Parallel MPC for Transient Thermal Error Attenuation

C.Andrade-Cabrera*

[1] School of Mechanical and Materials Engineering, University College Dublin, Belfield, Dublin 4, Ireland

ABSTRACT

This paper presents a sub-optimal predictive control method which, under the assumption of parallelization, reduces the solution time required for real-time simulation-assisted predictive control without sacrificing the temporal resolution inherent to move-blocking techniques. An abstract case study is introduced to demonstrate the advantages of the proposed methodology. Certainty equivalence is assumed to be known at first, and modelling uncertainty is later introduced to determine loss of performance due to mismatch in building response estimation. It is shown that the proposed method increases closed-loop performance as disturbances increase.

KEYWORDS

Building simulation, predictive control, simulation-assisted control, BCVTB

INTRODUCTION

Model Predictive Control (MPC) has received a great deal of attention by researchers in building science and control systems over the last decade. Researchers have demonstrated the viability of this approach while reporting considerable economic benefits (Oldewurtel et al. 2012). The core premise of this approach is that a linear state-space model can approximatively model the thermal behaviour of a building and the performance of its HVAC systems, which can be achieved either through semi-physical modelling (Lehmann et al. 2013) or system identification (Privara et al. 2011). In practice, the predictive controller compensates for model mismatch and errors in weather and occupancy forecasting.

Coupling Building Energy Model (BEMS) and heuristic optimization in a receding horizon manner (Corbin et al. 2013) has the potential to yield further economic savings, given that BEMS capture building performance (envelope and systems) better than linear models. BEMS have the potential to also capture building systems that cannot be accurately modelled in a linear framework. The heuristic algorithm need to parametrically evaluate hundreds of BEMS model runs as part of the cost minimization routine. The controller becomes impractical for a large number of inputs, unless larger control periods (1 hour) are considered or decision rules (Coffey 2013, May-Ostendorp et al. 2011) are extracted.

* Corresponding author email: carlos.andradecabrera@ucdconnect.ie

This paper proposes the use of a linear MPC methodology, Parallel MPC, which has the potential to reduce the solution time of Simulation-Assisted schemes, thus allowing for faster control rates and enhancing disturbance rejection. The work in this paper is limited to the linear framework in order to illustrate the concept clearly. The paper is structured as follows. First, the predictive control of a study case building is introduced. Then, the Parallel MPC algorithm is described and implemented. The results of applying the method under model uncertainty are show. The paper closes with a discussion on the potential of the method in predictive building control.

BACKGROUND

Simulation-Assisted Control

One of the early developments of this subtopic is described in Henze and Krati (2005). A TRNSYS model was evaluated with an iterative quasi-Newton method which iteratively find the optimal thermostatic set-points. The idea here was to combine the passive thermal storage with a subsequent optimization of the active thermal storage, which is found via dynamic optimization. The authors discarded the use of extensive search methods coupled with TRNSYS for passive thermal storage optimization because of the large number of iterations. Corbin et al. (2013) used Particle Swarm Optimization coupled with EnergyPlus in order to find optimal thermostatic set points of a large office building. Utility bill savings of 5% in utility bill costs were reported. The authors also explored the control of thermally activated building systems (TABS) by adjusting water circulation availability and water inlet temperature. In this case, the reported HVAC utility bill savings were 55%.

Coffey (2013) proposes a method to alleviate the computational load by decomposing the optimization in two parts: a pre-computed off-line sub-problem, which is solved for a conditions grid and an on-line problem, which consist in use a lookup table to find the solution of the optimization problem based on current building conditions. This approach relies on the correct setup of the conditions grid and requires that such conditions have a dimension small enough. Finally, Zhao et al. (2013) used an exhaustive search optimization algorithm coupled with EnergyPlus in order to optimize supply air temperature set-points using baseline logics coupled with receding horizon logic. The reported HVAC utility bill savings were 18%.

Parallel MPC

Parallel Model Predictive Control, also known in the literature as Channel Hopping MPC (Ling et al. 2011), is a predictive control method which aims to compensate for unknown disturbances by applying inputs at a faster control rate. This is achieved by sub-dividing a centralized MPC problem into smaller problems, which, when solved in parallel, result in an effective reduction of the sampling rate. The governing principle is illustrated in Figure 1. Assume that the MPC problem can be partitioned in q_n sub-problems. A *channel* in this context represents a cluster of variables. After measuring the current state of the building, the controller solves a reduced-order predictive control problem for each q_i channel.

