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Model Predictive Control of Climatic Chamber with On-off Actuators

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Abstract: This article presents modelling and control of a climatic chamber with on/off actuators. Controlled environmental variables in the chamber are temperature, relative humidity and illumination. The system is first decoupled by nonlinear transformation and a linear model is identified using subspace methods; further, a model predictive control strategy for processes with on/off actuators is presented. The controller incorporates set-point filtering to deliver smooth climate transitions. The control results from a real climatic chamber are attached.

Keywords: Climate control, Model predictive control, Temperature, Humidity

1. INTRODUCTION

Climatic chamber is a device that provides a desired climate irrespective to an outside environment. Climatic chambers are frequently used in biological research; nonetheless, they are also useful in material industry, electronic and mechanical testing and food production. The use of climate-controlled chambers in food production makes it possible to maintain high crop productivity and quality when outside air conditions are not favourable. In industrial testing the chamber repeatedly simulates extreme weather conditions and so the durability of materials/devices is tested. Climate control accuracy is crucial in every field of use of the climatic chamber.

A large amount of literature is available on greenhouse control which, despite a few differences, is equivalent to that of climatic chambers. Early control techniques of greenhouses used simple hysteresis control. Later, with an increase of computational power hysteresis control with heuristic laws arose (Caponetto and Fortuna, 1998; Xibilia et al., 2000) altogether with PID controllers. Owing to a heavy coupling between climatic variables, these techniques are not very successful in reference tracking and disturbance rejection unless they use excessive control authority. As a consequence, the control was either inaccurate or energy demanding, i.e. expensive. Optimal control strategies are later spotted in the greenhouse control, (Tawegoum et al., 2006) shows a performance of an Linear Quadratic Integral controller in tracking inside temperature while maintaining constant inside relative humidity. As computational power was further growing, predictive control strategies gained popularity. A pioneering work by (Dion et al., 1991) shows a successful application of a multiple-input multiple-output (MIMO) adaptive constrained predictive control to an environmental chamber. It also shows the big qualitative difference between PID and predictive control. All different variations of this concept emerged in the last ten years; greenhouse temperature control using feedback linearization and Model Predictive Control (MPC) is demonstrated in (Piñón et al., 2000, 2005) and it is compared to Non-linear MPC applied to the same problem. Example of greenhouse temperature control using Modified Extended Linearized Predictive Controller is given in (Ghoumari and Tantau, 2002). MPC strategy for MIMO system with delays is presented in (Cavalcante, 2010) altogether with its application to a temperature and humidity control of a neonatal incubator.

According to the European Energy Efficiency Plan 2020, the total consumption of electricity is planned to drop by 20% (European Commision, 2010). Energy efficient control techniques are one of the tools that have the potential to help to achieve this ecological goal.

Despite the amount of literature available on the subject no paper related to a model predictive control of a climatic chamber with on/off actuators had been found.

1.1 Climatic Chamber Description

Climatic chamber is composed of an isolated chamber, temperature control equipment, humidity control equipment and light emitting devices.

This paper focuses on deriving a control algorithm for one particular climatic chamber (Figure 1) developed by (Dostál, 1985) in years 1976-1985. The mayor improvement of the research held by (Dostál, 1985) on the climatic chamber was the separation of the heat-producing illumination from the growth chamber. He therefore saved vast amounts of energy which would otherwise be necessary for a removal of the heat from the chamber.

The climatic chamber in question has inner volume of approximately 1m^3, it is equipped with a heating rod, a compressor based cooling coil unit (CCU) for cooling and dehumidification and a humidifier. There are further four 250W gas tubes and ten fluorescent tubes present and a battery of fans devoted to stir the inside air.

Measured variables are: chamber air temperature T_i [°C], chamber air relative humidity ϕ_i [%], cooling coil evaporator temperature T_c [°C], laboratory temperature T_l [°C] and laboratory relative humidity ϕ_l [%].

Fig. 1. Climatic chamber by (Dostál, 1985)

The paper is organized as follows. A derivation of a climatic chamber model will be given in the section 2, control algorithm will be presented in the section 3 and results of simulations and application of the controller to the real chamber will be presented in the section 4. The paper is based on a preliminary work (Dostál, 2009, 2013).

