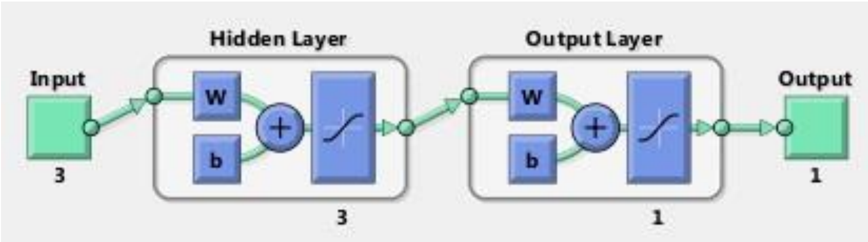

Figure 3.30. Architecture of the multilayer perceptron

The number of neurons (m) in the hidden layer is defined according to the following expression [91]:

$$m \leq (N_{\text{tr}} - 1)/(n + 2) \tag{3.2}$$

where N_{tr} is the number of available data for network training and n is number of input parameters.

Model testing and validation is performed using datasets that have not yet been presented to the artificial neural network. Before the actual training process, the initialization of weight connections and thresholds of the neurons of the hidden and output layers of the perceptron was performed using the Nguyen-Widrow method. Thus, the weights are spread out in a way that prevents saturation while still maintaining an appropriate range. This helped to speed up the training process and improve the overall performance of the neural network.

The tansigmoid function in the hidden layer and the simple linear function in the output layer of the multilayer perceptron were used as activation functions.

Multi-layer perceptron training was done for establishing connections between process input factors and analyzed responses, i.e. determination of parameter values of w_{ji} (weight connections between input i and hidden j neuron), b_j (threshold of the hidden j neuron), w_{kj} (weight connections between the j hidden neuron and the k output neuron) and b_k (threshold of the output neuron).

The creation of mathematical models of all responses was performed using the Levenberg-Marquardt algorithm. It is one of the fastest algorithms for training a multilayer perceptron of small and medium sizes (up to a hundred free parameters). This algorithm can converge 10 to 1,000 times faster compared to conventional training algorithms, which means there is less danger of getting stuck in a local minimum, and at the same time it achieves a high prediction accuracy [92]. Iterative weight change when applying the Levenberg-Marquardt algorithm is performed according to the following expression [91]:

$$w_{t+1} = w_t + [J_t^T\, J_t + \mu\, I]^{-1}\, J_t^T\, E_t \tag{3.3}$$

where J is the Jacobian matrix of error derivatives by weight, I is the identity matrix and μ momentum (the learning parameter), t is number of iterations, and E is error.

The learning parameter μ, momentum, is a small scalar quantity that controls the training process of an artificial neural network. Its value changes during the training process itself. Starting from the initial value, after each successful iteration when the error is reduced, μ is reduced by $\Delta\mu$.

The mean square error (MSE) was chosen as the objective function in the training process. For each combination of process input factors, a comparison was made between the predicted response value obtained by the model and the one obtained experimentally. This was done using the root mean square error according to the following expression [91]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - d_i)^2 \tag{3.4}$$

where N is the number of randomly selected data from the specific group, y_i represents the estimated value gained by the model, and d_i represents the value gained by experiment.

In each iteration, the value of the weight link is changed by the partial derivative of the error in relation to the set weight link via the learning coefficient and the change of the same weight link in the previous iteration via momentum. Learning coefficient and momentum control the stability and training speed of an artificial neural network.

Training epochs denote the iterations in which the developed artificial neural network is presented with input data. The error backpropagation algorithm ensures that the network training error decreases in parallel as the number of epochs increases. However, with too many epochs, the so-called "over-training problem" or the problem of network overtraining. In this case, the artificial neural network has learned the training data very well, but not the relationships between the input factors and the response, and then its generalization is very poor. Most often, the number of training epochs of a network that has good generalization is determined by the "trial-error" method, by the method of early stop training, or by Bayesian regularization [93].

After the training of the artificial neural network model was completed, the values of approximately optimal weight connections and thresholds of the hidden and output layers of the multi-layer perceptron were determined. The obtained values are listed for each model in the following tables (Table 3.46 to Table 3.51).

Table 3.46. Weights and thresholds of the artificial neural network model for Model 1

	w_{ji}		w_{kj}	b_j	b_k
-6.5338	-4.681	-6.3905	6.563	7.1178	-7.4991
-3.2362	27.2847	8.2502	9.2956	17.0489	
4.973	-36.2664	-11.1241	8.6416	-21.9668	

Table 3.47. Weights and thresholds of the artificial neural network model for Model 2

	w_{ji}		w_{kj}	b_j	b_k
78.7585	-21.6102	104.4434	-2.1018	8.0617	-1.0025
-48.9851	50.5038	-99.3929	-2.1638	-10.0954	
39.8134	-28.16	10.9721	0.17015	52.834	

Table 3.48. Weights and thresholds of the artificial neural network model for Model 3

	w_{ji}		w_{kj}	b_j	b_k
-6.9747	8.7169	-11.129	9.5356	-9.7814	1.1527
-3.7378	-46.3746	-3.4533	0.26391	-31.8661	
-17.2123	-14.8331	16.9222	8.3466	8.1478	

Table 3.49. Weights and thresholds of the artificial neural network model for Model 4

	w_{ji}		w_{kj}	b_j	b_k
1.4799	1.405	0.10561	-1.7263	-1.4532	-0.76881
-0.2961	-2.6878	-1.6867	-0.73367	2.5293	
-2.6704	0.53954	1.7618	-1.2042	-0.50402	

Table 3.50. Weights and thresholds of the artificial neural network model for Model 5

	w_{ji}		w_{kj}	b_j	b_k
-0.23761	0.077486	-0.40571	-16.0506	0.29646	-2.2141
11.6091	5.4869	6.384	1.0135	-9.238	
2.5787	-0.060617	3.4739	-9.3951	-0.89577	

Table 3.51. Weights and thresholds of the artificial neural network model for Model 6

	w_{ji}		w_{kj}	b_j	b_k
43.4967	-1.506	37.6886	38.9685	0.45429	-39.329
65.8096	-1.6068	44.9961	-39.4559	-2.852	
30.0186	3.5846	-6.5589	39.0788	8.013	

Based on the obtained weights and thresholds values of the artificial neural network model, taking into account the shape of the activation functions in the hidden and output layers and the architecture of the multilayer perceptron, the relationship between the input factors of the process and the response can be expressed with a mathematical equation:

$$M = \left[\frac{2}{1 + e^{-2\,(X\,w_{ji} + b_j)}} - 1\right] w_{kj} + b_k \tag{3.5}$$

where:

M represents output vector (MET),

X represents vector of input parameters, $X = \{t_{\mathrm{a}}, \mathrm{CO}_2, RH\}$,

w_{ji} represents weight connections between input i and hidden j neuron,

b_j represents threshold (bias) of the hidden j neuron,

w_{kj} represents weight connections between the j hidden neuron and the k output neuron,

b_k represents threshold of the output neuron.

Table 3.52 shows the characteristics of these models, the numbers of training epochs and the values of the obtained mean square errors during training, testing and validation of the artificial neural network.

Table 3.52. Artificial neural network models' characteristics obtained on the basis of all available experimental results

ANN model	Number of training epochs	Mean square error (MSE)		
		Training Data	Testing Data	Validation Data
Model 1	20	0.1011	0.3516	0.4784
Model 2	20	0.05789	0.01825	0.008767
Model 3	20	0.1312	0.2974	0.2358
Model 4	20	0.05839	0.08044	0.0412
Model 5	22	0.06265	0.1188	0.06506
Model 6	20	0.05984	0.131	0.07315

The outcomes presented in Table 3.52 indicate that the developed artificial neural network models exhibit a satisfactory level of accuracy in prediction and generalization. Consequently, these models can be effectively employed for both identifying and examining the connections between input variables related to environmental parameters and the corresponding attributes of MET values.

Furthermore, these models serve as the foundation for forthcoming experiments. Upon receiving new measurements, the existing models are retrained, leading to enhanced and more comprehensive models. This iterative approach ultimately contributes to the formation of an expert system. This system's primary function is to forecast the response attributes of metabolic rate predictions based on variations in input variable values.

The graphic representations of the influence of factors on the analyzed responses are given in the following figures (Figure 3.31 to Figure 3.36), together with correlation coefficients on data sets for training, testing and validation during model creation. As an additional measure of the prediction accuracy of the obtained artificial neural network models, comparison of simulation models with experimental data are also presented.

