Towards Real-Time Model-Based Monitoring and Adoptive Controlling of Indoor Thermal Comfort

Ali Youssef*[1], Pieter Truyen[1], Peter Bröde[2], Dusan Fiala[3], and Jean-Marie Aerts[1]

[1] KU Leuven, M3-BIORES
Kasteelpark Arenberg 30 bus 2456
3001 Heverlee, Belgium

[2] Leibniz Research Centre for Working Environment and Human (ifADo)
Ardeystraße 67
44139 Dortmund, Germany

[3] Institute for Building Materials, Building Physics, Building Technology and Design (IBBTE)
Keplerstraße 11
D-70174 Stuttgart, Germany

ABSTRACT

Thermal comfort is an important aspect of the building design and indoor climate control as modern man spends most of the day indoors. Conventional indoor climate design and control approaches are based on static thermal comfort models that views the building occupants as passive recipients of their thermal environment. Assuming that people have relatively constant range of biological comfort requirements, and that the indoor environmental variables should be controlled to conform to that constant range. The (r)evolution in modern sensing and computing technologies (price, compact size, flexibility and stretchability) is making it possible to continuously measure signals in real-time from human body using wearable technologies and smart clothing. Many advanced and accurate mechanistic thermoregulation models, such as the 'Fiala thermal Physiology and Comfort' model, are developed to assess the thermal strains and comfort status of humans. However, the most reliable mechanistic models are too complex to be implemented in real-time for monitoring and control applications. Additionally, such models are using not-easily or invasively measured variables (e.g., core temperatures), which are often not practical and undesirable measurements for monitoring during varied activities over prolonged periods. The purpose of this work is to develop a databased mechanistic (grey box) model, with minimum number of parameters and non-invasive input variables, for real-time monitoring and controlling of individual occupant's thermal comfort. Eight healthy males (mean ± standard deviation: age 22.8 ±1.3 years, height 1.81 ±0.06m, body surface area 1.94 ±0.11 m^2) are used as test subjects to perform the designed experiments. The experimental protocol involved step-changes of exercise on treadmill inside to simulate step-changes in activity level. Metabolic heat production was calculated based on the continuously measured O_2 consumption and CO_2 production. Rectal temperature are continuously measured. Mean clothing layer and mean skin temperatures were calculated based on measured temperatures from eight body locations. The experiments were performed with the subjects wearing dry and wet underwear layer and constant ventilation rate. First-order multi-inputs-single-output discrete time transfer function, with only mean skin temperature and metabolic heat production or mean underwear temperature as inputs, was found to be the best to describe the dynamic responses of the rectal temperature. That with average coefficient of determination R^2 = 0.96±0.2 and average Young Identification Criterion YIC = -9.20 ±4.2). to The resulted models were compact enough (two inputs) to be implemented in real-time. Hence, the resulted model

structure can be implemented in closed-loop algorithm for online identification of the model and parameters estimation is foreseen to be employed for occupant-based climate control applications and smart clothing.

KEYWORDS

thermal comfort, indoor climate control, dynamic modelling, model-based control

1 INTRODUCTION

Thermal comfort is an important aspect of the building design and indoor climate control as modern man spends most of the day indoors. Conventional indoor climate design and control approaches are based on static thermal comfort models that views the building occupants as passive recipients of their thermal environment. the primary purpose of HVAC was to maintain constant thermal environmental conditions throughout the interior aiming for an optimum 'steady-state' temperature setting based on Fanger's Predicted Mean Vote and Predicted Percentage Dissatisfied (PMV-PPD) model (Fanger, 1970; Parsons, 2014). Many advanced and accurate mechanistic thermoregulation models, such as the 'Fiala thermal Physiology and Comfort' model, are developed to assess the thermal strains and comfort status of humans (Havenith and Fiala, 2015). Most accurate and reliable models however, are too complex to enable real-time monitoring and control of the environmental conditions. Therefore, new models need to be found that are both simple and accurate. Early detection of core body temperature gain is key to the implementation of suitable strategies (i.e. cooling) to avoid exertional heat stroke (Niedermann et al., 2014). However, on the one hand, existing methods are invasive (inserting rectal or oesophageal temperature probes, etc.) and not convenient for long-term monitoring due to subject discomfort. On the other hand, the application of noninvasive measurement methods (tympanic membrane, oral, axillary) have demonstrated only limited accuracy for use in working environments. Most of the current methods to measure and predict the core body temperature in comparison to the rectal temperature method, neither meet the requirement of an accurate measurement of the core body temperature (±0.1 °C) nor do they enable the continuous measurement of the core body temperature in changing working conditions (Niedermann et al., 2014). Therefore, the purpose of this work was to develop a an adaptive dynamic model with minimum number of parameters and non-invasive input variables, to predict the core body temperature for real-time monitoring and controlling of individual occupant's thermal comfort.

