Open and Closed Loop Simulation for Predictive Control of Buildings

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Abstract— **The paper presents the system modeling, controller design and numerical simulation results for thermal energy management of a real office building. Focus is set on an *efficient* and unitary approach which leads from detailed civil engineering specifications of the building elements to compact and effective models which are suitable for control. A modular semi-automated approach in used in order to derive the discrete state-space representation of the system model. This combines the key thermal dynamics of the constructions with a modular list of thermal loads and losses, defined as external heat fluxes. A balanced trade-off is thus achieved between model accuracy and complexity through a compact and effective representation of the plant dynamics. The control strategy is based on a predictive controller which evolves an optimized system input vector, in a closed loop. Paths for occupant feedback integration into a single framework, by using human-in-the-loop models via disturbance channels are also discussed.**

I. INTRODUCTION

As, through a long term global trend towards urbanization, people spend more of their time within buildings, these have become a key driver of energy demand. Efficient building energy management thus becomes a key engineering challenge which produces both environmental and economic impact. This happens by reducing air, water and ground pollution while lowering overall costs. Also, by optimizing electrical and thermal loads, integration with next generation grids is facilitated through better matching and real-time response of consumption patterns with intermittent generation from renewable energy sources.

Control methods for building HVAC (Heating Ventilation Air Conditioning) systems can be traced back to simple open-loop on-off control based on predefined schedules with optional weather compensation. A step forward is represented by local unidimensional PID loops at the thermal zone level, which can operate independently or in a coordinated fashion by means of a central controller. As modern building automation systems (BAS) technology has been deployed, especially in the case of new, energy efficient buildings, instrumentation by means of networked sensors and actuators with intelligent controller units has allowed more advanced approaches to building control. In the case of older buildings which are difficult and costly to refurbish, the application of wireless sensor and actuator networks (WSAN) has emerged [1]. One salient example of technique that can best leverage these types of dense instrumentation and connectivity is represented by model predictive control (MPC) which is a powerful tool for optimal multivariable control.

MPC relies on an iterative optimization routine which, based on an internal plant model, decides at each discrete sampling interval the control input to be applied to the real system. The main technique used is called receding horizon control which assumes the computation of a sequence of optimal control inputs, while applying only a subset of these to the plant. By acquiring, through measurements, the system state at each step, the loop is closed, new information is incorporated into the controller and the process is repeated [2]. Also the inclusion into the controller of contraints, related mainly to physical limitations or safety limits of the plant subsystems, and cost restrictions allows precise specification of the plant operational environment.

A critical challenge in developing feasible MPC controllers is the derivation of accurate yet computationally efficient models. These have to balance the need for exact description of the building construction characteristics and environment along with solving the optimization problem in due time. While system identification has been done, even at a large scale, this currently represents a niche application given the significant resources and the challenge of stimulating the building across longer periods of time and varying conditions that allow for representative models to be extracted [3]. As some of these approaches are available in the literature and complex tools exist that can provide fine grained thermal building modeling, for control purposes, an often used approach consists of an electrical circuit analogy. This assumes the description of the individual thermal zones, i.e. a homogenous constant-temperature volume of air, their mutual interaction and that with the outside world through resistive-capacitive (RC) equivalent networks. Depending on building destination, construction regulations and applicable norms and standards, also various types of HVAC systems have to be accounted for. These might use different mechanisms to deliver the required energy flux to the thermal zones, while relying on a different mix of primary energy sources: electricity, natural gas or renewables, for generation.

Main contribution of the work consists of system modeling and control for a reference multiple thermal zone building. We use an intermediary toolchain to obtain a (bi-)linear state space system representation around which the control strategy is designed and simulated. In our case, a two-stage air heating and cooling system is employed. It uses a primary

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AHU (Air Handling Unit) loop which cools the air to the minimum required temperature in the building and also handles the balance between ventilation and recirculation. The local supply of thermal energy is handled by VAV (Variable Air Volume) units, assigned to the individual thermal zones. These are intelligent units that, based on external inputs adjust dynamically the balance between the mass air flow and its temperature, heated through a local heating loop.

