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IEA Annex 60 Activity 2.3: model use during operation, approach and case studies

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Abstract

IEA Annex 60 is developing and demonstrating new generation computational tools for building and community energy systems based on the non-proprietary Modelica modeling language and Functional Mockup Interface (FMI) standards. The anticipated outcomes are open-source, freely available, documented, validated and verified computational tools that allow buildings, building systems, and community energy grids to be designed and operated as integrated, robust, performance based systems with low energy use and low peak power demand. The target audience is the building energy research community, design firms, energy service companies, equipment and tool manufacturers, as well as students in building energy-related sciences. Currently fragmented duplicative activities in modeling, simulation, and optimization of building and community energy systems that are based on the Modelica and FMI standards will be coordinated. Tool-chains will be created and validated that link Building Information Models to energy modeling, building simulation to controls design tools, and design tools to operational tools. Invention and deployment of integrated energy-related systems and performance-based solutions for buildings and communities will be accelerated by extending, unifying and documenting existing Modelica libraries, and by providing technical capabilities to link existing building performance simulation tools with such libraries and with control systems through the Functional Mockup Interface standard. Demonstrations will include optimized design and operation of building and community energy systems. Activity 2.3 focuses on the use of models to augment monitoring, control, and fault detection and diagnostics methods. This promises to detect a degradation of equipment efficiency over time because measured performance can be compared to expected performance at the current operating conditions. Furthermore, use of models during operation allows operational sequences to be optimized in real-time to reduce energy or cost, subject to dynamic pricing. This paper will offer an overview of the work carried out within this

IEA Annex 60 Activity 2.3 both in terms of approach and case studies with a particular focus on Modelica models use during operation for model predictive control.

Keywords: Model Predictive Control, Building Energy Simulation, Model Use During Operations

1. Introduction

The control of building systems were widely studied and many approaches were proposed to improve the control. Among those approaches, a large body can be categorized as model predictive control (MPC) [1]. The basic idea of MPC is to use the model of the studied system to predict the future evolution. Compared with traditional control approaches, the MPC eliminates many drawbacks, such as laborious parameter tuning, weak prediction capability, difficult implementation of supervisory control, and weak adaptability to varying operating conditions. In addition, MPC is also able to handle constraints on control and states [2].

In the design of MPC, how to build the system models is critical. On one side, the models should be able to provide accurate predictions of future states; on the other side, they should have lower computational demand, so that they are compatible with cost-effective computational resources for the on-site deployment. Those competing requirements for the system modeling can be fulfilled by Modelica [3]. Modelica is an equation-based, object oriented modelling language for complex multi-physics systems. It can be used to model multiple physical phenomena (such as heat transfer and fluid distribution) [4] with different system dynamics (continuous, discrete, or hybrid time and discrete event) [5] and different system sizes, ranging from single equipment to a building and even for communities with district energy system connected to electrical grids [6]. In addition, Modelica employs the use of a variable time step size solver, which significantly reduces the computational demand compared to the conventional building simulation tools for which the time step size is fixed [7]. In fact, Modelica is widely used in the building field for different purposes [8-21].

In this paper, to demonstrate the usage of Modelica in the MPC, we present two case studies. In the case studies, we discuss how we implement the MPC with Modelica and also compare the performance of those MPC with that of the traditional control approaches.

2. Case Studies

MPC for heat pumps

In this case study, we developed an MPC approach to optimize the heat production of two identical heat pumps and a gas boiler. We have implemented and tested the MPC [22] (using the Modelica environment) at the headquarters office building of 3E which is located in the center of Brussels, Belgium. We start with a description of the specificities of the building followed by the methodology for MPC approach and we end with some results.

The MPC ensures thermal comfort while trying to minimize the heating costs. During office hours, comfortable temperatures in the conditioned zones lie between 20 ℃ (293.15K) and 24 ℃ (297.15K), which requests the MPC to be available for heating from about September all the way through May. The produced heat is distributed by three parallel hydraulic circuits through fan coil units (FCU), radiators and an air handling unit (AHU) to directly or indirectly emit the heat to the zones. These three circuits, of which the radiators are rarely used, are shown schematically alongside the production in Fig. 1.