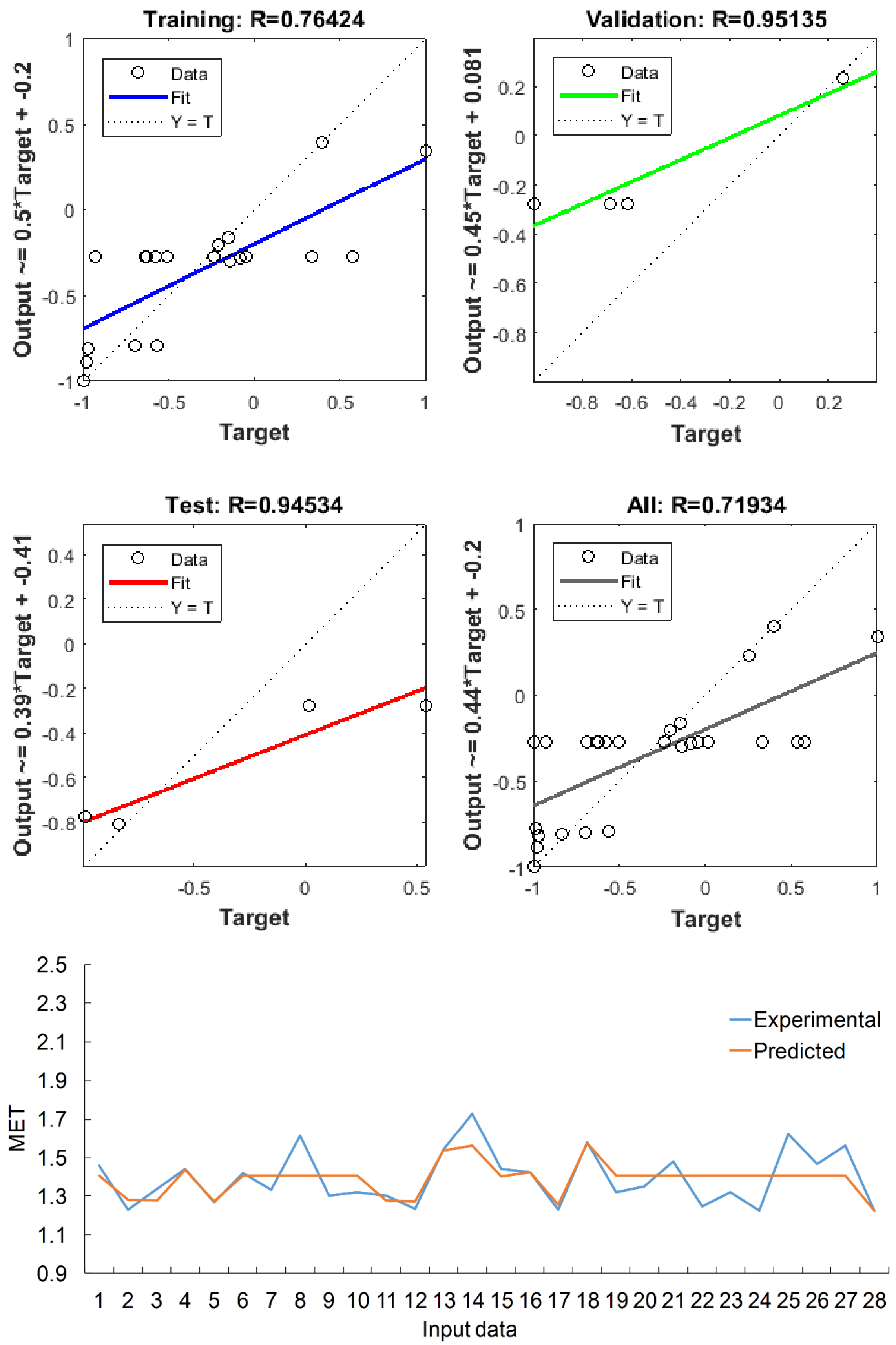

Figure 3.31. Comparison between simulation model with experimental MET response of Group 1 during cooling period

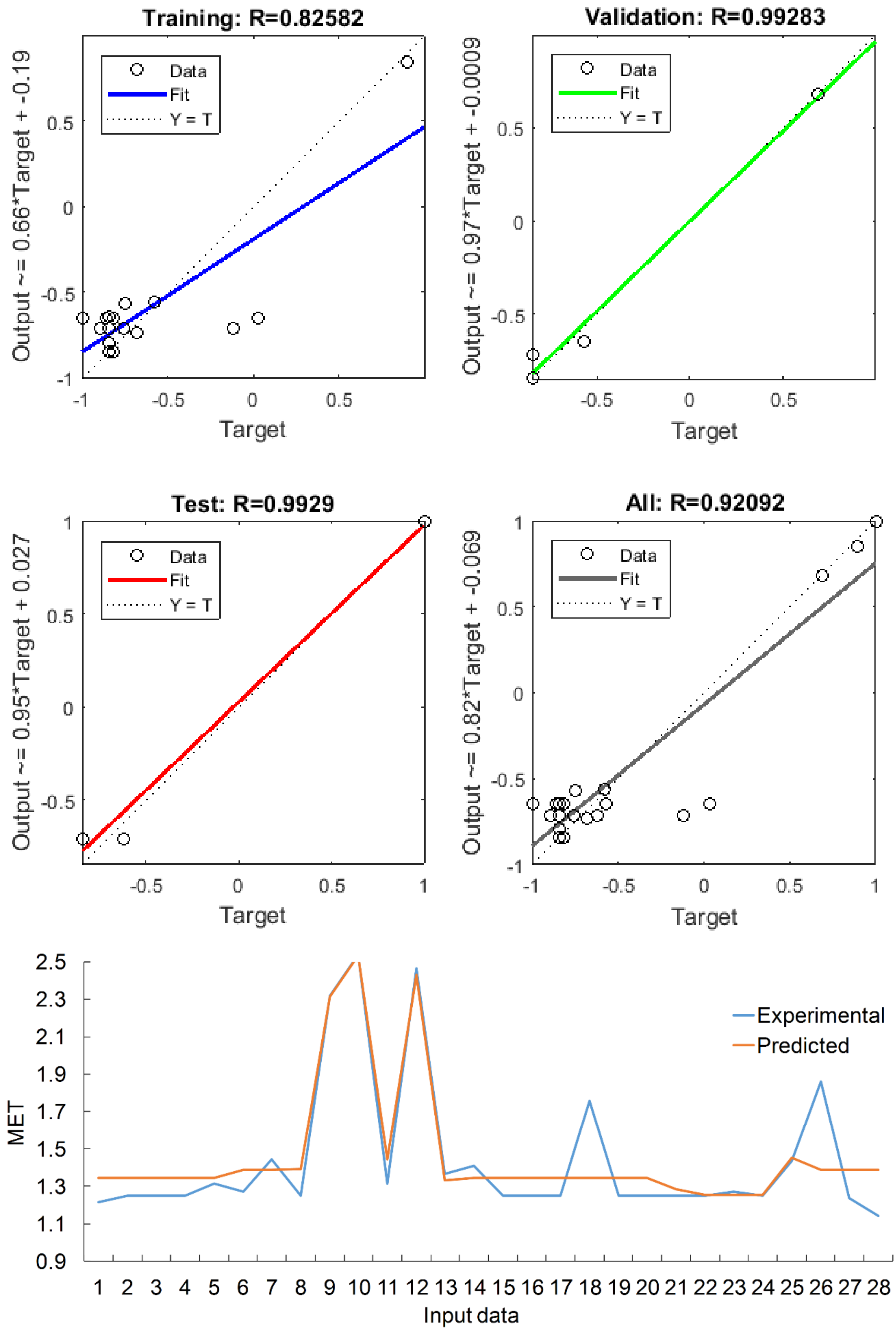

Figure 3.32. Comparison between simulation model with experimental MET response of Group 2 during cooling period

