INDOOR AIR CLIMATE CONTROL

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ABSTRACT

An on-line mathematical approach was used to model the spatio-temporal temperature distribution in an imperfectly mixed forced ventilated room. A second order model proved to be a sufficiently good description of the temperature dynamics ($R^2 = 0.929$) of the system. Furthermore, it was possible to fully understand the physical meaning of the second order model structure.
Using this model, a Model Based Predictive (MBPC) climate controller was developed for a Single Input Single Output (SISO) system. The controller was able to follow the mean temperature of 4 points, and to robustly react to a random local disturbance.
The results presented in this paper show that Model Based Predictive Control using Data-Based Mechanistic modeling can be of significant importance in the development of a new generation of climate controllers.

KEYWORDS

imperfectly mixed fluids, uniformity, data-based mechanistic modeling, identification, model based predictive control

INTRODUCTION

In everyday life, one is constantly confronted with imperfectly mixed fluids. Every fluid in nature, whether it is a gas or a liquid, is imperfectly mixed and is characterised by spatio-temporal gradients of heat and mass variables. In ventilated airspaces (domestic buildings, office rooms, supermarkets, transport systems, medical facilities, …) and in agricultural and industrial process rooms (greenhouses, animal houses, chemical vessels, bio-reactors, …) it is desirable to control the spatio-temporal heat and mass distribution in the imperfectly mixed fluid in order to achieve optimum process quality (production results, comfort, …) with a minimum use of energy.

In many of these applications one strives to achieve a spatially homogeneous distribution of heat and mass. For example, in egg incubators spatial gradients about the optimum breeding temperature of 37.5 - 37.8 °C must be avoided to guarantee a spatially uniform embryo development and quality (Zhang, Q. *et al.*, 1992; French, N.A., 1994).

There are also many applications in which one strives to achieve a spatially heterogeneous heat and mass distribution. For example, in ventilated rooms which are not entirely occupied, it is important to achieve good air quality and thermal comfort in the occupied zone, without providing too large amounts of fresh air and heat in those parts of the room where it is not required (Sandberg, M., 1981).

This paper has the intention to present the application of Data-Based Mechanistic (DBM) modelling for controlling the temperature dynamics in a forced ventilated room. Most existing models for control purposes can be translated into two main groups: mechanistic or white box models and Data-Based or black box models. Mechanistic models describe a system's behaviour based on a priori known physical, mechanical, chemical and/or biological mechanisms underlying the functioning of the system (France J. *et al.*, 1984; Baldwin R.L., 1995). When applied to the problem of controlling the spatio-temporal heat and mass distribution in an indoor environment such as ventilated airspaces, agricultural and industrial process rooms, these mechanistic models (e.g. Computational Fluid Dynamics (CFD) models) are restrictive owing to their exceptional complexity. One must be aware of the fact that a mechanistic model, such as CFD models, constitutes the culmination of a large number of assumptions and approximations (Bruce J.M. *et al.*, 1979; Oltjen J.W. *et al.*, 1987; Kettlewell, P.J. *et al.*, 1992) resulting in a model that is a valuable tool for design purposes, but lacks the necessary accuracy to be appropriate for control purposes.

Opposite to 'mechanistic or white box modellers' who feel that computer-based models should reflect the perceived complexity of the process, there are scientists with a more 'black box' turn of mind who favor 'data-based' procedures. In the data-based modelling approach, the model structure is inferred and the model parameters are estimated by reference to experimental data using more objective, statistically based methods (e.g. (Aerts J.-M. *et al.*, 2000)). This technique can deliver accurate models but the complete lack of physical insight is a major drawback in control purposes, making it an application specific model.

However, there is an intermediate type of model, that exploits the availability of time-series data in statistical terms but which overtly attempts to produce models which have a physical (mechanistic) meaning. As a hybrid between the extremes of mechanistic and data-based modelling, these so called data-based mechanistic (or grey box) models provide a physically meaningful description of the dominant internal dynamics of heat and mass transfer in the imperfectly mixed fluid (Berckmans, D. *et al.*, 1992a; Berckmans, D. *et al.*, 1992a; Barnett V *et al.*, 1993; Janssens, K. *et al.*, 2004; Janssens, K. *et al.*, 2004). The strength of these models is that they combine the advantages of both mechanistic or white box (generality, knowledge based) and data-based or black box (compact, accurate) models and is, therefore, an ideal basis for model-based control system design (Camacho, E. *et al.*, 1999; Maciejowski, J.M., 2002). In the present paper, the DBM approach to modelling is applied to the problem of modelling imperfect mixing in the forced ventilation of buildings.

MATERIALS AND METHODS

Test installation

The laboratory test room, represented in figure 1, is a mechanically ventilated room with a length of 3 m, a height of 2 m and a width of 1.5 m. It has a slot inlet (1 in figure 1) in the left sidewall just beneath the ceiling and an asymmetrically positioned, circular air outlet (2 in figure 1) in the right sidewall just above the floor. The volume of air in the test room (vol_{room}) is 9 m^3. An enveloping chamber of length 4 m, width 2.5 m and height 3 m (6 in figure 1) is built around the test room to reduce disturbing effects of varying laboratory conditions (fluctuating temperature, opening doors, …). The volume of the buffering interspace or buffer zone is 21 m^3. The test room and the enveloping chamber are both constructed of transparent plexiglass through which the airflow pattern can be observed during flow visualization experiments.

A mechanical ventilation system enables an accurate control of the ventilation rate in the range 70 - 420 m^3/h and this with an accuracy of 6 m^3/h. A heat exchanger and a moisture conditioning unit are provided in the supply air duct to regulate the temperature and moisture content of the inflowing air. A series of five aluminium heat sinks (4 in figure 1), in which a semi conductor heat source is used and a shallow hot water reservoir (3 in figure 1) is located at the floor of the test room to simulate the heat and moisture production of the occupant(s).