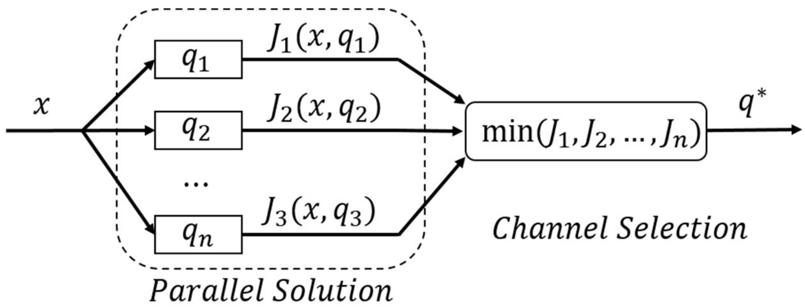

***Figure 2**. Parallel MPC operation: selection of the best sub-problem (channel)*

Assume that all channels share a global knowledge of the future planned inputs of the other channels. The reduced-order problem is able to sub-optimally solve the predictive control problem by optimizing only for the variables involved with such channel while assuming the other variables are applied as planned. All channels are solved in parallel, and the channel that produces the minimum cost J_n is selected as the solution of the predictive control problem. A detailed explanation of the implementation of this algorithm can be found in Andrade-Cabrera and Maciejowski (2013).

The method sacrifices optimality in favour of applying a control action faster (i.e. it is more favourable to make a sub-optimal control decision now, than making an optimal control decision too late). This trade-off is highly relevant to Simulation-Assisted MPC. As mentioned earlier, computational delays can be considerable if the number of variables is large. By solving the control problem at a faster sampling rate, the controller is able to deal with short term disturbances while also compensating for model mismatch, since BEMS are an accurate but not exact representation of building physics.

METHODOLOGY

Abstract case study: Cantilevered building

The abstract case study is derived from the Architecture Studio building at the University of Cambridge, UK. The building is a two-floor cantilevered building used as study space for undergraduate students. The first floor consists of a workshop enclosed by a solid construction, which will be assumed to be conditioned at 20°C. The second floor consist of a study and work area of 325 m^2. The space is conditioned by 144 radiant ceiling panels which provide low water temperature heating and cooling.

The panels are connected with a Ground Source Heat Pump via a heat exchanger. In cooling mode, the heat exchanger has a cooling capacity of 7 kW. This abstract case studies the conditioning of this area when using blinds and natural ventilation (for nightly free cooling) combined with a simplified convective heating/cooling power input that can be translated into building set-points. The geometry of the original building has been significantly modified to feature a southern façade in order to provide the control authority than in the case of a north-facing blind.

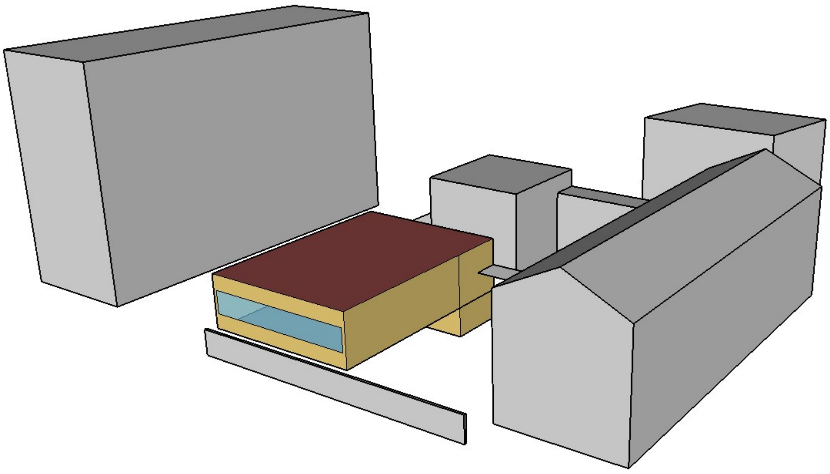

***Figure 1**. Abstract case study– cantilevered building with south-facing window*

The objective of this study is to minimize the electrical energy consumption due to cooling and lighting. No energy price information is fed to the controller at this stage. The Electricity Power due to cooling at time-step k ($E_{cooling,k}$) is modelled as the ratio between the cooling power $W_{cooling}$ and the Coefficient of Performance (COP)