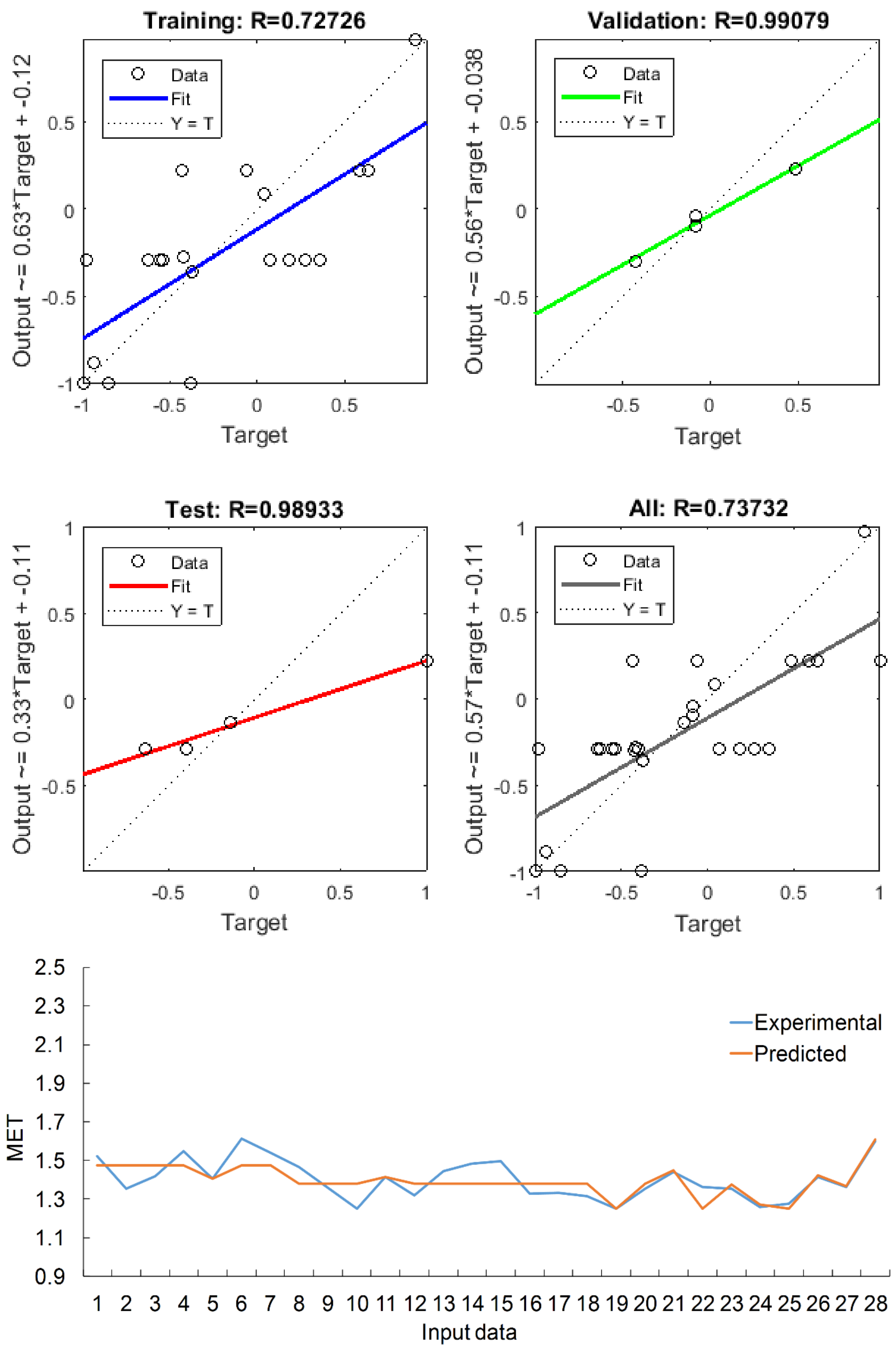

Figure 3.33. Comparison between simulation model with experimental MET response of Group 3 during cooling period

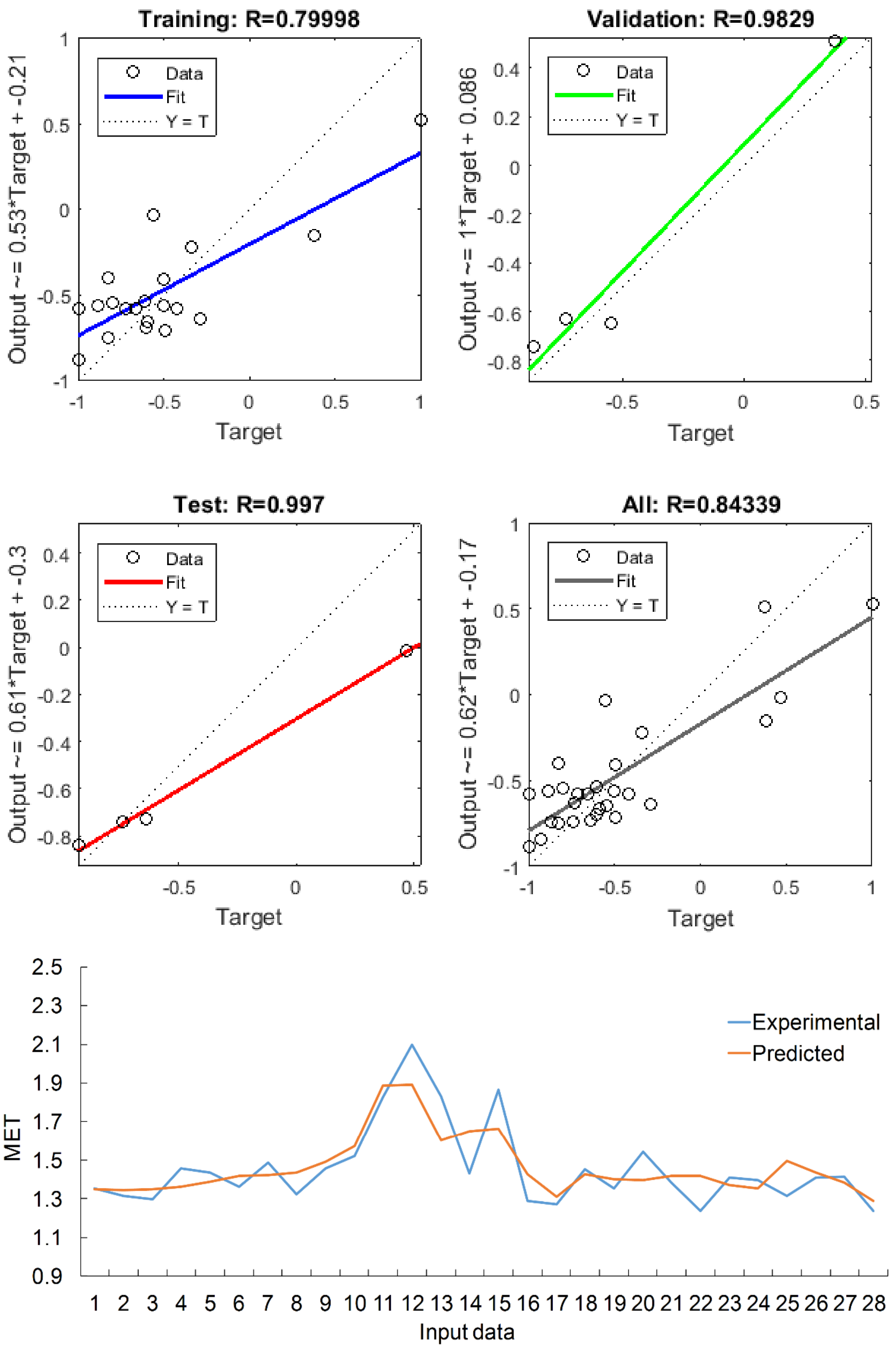

Figure 3.34. Comparison between simulation model with experimental MET response of Group 1 during heating period

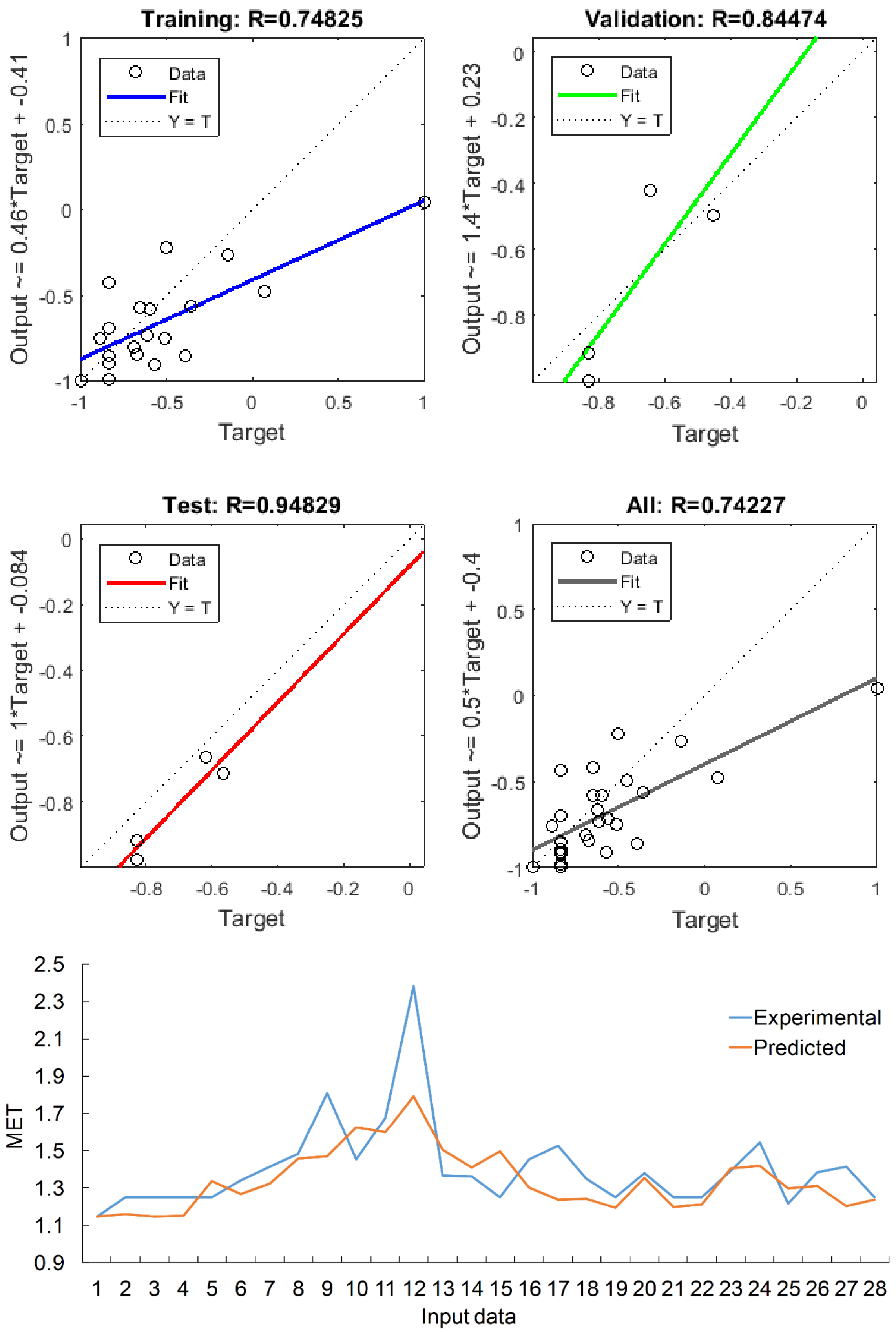

Figure 3.35. Comparison between simulation model with experimental MET response of Group 2 during heating period