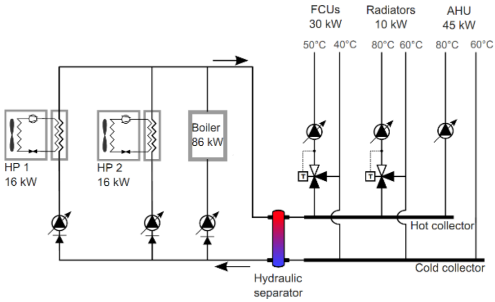

Fig. 1 heating system with heat production on the left hand side and heat emission on the right hand side coupled by a pressure balancing tank.

The original rule based controller (RBC) is a combination of high level control and low level control. On the high level, the amount of heat to be produced is determined based on a heating curve. Using the measurement of the outside temperature, this curve dictates the water temperature for the hot collector. When this hot collector water temperature drops too low because of heat emission to the building zones, the PI controller increases the thermal production and vice versa. Whether one of the heat pumps, the gas boiler or any combination of these takes up this heat demand, is decided based on a set of rules implemented by the heating system installer. The high level controller is bound by the low level control regardless whether the RBC or the MPC is controlling it. The lower level influences more directly the heat emission. The set points of the pressure controlled water pumps of the FCU and AHU's circuit determine their respective water mass flow rates. The pressure levels can be changed, but this set point is typically not taken up by a high level controller. Besides the uncontrolled FCU mass flow rate, a three way valve controls mixing of return water with supply water to reach a PI controlled set point for the FCU. The air mass flow rate in the AHU is only on/off-controlled and the supply air temperature is not measured. To conclude, we state that the low level influences the high level controller, but the heating is still mainly controlled by the high level controller.

The optimal control problem can be expressed as follows:

$$\min_{u} J \tag{1}$$

Subject to

$$F(t, \dot{x}, x, w, y, u) = 0 \tag{2}$$

$$g(t, \dot{x}, x, y, u) = 0 \tag{3}$$

$$h(t, \dot{x}, x, y, u) \geq 0 \tag{4}$$

$$x(0) = x_0 \tag{5}$$

In this formulation, $t \in [0, t_h]$ is time with t_h the prediction horizon, $u \in \mathbb{R}^n$ is the control signal, J the objective, $F(\cdot)$ is the system model with states x, algebraic variables y, and disturbances . $g(\cdot)$ and $h(\cdot)$ are additional equality and inequality constraints. $\dot{x}, x, w, y$ and u are all time-dependent but for readability we have omitted the time dependency notation. The goal for MPC is to minimize the operating cost for heating while guaranteeing thermal comfort. These two goals are specified in the objective turning J into a multi-objective cost function.

$$J = J_c + \gamma * J_d \tag{6}$$

where

$$J_c = \int_0^{t_h} (c_g * P_g + c_e * P_e)\, dt \tag{7}$$

$$J_d = \int_0^{t_h} \theta_{occ}(T_{zon} - T_{set})^2\, dt \tag{8}$$

The energy cost J_c consists of the gas price (g) and the electricity price (e) respectively at tariff $c_g = 4.3458\ c€/kWh$ and time-of-use $c_e = 9.431\ and\ 7.324\ c€/kWh$ (day and night). $\gamma * J_d$ represents the weighted discomfort cost in the overall objective function, where it penalizes the zone temperature deviating from the set point during occupied hours ($\theta_{occ} = 1$).The optimal control problem which is repeatedly calculated in the MPC is solved using JModelica [23], based on a toolbox written in Python to implement optimization problems using Modelica models. The drive to use JModelica in our approach of MPC is twofold. Firstly, the models we implement to represent the thermal behavior of the building and heating system are constructed in Modelica. The object-oriented implementation allowed constructing a library[1] of low order Resistance-Capacitance models which can represent a thermal system. A python toolbox (grey-box-toolbox) implemented in JModelica allows us to identify the model parameter values by solving an optimization problem that fits the model outputs to building temperature measurements [24]. Several model structures can be parameter-identified and from these the best fitted model is selected. Secondly, JModelica is used to set up the optimal control problem. Since JModelica uses gradient-based methods for solving an optimal control problem, the equation based Modelica models are particularly well suited.