The rest of the paper is structured as follows. In Section 2 we briefly review the key recent contributions that define the context of our work. We describe the system modeling approach in Section 3 from both control and optimization perspective, along with the tools that enable the simulation results. These are highlighted in Section 4, for both open loop and closed loop scenarios, while detailing system specifications. Perspectives for future developments of ongoing work are discussed in Section 5.

II. STATE OF THE ART

The authors of [4] have detailed the derivation of *grey box* RC building models as alternative to conventional system identification. System parameters: capacitance and resistance values, are obtained by using the interior point algorithm to find local minima of the error function characterizing the model. Thermal control of an oven is done via a deterministic state-space controller. An increasing body of work has been dedicated to building energy modeling and control. An integrated top-level view is described in [5]. The system of systems definition encompasses both thermal and electrical subsystems and their bi-directional integration to/from the grid.

Large scale applications of MPC for these types of goals have been presented in [6] where the optimization is aimed at the central plant of a university campus. A predictive control strategy has also been developed for a shopping center [7]. The authors argue several extensions related to economic optimization and hybrid control, combining discrete and continuous signals. Several testing scenarios are carried out in order to compare the MPC approach to an on-off baseline strategy. These cover the variation of the supply water temperature, operating cost minimization up to renewable energy generation tracking.

An important tool that we leverage in our work is the Building Resistive Capacitive Modeling (BRCM) toolbox [8]. It provides a convenient mechanism of defining physical buildings along with a modular structure of including internal and external thermal gains and losses. Extensive results analysis has been provided in [9], where the authors describe their long term study on a full building. This uses both a floor heating system, individual zone-level radiators and a central AHU with heat recovery, baseline heating/cooling and ventilation. Another hardware feature is that additional control inputs are required for the external blinds systems, useful for adjusting the impact of solar gains. In our case a suitable module has to be defined to define the two-stage HVAC model defined in the previous section.

An important issue to consider is the, mildly nonlinear, bi- linear formulation that occurs in modeling most HVAC systems. This due to the expression of the heat flux as a product of mass airflow, heat capacity of air and temperature: $q = \dot{m}c\Delta T$. This links a control input: zone damper position (which determines $\dot{m}$) with a system state: supply temperature of the main AHU loop. In [10], sequential quadratic programming (SQP) is proposed as solution to mitigate this drawback. The method involves linearization at each step along with adding a convex quadratic term to the cost function that approximates the Hessian of the Lagrangian. A method for efficient computation is also described.

The current paper presents an alternative approach to our previous work which relied on identified multivariable models for the MPC formulation. The model of a single-zone home in a temperate climate has been used to compare PID and MPC controllers outcome in terms of energy efficiency and occupant comfort [11].

III. SYSTEM MODEL

Our reference high-level control loop is illustrated in Figure 1. The controller optimizes the manipulated variables in order to minimize the global cost function, subject to constraints. Cost and constraints can be either predefined or dynamically supplied at run time. The reference signal is the vector of zone temperature set-points. The modeling approach distiguishes between the building thermal dynamics, including zone interconnections, and modular heat fluxes. The latter are aggregated by a disturbance model within the main plant model. Disturbance signals include: internal gains due to occupancy and zone equipment, solar gains, heat exchanges with the exterior and the ground. An additional disturbance signal is added on the plant output to account for stochastic disturbances and uncertainity as for future integration of human-in-the-loop models. The loop is closed by updating the current state of the real plant at each sample time and feeding the information to the controller.

This approach is scalable to accomodate larger buildings in terms of number of states, inputs, constraints, etc., and the choice of sampling time is made given the desired optimization and control horizons and model complexity. Model order reduction strategies can also be employed while preserving internal structure and evaluating the differences. For the current approach, in preparation of a real deployment, we use the same model for both the MPC and the plant. However, robustness of the control strategy is specifically tested through model uncertainty within specific bounds.