To measure the spatio-temporal temperature distribution in the test chamber, 36 calibrated type T thermocouples are located in a 3-D measuring grid (5 in figure 1) covering a large part of the room. The temperature sensors are located in two vertical xy-planes: a ‘front sensor plane’ (0.375 m from the front wall) and a ‘rear sensor plane’ (0.375 m from the back wall). Thermocouples are further located in the slotted air inlet, in the exhaust outlet, in the buffer zone and in the laboratory hall. The accuracy of the thermocouples is 0.1 °C and the time constant is less than 3 seconds. An intelligent measurement and data collection unit with programmable measurement speed is used for the data acquisition with a sampling rate of 10 s for 36 thermocouple channels. A more detailed description of the laboratory test room is given in literature (Berckmans, D. *et al.*, 1992b; Janssens, K. *et al.*, 2000).

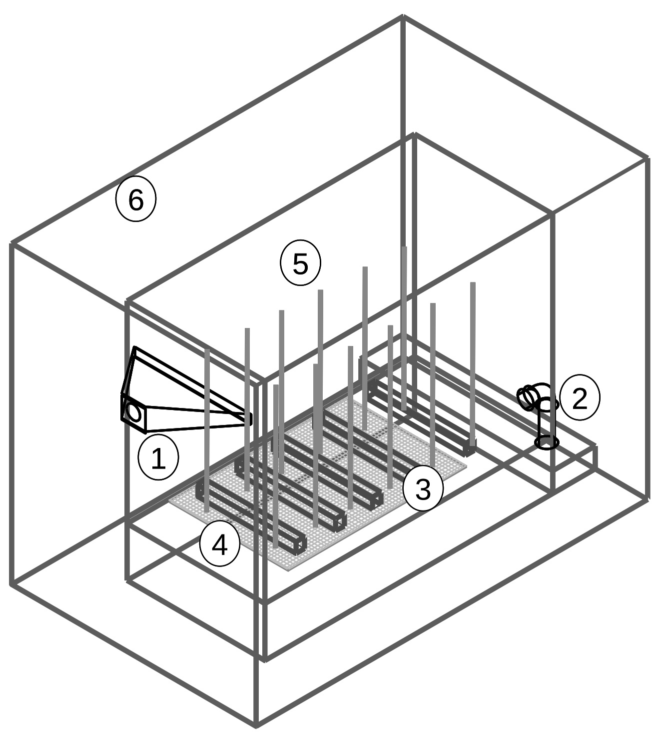

Figure 1: Laboratory test chamber: 1**.** air inlet, 2. air outlet, 3. aluminium conductor heat sink, 4. shallow hot water reservoir, 5. 3-D sensor grid, 6. envelope chamber or buffer zone

Optimization of uniformity

Since in many biological processes one strives to achieve a maximal uniformity of micro-environmental variables to ensure a homogenous product quality, an objective criterium is needed to quantify spatio-temporal uniformity. Moreover, it should quantify the uniformity of e.g. the temperature distribution measured in a three dimensional grid of temperature sensors in the whole installation. Therefore, to measure the variability of the temperature, the standard deviation of the spatial temperature measurements was used.

As pointed out in the introduction, it is very important in many processes to strive to achieve a perfectly mixed airspace with a uniform three-dimensional temperature distribution. Spatial temperature gradients which exceed an acceptable gradient, which is process depending (e.g. in the baking process of Integrated Circuits it is 10°C at 800°C, in the incubation process of chicken eggs it is 0.3°C at 37.8°C), have a negative effect on the quality and efficiency of the process.

The extend to which a process in which heat, moisture and gas production sources are present becomes perfectly mixed, is complex and depends on the air flow pattern (Barber, E.M. *et al.*, 1982; Barber, E.M. *et al.*, 1984). The air flow pattern in a ventilated room is primarily determined by the momentum and trajectory of the air jet and its mixing with the indoor air (Li, Z.H. *et al.*, 1993). The trajectory of an air jet depends on the inlet type and its proximity to the ceiling (1974) and on the ratio of the thermal buoyancy to the inertial forces (Koestel, A., 1955). It is clear that the ventilation rate of the fresh air has a crucial influence on the air flow pattern.

Data-based mechanistic model

In DBM models, the model structure is first identified using objective methods of time series analysis based on a given, general class of time series model (here linear, continuous-time transfer functions (TF) or the equivalent ordinary differential equations). But the resulting model is only considered fully acceptable if, in addition to explaining the data well, it also provides a description that has relevance to the physical reality of the system under study.

Identification of a reduced-order, linear model

The ability to estimate parameters represents only one side of the model identification problem. Equally important is the problem of objective model order identification. This involves the identification of the best choice of orders of the numerator and denominator polynomials together with the time delay. The parameters of a TF model may be estimated using various methods of identification and estimation (Ljung, L. *et al.*, 1983; Young, P.C., 1984; Norton, J.P., 1986; Ljung, L., 1987). However, most of these methods are based on discrete-time TF models and not on their continuous-time model equivalents, which impedes the interpretation of the model in physically meaningful terms. Although Least Squares (LS) is one of the most commonly used model estimation algorithms, the estimated model parameters become asymptotically biased away from their true values in the presence of measurement or disturbance noise (Young, P.C., 1984). The more complex Simplified Refined Instrumental Variable (SRIV) algorithm developed by Young (Young, P.C., 1984), uses the Instrumental Variable (IV) approach coupled with special adaptive prefiltering to avoid this bias and to achieve good estimation performance. The SRIV structure identification criterion has been proven very successful in practical applications (Young, P.C. *et al.*, 1979; Young, P.C. *et al.*, 1980; Wang, C.L. *et al.*, 1988; Quanten, S. *et al.*, 2003). A continuous-time TF model for a single-input single output (SISO) system has the following general form:

$$y(t) = \frac{B(s)}{A(s)} u(t-\tau) + \xi(t) \tag{1}$$

where: s is the time derivative operator, i.e. $s = d/dt$; y(t) is the noisy measured output; $u(t)$ is the model input; τ is the time delay; $\xi(t)$ is additive noise, assumed to be a zero mean, serially uncorrelated sequence of random variables with variance σ^2 accounting for measurement noise, modelling errors and effects of unmeasured inputs to the process; and finally, *A(s)* and *B(s)* are polynomials in the s operator of the following form:

$$A(s) = s^n + a_1 s^{n-1} + ... + a_n \tag{2}$$

$$B(s) = b_0 s^m + b_1 s^{m-1} + ... + b_m \tag{3}$$

where $m \leq n$; $a_1, a_2, \ldots, a_n$ and $b_0, b_1, \ldots, b_m$ are the TF denominator and numerator parameters respectively.

RESULTS AND DISCUSSION

Static experiments

In the described laboratory test chamber, experiments was conducted to examine the effect of the ventilation rate on the spatial temperature homogeneity, while keeping the average temperature inside the ventilated chamber constant at 23°C. For different ventilation rates (120, 160, 200, 240 and 300 m³/h) the 3-D temperature distribution was measured in steady state regime. The internal heat and moisture production during the experiments were respectively 300 W and 0.5 l H_2O/h. From the measured 3-D temperature distribution in the experiments the uniformity of the temperature distribution was quantified as the standard deviation of the 36 temperature measurements for different levels of the ventilation rate, which is shown in figure 2.

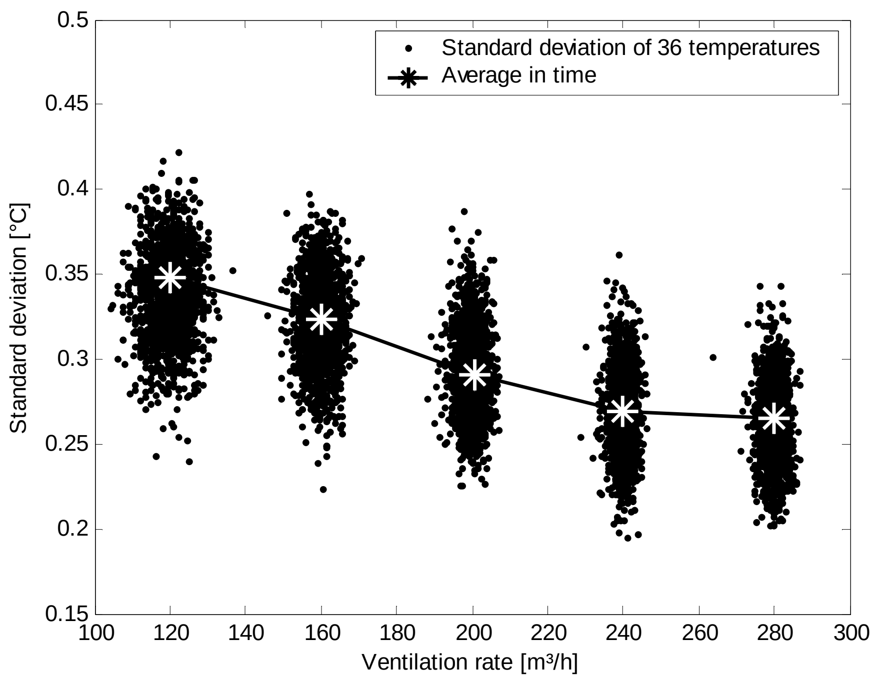

Figure 2: The effect of the ventilation rate on standard deviation of the 36 temperature readings

It is clear from figure 2 that increasing the ventilation rate from 120 to 280 m³/h (or by 133.3%) decreases the standard deviation by 23.9 %. It can be concluded that a ventilation rate of 280 m³/h gives the maximal spatial uniformity. However, increasing the production efficiency is a trade off between energy consumption and product quantity and quality. The decrease in the standard deviation due to an increase of the ventilation level from 240 to 280 m³/h (or by 16.6 %) is only 1.6 %, and would only increase the energy consumption and not optimise the uniformity of the 3-D temperature distribution. Therefore, the optimal ventilation rate that reduces the variability of the three-dimensional temperature distribution (0.27 °C) in an energy efficient way is 240 m³/h.

Identification of a reduced-order linear model

When a set of usable input-output time-series data is generated, a reduced order, linear model can be estimated to describe the data in a sufficiently accurate way for control purposes. An experiment has been carried out with a step increase in air supply temperature. In this experiment, an initial working point was selected, with the initial supply temperature set at 14.7°C for 25 min in order to establish steady airflow conditions before the required step supply air temperature change was introduced (figure 3). In order to identify and model the temperature dynamics in the test chamber, it would be preferable to perform experiments in which the supply air temperature is changed sharply in a 'sufficiently exciting' manner (Young, P.C., 1984).