2. CLIMATIC CHAMBER MODEL

In this part, the paper present how a dynamic model of the system suitable for control purposes was derived. It is known from psychrometric properties of air that air temperature (dry bulb) and relative humidity are strongly coupled. So the first observation done was not to model and control the system on the basis of temperature and relative humidity but to switch to the domain of temperature and absolute humidity that are physically decoupled. The psychrometric transformation is available in (Wilhelm, 1976; WMO, 2008; Buck, 1981; Dostál, 2013) and is generally denoted as

$$\varrho = \mathcal{P}(T, \phi) \tag{1}$$

where $\varrho\,[\mathrm{g/m^3}]$ is the resulting absolute humidity, $T\,[^\circ\mathrm{C}]$ is a measured dry bulb temperature, $\phi\,[\%]$ is a measured relative humidity. Absolute humidity of the chamber ϱ_i, the laboratory room ϱ_l as well as the absolute humidity reference signal ϱ_r and hysteresis h_ϱ are obtained this way.

State variables of the system are: chamber air temperature $T_i\,[^\circ\mathrm{C}]$, chamber air absolute humidity $\varrho_i\,[\mathrm{g/m^3}]$ and cooling coil unit evaporator temperature $T_c\,[^\circ\mathrm{C}]$.

Manipulated variables are: heating rod relay $u_h\,[0,1]$, cooling coil unit relay $u_c\,[0,1]$ and humidifier relay $u_m\,[0,1]$, where $[0,1]$ denotes that the variable is binary, i.e. it either has value 0 or 1.

Non-manipulated variables are: gas tube relay $u_g\,[0,1]$ and relay of the fans $u_f\,[0,1]$.

Disturbance variables are: laboratory air temperature $T_l\,[^\circ\mathrm{C}]$ and laboratory air absolute humidity $\varrho_l\,[\mathrm{g/m^3}]$.

The chamber air temperature is governed by the following equation

$$\begin{aligned} C\dot{T}_i(t) = {} & P_h u_h(t) + k_{mt} u_m(t) + \\ & + H_c(T_c(t) - T_i(t)) + P_f u_f(t) + \\ & + k_g u_g(t) + H_l(T_l(t) - T_i(t)) \end{aligned} \tag{2}$$

where $C\,[\mathrm{W/K}]$ is a heat capacity of the chamber, $P_h\,[\mathrm{W}]$ is a heating rod power, $k_{mt}\,[\mathrm{W}]$ is a latent heat of the water sprayed out by the humidifier, $H_c\,[\mathrm{W/K}]$ is a heat transfer coefficient of the cooling coil evaporator, $P_f\,[\mathrm{W}]$ is a power produced by the fans, $k_g\,[\mathrm{W}]$ sums an effect of the gas tubes onto the chamber air temperature (mainly radiative heat), $H_l\,[\mathrm{W/K}]$ is a heat transfer coefficient of heat losses to the laboratory room.

The chamber absolute humidity dynamics is driven by

$$\begin{aligned} V\dot{\varrho}_i(t) = {} & k_m u_m(t) + k_l(\varrho_l(t) - \varrho_i(t)) + \\ & + f(T_c, \varrho_i, u_h, u_f, t) \end{aligned} \tag{3}$$

where $V\,\left[\mathrm{m^3}\right]$ is a chamber volume, $k_m\,[\mathrm{g/s}]$ is a mass flow rate of the humidifier and $k_l\,\left[\mathrm{m^3/s}\right]$ is a volumetric flow rate of air leakage to the laboratory room and $f(T_c, \varrho_i, u_h, u_f, t)$ denotes a non-linear function of water phase changes occurring on the CCU evaporator surface (condensation, evaporation, freezing, melting, draining of a condensate).

The dynamics of the temperature of the CCU evaporator is denoted by

$$\begin{aligned} C_c\dot{T}_c(t) = {} & H_c(T_i(t) - T_c(t)) + P_c u_c(t) + \\ & + h(T_c, \varrho_i, u_h, u_f, t) \end{aligned} \tag{4}$$

where $C_c\,[\mathrm{W/K}]$ is a heat capacity of the evaporator, $P_c\,[W]$ is a power of the cooling coil unit and $h(T_c, \varrho_i, u_h, u_f, t)$ sums the effect of water phase changes on the evaporator surface.