$$E_{cooling,k} = \frac{W_{cooling}}{COP} = \frac{u_{cooling,k} \cdot A_r}{COP} \quad (1)$$

where $u_{cooling,k}$ is the cooling input, which is expressed as cooling power rate and A_r is the conditioned area. The Electricity Power due to lighting demands ($E_{lighting,k}$) is the ratio between the luminosity demand in Lux levels (or Lux level deficit, $Lighting_{Lux,k}$) and the efficiency of the lighting systems (η, assumed to be 87 W/m^2 for metal-halide lamps)

$$E_{lighting,k} = \frac{Lighting_{Lux,k} \; A_r}{\eta} \quad (2)$$

This deficit in Lux levels can be expressed as a constraint by means of using the linearised blind model (Lehmann et al. 2013)

$$Room_{LuxLevels,k} = ilum_k + b_{pos} dilim_k + Lighting_{Lux,k} \geq SP_{LuxLevels,k} \quad (2)$$

where $ilu \quad _k$ is the pre-computed or estimated room Lux levels when the blinds are deployed and $dilim_k$ represents the additional Lux levels added to the room when the blinds are not deployed. This formulation is added into the problem as an inequality constraint by means of adding a set-point ($SP_{LuxLevels,k}$). Without this constraint, the blinds will be deployed all the time, as they would try to minimize the solar gains.
The cooling power due to free cooling can be expressed as:

$$u_{freecooling,k} = \frac{ACH_k}{3600} \frac{V_r}{A_r} \rho_{air} cp_{air} (T_{amb,k} - T_{room,k}) \quad (3)$$

where ACH_k is the required level of air changes per hour (which should be translated into window opening/closing commands at a later stage), V_r and A_r are the volume and area of the room, ρ_{air} and cp_{air} are the density and specific heat of air at 20°C, $T_{amb,k}$ is the outdoor air temperature and $T_{room,k}$ is the room temperature. The thermal dynamics of the building fabric were generated using BRCM (Sturzenegger and Semeraro, 2014). The BRCM toolbox allows the user to obtain a bi-linear building energy model of the form:

$$x_{k+1} = Ax_k + B_u u_k + B_v v_k + \sum_{i=1}^{n_u} B_{xu,i} x_k + B_{vu,i} v_k \qquad (4)$$

where the room temperature $T_{room,k}$ is part of the state x_k. The free cooling power $u_{freecooling,k}$ as an input of a pseudo-input vector u_k which is seen as the input by vector by the BRCM model. The input $u_{freecooling,k}$ contains two bi-linearities: $ACH_k T_{room,k}$ (input/state bi-linearity) and $ACH_k T_{amb,k}$ (input/disturbance bi-linearity). Assume that for the sake of simplicity the only pseudo-input is $u_{freecooling,k}$. Then, the model could be re-written as:

$$x_{k+1} = Ax_k + B_u(ACH_k c)T_{amb,k} - B_u(ACH_k c)T_{room,k} + B_v v_k \qquad (5)$$

where $c = \frac{\mathrm{V_r}\ \rho_{air}\ cp_{air}}{\mathrm{A_r}\ 3600}$ is a constant.

The internal gains due to lighting are added as per CIBSE 6.4 (Lighting). For a metal-halide lamp, the ratio of Task Illuminance to average installed power density is 27.7 lux/W-m^2. Thus, the internal gains due to lighting are given by the relationship

$$IG_{lighting} = \frac{\mathrm{Lighting_{Lux,k}}\ A_r}{27.7} \qquad (6)$$

Controller Implementation.