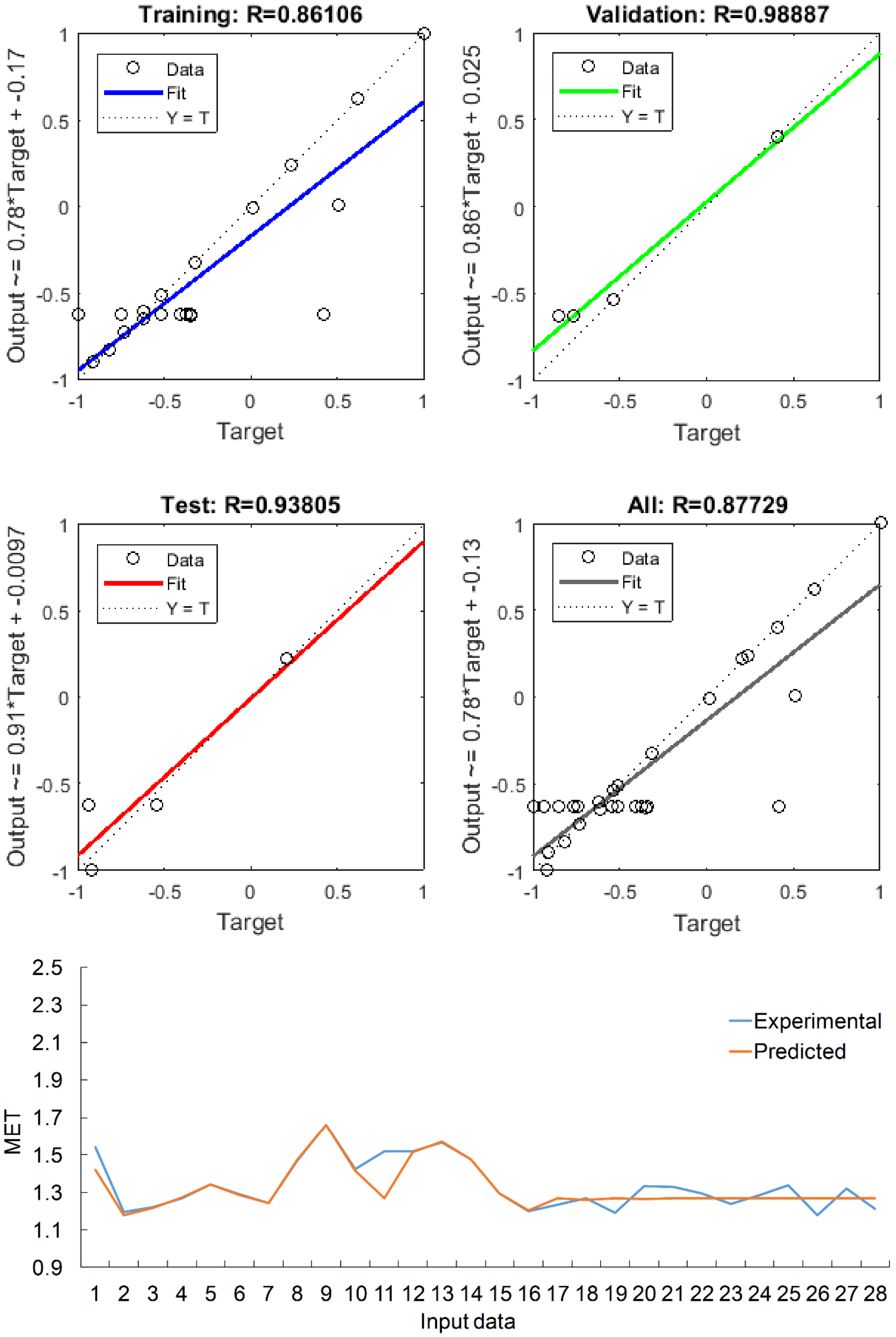

Figure 3.36. Comparison between simulation model with experimental MET response of Group 3 during heating period

The overall models’ prediction accuracy was above 70%. The created artificial neural network models have a satisfactory prediction and generalization accuracy (above 90%), and accordingly can be used further to define and analyze the relationship between the residential conditions and the response characteristics of the user's metabolic rate. Also, developed models obtained in this way represent the basis for further experiments and the smart systems creation will serve to predict the thermal comfort conditions in the room depending on changes in values input factors. Thus, more reliable management of room conditions to achieve individual occupants' thermal could be established.

4. OVERVIEW OF THE SCIENTIFIC CONTRIBUTIONS

The main scientific contributions achieved are as follows:

i) Proposal and development of a novel methodological approach of connecting the measured data of indoor thermal conditions with the occupant's subjective response (thermal sensation votes).

ii) Model development of an occupant's metabolic rate as a function of the office building thermal conditions ($t_{\mathrm{a}}, \mathrm{CO}_2, RH$) using neural networks as well as contribution to the methodological analysis and the general approach to understanding the trends of changes in the value of the occupant's metabolic rate in office spaces during working hours.

iii) Proposal of a correction of metabolic rate's standardized values with regard to individual characteristics of people.

5. CONCLUSION

As learned from reviewed studies in field of thermal comfort, in most buildings, HVAC systems are regulated according to room temperature and humidity conditions, assuming a constant value for occupants' clo and MET based on standard values. Those human factors often do not accurately reflect the real-life, dynamic behavior of occupants as there is a significant deviation in meny cases.

Most thermal comfort model investigations are confined to specific environments, with only a few addressing human responses under both non-uniform and transient conditions, incorporating detailed thermoregulation models. Furthermore, even the established standards are unsuitable to take into account the comfort level in real-life circumstances. This occurs because these methods are designed to forecast the average comfort of a broad population. Consequently, their precision diminishes when forecasting the thermal comfort responses of individuals, as there are substantial variations in thermal comfort among people.

It is crucial to move beyond the existing standards of indoor environmental quality, which are based on population-centered criteria, and instead, focus on meeting the needs and preferences of individuals as and when required. To improve occupant's PMV index, it is necessary to improve accuracy of its parameter, metabolic rate.

Due to the challenges associated with directly measuring MET using simple sensor devices, it is commonly approximated as a fixed default value when calculating the PMV index. Therefore, the methodology investigated in this study using artificial intelligence enables reflecting the real-time MET model based on input data of the occupants' physical activities, considering their individual differences.

For the purpose of determinations which of the comfort parameters of the working environment are statistically significant for office space occupants, a preliminary study was conducted using surveys. According to the sample of 35 randomly selected occupants of different age, gender, and years of experience working in a different job position in the same office building, physical parameters which significantly affect the occupants' satisfaction of the thermal environment are obtained. They are indoor air temperature and air quality in terms of relative humidity and carbon dioxide.

These parameters are considered in subsequent investigations to ensure that ventilation systems, particularly in high-density occupancy zones, are delivering the recommended minimum quantities of outside air to the building's occupants.

Improved air quality would make occupants feel safer, especially considering recent pandemic cirumstances. Optimum air quality is paramount for employee health and confidence in returning to the workplace.

The year-round centered on observing 8 occupants in two office buildings following identical schedules and patterns, albeit situated in contrasting climates: the typical continental city of Zagreb and the Mediterranean city of Split, Croatia. The research focused on monitoring the thermal comfort conditions in these settings using *TROTEC BZ30 Data Logger* devices and evaluated both qualitatively and quantitatively.

The primary focus of the study was to explore the potential provided by the integration of wearable sensors in investigating thermal comfort conditions and modeling the individual and dynamically changing metabolic rates of occupants, considering their unique differences in office buildings. The thermal perception of individuals within their working surrounding was also assessed using wearable sensory device *movisens Move 3*.

The measurement took place 4 times during the year encompassing all seasons (spring, summer, autumn and winter) lasting 7 working days each time.

Sensors recorded data on a 1-minute scale, so the total number of collected data for air temperature is 53,760, relative humidity is 53,760, carbon dioxide is 53,760 and raw data for metabolic rate calculation is 93,856. Apart from sensor data, the total number of occupants' TSV collected is 672.