[1] Fast Buildings: Open source Modelica library for low order building models. https://github.com/open-ideas/FastBuildings, Available: 27/01/2016.

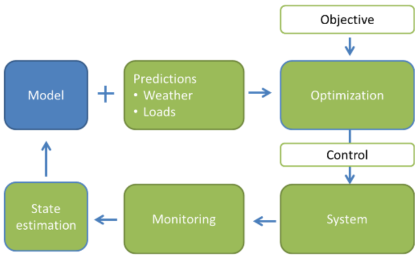

Fig. 2 the MPC framework for heat pumps

The MPC runs online and will repeatedly run through the loop presented in Fig. 2. With a system model and weather and internal load predictions, an optimal control problem is solved to find the control variables which are expected to minimize the objective function over the prediction horizon. Since neither the model nor the predictions are perfect a feedback loop is implemented. The heating system water temperature and the zone air temperature measurements from the building monitoring system are used to correct deviating predictions. A simple moving horizon state estimation algorithm updates the model's states based on the measurements. With the new model state the next optimization loop starts.

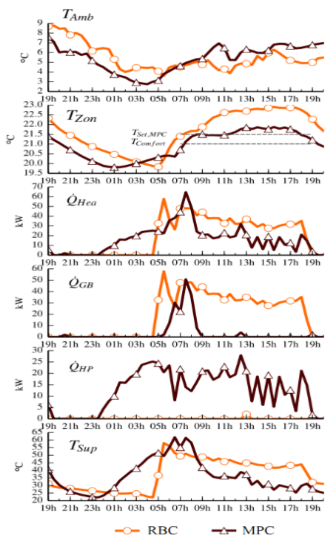

Fig. 3 Comparison of RBC and MPC quantities (from top to bottom): the ambient temperature around the building(T_{Amb}), the average zone temperature in the building(T_{Zon}), the total heat going to the zones(Q_{Hea}), heat production gas boiler(Q_{GB}), heat production heat pumps (Q_{HP}), supply water temperature (T_{Sup}).

The results of MPC on the 3E building are shown in Fig. 3 for a prediction horizon of one day, an open loop horizon of one hour and a time resolution of 15 minutes. On about 30% of the winter days in the heating season in 2014-2015, the MPC has been running. As the RBC is not running whenever the MPC is running, the controllers cannot be compared on identical experiments. Therefore we use the amount of heating degree days to identify the heating needs on a specific day which enables comparing different days with similar conditions. Furthermore it allows to compare the trends of RBC and MPC‘s energy costs with heating needs. This revealed a trend of 30-40% lower energy costs when using an MPC as opposed to an RBC. The main differences between both controllers are compared in Fig. 3, where two days with similar heating needs and a different controller (MPC versus RBC) are compared. A first main difference is the use of heat pumps over the gas boiler. Using the dynamic model of the heat pumps and the gas boiler, the MPC can easily choose the most cost effective heat production unit, which appears to be the heat pump. The MPC starts heating much earlier in the day, to take advantage of the cheaper night tariff and higher efficiency of the heat pumps at part load. Furthermore, the supply water going to the heat emission units is kept at much lower temperature, since it is not a fixed heating curve relation between outside temperature water supply set point. The MPC can choose the desired water supply freely as long as it is able to reach thermal comfort.

MPC approach for chiller plants

In this case study, we established a MPC approach for the chiller staging [4]. The studied case is a chiller plant with three identical chillers, three identical chilled water pumps, three identical condenser water pumps, and three identical cooling towers. Each chiller has one dedicated chilled water pump, one dedicated condenser water pump, and one dedicated cooling tower. The model of the chiller is a York_YK2771kW, which has the nominal cooling capacity as 2,771 kW (788 ton). For the cooling tower, the nominal fan power is 37 kW (50 HP) and is assumed to be proportional to the cubic of the fan speed ratio. The nominal wet bulb temperature and the nominal approach temperature is 23.89°C (75.00°F) and 0.89°C (1.60°F), respectively. The chilled water and the condenser water pumps are constant speed pumps and their powers are 34 kW and 47 kW, respectively. In the condenser water loop, a three-way valve is employed to modulate the condenser flow rates through the cooling towers so that the temperature of the condenser water entering the chiller, $T_{cw,ent}$ will not be less than 12.78°C (55.00°F), which is the lowest $T_{cw,ent}$ can be accepted by the chillers.