Beside the condensation process, the dynamics is linear in all variables so a linear model was identified using subspace state-space system identification algorithm (4SID). The subspace identification algorithms are especially suitable for the problem because they deliver linear MIMO models, efficiently handle large data sets and the resulting model is optimized for multiple step predictions - useful for further use in MPC. More information on subspace identification methods is available in (Ljung, 1987; van Overschee and de Moor, 1996; Trnka, Pavel, 2007; Katayama, 2005).

The 4SID algorithms identify state space models that are in arbitrary basis. In order to have better insight to the identified dynamics, the obtained model was transformed such that the states and outputs were equal(i.e. $\mathbf{C} = \mathbf{I}_3$). The identified discrete state-space model is:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}_c\mathbf{u}(k) + \mathbf{B}_v\mathbf{v}(k) + \mathbf{B}_d\mathbf{d}(k) \tag{5}$$

$$\mathbf{y}(k) = \mathbf{C}\mathbf{x}(k) \tag{6}$$

where $\mathbf{x}(k) = \mathbf{x}(t_0 + nT_s)$ with T_s being the sampling period, t_0 an initial time and $n \in \mathbb{N}$, $\mathbf{x}(k) = [T_i(k), \varrho_i(k), T_c(k)]^T$ is the state vector, $\mathbf{y}(k) = [T_i(k), \varrho_i(k), T_c(k)]^T$ is the output vector, $\mathbf{u}(k) = [u_h(k), u_c(k), u_m(k)]^T$ is the input vector (manipulated variables), $\mathbf{v}(k) = [u_g(k), u_f(k)]^T$ is the vector of non-manipulated variables, $\mathbf{d}(k) = [T_l(k), \varrho_l(k)]^T$ is the vector of disturbances, $\mathbf{A} \in \mathbb{R}^{3\times3}$, $\mathbf{B}_c \in \mathbb{R}^{3\times3}$, $\mathbf{B}_v \in \mathbb{R}^{3\times2}$, $\mathbf{B}_d \in \mathbb{R}^{3\times2}$, $\mathbf{C} = \mathbf{I}_3$.

The model's normalized root-mean-square measure of the goodness of fit (NRMSE) of a 20-step-ahead prediction

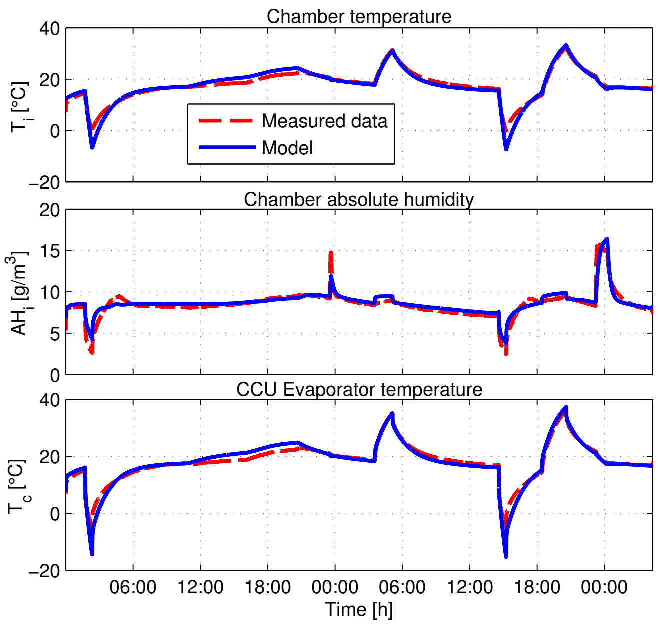

Fig. 2. Climatic chamber model (4SID): verification data fit

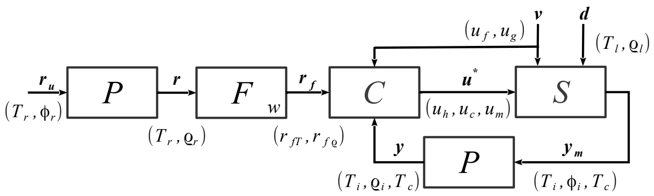

Fig. 3. Control scheme: P is the psychrometric conversion block, F the reference filter, C the MPC controller, S the climatic chamber system.

is $[96.4\%, 71.7\%, 96.2\%]^T$ respectively for the outputs $\mathbf{y}$ on identification data. On verification data, the model scores the NRMSE goodness of fit $[72.5\%, 62.4\%, 72.9\%]^T$. The measured and estimated output trajectories for the verification data are plotted in figure 2. The misclassification probability of the model is MSE $= 0.1055$, the final prediction error is FPE$=3.099 \cdot 10^{-4}$.