The full discrete state space model of the building is listed below:

$$\begin{aligned} x[k+1] = Ax[k] + B_u u[k] + \sum_{i=1}^{n_u} B_{xui} x[k] u_i[k] + \\ + B_v v[k] + \sum_{i=1}^{n_v} B_{vui} v[k] u_i[k] + d[k] \end{aligned} \quad (1)$$

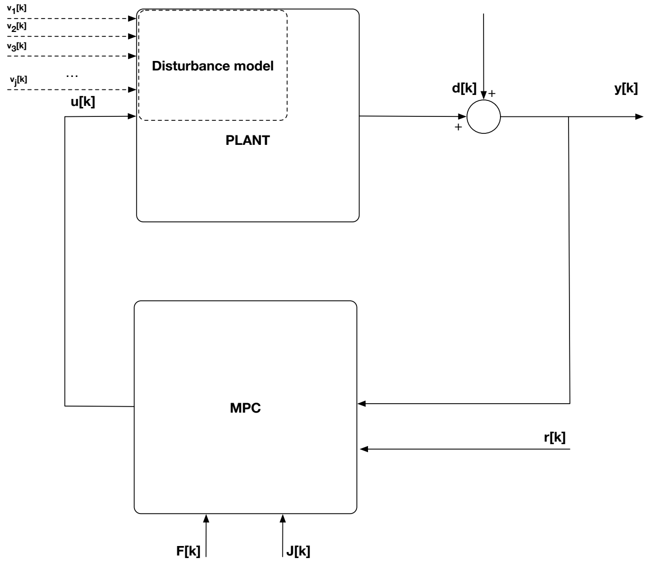

Fig. 1. System diagram

System states $x[k]$ are the temperatures for each of the zone and construction elements. The input vector u_k consists of the requested energy flow to each of the zones. In the case of the VAV boxes, it can either be a single value, achieved by the internal PID loop of the box or it can be split among two inputs: one for the damper position, regulating mass air flow, and one for the heating coil temperature, which in conjunction with the supply air temperature from the AHU, determines the temperature of the air entering the zone. In the former case, the bi-linear term $B_{xui}x[k]u_i[k]$ appears only in the AHU model [12] where the return air is mixed with fresh air for ventilation and passed through a temperature controlled cooling coil. The speed of the supply fan of the AHU is implicitly controlled by summing up the individual air flow requested by the zones.

The state-space discrete bilinear model representation is implemented by an alternative approach to building modeling and control using BRCM and Simulink. Detailed parametrization with constants in accordance to the physical system characteristics and restrictions and MPC cost and constraints tuning is carried out. The diagram in Figure 2 presents the high-level abstraction of using BRCM for two different types of building HVAC systems: the first one for a Swiss building and the second one for a building in Merced, California, with a hotter climate.

Concerning the MPC optimization problem, this aims at minimizing a cost function, subject to a series of constraints. Constraints can be either hard or soft, with an associated penalty factor imposed on breaking them. In particular related to building thermal control, the basic tradeoff is that between cost to the building operator to supply the heat/cooling load, implicitly depending on the energy source type and pricing schemes, and the occupant comfort. Constraints are linked to physical limitations of actuators and other mechanical components as well as the dynamics and stress incurred by too ample or too dense control inputs. There are also bounds on the flows of air and temperature values and differentials that can be achieved by the HVAC system. For occupant comfort, zone temperature and zone temperature variations are also bounded.

The typical objective function we are currently using is defined as follows:

$$J(z_k) \;=\; J_y(z_k) \,+\, J_u(z_k) \,+\, J_{\Delta u}(z_k) \,+\, J_\epsilon(z_k) \quad (2)$$

where the optimization routine aims at minimizing a (weighted) combination of the four terms, each corresponding to complementary control goals.