The conventional way to control the operation of the multiple chillers is: one chiller will not be brought online/offline unless the cooling load is larger/smaller than the total available cooling capacity of the operating chillers. The total available cooling capacity of i operating chillers can be referred as a Critical Point (CP):

$$CP_i = \eta \sum_{j=1}^{i} CC_{nom,j}, \tag{9}$$

Where $CC_{nom,j}$ is the nominal capacity of the chiller, η is the safety factor to mitigate the risk of insufficient cooling supply during the chiller start-up period. To avoid a chiller short circling, a waiting time t_{wait} and a dead band CP_{db} are usually employed.
The proposed MPC for the chiller staging can be formulated as:

$$J = \min\left(E_{tot}\big|_{t_0}^{t_0+\Delta t}\right) =$$
$$\min\left(\int_{t_0}^{t_0+\Delta t} f_2\left(T_{cw,set}(t_0), CP_1(t_0), \dots, CP_{M-1}(t_0), \dot{Q}^P(t), {T_{wb}}^P(t), \vec{S}(t_0)\right)dt\right), \tag{10}$$

s.t.

$$T_{cw,set,L} \leq T_{cw,set}(t_0) \leq T_{cw,set,H}, \tag{11}$$

$$CP_1^{min} < CP_1(t_0) \leq CP_1^{max}, \tag{12}$$

$$CP_{i-1}(t_0) < CP_i(t_0) \leq CP_i^{max}\ (i > 1), \tag{13}$$

$$D_{chw,lea} \leq D_{chw,lea,base}. \tag{14}$$

$E_{tot}\big|_{t_0}^{t_0+\Delta t}$ is the total energy consumption by the chillers, the cooling towers, the condenser water pumps, and the chilled water pumps for a period from t_0 to $t_0 + \Delta t$, ${T_{wb}}^P(t)$ is the predicted wet bulb temperature, $\vec{S}$ is the state vector of the system (e.g. equipment operating status, water temperature in the condenser and the evaporator of the chiller), $\dot{Q}^P(t)$ is the predicted cooling load, $T_{cw,set}$ is the set point for the temperature of the condenser water leaving the towers, which is called condenser water set point. $T_{cw,set,L}$ and $T_{cw,set,H}$ is the low bound and the high bound for $T_{cw,set}(t_0)$. CP_1^{min} is the low bound for $CP_1(t_0)$ while CP_i^{max} is the high bound for CP_i. $D_{chw,lea}$ is the deviation of temperature of chilled water leaving the chiller, $T_{chw,lea}$, from $T_{chw,set}$ (chilled water set point) which is calculated by:

$$D_{chw,lea} = \int_{t_0}^{t_0+\Delta t} \left|T_{chw,lea}(t) - T_{chw,set}\right| dt \tag{15}$$

$D_{chw,lea,base}$ is $D_{chw,lea}$ at the conventional control in which no optimization occurs. In this MPC, the $\dot{Q}^P(t)$, ${T_{wb}}^P(t)$ and $\vec{S}(t_0)$ are the input variables while $T_{cw,set}(t_0), CP_1(t_0), \dots, CP_{M-1}(t_0)$ are the independent variables. In this study, the Modelica Buildings library [5] and the Modelica_StateGraph2 library [25] were used to model the chiller plant system. In this model, $\dot{\mathrm{Q}}$ and $\mathrm{T_{wb}}$ data is read externally. The detail of the system model can referred to [26].