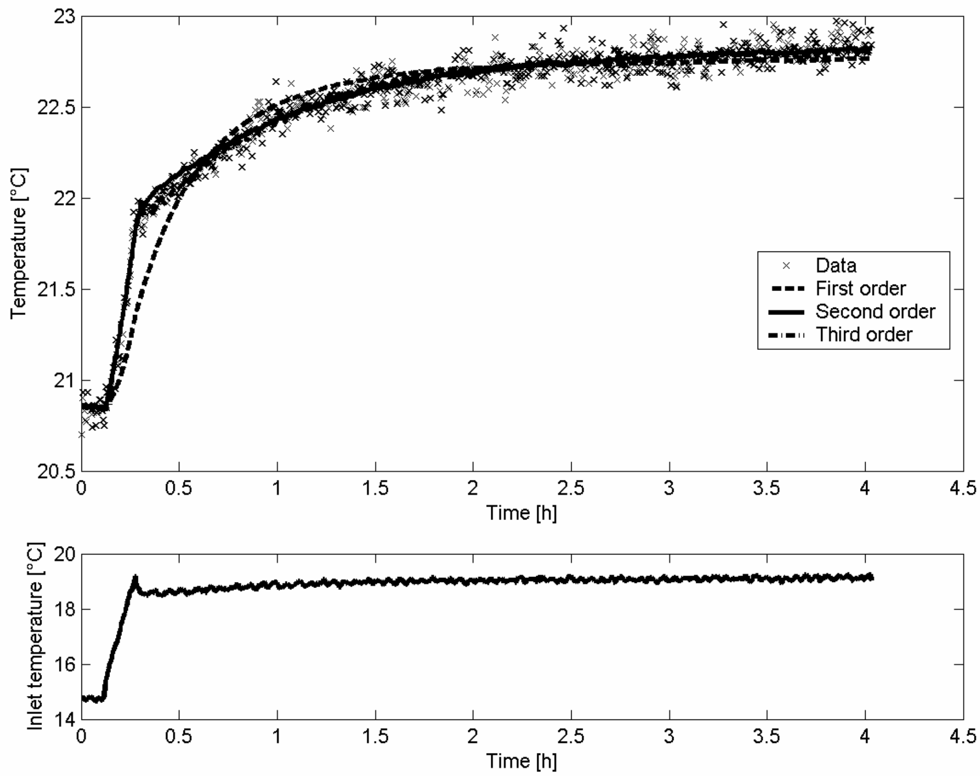

Figure 3: The output of a first order, second order and third order TF model compared with the measured temperature response at sensor position 15

In the present application, a second-order model proves to be a sufficiently accurate description of the temperature dynamics of the system according (figure 3) to the three basic principles of the SRIV algorithm: minimal number of parameters, high reliability of the parameters estimation and high accuracy of the model to proceed with the development of the model-based climate controller, as long as the model provides a physical meaningful description of the temperature dynamics (table 1). When applied to all 36 sensor positions, the second order model describes the data with an average R_t^2 of 0.929 and an average YIC-value of -7.64.

TABLE 1
The model parameter estimates with associated relative standard error, the YIC value and the coefficient of determination R^2_T of a first, second and third order continuous-time TF model for sensor position 15

order of TF	parameter estimates	relative standard error [%]	RT² [-]	YIC value [-]
[1 1 0]	a_1 = 0.010	ξ (a_1)= 0.66	0.961	-12,656
	b_0 = 0.004	ξ (b_0)= 0.61		
[2 2 10]	a_1 = 0.060	ξ (a_1)= 1.58	0.981	-10,048
	a_2 = 0.000	ξ (a_2)= 3.13		
	b_0 = 0.016	ξ (b_0)= 1.13		
	b_1 = 0.000	ξ (b_1)= 3.05		
[3 3 9]	a_1 = 0.749	ξ (a_1)= 8.10	0.982	-1,134
	a_2 = 0.460	ξ (a_2)= 14.18		
	a_3 = 0.002	ξ (a_3)= 13.10		
	b_0 = 0.010	ξ (b_0)= 423.47		
	b_1 = 0.106	ξ (b_1)= 13.98		
	b_2 = 0.001	ξ (b_2)= 13.13		

Data-based mechanistic model

The DBM approach represents the imperfectly mixed fluid in a process room by a number of well mixed zones (WMZ) which are defined around the nodes of a sensor grid. A well mixed zone is a zone of improved mixing with a certain volume wherein acceptably low spatial gradients occur. The value of these acceptable gradients and consequently the number of the WMZ's are determined by the application itself.
These WMZ's exist in every imperfectly mixed fluid. A schematic representation of a WMZ in a process room with fluid flow rate V (m^3/s) and with internal production of heat is given in figure 4.

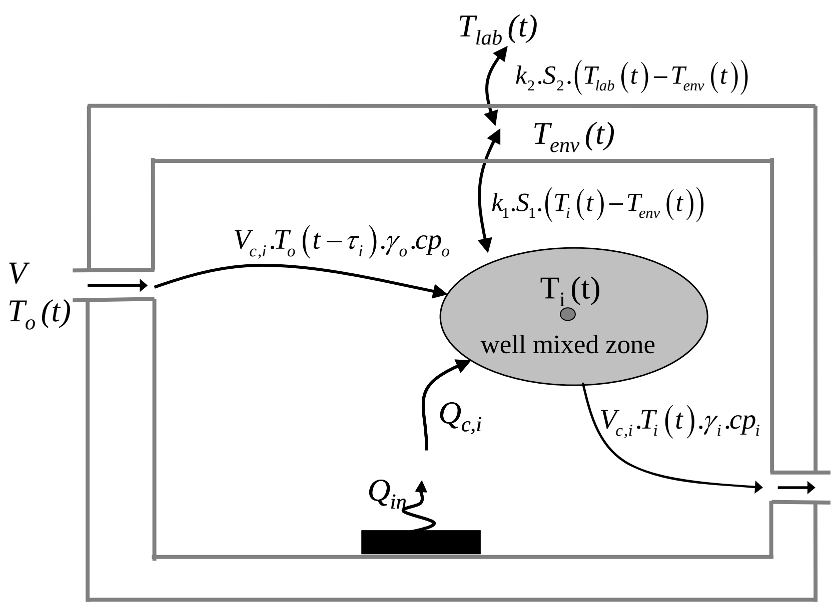

Figure 4: *Schematic representation of the WMZ concept.*

To describe the dynamic behaviour of temperature in the considered n WMZ's, standard heat transfer theory can be applied. In case of a constant ventilation rate, a linear, first-order differential equation can be formulated as:

$$\frac{dT_i(t).vol_i.\gamma_i.cp_i}{dt} = V_{c,i}.T_o(t-\tau_i).\gamma_o.cp_o - V_{c,i}.T_i(t).\gamma_i.cp_i + Q_{c,i} + k_1.S_1.\left(T_{env}(t) - T_i(t)\right) \tag{4}$$

$$\frac{dT_{env}(t).vol_{env}.\gamma_{env}.cp_{env}}{dt} = k_1.S_1.\left(T_i(t) - T_{env}(t)\right) + k_2.S_2.\left(T_{lab}(t) - T_{env}(t)\right) \tag{5}$$

where t is the time (s), τ_i is the advective time delay or travel time of the fresh supply air before it enters WMZ i (s); T_i is the temperature in the WMZ i (ºC); T_o is the supply air temperature (ºC); T_{env} is the temperature of the stagnant air in the enveloping zone (ºC); T_{lab} is the temperature in the outside laboratory remaining approximately constant throughout the experiments (ºC); vol_i is the volume of the WMZ i (m^3); vol_{env} is the volume of the enveloping zone (m^3); $V_{c,i}$ is the part of the ventilation rate entering WMZ i (m^3); $Q_{c,i}$ is the part of the total heat production in the room entering the WMZ i (Watt); k_1 and S_1 are the total heat transfer coefficient (Watt/m^2.°C) and the surface area of heat exchange (m^2) between the WMZ i and the enveloping zone; k_2 and S_2 are the total heat transfer coefficient (Watt/m^2.°C) and the surface area of heat exchange (m^2) between the enveloping zone and the laboratory; γ_i and cl_i are the density (kg/m^3) and the heat capacity (J/kg.°C) of the air in WMZ i; γ_0 and cl_0 are the density (kg/m^3) and the heat capacity (J/kg.°C) of the supply air.

The enveloping zone consists of a volume of air between the central chamber walls and the envelope chamber walls (6 in figure 7). There is no mass exchange between the air inside this buffer zone and the air in the central chamber, but heat is exchanged between the air in the buffer zone and the air in the central chamber.
In contrast to the zonal and nodal models in literature (Dalicieux, P. *et al.*, 1992; Li, Y. *et al.*, 1992), the different WMZ's are here considered as decoupled or non-interactive zones. Since the air inlet conditions are responsible for the thermal characteristics of the zone, the model only creates a link between the inlet and individual zones.

Since every living organism in a bio-process needs an adequate amount of oxygen rich fresh air, the focus on the WMZ model concept is to model the movement of fresh air to a particular zone. This is established by using local fresh air flow rate. The local fresh air flow rate is the air flow rate with the same temperature like the incoming air at the inlet that would have created the aggregate effect of the convective flux interaction with the neighbouring zones on the well mixed zone in consideration. This is a very useful assumption, because it creates a direct relationship between individual zones without the need for modelling zonal interactions. When considering non-interactive WMZ's, the spatio-temporal model is also less complex and it is an excellent basis for control purposes. The assumption results in n models (the response of each WMZ to changes in the inlet conditions is described by a single model, resulting in n 1^{st} order models for n WMZ's that can be used for controlling the conditions in the n well-mixed zones each time only using the air inlet conditions.

The advective time delay τ_i in equation (4) is a function of location, i.e., zones which are in the main jet has smaller advective time delay than zones in recirculation zone. In other words, it shows the time elapsed before a zone feels the change in temperature at the inlet.

Under steady state conditions, simplifying these equations and gives:

$$\frac{dt_i(t)}{dt} = \beta_i \cdot t_o(t-\tau) + K_1 \cdot t_{env}(t) - \alpha_1 \cdot t_i(t) \tag{6}$$

$$\frac{dt_{env}(t)}{dt} = K_3 \cdot t_i(t) - (K_3 + K_2) \cdot t_{env}(t) \tag{7}$$

where,

$$\begin{cases} \beta_i = \dfrac{V_{c,i}}{vol_i} \\ K_i = \dfrac{k_1 \cdot S_1}{vol_i \cdot \gamma_i \cdot cp_i} \\ \alpha_i = \dfrac{V_c}{vol_i} + \dfrac{k_1 \cdot S_1}{vol_i \cdot \gamma_i \cdot cp_i} = \beta_i + K_i \\ K_2 = \dfrac{k_2 \cdot S_2}{vol_{env} \cdot \gamma_{env} \cdot cp_{env}} \\ K_3 = \dfrac{k_1 \cdot S_1}{vol_{env} \cdot \gamma_{env} \cdot cp_{env}} \end{cases}$$

Converting (6) and (7) into the frequency domain using the Laplace operator and combining these transfer functions, we obtain the following second order, continuous-time transfer function model for the central chamber – envelope zone system:

$$t_i(t) = \frac{b_0 s + b_1}{s^2 + a_1 s + a_2} t_0(t - \tau) \tag{8}$$

where,

$$\begin{cases} b_0 = \beta_i \\ b_1 = \beta_i \cdot (K_2 + K_3) \\ a_1 = \alpha_i + (K_2 + K_3) \\ a_2 = (K_2 + K_3) \cdot \alpha_i - (\alpha_i - \beta_i) \cdot K_3 \end{cases}$$

It has been shown that the parameter β_i (s^{-1}) in equation (13) has a physical meaning (Janssens, K. *et al.*, 2004): it is the local refreshment frequency or the local outside air change rate in the WMZ.
The well mixed zone concept, that results in the formulation of the DBM model, and the associated heat balance differential equation can be applied to each of the spatially distributed monitoring positions in the test room.