3. CONTROL ALGORITHM

Climatic chambers historically used mainly 3-state bang-bang controllers (Dostál, 1985). Such control techniques, although being astonishingly simple to implement, do have drawbacks. Between the mayor ones stands that control precision only comes with high switching rates of actuators. Another big disadvantage is a high probability of a self-induced oscillations of the system.

This paper focuses on deriving energy efficient and actuator gentle (low number of actuator alternations) control algorithm for the climatic chamber (fig. 1). The control process is schematically depicted in figure 3. The first block F is a reference filter. A user-specified daily climate profile which typically is a set of day and night temperature and humidity levels is there smoothed in order to provide gradual transitions between the day and night climates. The reference filter is described in the section 3.1. The climatic chamber user also specifies an allowable hysteresis of the temperature and humidity with respect to the reference trajectory (h_T, h_ϱ). Model predictive control algorithm for the climatic chamber is presented in section 3.2.

3.1 Reference Smoothing

To ensure smooth climate transitions which are favourable for plant vegetation, it is important to limit a rate of change of the climate. A linear transition between two different climate settings is achieved by a centred moving average filter

$$\mathbf{r}_f(k) = \frac{1}{w} \sum_{i=-\mathrm{w}/2}^{\mathrm{w}/2} \mathbf{r}(k+i) \tag{7}$$

where w [min.] is a length of the transition (given by user), $\mathbf{r}(k) = [T_r(k), \varrho_r(k)]$ is the chamber temperature and humidity set-point at time k (given by user) and $\mathbf{r}_f(k) = [r_{f,T}(k), r_{f,\varrho}(k)]^T$ is a vector of filtered reference trajectories.

3.2 Model Predictive Controller

The control algorithm is one of the general class of optimal control strategies, namely a Model Predictive Control (MPC) method. The main idea is to optimize future control inputs over a finite prediction horizon in order to minimize given criteria (cost functional), while complying to given constraints. Every sampling period only the first calculated input is applied and the algorithm is repeated again. The described algorithm is also called receding horizon control. For a current system state $\mathbf{x}_k = \mathbf{x}(k)$, the control input is determined by the solution of

$$\mathbf{u}_k^\star = [1\ 0\ \cdots\ 0] \left(\arg \min_{[\mathbf{u}_k, \ldots, \mathbf{u}_{k+M}]^T} J(\mathbf{x}_k, \mathbf{u}_{k-1}) \right) \tag{8}$$

subject to system, control and optimization constraints (described further in the text). $\mathbf{u}_k^\star$ is the first control input from the calculated set of optimal control inputs $\{\mathbf{u}_k^\star, \ldots, \mathbf{u}_{k+M}^\star\}$ for a control horizon of length M.

The control objective is expressed in a discrete-time linear quadratic functional

$$J(\mathbf{x}_k, \mathbf{u}_{k-1}) = J_y(k) + J_u(k) + J_{du}(k) + J_e(k) \tag{9}$$

$$J_y(k) = \sum_{i=0}^{N} \left\| \mathbf{y}_{k+i|k} - \mathbf{z}_{i|k} \right\|_{\mathbf{Q}}^2 \tag{10}$$

$$J_u(k) = \sum_{i=0}^{M} \left\| \mathbf{u}_{k+i|k} \right\|_{\mathbf{R}}^2 \tag{11}$$

$$J_{du}(k) = \sum_{i=0}^{M} \left\| \mathbf{u}_{k+i|k} - \mathbf{u}_{k+i-1|k} \right\|_{\mathbf{S}}^2 \tag{12}$$