On the basis of the conducted field measurements, as well as the implementation of a survey, the conditions of thermal comfort in the considered premises were analyzed, and the satisfactions of the occupants in specific working conditions were verified. The level of clothing and the metabolic rate were analyzed for each individual occupant.

The research showed that office occupants of Building A and Building B consider the average office air temperature of 26 °C high, while in spring; occupants are the most dissatisfied with the air temperature in the room. The transitional regime from one season to another has proven to be critical for thermal comfort conditions. Hence, it is recommended to consider technical interventions on the existing regulation systems in buildings (or introduce new, more energy efficient technologies). An average carbon dioxide level of 670 ppm is deemed highly satisfactory, and dissatisfaction arises as the CO_2 concentration in the air approaches the 700 ppm threshold. The feeling of fresh air is achieved by frequent changes of air in the room mechanically by ventilation, as well as naturally by opening windows. Furthermore, the investigation conducted herein revealed the significance of carbon dioxide levels in relation to thermal comfort. The CO_2 concentrations observed in the surveyed offices were notably lower than the levels recommended by standards. It's crucial to emphasize the strong correlation between CO_2 levels and indoor air temperature. Importantly, this factor is largely influenced directly by the occupants.

Relative air humidity of 40% is perceived by occupants as "dry to satisfactory" air. Occupants of both buildings perceive the air as humid when the average relative humidity in the air is 50%. The fact of very low humidity during the heating period, primarily in Building B indicates the adaptation of occupants to non-standard conditions.

The calculated PMV value according to Fanger's model for predicting thermal comfort mostly does not fit into the given standards for considered case. In the summer, the air conditioning system is not able to achieve lower temperatures. On the other hand, the set temperature does not represent sufficient comfort for the occupants in terms of heating the office spaces in the winter.

Moreover, both humidity and temperature levels were found to deviate from acceptable limits. The analyzed data illustrated how a compact office housing only two employees could result in environmental conditions surpassing acceptable thresholds.

In general, it has been observed that elderly individuals tend to favor lower temperatures in the warmer months. The range of air temperatures considered comfortable for older people is narrower than for younger people. The cause of this is most likely the decline in the ability to regulate thermoregulation with age. With regard to gender, the female population is more critical in relation to indoor thermal comfort conditions and is also more sensitive to deviations from optimal thermal comfort conditions, especially in colder conditions. This is also supported by the fact that the female population usually has a higher level of clothing than men during the same season.

Nevertheless, women are more inclined to change the level of clothing during working hours, which allows them a greater level of adaptability to different thermal conditions, as well as a greater range of acceptable temperatures than men. Furthermore, it has been observed that people with a higher BMI have a lower level of clothing and are generally more sensitive to changes in temperature, especially when it rises to higher values compared to the optimal value.

Based on the analysis of the feasibility of utilizing the wearable sensor in thermal comfort investigation, a great potential of possible application was observed as they can personally, unobtrusively and dynamically measure desired parameters. After the conducted study, occupants stated the wearable sensors did not elicit any discomfort for them. Additionally, *Move 3* contributed valuable input data for the analysis and the modeling of personal thermal comfort, particularly by offering precise information regarding the dynamic fluctuations in the occupants' metabolic rates throughout working hours. The MET response typically fluctuated between values of 1.0 and 2.0, which, according to standards, is relatively high for office activities. This suggests the impracticality of using static MET values in computing PMV indexes. In contrast to traditional table reading methods, this study demonstrated that *Move 3* is better suited for this type of testing.

The gathered data served the purpose of analyzing occupants' thermal preferences and forming the foundation for creating the model (Table 3.45). Additionally, the collected data were utilized to assess the impact and significance of individual factors such as age, gender, and BMI on changes in occupants' metabolic rates. The results from the Mann-Whitney Test revealed a statistically significant difference in the mean metabolic rate during the working day between males and females. Furthermore, the Kruskal-Wallis Test indicated a statistically significant difference among building occupants of varying ages and BMI.

Main conclusions about personal comfort parameters in correlation with metabolic rate are one that men usually have higher MET values than women. However, there is age as important variable to be considered when observing MET variations. Older people on average have a lower level of activity, and therefore lower MET values. Furthermore, occupants with high BMI have lower average metabolic rate.

In addition, there is an observed correlation between energy expenditure and variations in individuals' comfort sensations. Energy expenditure is inherently linked to the metabolic rate of occupants. It has been demonstrated that the metabolic rate not only changes over time in the case of an individual but also differs among different people engaging in similar daily activities.

Artificial neural network models were created for certain groups of occupants and for certain seasons. As per the formulated group models, algorithms are tailored to specific occupant profiles, considering an individualized approach and accounting for various potential circumstances within the office premises.

The proposed models include the most important input comfort variables (air temperature, carbon dioxide variation and relative humidity) according to the preliminary study and MET variable as an output.

From total number of 419 averaged MET values per occupant, per season, reading was reduced on a 15-minutes level. Further, 70% of data was used for training, 15% for testing and 15% for validation. The models were created based on the training data, and then it was verified based on the validation and testing data. The training data’s coefficient of correlation was above 0.7, which aligns well with the conducted measurement’s data. More importantly, the validation and testing data’s coefficient of correlation was above 0.9 for all six models, which means that the models exhibit favorable predictive and generalization accuracy. The modeling approach demonstrated that reasonable and fairly accurate results could be achieved, providing a foundation for ensuring optimal thermal conditions in office buildings.

Obtained MLP models are highly parameterized models. Each neuron in the network has its set of weights and biases, making the model expressive and capable of learning complex relationships in the data. Adjusting these parameters allows the model to fine-tune its performance on a specific task. MLPs can be scaled up by adding more layers and neurons to the network, which often improves their performance.

If hyperparameters, architecture design, and regularization techniques to avoid overfitting and achieve the best performance on a given task are carefully considered, adjusting MLP models is relatively easy.

Furthermore, the models that were developed through this approach provide the fundamental framework for subsequent experimentation. They laid the groundwork for the creation of intelligent systems, which will play a role in forecasting office's thermal comfort conditions based on fluctuations in input parameter values. This, in turn, enables more dependable control of room conditions, ultimately leading to the attainment of personalized thermal comfort for individual occupants.

5.1. Future research work

Future research work will concentrate on refining the logic of control regulation algorithms tailored for specific occupant profiles, incorporating an individualized approach and addressing various potential circumstances within office premises. This includes the necessity for standardization and the development of procedures to determine occupant MET profiles.

It is also possible to upgrade current models by taking other individual differences such as pregnancy situation and race of the subjects into account.

In addition, newly available and herein developed MET models based on environmental data as well as occupants' individual comfort have a high potential for developing new personal models to predict human thermal sensation. Furthermore, these models are perfectly suitable to create an integrated smart building system which could adjust the indoor environment to a required comfort level of the building occupants. Finally, with an upgraded energy system regulation, it would be possible to evaluate the potentials of energy savings in buildings and which is one of the key goals of ongoing energy transition.

BIBLIOGRAPHY

[1] D. Yan *et al.*, “Occupant behavior modeling for building performance simulation: Current state and future challenges,” *Energy Build.*, vol. 107, pp. 264–278, 2015.

[2] P. Antoniadou, E. Giama, and A. M. Papadopoulos, “Analysis of environmental aspects affecting comfort in commercial buildings,” *Therm. Sci.*, vol. 22, pp. 819–830, 2018.

[3] O. A. Nisiforou, S. Poullis, and A. G. Charalambides, “Behaviour, attitudes and opinion of large enterprise employees with regard to their energy usage habits and adoption of energy saving measures,” *Energy Build.*, vol. 55, pp. 299–311, 2012.

[4] P. Antoniadou and A. M. Papadopoulos, “Development of an integrated, personalized comfort methodology for office buildings,” *Energies*, vol. 10, no. 8, 2017.

[5] G. Bagarella, R. Lazzarin, and M. Noro, “Annual simulation, energy and economic analysis of hybrid heat pump systems for residential buildings,” *Appl. Therm. Eng.*, vol. 99, pp. 485–494, 2016.

[6] S. Nižetić, A. M. Papadopoulos, G. M. Tina, and M. Rosa-Clot, “Hybrid energy scenarios for residential applications based on the heat pump split air-conditioning units for operation in the Mediterranean climate conditions,” *Energy Build.*, vol. 140, pp. 110–120, 2017.

[7] ANSI/ASHRAE Standard 55-2020, *Thermal Environmental Conditions for Human Occupancy*. 2021.

[8] ISO 7730:2005, *Ergonomics of the thermal environment — Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria*. 2005.

[9] EN 16798-1:2019, “Energy performance of buildings - Ventilation for buildings - Part 1: Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics - Module M1.” 2019.

[10] M. J. Mendell *et al.*, “Improving the Health of Workers in Indoor Environments: Priority Research Needs for a National Occupational Research Agenda,” *Am. J. Public Health*, vol. 92, no. 9, pp. 1430–1440, Sep. 2002.

[11] G. Brager, H. Zhang, and E. Arens, “Evolving opportunities for providing thermal comfort Evolving opportunities for providing thermal comfort,” *Build. Res. Inf.*, vol. 43, no. 3, pp. 274–287, 2015.