2 MATHERIALS AND METHODS

2.1 Experiments and test subjects

The data used in this paper was obtained from conducted human experiments at Leibniz Research Centre for Working Environment and Human Factors at the University of Dortmund (*IfADo*) (Bröde et al., 2008; Niedermann et al., 2014). During these experiments, measurements from eight healthy male students (mean ± standard deviation: age 22.8 ± 1.3 years, body height 1.81 ± 0.06 m, body mass 75.1 ± 6.6 kg and body surface area 1.94 ± 0.11 m^2) were collected. In order to reduce the evaporation to the environment, the experiments were carried out under a high humidity condition with air temperature (T_a) of 20 ^{o}C, relative humidity (RH) of 80%, yielding ambient water vapour pressure (P_a) of 1.87 kPa, and air velocity of 0.5 ms^{-1}. Globe temperature was equal to T_a. The subjects wore their own briefs, socks and sport shoes, and a four layer clothing ensemble consisting of polypropylene underwear (HHS, Helly Hansen Super Bodywear 140 g.m^{-2}), a hooded TYCHEM ® C Standard coverall as intermediate layer preventing both wicking and evaporation, additional cotton (CO, type ‘‘Gnägi’’, Switzerland) mid layer and an impermeable PVC outer layer. Trials were performed with the CO mid layer either dry (dry condition) or wetted using 618 $\pm$ 16 g of water (wet condition). The sequence of those conditions was balanced across subjects who visited the laboratory at the same time of day (for more information about the experiments see Bröde et al. 2008; Niedermann et al. 2014). The experimental protocol itself contained of a 30-minute resting phase followed by three phases inside a climatic chamber, each lasting 30 minutes and separated by a 3-minute period where the fully clothed person’s weight was determined. The first exercising phase comprised of 2 minutes of treadmill walking at 4.5 km.h^{-1} followed by 28 minutes of standing in the room. Treadmill work was performed during the second and third phase.

2.2 Measurements

Metabolic heat production rate (Q_{met}, W.m^{-2}) was calculated according to ISO 8996 (ISO, 2004) from the analysis of O_2 consumption (Servomex Series 1100, Servomex Ltd., UK) and CO_2 production (UNOR Infrarot-Gasanalysator, maihak AG, Germany) of expired air collected with Douglas bags during the last 10 minutes of phases 1 and 3, respectively. Mean skin temperature (T_{skm}, ºC) was calculated as the average of thermistor recordings (YSI 427, Yellow Springs, USA) at eight body sites (forehead, left chest, right frontal thigh, left dorsal thigh, right scapula, right upper arm, left lower arm and left hand) according to a variant of the ISO 9886 scheme (ISO, 1992). The rectal temperatures (T_{re}, ºC) were continuously recorded with a flexible thermistor probe at a depth of 10 cm from the anal sphincter (YSI 401, Yellow Springs, USA). Water vapour pressure (uwP_{air}, kPa) and air temperature (uwT_{air}, ºC) in the clothing’s microclimate were measured by data loggers (HandyLog DK502, Driesen + Kern GmbH, Germany) positioned at the right chest and left scapula between the underwear HHS layer and TYCHEM® layer and, correspondingly, at the contra lateral sites between the CO mid and PVC outer layer. An example of the different measured variables during the conducted experiments is shown in Figure 1 for subject #1 under dry conditions.