The objective of this control problem is to minimize the energy consumption (Equations 1 and 2) subject to the model dynamics and constraints (Equation 3-6). A fixed setpoint (9AM to 6PM) was selected. The controller was implemented in MATLAB and developed using Yalmip (Lofberg 2004). The control signals were fed to the EnergyPlus model via BCVTB. The controllers implemented in a dual-core Dell Precision 7500 PC. Since the resulting model is bi-linear the selected solver chosen is IPOPT. An iterative approach to solve this optimization problem (as suggested in Lehmann et al. 2013) would complicate the measurement of total computational time. Cooling power is constrained to a maximum of 7 KW. The blind input is deemed to be binary. The value obtained from IPOPT is rounded up before being sent to EnergyPlus. The natural ventilation variable is constrained between 0 and 3, and fed back to EnergyPlus using a ventilation rate object. The weather file corresponds to the IWEC Gatwick weather file. A moderate infiltration rate of 0.5 ACH is considered.

RESULTS

Figure 3 compares the performance of a predictive controller under certainty equivalence with respect to the performance of the same controller under modelling uncertainty. Certainty equivalence means that the EnergyPlus model was simplified in to match the assumptions made in the BRCM model. This can be considered as the Performance-Bound solution of the controller. The simplifications are: fixed convective heat transfer functions, entirely convective heat gains and use of natural ventilation expressed as a convective cooling power. Uncertainty, in this context means that realistic building physics (e.g., adaptive heat transfer coefficients) are used. Figures 2 and 3 show that excessive cooling power is applied to the zone as a result of model mismatch (zone temperature significantly below upper constraints).