[12] J. Gao, Y. Wang, and P. Wargocki, “Comparative Analysis of Modified PMV Models and SET Models to Predict Human Thermal Sensation in Naturally Ventilated Buildings,” *Build. Environ.*, vol. 92, May 2015.

[13] R. De Dear, “Thermal comfort in practice,” *Indoor Air*, vol. 14, no. SUPPL. 7, pp. 32–39, 2004.

[14] J. F. Nicol and M. A. Humphreys, “Adaptive thermal comfort and sustainable thermal standards for buildings,” *Energy Build.*, vol. 34, no. 6, pp. 563–572, 2002.

[15] S. Zhang, Y. Cheng, M. Olaide Oladokun, Y. Wu, and Z. Lin, “Improving predicted mean vote with inversely determined metabolic rate,” *Sustain. Cities Soc.*, vol. 53, no. September 2019, p. 101870, 2020.

[16] J. Van Hoof, "Forty years of Fanger's model of thermal comfort: comfort for all?," *Indoor Air*, vol. 18, no. 3, pp. 182–201, Jun. 2008.

[17] J. Khodakarami, *Achieving Thermal Comfort: In Iranian Hospitals*. VDM Verlag, 2009.

[18] E. E. Broday, A. A. de Paula Xavier, and R. de Oliveira, "Comparative analysis of methods for determining the metabolic rate in order to provide a balance between man and the environment," *Int. J. Ind. Ergon.*, vol. 44, no. 4, pp. 570–580, 2014.

[19] S. I.-H. Gilani, M. H. Khan, and M. Ali, "Revisiting Fanger's thermal comfort model using mean blood pressure as a bio-marker: An experimental investigation," *Appl. Therm. Eng.*, vol. 109, pp. 35–43, 2016.

[20] M. Luo, Z. Wang, K. Ke, B. Cao, Y. Zhai, and X. Zhou, "Human metabolic rate and thermal comfort in buildings: The problem and challenge," *Build. Environ.*, vol. 131, pp. 44–52, 2018.

[21] F. R. d'Ambrosio Alfano, B. I. Palella, and G. Riccio, "The role of measurement accuracy on the thermal environment assessment by means of PMV index," *Build. Environ.*, vol. 46, no. 7, pp. 1361–1369, 2011.

[22] M. Luo, X. Zhou, Y. Zhu, and J. Sundell, "Revisiting an overlooked parameter in thermal comfort studies, the metabolic rate," *Energy Build.*, vol. 118, pp. 152–159, 2016.

[23] B. Kingma and W. van Marken Lichtenbelt, "Energy consumption in buildings and female thermal demand," *Nat. Clim. Chang.*, vol. 5, p. 1054, Aug. 2015.

[24] H. Zhang, E. Arens, and C. Arens, "Using a driving game to increase the realism of laboratory studies of automobile passenger thermal comfort," *SAE Tech. Pap.*, 2003.

[25] I. P. Herman and I. P. Herman, "Feedback and Control," *Phys. Hum. Body*, pp. 873–888, 2016.

[26] M. P. E. Wouters-Adriaens and K. R. Westerterp, "Low Resting Energy Expenditure in Asians Can Be Attributed to Body Composition," *Obesity*, vol. 16, no. 10, pp. 2212–2216, Oct. 2008.

[27] J. J. Cunningham, "Body composition as a determinant of energy expenditure: a synthetic review and a proposed general prediction equation," *Am. J. Clin. Nutr.*, vol. 54, no. 6, pp. 963–969, 1991.

[28] A. Nomoto *et al.*, "Indirect calorimetry of metabolic rate in college-age Japanese subjects during various office activities," *Build. Environ.*, vol. 199, no. April, p. 107909, 2021.

[29] S. Szokolay, *Introduction to Architectural Science: The Basis of Sustainable Design*, 3rd ed. Routledge, 2014.

[30] H. Na and T. Kim, "Development of metabolic rate prediction model using deep learning via Kinect camera in an indoor environment," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 609, no. 4, 2019.

[31] M. W. Qi, X. F. Li, L. B. Weschler, and J. Sundell, "CO2 generation rate in Chinese people," *Indoor Air*, vol. 24, no. 6, pp. 559–566, Dec. 2014.

[32] M. T. Baquero and N. Forcada, "Thermal comfort of older people during summer in the continental Mediterranean climate," *J. Build. Eng.*, vol. 54, p. 104680, 2022.

[33] K. Tsuzuki and T. Ohfuku, "Thermal sensation and thermoregulation in elderly compared to young people in Japanese winter season," *Proc. Indoor Air*, pp. 659–664,

2002.

[34] Y. Zhai *et al.*, "Indirect calorimetry on the metabolic rate of sitting, standing and walking office activities," *Build. Environ.*, vol. 145, no. September, pp. 77–84, 2018.

[35] S. M. Gauthier and D. Shipworth, "Generating empirical probabilities of metabolic rate and clothing insulation values in field studies using wearable sensors," in *13th International Conference on Indoor Air Quality and Climate*, 2014.

[36] R. Passmore, *Energy, work and leisure*. Heinemann Educational Books, 1967.

[37] N. M. Byrne, A. P. Hills, G. R. Hunter, R. L. Weinsier, and Y. Schutz, "Metabolic equivalent: One size does not fit all," *J. Appl. Physiol.*, vol. 99, no. 3, pp. 1112–1119, 2005.

[38] N. Djongyang, T. René, and D. Njomo, "Thermal comfort: A review paper," *Renew. Sustain. Energy Rev.*, vol. 14, pp. 2626–2640, 2010.

[39] ISO 8996:2021, *Ergonomics of the thermal environment — Determination of metabolic rate*. 2021.

[40] S. Brighenti-Zogg *et al.*, "Physical workload and work capacity across occupational groups," *PLoS One*, vol. 11, no. 5, pp. 1–17, 2016.

[41] Y. Zhang, X. Zhou, Z. Zheng, M. O. Oladokun, and Z. Fang, "Experimental investigation into the effects of different metabolic rates of body movement on thermal comfort," *Build. Environ.*, vol. 168, no. July 2019, p. 106489, 2020.

[42] J. Liu, I. W. Foged, and T. B. Moeslund, "Automatic estimation of clothing insulation rate and metabolic rate for dynamic thermal comfort assessment," *Pattern Anal. Appl.*, no. 0123456789, 2021.

[43] G. Havenith, I. Holmér, and K. Parsons, "Personal factors in thermal comfort assessment: Clothing properties and metabolic heat production," *Energy Build.*, vol. 34, no. 6, pp. 581–591, 2002.

[44] S. Vhaduri and C. Poellabauer, "Multi-modal biometric-based implicit authentication of wearable device users," *IEEE Trans. Inf. Forensics Secur.*, vol. 14, no. 12, pp. 3116–3125, 2019.

[45] S. Liu, S. Schiavon, H. P. Das, M. Jin, and C. J. Spanos, "Personal thermal comfort models with wearable sensors," *Build. Environ.*, vol. 162, no. July, p. 106281, 2019.

[46] C. Sugimoto, "Human sensing using wearable wireless sensors for smart environments," *Proc. Int. Conf. Sens. Technol. ICST*, pp. 188–192, 2013.

[47] H. S. Na, J. H. Choi, H. S. Kim, and T. Kim, "Development of a human metabolic rate prediction model based on the use of Kinect-camera generated visual data-driven approaches," *Build. Environ.*, vol. 160, no. December 2018, p. 106216, 2019.

[48] H. Na, H. Choi, and T. Kim, "Metabolic rate estimation method using image deep learning," *Build. Simul.*, vol. 13, no. 5, pp. 1077–1093, 2020.

[49] M. F. Özeby, A. E. Çeter, and C. Turhan, "Determination of Metabolic Rate from Physical Measurements of Heart Rate, Mean Skin Temperature and Carbon Dioxide Variation," *Sak. Univ. J. Sci.*, vol. 26, no. 67934, pp. 74–90, 2021.

[50] G. M. Revel, M. Arnesano, and F. Pietroni, "Integration of Real-Time Metabolic Rate Measurement in a Low-Cost Tool for the Thermal Comfort Monitoring in AAL

Environments," in *Ambient Assisted Living: Italian Forum 2014*, B. Andò, P. Siciliano, V. Marletta, and A. Monteriù, Eds. Cham: Springer International Publishing, 2015, pp. 101–110.

[51] L. Tsao, L. Li, and L. Ma, "Human work and status evaluation based on wearable sensors in human factors and ergonomics: A review," *IEEE Trans. Human-Machine Syst.*, vol. 49, no. 1, pp. 72–84, 2019.

[52] S. Kang, A. Paul, and G. Jeon, "Reduction of mixed noise from wearable sensors in human-motion estimation," *Comput. Electr. Eng.*, vol. 61, pp. 287–296, 2017.

[53] M. Stikic, D. Larlus, S. Ebert, and B. Schiele, "Weakly Supervised Recognition of Daily Life Activities with Wearable Sensors," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2521–2537, 2011.