To enable the MPC, we developed an optimization framework (Fig. 4). The $\dot{Q}^P(t)$, ${T_{wb}}^P(t)$ and $\vec{S}(t_0)$ are used as input variables. Then the generated optimal $CP_i(t_0)$ and/or $T_{cw,set}(t_0)$ will then be used to obtain $\vec{S}(t_0 + \Delta t)$ as initial values for the next optimization period starting from $t_0 + \Delta t$.

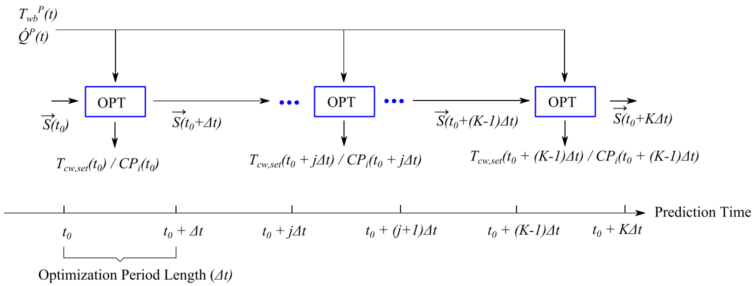

Fig. 4 the MPC framework for chillers

We performed an offline simulation to evaluate the performance of the proposed MPC. In this simulation, we used real historic data for $\dot{Q}$ and T_{wb} from an actual chiller plant in Washington D.C., USA as the input variables for the optimization. The $\dot{Q}$ is from on-site measurement and T_{wb} is from a nearby weather station [27]. Since both $\dot{Q}$ and T_{wb} are hourly data, they were linearly interpolated during one hour for provide the inputs for the dynamic simulation. We used the Hooke Jeeves algorithm [28] in the GenOpt [29] optimization engine to perform the searching. The optimization was set to be performed every day. We set the safety factor $\eta = 90\%$.

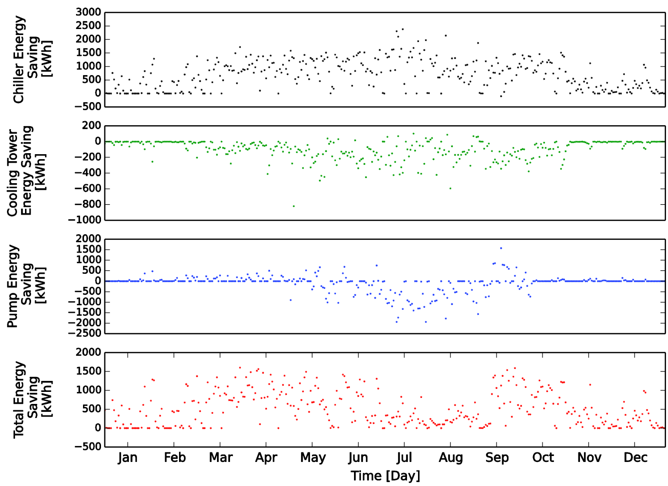

Fig. 5 Daily energy saving by the MPC compared to the conventional chiller stage control

The result of the offline simulation is shown in Fig. 5. The MPC provided 5.6% annual total energy saving. The chiller energy saving ratio was 11.8% with the cost of 43.8% higher cooling tower energy consumption. In addition, the pump energy also rose by 3.7%. The chiller energy consumption was saved for the most of time in the studied year, which could be attributed to both the optimal load distribution and the lower $T_{cw,ent}$. The cooling tower energy consumption was mostly increased. The pump energy consumption was increased or reduced around the year. In the summer, the pump energy consumption was usually increased which indicates that more chillers were operating compared with the conventional control. In the rest time, the pump energy consumption was reduced which means the cooling load was met with fewer chillers.

3. Conclusions

In this paper, we demonstrate two case studies in which Modelica models were used in model predictive control approaches. Based on the results, we can draw the following conclusions:

1) Modelica can be used in MPC for different building systems;
2) MPC can achieve significant energy saving compared to the traditional control approaches.

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This work emerged from the Annex 60 project, an international project conducted under the umbrella of the International Energy Agency (IEA) within the Energy in Buildings and Communities (EBC) Programme. Annex 60 will develop and demonstrate new generation computational tools for building and community energy systems based on Modelica, Functional Mock-up Interface and BIM standards.

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