$$J_e(k) = \left\| \mathbf{x}_{k+N|k} \right\|_{\mathbf{P}}^2 \tag{13}$$

where N is a prediction horizon length, $M \leq N$ is the control horizon length, $J_y(k)$ is a cost functional of reference tracking, $\mathbf{y}_{k+i|k} = [T_i(k+i|k), \varrho_i(k+i|k)]^T$ is a vector of predicted outputs, $\mathbf{z}_{i|k} = [z_T(i|k), z_\varrho(i|k)]^T$ is a vector of soft-constraint variables (described further in the text), $J_u(k)$ is a cost of energy consumption, $\mathbf{u}_{k+i|k} = [u_h(k+i|k), u_c(k+i|k), u_m(k+i|k)]^T$ is a vector of future control inputs, $J_{du}(k)$ is a cost of input switching. Note that the actual control input $\mathbf{u}_{k-1|k} = \mathbf{u}^\star_{k-1}$ is also considered, $\|\cdot\|^2_{(\cdot)}$ denotes a square of an Euclidean vector norm weighted over a specified matrix $\left(\|\mathbf{x}\|^2_{\mathbf{W}} = \mathbf{x}^T\mathbf{W}\mathbf{x}\right)$ and $\mathbf{Q} = \mathbf{Q}^T \succeq 0$, $\mathbf{R} = \mathbf{R}^T \succ 0$, $\mathbf{S} = \mathbf{S}^T \succeq 0$. The term $J_e(k)$ ensures a closed-loop stability (Mayne et al., 2000), where $\mathbf{P} \succ 0$ is a solution of an algebraic Riccati equation for an unconstrained problem ($(\mathbf{A}, \mathbf{B})$ is stable).

The minimization of the criterion $J(\mathbf{x}_k, \mathbf{u}_{k-1})$ is subject to the system model

$$\mathbf{x}(k+1+i) = \mathbf{A}\mathbf{x}(k+i) + \mathbf{B}_c\mathbf{u}(k+i) + +\mathbf{B}_v\mathbf{v}(k+i) + \mathbf{B}_d\mathbf{d}(k) \quad (14)$$

$$\mathbf{y}(k+i) = \mathbf{C}\mathbf{x}(k+i) \quad (15)$$

where $i = 0, \ldots, N$, the control inputs (manipulated variables) are all on/off

$$\mathbf{u}_{k+i|k} \in \{0,1\}^3, \; i = 0, \ldots, M \quad (16)$$

and constant for $i > M$

$$\mathbf{u}_{k+M+j|k} = \mathbf{u}_{k+M|k}, \; j = 1, \ldots, N-M \quad (17)$$

The minimization of the criterion is also subject to the state hard-constraints

$$\mathbf{x}_{min} \leq \mathbf{x}_{k+i|k} \leq \mathbf{x}_{max}, \; i = 0, \ldots, N \quad (18)$$

where $\mathbf{x}_{min} = [0, 0, -30]^T$, $\mathbf{x}_{max} = [50, 50, 50]^T$ are minimal and maximal state bounds of the state $\mathbf{x}_{k+i|k} = [T_i(k+i|k), \varrho_i(k+i|k), T_c(k+i|k)]^T$. The minimization further subjects to the reference tracking constraints

$$\mathbf{r}_f(k+i) - \mathbf{h} \leq \mathbf{z}(i|k) \leq \mathbf{r}_f(k+i) + \mathbf{h}, \; i = 0, \ldots, N \quad (19)$$

where $\mathbf{r}_f(k+i) = [r_{f,T}(k+i), r_{f,\varrho}(k+i)]^T$ is a vector of future filtered references, $\mathbf{h} = [h_T, h_\varrho]^T$ is a vector of the temperature and absolute humidity hystereses and $\mathbf{z}(i|k) = [z_T(i|k), \; z_\varrho(i|k)]^T$ is a vector of soft-constraint variables for temperature and absolute humidity respectively. The soft-constraint variables secure that no penalization occurs while the output $\mathbf{y}_{k+i|k}$ is within the allowed reference interval $\langle \mathbf{r}_f(k+i) - \mathbf{h}, \, \mathbf{r}_f(k+i) + \mathbf{h} \rangle$. Note that control algorithm uses known future states of the non-manipulated variables $\mathbf{v}(k+i)$ (given by daily climate reference). The disturbance vector $\mathbf{d}(k)$ (laboratory air state) is not known into the future and is assumed constant over the whole prediction horizon.

Due to the binary nature of the manipulated variables, the optimization problem becomes a mixed-integer QP problem which is not convex, but it is still solvable in a reasonable time (Bemporad and Morari, 1999).

4. SIMULATION AND EXPERIMENTAL RESULTS

Simulations were performed in Matlab® using Yalmip (Löfberg, 2004) and IBM CPLEX® solver. Calculation of one optimal input set for a sampling time $T_s = 30$s and a prediction and control horizon $N = M = 20$ was $0.2 - 3$ s using Intel® Pentium Dual-Core 2.4 GHz.