[54] M. Nakanishi *et al.*, "Estimating metabolic equivalents for activities in daily life using acceleration and heart rate in wearable devices," *Biomed. Eng. Online*, vol. 17, no. 1, pp. 1–18, 2018.

[55] S. C. Mukhopadhyay, "Wearable sensors for human activity monitoring: A review," *IEEE Sens. J.*, vol. 15, no. 3, pp. 1321–1330, 2015.

[56] J. Zhu, A. Pande, P. Mohapatra, and J. J. Han, "Using Deep Learning for Energy Expenditure Estimation with wearable sensors," *2015 17th Int. Conf. E-Health Networking, Appl. Serv. Heal. 2015*, pp. 501–506, 2015.

[57] W. Ji, M. Luo, B. Cao, Y. Zhu, Y. Geng, and B. Lin, "A new method to study human metabolic rate changes and thermal comfort in physical exercise by CO2 measurement in an airtight chamber," *Energy Build.*, vol. 177, pp. 402–412, 2018.

[58] G. P. Kenny, S. R. Notley, and D. Gagnon, "Direct calorimetry: a brief historical review of its use in the study of human metabolism and thermoregulation," *Eur. J. Appl. Physiol.*, vol. 117, no. 9, pp. 1765–1785, 2017.

[59] I. Ruiz, M. Sprowls, Y. Deng, D. Kulick, H. Destaillats, and E. S. Forzani, "Assessing metabolic rate and indoor air quality with passive environmental sensors.," *J. Breath Res.*, vol. 12, no. 3, p. 36012, Apr. 2018.

[60] A. Dimara, C.-N. Anagnostopoulos, S. Krinidis, and D. Tzovaras, "Personalized thermal comfort modeling through genetic algorithm," *Energy Sources, Part A Recover. Util. Environ. Eff.*, vol. 00, no. 00, pp. 1–22, 2021.

[61] K. Zaninović *et al.*, *Klimatski atlas Hrvatske / Climate atlas of Croatia 1961-1990., 1971-2000.* 2008.

[62] Climatestotravel.com, "Split Climate," *World climate guide*. [Online]. Available: https://www.climatestotravel.com/climate/croatia/split. [Accessed: 15-Jan-2020].

[63] Climatemps, "Zagreb Climate & Temperature," *Climate Data*. [Online]. Available: https://www.zagreb.climatemps.com/. [Accessed: 15-Jan-2020].

[64] "MadgeTech Data Loggers Solutions for Critical Applications." [Online]. Available: https://www.madgetech.com/. [Accessed: 15-Jan-2020].

[65] "TROTEC." [Online]. Available: https://en.trotec.com/. [Accessed: 15-Jan-2020].

[66] S. Hey, P. Anastasopoulou, and B. von Haaren, "Erfassung körperlicher Aktivität mittels -Akzelerometrie – Möglichkeiten und Grenzen aus technischer Sicht TT - Assessment of Physical Activity by Accelerometry: Technical Possibilities and Limits," *Aktuelle*

Rheumatol., vol. 39, no. 05, pp. 317–321, 2014.

[67] D. John and P. Freedson, “ActiGraph and Actical physical activity monitors: a peek under the hood.,” *Med. Sci. Sports Exerc.*, vol. 44, no. 1 Suppl 1, pp. S86-9, Jan. 2012.

[68] G. J. Welk, J. McClain, and B. E. Ainsworth, “Protocols for evaluating equivalency of accelerometry-based activity monitors,” *Med. Sci. Sports Exerc.*, vol. 44, no. 1 Suppl 1, p. S39—49, 2012.

[69] M. J. Fletcher, D. W. Glew, A. Hardy, and C. Gorse, “A modified approach to metabolic rate determination for thermal comfort prediction during high metabolic rate activities,” *Build. Environ.*, vol. 185, no. May, p. 107302, 2020.

[70] N. F. Butte, U. Ekelund, and K. R. Westerterp, “Assessing physical activity using wearable monitors: Measures of physical activity,” *Med. Sci. Sports Exerc.*, vol. 44, no. SUPPL. 1, 2012.

[71] K. L. Campbell, P. R. E. Crocker, and D. C. McKenzie, “Field evaluation of energy expenditure in women using Tritrac accelerometers,” *Med. Sci. Sports Exerc.*, vol. 34, no. 10, pp. 1667–1674, 2002.

[72] P. Anastasopoulou, M. Tubic, S. Schmidt, R. Neumann, A. Woll, and S. Härtel, “Validation and Comparison of Two Methods to Assess Human Energy Expenditure during Free-Living Activities,” *PLoS One*, vol. 9, no. 2, p. e90606, Feb. 2014.

[73] S. Härtel, J.-P. Gnam, S. Löffler, and K. Bös, “Estimation of energy expenditure using accelerometers and activity-based energy models—validation of a new device,” *Eur. Rev. Aging Phys. Act.*, vol. 8, no. 2, pp. 109–114, 2011.

[74] K. Lyden, S. L. Kozey, J. W. Staudenmeyer, and P. S. Freedson, “A comprehensive evaluation of commonly used accelerometer energy expenditure and MET prediction equations,” *Eur. J. Appl. Physiol.*, vol. 111, no. 2, pp. 187–201, 2011.

[75] P. Anastasopoulou, M. Tansella, J. Stumpp, L. Shammas, and S. Hey, “Classification of human physical activity and energy expenditure estimation by accelerometry and barometry,” in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012, pp. 6451–6454.

[76] movisens GmbH, “movisens GmbH.” [Online]. Available: https://www.movisens.com/en. [Accessed: 15-Jan-2020].

[77] ISO 10551:2019, *Ergonomics of the physical environment—subjective judgement scales for assessing physical environments*. 2019.

[78] R. F. Goldman, “ENVIRONMENTAL ERGONOMICS: WHENCE-WHAT-WITHER,” in *11th International Conference on Environmental Ergonomics*, 2005, pp. 39–47.

[79] S. Pivac, “Statističke metode.pdf,” in *Statističke metode*, Split: Sveučilište u Splitu, Ekonomski fakultet, 2011, p. e-nastavni materijal.

[80] A. S. Shirazi and I. Frigaard, “Slurrynet: Predicting critical velocities and frictional pressure drops in oilfield suspension flows,” *Energies*, vol. 14, no. 5, pp. 1–21, 2021.

[81] C. Turhan, T. Kazanasmaz, and G. G. Akkurt, “Performance Indices of Soft Computing Models To Predict the Heat Load of Buildings in Terms of Architectural Indicators,” *J. Therm. Eng.*, vol. 3, no. 4, pp. 1358–1374, 2016.

[82] © Ministry of Social Affairs and Health, “No. 738/2002,” Dec. 2004.

[83] I. W. B. Grant, “The sick building syndrome,” *J. Allergy Clin. Immunol.*, vol. 94, no. 6464, pp. 335–343, 1994.

[84] T. Hong, H. Sun, Y. Chen, S. C. Taylor-Lange, and D. Yan, “An occupant behavior modeling tool for co-simulation,” *Energy Build.*, vol. 117, pp. 272–281, 2016.

[85] J. M. Martrette, C. Egloff, C. Clément, K. Yasukawa, S. N. Thornton, and M. Trabalon, “Effects of prolonged exposure to CO2 on behaviour, hormone secretion and respiratory muscles in young female rats,” *Physiol. Behav.*, vol. 177, pp. 257–262, 2017.

[86] K. W. Tham, “Indoor air quality and its effects on humans - A review of challenges and developments in the last 30 years,” *Energy Build.*, vol. 130, pp. 637–650, 2016.

[87] ANSI/ASHRAE Standard 62.1-2022, *Ventilation and Acceptable Indoor Air Quality*. 2022.

[88] C. Yang, T. Yin, and M. Fu, “Study on the allowable fluctuation ranges of human metabolic rate and thermal environment parameters under the condition of thermal comfort,” *Build. Environ.*, vol. 103, pp. 155–164, 2016.

[89] V. R. Preedy and R. R. Watson, Eds., “5-Point Likert Scale,” in *Handbook of Disease Burdens and Quality of Life Measures*, New York, NY: Springer New York, 2010, p. 4288.

[90] “CBE Thermal Comfort Tool.” [Online]. Available: http://comfort.cbe.berkeley.edu/. [Accessed: 04-Jul-2019].

[91] I. Peko, “Utjecaj faktora procesa rezanja plazmenim mlazom na kvalitetu reza kod aluminijskih legura,” FESB, Sveučilište u Splitu, 2018.

[92] M. H. Beale, M. T. Hagan, and H. B. Demuth, *Neural Network Toolbox TM User’s Guide*. 2017.

[93] M. J. Madić and V. J. Marinković, “Assessing the sensitivity of the artificial neural network to experimental noise: A case study,” *FME Trans.*, vol. 38, no. 4, pp. 189–195, 2010.