The DBM model and classical heat transfer theory

It is clear from the relationships between the parameters in the TF model (8) and the equivalent parameters in the estimated TF model, that the classical heat transfer coefficients are not uniquely 'identifiable' from the experimental data. On the other hand, the heat transfer dynamics of the chamber are completely specified by the DBM parameters, which can be interpreted as specific combinations of these classical parameters. Consequently, this DBM model represents an alternative approach to modelling the system in physically meaningful, albeit not the normal, classical terms. And the model, in this identifiable form, is entirely adequate for both understanding the heat transfer dynamics of the chamber and designing a ventilation control system. It provides, in other words, an alternative way of presenting heat transfer theory within the context of imperfectly mixed flow processes, such as those encountered in real forced ventilation systems.

Parameter contour plots

Figure 5 shows the spatial contours of the parameter β_i (s^{-1}) in the front and the rear sensor plane of the test installation at a ventilation rate of 240 m³/h. The front sensor plane is the vertical xy-plane of the test chamber which consists of the temperature sensors 4, 5, 6, 10, 11, 12, 16, 17, 18, 22, 23, 24, 28, 29, 30, 34, 35 and 36 and which lies at a z-distance of 0.375 m from the front wall of the chamber (see figure 1). The rear sensor plane consists of the sensors 1, 2, 3, 7, 8, 9, 13, 14, 15, 19, 20, 21, 25, 26, 27, 31, 32 and 33 and lies at a z-distance of 0.375 m from the back wall of the chamber (see figure 1). The lower sensors in both sensor planes lie at a height of 0.8 m above the floor, the upper sensors lie 0.4 m beneath the ceiling, the left sensors are positioned 0.4 m from the inlet wall and the right sensors are positioned 0.6 m from the outlet wall.

Further, the contour plots relate well to the air flow pattern, which is presented in figure 6. At high ventilation rates, the incoming fresh air rapidly moves across the top of the chamber, hits the right sidewall and then descends towards the exit at the lower right, where some of the airflow recirculates in a clockwise direction. A decrease in the air freshness in the direction of the air flow is quite noticeable from the contours of the local volumetric concentration of fresh air flow rate β_i.

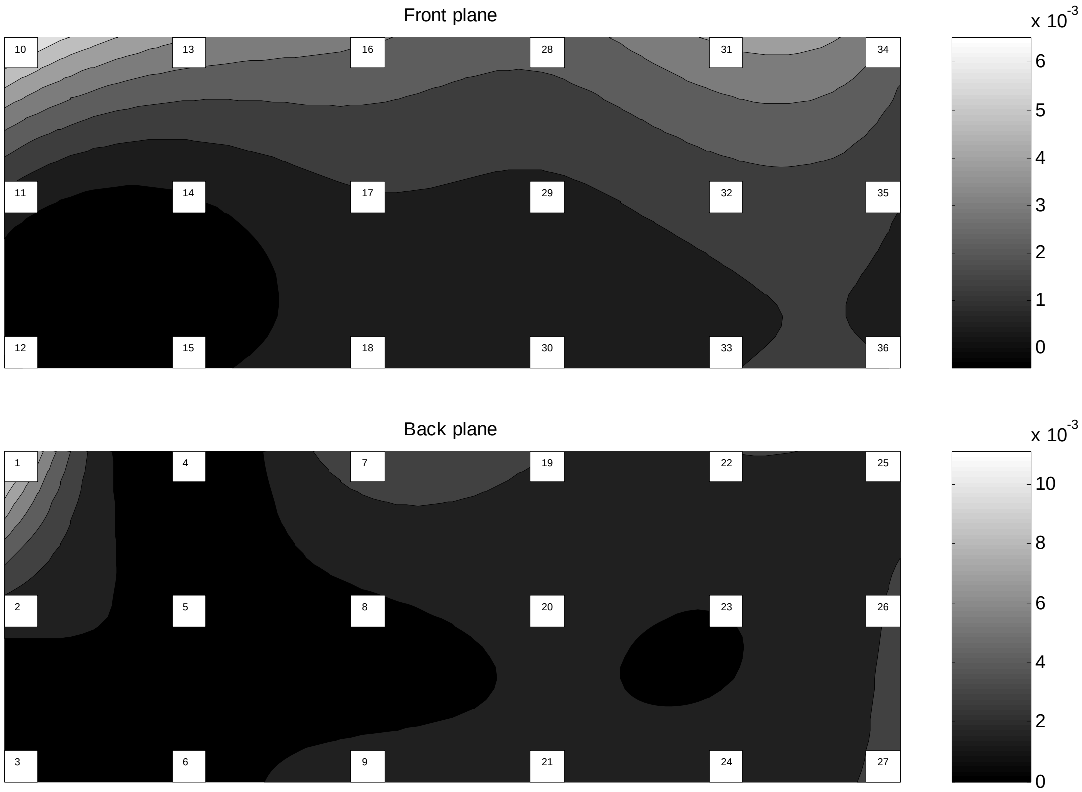

Figure 5: Spatial contour plots of parameter β_1 (s^{-1})


Figure 6: The visualised air flow pattern at 240 m³/h

Development of a model based control system

For achieving the objective of making an introduction in the development of a new generation of climate controllers, the Model Based Predictive Control (MBPC) approach is used, which has been introduced by Richalet et al. (Richalet, J. *et al.*, 1978) and Cutler and Ramaker (Cutler, C.R. *et al.*, 1980) in the late seventies. MBPC involves the computation of a sequence of imminent control moves such that the predicted behaviour of the process over a certain horizon is as close as possible to the reference trajectory (usually defined by the user) and subject to a given constraint. The theoretical background of the control algorithm is described in more detail in literature by Clarke et al. (Clarke, D.W. *et al.*, 1987a; Clarke, D.W. *et al.*, 1987b) and Garcia et al. (Garcia, C.E. *et al.*, 1989).