The reference penalization matrix $\mathbf{Q}$ was set to relatively high values compared to the other penalization matrices in order to ensure good reference tracking. The matrix was set to

$$\mathbf{Q} = \begin{bmatrix} 1200 & 0 \\ 0 & 100 \end{bmatrix} \quad (20)$$

meaning, that while the temperature reference should be followed tightly, the relative humidity reference tracking is not enforced hardly (short-term violations during climate transitions allowed). The energy preservation matrix $\mathbf{R}$ is determined by the power consumption of individual actuators, in the particular a wattage of each actuator:

$$\mathbf{R} = \kappa \begin{bmatrix} 360 & 0 & 0 \\ 0 & 1035 & 0 \\ 0 & 0 & 23 \end{bmatrix} \quad (21)$$

where $\kappa = 4,3 \cdot 10^{-3}$ is a relative importance factor. The matrix $\mathbf{S}$ contains penalization of input changes along the control horizon including the change from a current input state. The heavier an input change is penalized the less switching is expected. The setting

$$\mathbf{S} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 400 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (22)$$

formulates the fact that while a switching of the heating rod is arbitrary - there is no mechanical part in the heating rod, a switching of the cooling coil unit should as low as possible - due to the compressor present in the cooling circuit. The humidifier switching is fairly unimportant; there is an A/C motor in the humidifier. The final state penalization matrix $\mathbf{P}$, whenever positive definite, assures a closed-loop stability of the system with the MPC controller and it was chosen to be

$$\mathbf{P} = 0.01\mathbf{I}_3 \quad (23)$$

The reference trajectory for a pepper plant in a prior to blooming period (Dostál, 1985) was chosen for a controller evaluation. It has the following daily pattern: $\mathbf{r}_u(5\text{am} - 21\text{pm}) = [25°\text{C}, 55\%]^T$, $\mathbf{r}_u(21\text{pm} - 5\text{am}) = [15°\text{C}, 63\%]^T$, $h_T = 0.5°\text{C}$ and $h_\phi = 7\%$. The reference smoothing was set to $w = 120$ min. and winter conditions were assumed $T_l = 10°\text{C}$, $\phi_l = 85\%$.

4.1 Simulation Results

Figure 4 depicts the simulation results of a particular section of a day-time climate maintenance and a night-setback climate transition. The controller successfully steers the system within given reference bounds. An energy consumption for the simulation setup was calculated to be $2.4\,{}^{\text{kWh}}/_{\text{day}}$. The energy consumption of the system with a bang-bang controller is very similar (Dostál, 2013) - both controllers managed to track the reference trajectory well. However, the MPC controller switched on the CCU just 3 times during the entire day whilst the bang-bang controller 12 times. Assuming summer conditions ($T_l = 20 - 25°C, \phi_l = 50 - 60\%$) where there is a higher cooling demand, the CCU switching reduction by the MPC is more evident - the MPC switched on the CCU 51 times while the bang-bang controller 211 times; with temperature hysteresis $\pm 0.5°$C the MPC turns the CCU on about 4 times less then a bang-bang controller. The benefit of the

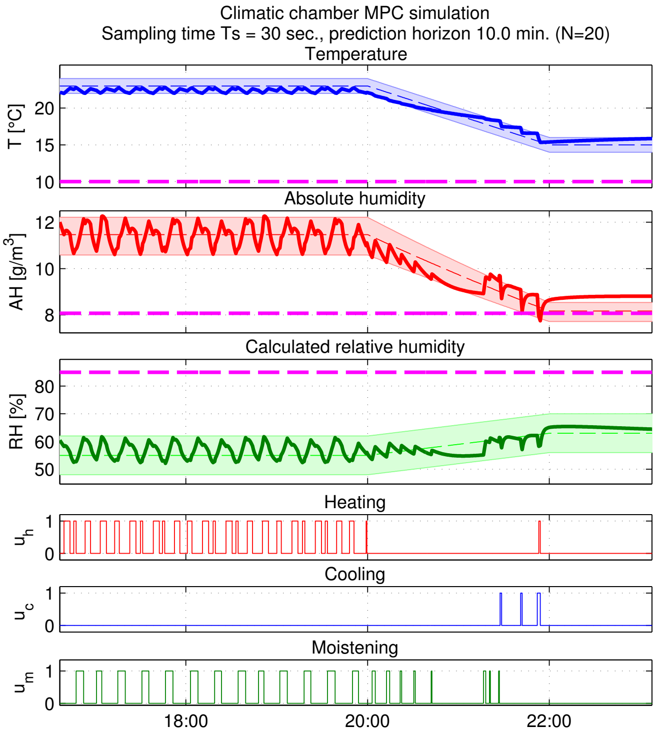

Fig. 4. Simulation results of the MPC strategy applied to the climatic chamber: chamber (bold continuous line), laboratory room (bold dashed line), reference funnel (colored area)