$J_y(z_k)$ emphasizes reference tracking:

$$J_y(z_k) = \sum_{j=1}^{n_y}\sum_{i=1}^{p}\Big\{\frac{w_{i,j}^y}{s_j^y}[r_j(k+i|k) - y_j(k+i|k)]\Big\}^2 \quad (3)$$

$J_u(z_k)$ accounts for control input level:

$$J_u(z_k) = \sum_{j=1}^{n_u}\sum_{i=0}^{p-1}\Big\{\frac{w_{i,j}^u}{s_j^u}[u_j(k+i|k) - u_{j,target}(k+i|k)]\Big\}^2 \quad (4)$$

$J_{\Delta u}(z_k)$ accounts for control input variation:

$$J_{\Delta u}(z_k) = \sum_{j=1}^{n_u}\sum_{i=0}^{p-1}\Big\{\frac{w_{i,j}^{\Delta u}}{s_j^u}[u_j(k+i|k) - u_{j,target}(k+i|k)]\Big\}^2 \quad (5)$$

$J_\epsilon(z_k)$ minimizes constraints violation in the case of soft constraints, without which the optimization problem might be unfeasible:

$$J_\epsilon(z_k) = \rho_\epsilon \epsilon_k^2 \quad (6)$$

z_k represents the quadratic programming solution. Adjusting the static or dynamic weights allows for fine tuning of the controller output for better guiding of the controlled plant. Further details regarding this particular cost function can be found in [13].

For the simulation case study we focus on an administrative building from our campus. A detailed Energy+ model is available for the whole building which richly specifies the construction elements, materials and other relevant information from a thermal and ventilation perspective. Out of the full model representation, we focus on a subset of nine thermal zones, grouped together in one area of the ground floor. Ventilation percentage requirements are set by applicable standards and relate to the occupancy level in each zone. Comfort is usually approximated by the Predicted Mean Vote (PMV) indicator ranged -3 to +3, with 0 indicating ideal individual thermal confort. The facilities building has the layout and orientation illustrated in Figure 3 and zone specifications in Table 1.