MBPC has proved to be a very successful controller design strategy, both in theory and practice (Van den Boom, T.J.J., 1996). The provided high performance controllers are readily applicable to high-order and multivariable processes. MBPC are known as quite robust to disturbances and to uncertainties in the model parameters, which might originate from environmental conditions that are not included in the model.

It is important to investigate to what extent the control system is able to facilitate an optimal control of the spatial temperature distribution in the considered ventilation test room, allowing different control objectives to be realized (e.g. spatial homogeneity, spatial heterogeneity, tracking of reference trajectories at positions of interest,…). Also, aspects like the robustness of the control system to disturbances and tracking capability of the reference trajectory need to be checked.

The last stage in this approach involves the evaluation of the MBPC controller. In most processes, it is the aim is to achieve a uniform temperature distribution through the volume of the process. This means that the difference or the variability of the levels of the air temperature in time and space need to be reduced. When having *n* points in space in between the temperature difference and variability need to be reduced, this can be accomplished by *n* independent control inputs that affect the temperature of these *n* points. However, in this test installation, there are not enough inputs to control e.g. 4 points independently, since there is only one air inlet of which air temperature and ventilation level can be changed. Therefore, the ventilation level at which the uniformity is optimal (240 m³/h) is chosen to evaluate a MBPC of the average temperature of 4 points in space: two sensors in the front plane (13 and 15) and two sensors in the rear plane (22 and 24). The TF

describing the average temperature response of these sensor positions to changes in temperature of the supply air temperature is calculated by combining the TF's of the four sensor positions in series and dividing by 4 (equation (9)).
The controller behaviour is evaluated on a simulation basis and by performing a control experiment. In the present simulation and experiment, a sampling rate of 10 seconds is used and the control actions are subjected to hard constraints with maximum and minimum inlet temperature limits of 20 °C and 9 °C respectively. The allowable dynamic raise and drop in inlet temperature is set to 0.011 °C and 0.025 per 10 seconds respectively.

$$t_i\left(t\right)=\frac{b_0s^7+b_1s^6+b_2s^5+b_3s^4+b_4s^3+b_5s^2+b_6s+b_7}{s^8+a_1s^7+a_2s^6+a_3s^5+a_4s^4+a_5s^3+a_6s^2+a_7s+a_8}\cdot t_0\left(t\right)$$

$$\begin{array}{ll} b_0=0.09054 & a_1=1.177 \\ b_1=0.03285 & a_2=0.2038 \\ b_2=0.003071 & a_3=0.01278 \\ b_3=9.711\cdot 10^{-5} & a_4=0.0003111 \\ b_4=8.07\cdot 10^{-7} & a_5=2.205\cdot 10^{-6} \\ b_5=2.503\cdot 10^{-9} & a_6=6.057\cdot 10^{-9} \\ b_6=2.855\cdot 10^{-12} & a_7=6.266\cdot 10^{-12} \\ b_7=8.878\text{e}\cdot 10^{-16} & a_8=1.778\cdot 10^{-15} \end{array} \quad (9)$$

In the simulation, measurement noise with a standard deviation of 0.2 °C was added to the plant model. To assess the robustness of the controller, a constant input disturbance of 0.2 °C and an output disturbance which switches from -5 °C to 5 °C after 5 hours was simulated and the result is shown in figure 6. The prediction horizon was optimised to 150 samples and the control horizon was 1 sample. The controller demonstrates its robustness for disturbance effects by immediately responding at the inlet temperature profile as the disorder is detected. Consequently the disturbance effect is compensated and the output trajectory follows a path that brings the process output trajectory as close as possible to the desired reference trajectory of the system.