APPENDIX

Datum i vrijeme:_____________

- BLIC ANKETA -

Pred Vama se nalazi anketni upitnik koji je namijenjen zaposlenicima tvrtke HEP ESCO d.o.o., kao i zaposlenicima Fakulteta elektrotehnike, strojarstva i brodogradnje. Cilj ankete je utvrđivanje toplinske ugodnosti zaposlenika u prostorijama u kojima borave. Anketa je anonimna, a Vaši odgovori bit će korišteni isključivo u svrhu istraživanja u sklopu doktorske disertacije. Molimo Vas da nam svojim iskrenim odgovorima pomognete da dobijemo što jasniju sliku vezano za razmatranu tematiku. Unaprijed zahvaljujemo na Vašem trudu i vremenu!

Spol: M / Ž

Pušač: DA / NE

Stručna sprema: SSS / VŠS / VSS

Koliko imate godina? _____ Visina:______ Težina:______Godine radnog staža:_______

1) Kako se osjećate s obzirom na trenutnu temperaturu u uredu?

a) Vruće
b) Toplo
c) Neutralno
d) Prohladno
e) Hladno

2) U kakvom je stanju prostorija u kojoj trenutno boravite?

a) Jako uredna	a) Dugo je bila zračena	a) Zrak u prostoriji je dosta suh
b) Uredna	b) Umjereno prozračena	b) Zrak u prostoriji je umjereno suh
c) Umjereno uredna	c) Neutralna	c) Zrak u prostoriji nije ni suh ni vlažan
d) Neuredna	d) Zagušljiva	d) Zrak u prostoriji je umjereno vlažan
e) Jako neuredna	e) Jako zagušljiva	e) Zrak u prostoriji je jako vlažan

3) Kako biste ocijenili razinu produktivnosti u ovom trenutku?

a) Jako visoka – osjećam entuzijazam obavljajući poslovne zadatke
b) Visoka – pokušat ću napraviti što više posla
c) Srednja – obavljam zadatke normalnom brzinom i učinkovitošću
d) Niska – obavljam samo nužne zadatke
e) Jako niska – osjećam umor od obavljanja zadataka

4) Koliki vam je obim posla u ovom trenutku?

a) Jako velik
b) Velik
c) Umjeren
d) Malen
e) Jako malen

Datum i vrijeme:_____________

5) Označite odjevne predmete koje imate u ovom trenutku na sebi:

a) Debeli džemper dugi rukav – 0,35
b) Tanki džemper dugi rukav – 0,2
c) Majica dugi rukav – 0,25
d) Majica kratki rukav – 0,09
e) Košulja dugi rukav – 0,3
f) Košulja kratki rukav – 0,2
g) Bluza dugi rukav – 0,15
h) Vesta dugi rukav – 0,13
i) Tanka dočevita – 0,26
j) Debela dolčevita 0,37
k) Jaketa – 0,35

a) Cipele – 0,04
b) Tenisice – 0,02
c) Čizme – 0,05
d) Sandale – 0,02

a) Potkošulja (donja majica) – 0,06
b) Čarape – 0,02
c) Dokoljenke – 0,10
d) Hulahopke – 0,02

a) Hlače (duge) – 0,25
b) Suknja ispod koljena – 0,18
c) Suknja iznad koljena – 0,01
d) Odijelo (Hlače, košulja, sako) – 1,5
e) Haljina – 0,3

a) Spuštena kosa – 0,1
b) Podignuta kosa – 0,03
c) Kratka kosa – 0,05
d) Marama ili šal – 0,01

6) Nosite li naočale za vid u ovom trenutku? DA NE

7) U prostoriji je trenutno upaljeno svjetlo: DA NE

8) Znojite li se u ovom trenutku? Uopće ne 1 2 3 4 5 Vrlo

9) Zaokružite razinu prirodnog svjetla u prostoriji:

Odsutnost prirodnog svjetla 1 2 3 4 5 Velika prisutnost prirodnog svjetla

10) Zaokružite razinu buke u prostoriji:

Odsutnost buke 1 2 3 4 5 Velika prisutnost buke

CURRICULUM VITAE

Nikolina Pivac was born on August 15, 1989, in Split. After finishing elementary school in Manuš and the V. Gymnasium Vladimir Nazor in Split, she pursued her academic journey at the Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture (FESB), specializing in industrial engineering. In September 2012, she attained her university bachelor's degree with a thesis titled "Creation of elements of an active information system". She pursued further studies in industrial engineering, specializing in production management. In September 2014, she successfully defended her master's thesis "Efficiency analysis of a micro-cogeneration system", earning the title of a university master's degree holder. During the same year, she joined the team led by Professor Frane Barbir, as an associate for finance and administration working on the EU project "Research and development of the hydrogen energy system in conjunction with renewable energy sources". In January 2015, she was elected for the role of president of the ASHRAE (American Society of Heating, Refrigerating, and Air-Conditioning Engineers) University of Split, a position which she held for one year. In the subsequent year, she commenced her doctoral studies in mechanical engineering at FESB under the mentorship of Professor Sandro Nižetić, concurrently advancing her professional endeavors through participation in EU projects Horizon 2020 AutoRE and GiantLeap led by Professor Frano Barbir. Collaborating with her mentor, she prepared and submitted a scientific research project in cooperation with HEP ESCO d.o.o., titled "The use of biosensors for the purpose of researching thermal comfort conditions in public office buildings with the aim of rationalizing energy consumption and data integration in ESCO MONITOR", wherein she worked as the main researcher and project administrator. This project’s outcomes laid the groundwork for her doctoral thesis. Simultaneously, she engaged as an external associate in teaching, facilitating auditory exercises for graduate students in industrial engineering on the Rational Use of Energy course, as well as construction exercises for undergraduate industrial engineering and graduate mechanical engineering students on the Computer Design 1 course. In December 2019, she joined the university's team at the project "Development of the incubator for the new technologies of the University of Split", funded by the EU and led by Professor Sven Gotovac. In February 2020, together with Professor Frano Barbir, she co-founded the Croatian Hydrogen Association (HUV). Her tenure at the Incubator for the new technologies persisted until June 2022, after which she assumed the role of a quality engineer for software, web and mobile applications at emovis tehnologie d.o.o., where she continues her professional journey to date.

ŽIVOTOPIS

Nikolina Pivac rođena je 15. kolovoza 1989. u Splitu. Nakon završetka osnovne škole Manuš i opće V. gimnazije Vladimir Nazor u Splitu upisuje Fakultet elektrotehnike, strojarstva i brodogradnje (FESB), studij industrijsko inženjerstvo. U rujnu 2012. stječe titulu sveučilišnog prvostupnika s temom "Izrada elemenata aktivnog informacijskog sustava". Nakon završetka preddiplomskog, upisuje diplomski studij industrijskog inženjerstva, smjer proizvodni menadžment, te u rujnu 2014. s diplomskim radom "Analiza učinkovitosti mikrokogeneracijskog sustava" stječe titulu sveučilišne magistre inženjerke industrijskog inženjerstva. Iste godine pridružuje se timu prof. dr. sc. Frane Barbira za vodik i vodikove tehnologije, gdje se zapošljava kao stručni suradnik za financije i administraciju na EU projektu "Istraživanje i razvoj vodikovog energetskog sustava u sprezi s obnovljivim izvorima energije". U siječnju 2015. izabrana je za predsjednicu ASHRAE (American Society of Heating, Refrigerating, and Air-Conditioning Engineers) University of Split, studentskog ogranka na čijem čelu ostaje godinu dana. Poslijediplomski doktorski studij strojarstva na FESB-u upisuje iduće godine pod mentorstvom prof. dr. sc. Sandra Nižetića, te ujedno nastavlja svoj profesionalni razvoj kao stručni suradnik i administrativni voditelj na EU projektima Horizon 2020 AutoRE i GiantLeap pod vodstvom prof. dr. sc. Frane Barbira. Zajedno s mentorom priprema i prijavljuje znanstvenoistraživački projekt u suradnji s HEP ESCO d.o.o., pod nazivom "Korištenje biosenzora u svrhu istraživanja uvjeta toplinske ugodnosti u uredskim zgradama javne namjene s ciljem racionalizacije potrošnje energije te integracije podataka u ESCO MONITOR" na kojem radi kao glavni istraživač i administrator. Projekt je trajao godinu dana, a rezultati i doprinosi tog projekta poslužili su kao osnova i temelj doktorskog rada. Paralelno radi i kao vanjski suradnik u nastavi izvodeći auditorne vježbe studentima diplomskog studija industrijskog inženjerstva iz kolegija Racionalno korištenje energije, te konstrukcijske vježbe studentima preddiplomskog studija industrijskog inženjerstva i diplomskog studija strojarstva iz kolegija Konstruiranje pomoću računala 1. U prosincu 2019. pridružuje se timu sveučilišnog strukturnog projekta financiranog iz EU pod nazivom "Razvoj poduzetničkog inkubatora za visoke tehnologije Sveučilišta u Splitu" pod vodstvom prof. dr. sc. Svena Gotovca. U veljači 2020., zajedno s prof. dr. sc. Franom Barbirom, osniva Hrvatsku udrugu za vodik (HUV). U poduzetničkom inkubatoru ostaje kao zaposlenik do lipnja 2022., nakon čega se zapošljava u emovis tehnologije d.o.o. kao inženjer za testiranje softvera, web aplikacija i mobilnih aplikacija, gdje i danas radi.