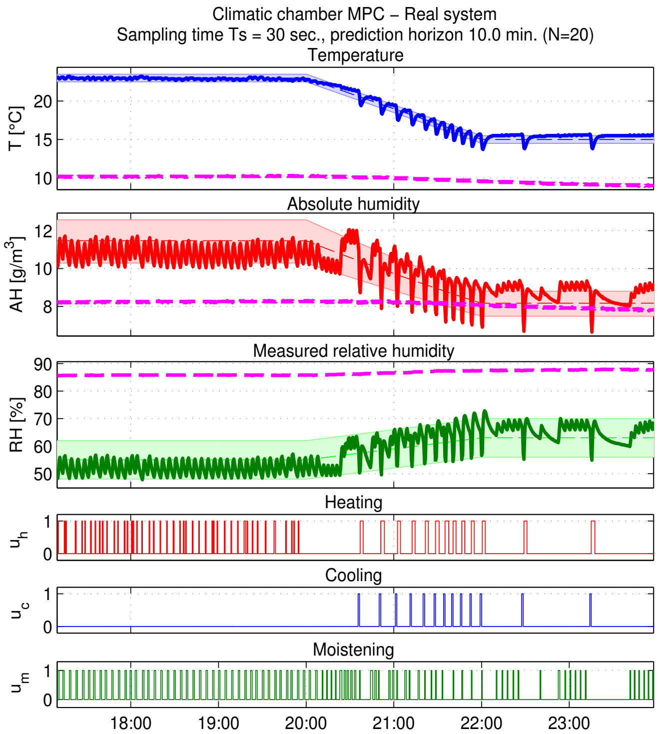

Fig. 5. MPC results on the real climatic chamber: chamber (bold continuous line), laboratory room (bold dashed line), reference funnel (colored area)

MPC in the reduction of the CCU switching is immense when the temperature hysteresis is tighter.

Simulation of the controller also show that the climatic chamber is under-actuated for humidity reduction. The only way to remove humidity from the chamber is by water vapour condensation on the CCU evaporator. The condensate drains from the evaporator through a sink in the chamber's bottom. The mass flow rate of dehumidification is low compared to a mass flow rate through air leaks; the chamber with the actual actuator set is in the long term not able to maintain the absolute humidity in the chamber lower then the absolute humidity in the laboratory room.

4.2 Experimental Results

An experiment similar to that performed in the simulation was done with the real climatic unit; temperature and relative humidity in the laboratory room during the experiment was also similar to those in the simulation. The results, presented in figure 5, show that the controller successfully controls the temperature and humidity through the desired reference trajectory. The controller used the CCU as few as possible; however, one can notice in the graph that during temperature descent every time the CCU is used, it is followed by the use of heating rod. It shall be said that this was caused by a hardware minimum switch-on safety interval of 1min. imposed on the CCU; the MPC in order to recover from the prolonged use the CCU must turn on the heater to keep the temperature in the reference funnel. Energy consumption of the device was calculated to be 2.7 $^{\mathrm{kWh}}/_{\mathrm{day}}$ with illumination not included.

5. CONCLUSION

The objective of this paper was to design a controller for a climatic chamber with on/off actuators such that a reference climate is followed, energy is efficiently used and such that the controller uses as least input changes as possible. A linear model using subspace identification method was derived. The model shows a good fit to the verification data and it is shown it sufficiently captures the system dynamics for the control purposes. The simulation of the proposed MPC algorithm show the controller is able to track the reference trajectory correctly and that it minimizes the switching of the cooling coil unit (the most likely component to be wear out by an excessive switching due to the presence of a compressor). Although the energy consumption of the system with the proposed control is similar to that with a bang-bang controller, the MPC drastically reduces the CCU switching. The main benefit of the MPC, aside from the capability of controlling both the temperature and humidity, is the minimization of the actuator switching. The maintenance costs of the climatic chamber are expected to drop and an audible noise of the operation of the chamber also decreased significantly.

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