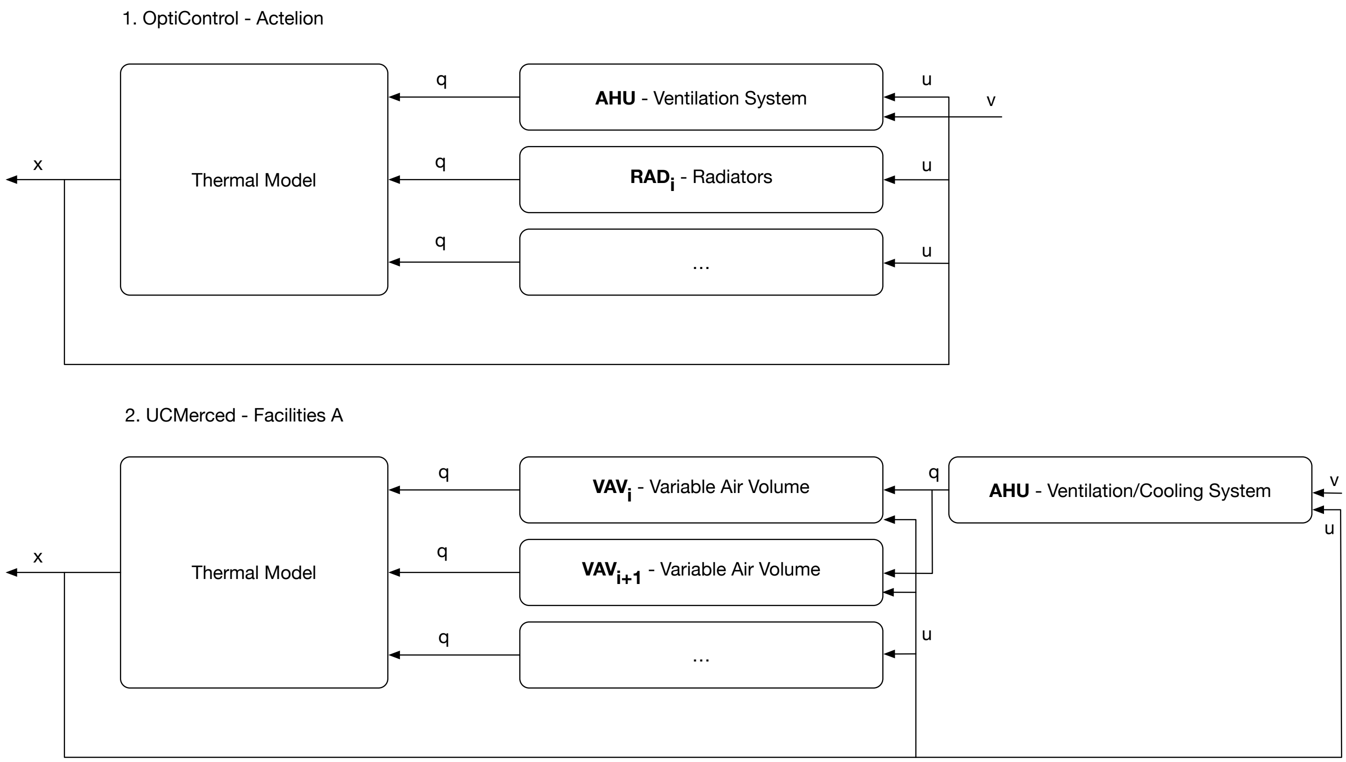

Fig. 2. Modular modeling concept using BRCM

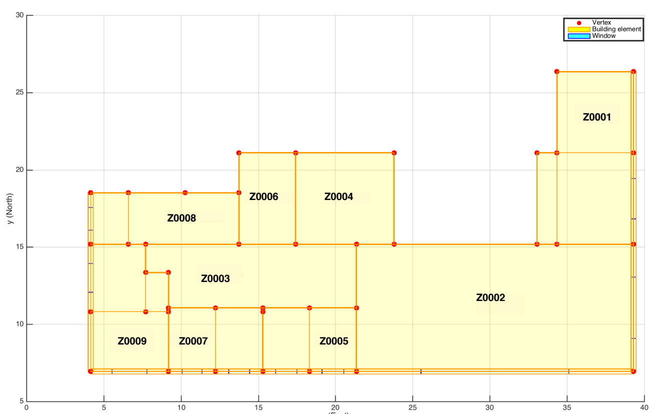

Fig. 3. Floor plan

TABLE I
ZONES

Thermal zone	sqm	Connected with
Zone 1	63	Z2
Zone 2	148	Z1, Z3
Zone 3	53	Z2, Z4, Z5, Z6
Zone 4	38	Z3, Z6
Zone 5	25	Z3, Z6, Z8
Zone 6	22	Z3, Z4, Z5, Z7
Zone 7	25	Z6
Zone 8	32	Z5
Zone 9	39	Z5

IV. RESULTS

We present next the numerical simulation results obtained in both open and closed loop testing scenarios. To obtain the discrete state space matrices of the system model we use the BRCM toolbox functionality that automates their generation from an existing Energy+ input data file. The current model of our campus building subset has: 211 states, 9 control inputs and 7 measured disturbances. States correspond to zone temperatures and temperatures of each construction element. By construction elements we refer to the walls, ceilings, floors and windows that make up the building. The number of the states is inherent to the building layout of the studied area. Control inputs are currently expressed by net energy flux to the thermal zone via the VAV units. For this applicative paper we have preserved the full model, without applying model reduction techniques, as to maintain the physical equivalence of the system states as temperature values. The modular approach of defining external heat fluxes which influence the core thermal model generates the following measured disturbances. These are defined and their influence on the state variables captures through a disturbance model matrix. The itemized list and data origin is shown below:

- Outside temperature T_{amb} - based on historical or forecast data from local weather stations (if available) or on-line weather services such as *wunderground* or *forecast.io*;
- Ground temperature T_{gnd} - currently a constant value accounting for heat exchange with the ground in the case of single-story or the ground floor of a building;
- Internal gains IG - account for occupancy and heating loads from electrical equipment in thermal zones; an

average 10W per m^2 has found suitable during the occupancy period 7-22;
- Solar radiation - measured solar radiation on N/S/E/W facades of the building; currently a weighted value based on global solar radiation data during the same time frame as the outside temperature;

The stimulation signals used for achieving the open loop response of the building are illustrated in Figure 4. The control inputs are simulated as staggered step signals of low amplitude in both positive and negative domains. We use an hourly sampling time and run the simulation for four days. Initial conditions are dynamicaly collected for the building automation server based on WebCtrl via a dedicated SMAP middleware server. This aggregates all building sensor and actuator status and provides a convenient http based interface for data variable access and adjustment.