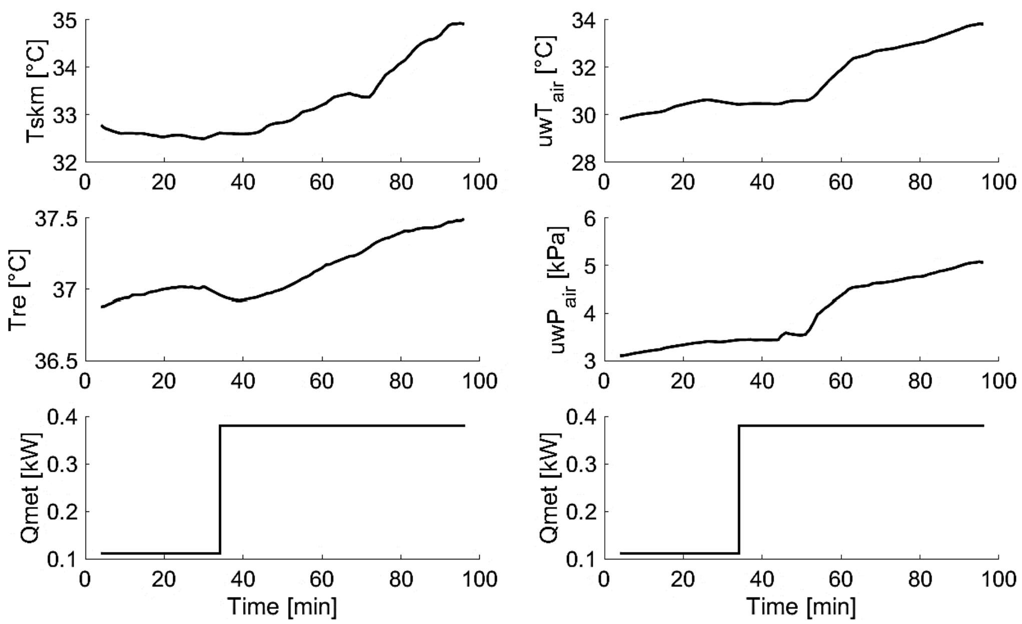

Figure 1. The dynamic response of mean skin temperature (T_{skm}, ºC), rectal temperature (T_{re}, ºC), mean underwear air temperature (uwT_{air}, ºC) and mean underwear water vapour pressure (uwP_{air}, kPa) to step increase in the metabolic heat production rate (Q_{met}, kW) for test subject #1 at dry conditions.

2.3 System identification and online modelling

The human system is considered as Complex, Individually different, Time varying and Dynamic (CITD) systems (Quanten et al., 2006; Youssef et al., 2014). Although the system (body thermoregulation) under study is inherently a non-linear system, the essential perturbation behaviour can often be approximated well by simple linearized transfer function (TF) models (Young et al., 1991; Youssef, 2014). The dynamic responses of the core body temperature, represented by the measured rectal temperature T_{re}, is modelled using different input variables using both single-input-single-output (SISO) and multiple-input-single-output (MISO) discrete-time transfer function (DTF). Mean skin temperature T_{skm}, mean underwear temperature uwT_{air}, underwear water vapour pressure uwP_{air} and metabolic heat production Q_{met} are considered separately and combined as input variables to model the rectal temperature T_{re}. For the purposes of the present paper, therefore, the following liner, discrete-time-system was considered,

$$T_{re}(k) = \sum_{i=1}^{nu} \frac{B_i(z^{-1})}{A(z^{-1})} u_i(k - \delta_i) + \xi(k) \quad (1)$$

where,

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \cdots + a_n z^{-n}$$
$$B_i(z^{-1}) = b_{0,i} + b_{1,i} z^{-1} + b_{2,i} z^{-2} + \cdots + b_{m,i} z^{-m} \quad (2)$$

where $T_{re}(k)$ is the model output and $u_i(k)$ is the i^{th} model input, while $A(z^{-1})$ and $B_i(z^{-1})$ are appropriately defined polynomials in the backshift operator z^{-1}, i.e., $z^{-i}y(k) = y(k-i)$. While, nu is number of model inputs (i.e., nu = 1 for SISO and nu > 1 for MISO systems) and $\xi(k)$ is additive noise, a serially uncorrelated sequence of random variables with variance σ^2 that accounts for measurement noise, modelling errors and effects of unmeasured inputs to the process (assumed to be a zero mean). The simplified refined instrumental variable (SRIV) algorithm was utilised in the identification and estimation of the models (model parameters and model structure) (Young et al., 2000; Young and Jakeman, 1980). The appropriate model structure was identified, i.e., the most appropriate values for the triad $[n, m, \delta]$ (see equations 1 and 2). Two main statistical measures were employed to determine the most appropriate values of this triad. Namely, the coefficient of determination R_2^T, based on the response error; and YIC (Young's Information Criterion), which provides a combined measure of model fit and parametric efficiency, with large negative values indicating a model which explains the output data well and yet avoids over-parameterisation (Young, 2011). The modelling procedures were applied on the data from both dry and wet conditions.