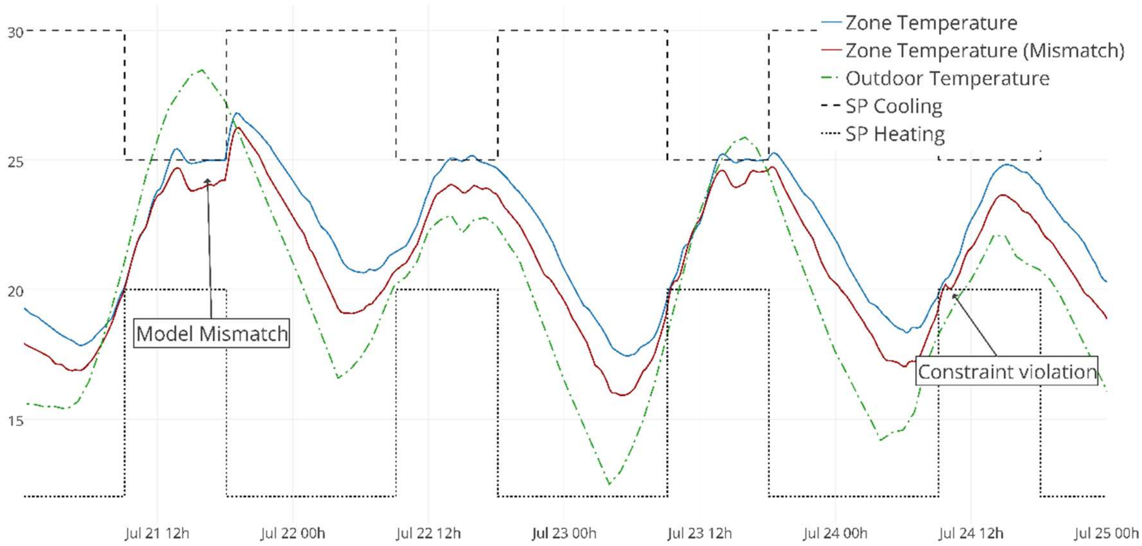

***Figure 2**. Performance Bound MPC vs MPC performance under model uncertainty*

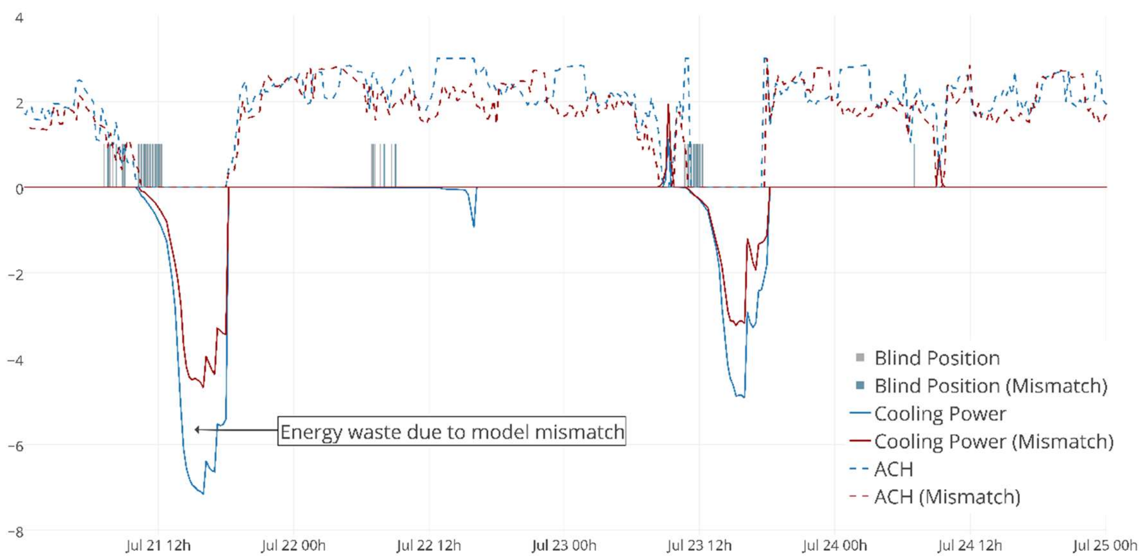

***Figure 3**. Performance Bound MPC vs MPC performance under model uncertainty*

Clearly, there are economic gains that can be achieved by minimizing model mismatch. While the Parallel MPC controller is unable to adjust model dynamics, it is able to capture model discrepancies at a faster rate and reduce the performance error. The proposed Parallel MPC controller consist of two channels: $PMPC_{CH1}$, which represents blinds and cooling power and $PMPC_{CH2}$, which represents natural ventilation and cooling power. The nominal controller (MPC) is applied every 10 minutes, whereas Parallel MPC is applied every 5 minutes. Table 1 shows the RMSE of Squares between predicted model response (as calculated by the controller) and actual performance (as measured from the EnergyPlus virtual sensor). A random disturbance is added to the external temperature and irradiance time-series, mimicking errors in weather forecast. The disturbance has zero mean and its maximum magnitude is expressed as a percentage of the measured magnitude. Under uncertain conditions (i.e., model mismatch) both controllers have the same performance. Once the disturbances increase, the PMC controller outperforms the centralized MPC controller.

Table 1. RMSE between predicted and measured performance

Disturbance	*MPC*	*PMPC*
Performance Bound – 0%	0.25	0.32
Model Mismatch – 0%	0.55	0.56
Model Mismatch – 5.00%	0.51	0.52
Model Mismatch – 10.00%	0.54	**0.53**
Model Mismatch – 20.00%	0.69	**0.67**

Table 2 shows the maximum computational time and average computational times (in parenthesis) under model mismatch. The solution time of the parallel controllers in unconstrained, linear MPC should be half of the centralized controller (2 channels). The maximum measured computational time (which is the relevant measure) exceeds this theoretical prediction. Tables 1 and 2 imply that, if 5% of measurement error is assumed, the controller can be safely implemented at a faster sample rate (5X) than centralized MPC, while having the same performance (Table 1).

Table 2. Maximum and Average Computational Time (seconds)

Disturbance	*MPC*	$PMPC_{CH1}$	$PMPC_{CH2}$
5%	6.27 (1.28)	1.28 (1.05)	2.1 (0.69)
10%	6.96 (1.2)	2.12 (0.97)	2.79 (0.64)
20%	8.02 (1.26)	3.42 (0.97)	2.29 (0.64)

CONCLUSIONS

The work in this paper introduces Parallel Building MPC as a methodology that can potentially reduce the complexity of simulation-assisted building control methods without major sacrifice of model performance. The proposed method is known to be more advantageous when the problem has a higher dimensionality. Further work will study the performance of the proposed method in a more realistic scenarios and disturbances (e.g. building with more thermal zones and control inputs).

ACKNOWLEDGEMENTS

This work was conducted in the Electricity Research Centre, University College Dublin, Ireland, which is supported by the Electricity Research Centre's Industry Affiliates Programme (http://erc.ucd.ie/industry/). This work has been funded by the National Council of Science and Technology of Ecuador (SENESCYT).

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