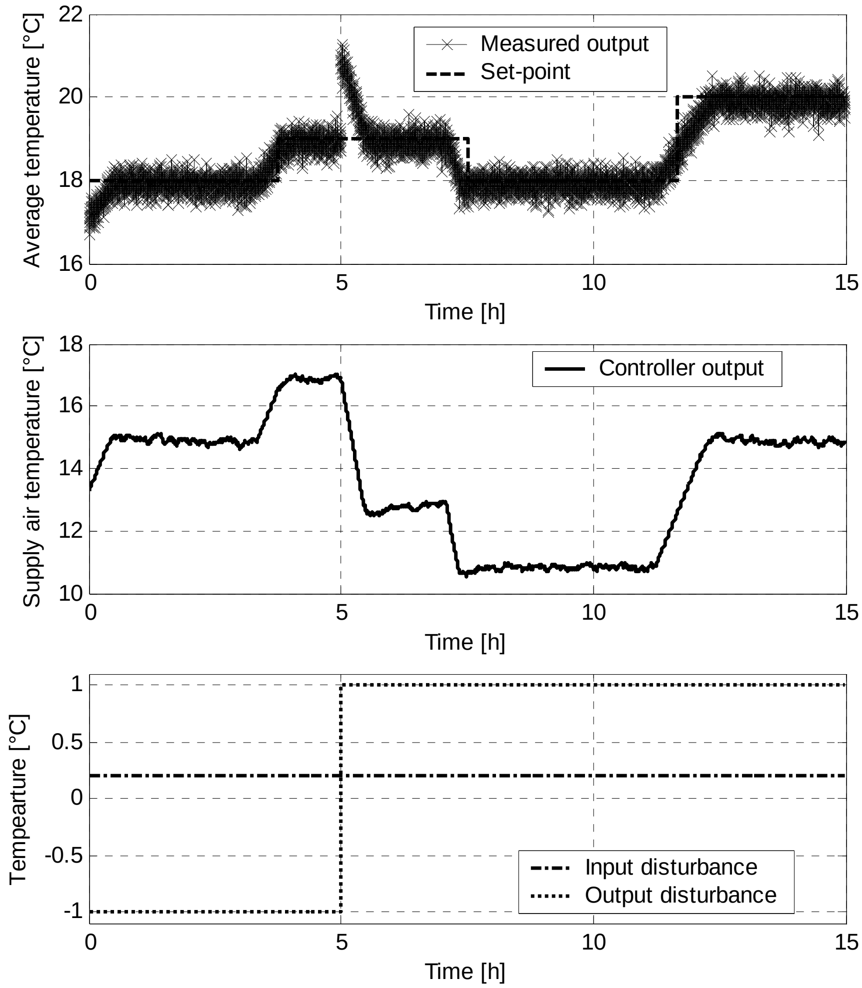

Figure 7: Simulation of the temperature response with measurement noise, input and output disturbances

The result of implementing this MBPC of the average temperature of 4 points in space is shown in figure 7. Also here, the controller demonstrates its robustness to possible modelling errors and measurement noise. The output trajectory follows the desired reference trajectory of the system. The average difference between the desired setpoint and the average measured temperature at the 4 points was 0.057 °C. The average variability of the temperature measurements was 0.27 °C, which is in the optimal level (figure 2).

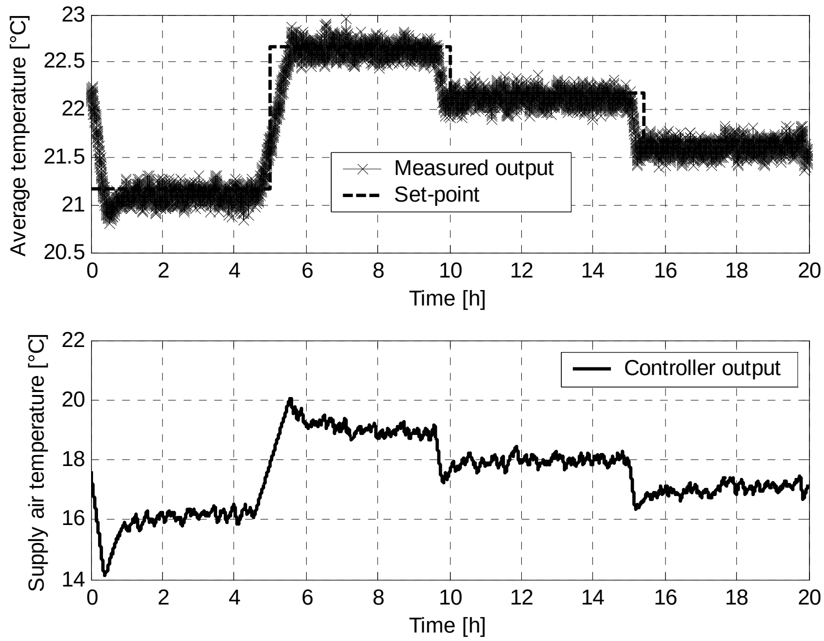

Figure 8: Temperature response as a result of the implemented MBPC

CONCLUSIONS

This paper has reported recent developments in the modelling and control of the forced ventilation in imperfectly mixed processes. It was shown that by using the ventilation rate, the variability of the air temperature distribution could be reduced to 0.27°C.

It has concentrated on the Data-Based Mechanistic (DBM) approach to modelling applied to data obtained from initial planned experiments in forced ventilated room. Here, in contrast to the normal hypothetico-deductive procedures that are most popular in this area of research, a minimally parameterised transfer function model is first identified and estimated from the experimental data without any prior assumptions about the physical nature of the system. Having objectively identified the dominant modes of dynamic behaviour in this manner, however, the model is then interpreted in physically meaningful terms, which have been shown to be in correspondence to the air flow pattern. This model not only explains the data very well (average $R_t^2 = 0.929$), with the minimum number of identifiable parameters, but it is also in a form that can provide the basis for the design of Model Based Predictive Control (MBPC) systems.

The MBPC behaviour to control the average temperature of 4 sensor positions was evaluated on simulation basis, where the robustness for disturbance effects is shown. Moreover, it has been shown by applying the developed MBPC to the forced ventilated room, that a reference trajectory of an average temperature could be achieved, while the variability of the air temperature distribution was still 0.27°C.

The results here presented can form the basis of the development of a MIMO climate controller. Based on the experiments performed and described in this paper, it becomes theoretically possible to control the three dimensional temperature distribution in ventilated processes. An even further extension can be achieved by including more input variables (like air flow direction, air flow pattern, opening of the air inlets,…) so that even more positions inside the car can be controller. This will enable the climate control system to achieve a spatially homogeneous or heterogeneous distribution of heat and mass. Future enhancements to climate controllers in ventilated spaces will include the integration of information from the central process part itself: the living organism.

All these innovations can sparkle off the development of a new generation of intelligent climate control systems, and increasing both optimal process quality (production results, comfort, …) with a minimum use of energy.

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