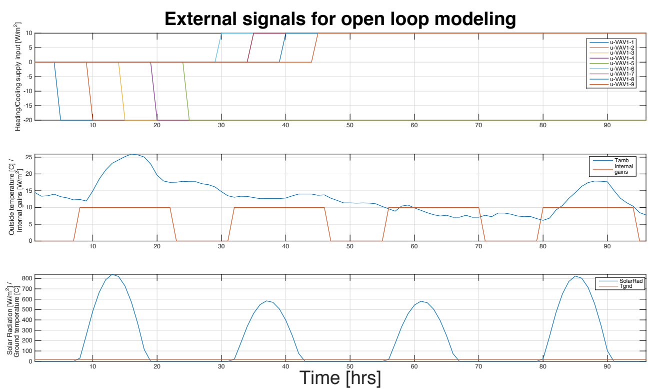

Fig. 4. Open loop stimulation

As first step we study the open loop thermal behaviour of the building, using the known stimulation signals. The idea was to model the signals as accurately as possible for our region, in a reference time period during November 2015. The simulation starts on day one at 00:00 and ends on day four at 24:00. Figure 5 shows the uncontrolled evolution of the zone temperatures over the reference. This behaviour models both external interaction of the building with the environment as well as interconnections among zones. The daily temperature swings are weighted by the room size, external walls and interconnections to neighboring zones.

Going forward we have designed an MPC controller based on the full discrete state space model of the building, including both the internal thermal dynamics and all external heat fluxes. The controller includes the 9 manipulated variables - control inputs and 7 measured disturbances - the known disturbance signals. The plant output is represented by the first 9 states - the zone level temperatures. A prediction horizon of 24 hours is used with a 3 hour control horizon, with the same one hour sampling period. With similar initial conditions, it can be seen how a significant negative overshoot occurs at the begining of the simulation, followed by good tracking of the reference signal. The reference has been defined based on a static occupancy schedule between 7-22, with corresponding set points at 22 and 17 degrees

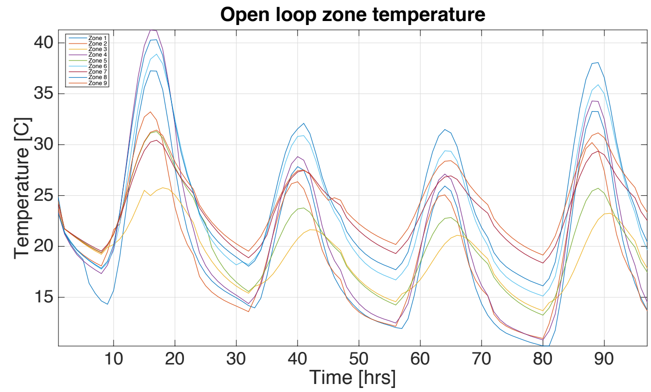

Fig. 5. Open loop system output

Celsius respectively. In the future this can be altered based on dynamic occupancy scheduled, sensed or inferred via dedicated subsystems. Figure 6 illustrates the closed loop behaviour of the plant.

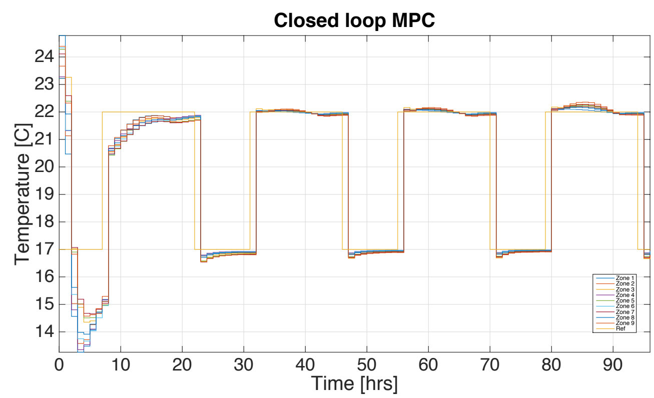

Fig. 6. Closed-loop control performance

In Figure 7 the unconstrained control inputs and the computed cost are presented. It is shown how, when the control input reaction is very sudden, the minimum value of the cost function also has a steep evolution.