3 RESULTS AND DISCUSSIONS

3.1 Model identification

- ***Dry condition***

The SRIV algorithm combined with the root mean square error (RMSE), YIC and R_2^T suggested, in general, that a first order (number of poles, n = 1) MISO DTF models, including the metabolic heat production Q_{met} and mean skin temperature T_{skm} as model inputs (i.e., nu = 2), described the dynamic responses of the rectal temperature T_{re} most accurately (i.e., R_2^T= 0.98±0.17 and YIC= -7.63 ±2.40). More specifically, the SRIV algorithm identified the following general discrete-time TF model structure represented by the triad [1 1 1 δ_1 δ_2],

$$T_{re}(k) = \begin{bmatrix} \frac{B_1(z^{-1})}{A(z^{-1})} & \frac{B_2(z^{-1})}{A(z^{-1})} \end{bmatrix} \cdot \begin{bmatrix} Q_{met}(k-\delta_1) \\ T_{skm}(k-\delta_2) \end{bmatrix} + \xi(k) \quad (3)$$

where the time delays δ_1 and δ_2 were different from test subject to another (Table 1).

Table 1. The resulted MISO model structures $[n\ m_1\ m_2\ \delta_1\ \delta_2]$ and the mean estimated polynomials $A(z^{-1})$, $B_1(z^{-1})$ and $B_2(z^{-1})$ with metabolic heat production Q_{met} and mean skin temperature T_{skm} as model inputs, showing the mean model identification criteria R_2^T, YIC and RMSE for all the test subjects under dry condition.

	n	***m***	***m***	$\boldsymbol{\delta_1}$	$\boldsymbol{\delta_2}$	$\boldsymbol{A(z^{-1})}$	$\boldsymbol{B_1(z^{-1})}$	$\boldsymbol{B_2(z^{-1})}$	$\boldsymbol{R_T^2}$	***YIC***	***RMSE***
Mean ± Standard deviation	**1**	**1**	**1**	**5** ± 4	**4** ± 3	**0.05** ± 0.076	**0.0012** ± 3.50×10^{-4}	**0.0026** ± 0.010	**0.98** ± 0.17	**-7.63** ± 2.40	**0.007** ± 2.70×10^{-4}

Additionally, the results have shown that a first MISO DTF models, with the mean skin temperature T_{skm} and the mean underwear temperature uwT_{air} as model inputs, were able to describe the dynamic responses of the rectal temperature T_{re} sufficiently (i.e., R_2^T= 0.95±0.05 and YIC= -9.66 ±3.22). More specifically, the SRIV algorithm identified the following general discrete-time TF model structure represented by the triad [1 1 1 δ_1 δ_2],

$$T_{re}(k) = \begin{bmatrix} \frac{B_1(z^{-1})}{A(z^{-1})} & \frac{B_2(z^{-1})}{A(z^{-1})} \end{bmatrix} \cdot \begin{bmatrix} T_{skm}(k-\delta_1) \\ uwT_{air}(k-\delta_2) \end{bmatrix} + \xi(k) \quad (4)$$

The mean estimated model polynomials, $A(z^{-1})$, $B_1(z^{-1})$ and $B_2(z^{-1})$, resulted from the data from all the eight test subjects are presented in Table 2.