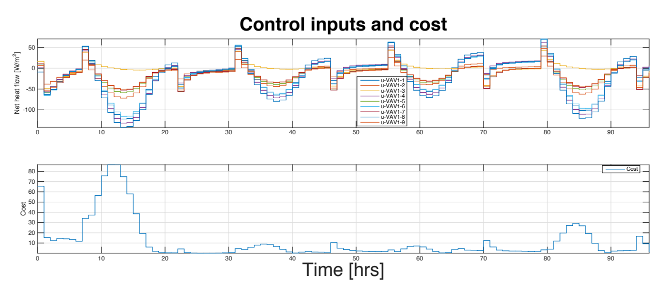

Fig. 7. Control inputs and cost

Constraints on the control inputs are defined and results are illustrated in Figure 8. It can be seen how in the days with increased solar radiation, namely day one and day four, the controller saturates and cannot compensate the external heat flux which leads to a significant overshoot of the reference temperature point for some of the zones.

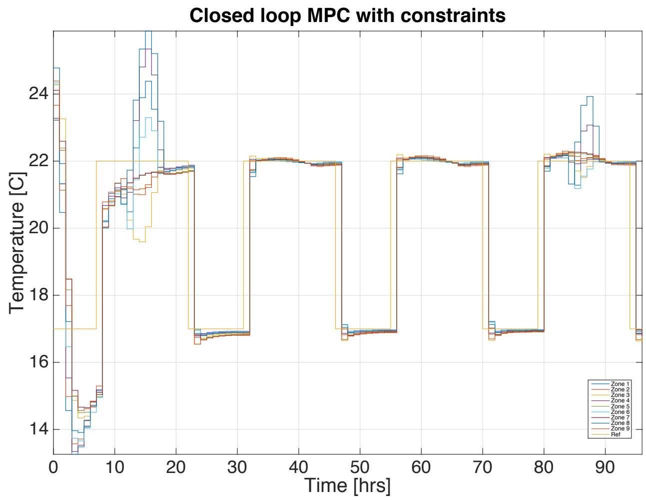

Fig. 8. Control inputs and cost

Several other techniques can be applied and are being considered in dealing with model uncertainties such as adaptive or robust MPC which offer the potential for better performance. MPC is generally considered to be a superior method for building control compared to conventional approaches, where the instrumentation of the building allows for its deployment. However, balancing operator cost and occupant comfort represents a delicate balancing act which implies dynamic weighting on the two criteria. New developments have aimed at human-in-the-loop models where occupant feedback is collected in order to further refine the control decision under both objectives. Thermovote [14] is one of these systems which collects user input on a scale from -3 to 3 regarding their current perception of the zone temperature.

V. CONCLUSIONS

The paper presented a modeling approach used for predictive control for building thermal energy optimization. The toolchain used: Energy+ / BRCM / MATLAB / Simulink was detailed and the numerical simulation results were presented for both open loop and closed loop MPC control scenarios.

Currently for the full control loop to be represented work is carried out on defining the two-stage AHU+VAV system in the reference facilities building. This is based on the equations of each subsystem and their interconnection e.g. AHU output temperature and flow are baseline input variables for the VAVs and VAV return air flow along with fresh air volume and temperature are inputs to the AHU, while using a pre-defined class template for the actual implementation. Along with reducing the sampling/control time to 10 minutes, this will allow for more realistic simulation.

As discussed, the described approach makes is relatively easy to incorporate user feedback into the model: either as discrete events influencing directly the zone-level set-points of the MPC when data is sparse or, when the data set density is above an arbitrary threshold, as dynamic, human-in-the-loop, transfer functions, also useful as prediction models, added to the model by disturbance channels.

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