Table 2. The resulted MISO model structures $[n\ m_1\ m_2\ \delta_1\ \delta_2]$ and the mean estimated polynomials $A(z^{-1})$, $B_1(z^{-1})$ and $B_2(z^{-1})$ with mean skin temperature T_{skm} and mean underwear temperature uwT_{air} as model inputs, showing the mean model identification criteria R_2^T, YIC and RMSE for all the test subjects under dry condition.

	n	***m***	***m***	$\boldsymbol{\delta_1}$	$\boldsymbol{\delta_2}$	$\boldsymbol{A(z^{-1})}$	$\boldsymbol{B_1(z^{-1})}$	$\boldsymbol{B_2(z^{-1})}$	$\boldsymbol{R_T^2}$	***YIC***	***RMSE***
Mean ± Standard deviation	**1**	**1**	**1**	**3** ± 2	**4** ± 3	**0.25** ± 0.22	**0.052** ± 4.2×10^{-3}	**0.0030** ± 0.023	**0.95** ± 0.05	**-5.63** ± 3.25	**0.022** ± 1.85×10^{-3}

- ***Wet condition***

The same MISO model structure, as resulted for the dry condition (i.e., [1 1 1 δ_1 δ_2]), was best to describe the dynamic responses of the rectal temperature of all the test subjects under wet condition (see Tables 3 and 4).

Table 3. The resulted MISO model structures $[n\ m_1\ m_2\ \delta_1\ \delta_2]$ and the mean estimated polynomials $A(z^{-1})$, $B_1(z^{-1})$ and $B_2(z^{-1})$ with metabolic heat production Q_{met} and mean skin temperature T_{skm} as model inputs, showing the mean model identification criteria R_2^T, YIC and RMSE for all the test subjects under wet condition.

	n	***m***	***m***	$\boldsymbol{\delta_1}$	$\boldsymbol{\delta_2}$	$\boldsymbol{A(z^{-1})}$	$\boldsymbol{B_1(z^{-1})}$	$\boldsymbol{B_2(z^{-1})}$	$\boldsymbol{R_T^2}$	***YIC***	***RMSE***
Mean ± Standard deviation	**1**	**1**	**1**	**4** ± 3	**7** ± 3	**0.03** ± 0.010	**0.00017** ± 5.42×10^{-5}	**-0.015** ± 0.007	**0.98** ± 0.15	**-8.88** ± 1.63	**0.03** ± 4.42×10^{-3}

Table 4. The resulted MISO model structures $[n\ m_1\ m_2\ \delta_1\ \delta_2]$ and the mean estimated polynomials $A(z^{-1})$, $B_1(z^{-1})$ and $B_2(z^{-1})$ with mean skin temperature T_{skm} and mean underwear temperature uwT_{air} as model inputs, showing the mean model identification criteria R_2^T, YIC and RMSE for all the test subjects under wet condition.

	n	m	m	δ_1	δ_2	$A(z^{-1})$	$B_1(z^{-1})$	$B_2(z^{-1})$	R_T^2	YIC	RMSE
Mean ± Standard deviation	**1**	**1**	**1**	**4** ± 2	**6** ± 3	**0.21** ± 0.32	**0.052** ± 4.2×10^{-3}	**0.0030** ± 0.023	**0.95** ± 0.05	**-5.63** ± 3.25	**0.022** ± 1.85×10^{-3}

The results showed that a higher time delays ($\delta_1\ \delta_2$) in case of wet condition in comparison to dry conditions. The used SRIV algorithm is suitable to be run in closed-loop for online model estimation. One of the main advantages of the above mentioned approach is that it is automatically accommodating with the multiple-time delays that were observed with the various identified TF models for different test subjects.

4 CONCLUSIONS

Eight healthy males (mean ± standard deviation: age 22.8 ±1.3 years, height 1.81 ±0.06m, body surface area 1.94 ±0.11 m^2) are used as test subjects to perform the designed experiments. The experimental protocol involved step-changes of exercise on treadmill inside to simulate step-changes in activity level. Metabolic heat production was calculated based on the continuously measured O_2 consumption and CO_2 production. Rectal temperature are continuously measured. Mean clothing layer and mean skin temperatures were calculated based on measured temperatures from eight body locations. The experiments were performed with the subjects wearing dry and wet underwear layer and constant ventilation rate. First order MISO DTF models were found to be the most suitable (i.e., R_2^T= 0.96±0.2 and YIC= -9.20 ±4.2) to describe the dynamic response of the rectal temperature of the tested subjects under both dry and wet conditions. Paring the mean skin temperature T_{skm}, with the mean underwear temperature uwT_{air} once and with the metabolic heat production Q_{met} another, was found the most suitable model inputs to the MISO DTF. It is suggested to use the mean skin temperature T_{skm} with the mean underwear temperature uwT_{air} for online prediction of the rectal temperature and further model-based controlling of the body thermal comfort.

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