Comparative study of neural network based and white box model predictive control for a room temperature control application

Phillip Stoffel, Max Berktold, Arman Gall, Alexander Kümpel, Dirk Müller
RWTH Aachen University, E.ON Energy Research Center, Institute for Energy Efficient Buildings and Indoor Climate, Mathieustraße 10, 52074 Aachen, Germany
E-mail: phillip.stoffel@eonerc.rwth-aachen.de

Abstract. On a global scale, buildings are a major cause for primary energy consumption. Since buildings are complex multiple input multiple output systems and characterized by slow dynamics, model predictive control is a promising approach to reduce building energy consumption. Due to the high individual modeling effort model predictive control lacks practical applicability. For that reason black box process models are gaining more and more interest in scientific literature. In this work we evaluate the performance of an ANN based controller against a white box controller with perfect knowledge. We show that the data driven controller achieves a similar control quality as the white box controller. We initially train the data driven controller in 20 days and then employ an online learning strategy to continuously improve the control quality.

1. Introduction
The increasing use of renewable energies for sustainable building air conditioning leads to increasingly complex and interconnected systems. In order to operate these systems efficiently and to reduce energy consumption as well as operation costs, model-predictive operation and control strategies are gaining relevance in the scientific community. These strategies use thermal storages and the building mass more efficiently, while also take volatile energy prices into account. For this purpose, model predictive control (MPC) predicts system states using a model of the controlled system and determines optimal manipulated variables by solving optimization problems. In this way disturbance variables such as weather or user influence can be explicitly considered. Several real life studies demonstrated the high energy saving potential of MPC [1,2].

The model creation and development for building energy systems is usually time-consuming and cost-intensive, as the models can only be transferred to different controlled building energy systems to a limited extent. This leads to an increased specific development effort which limits the practical applicability of the method [3]. For this reason data driven MPC (DDMPC) approaches, using a "learned" black box model, have gained increasing interest in recent years [4].

In this work, we will benchmark the performance of a data driven approach against a physically modeled controller with near-perfect system knowledge of the simulated building energy system. Furthermore, we examine if the DDMPC can be used to directly compute actuator set points.
like valve positions as inputs.  
In the following, we discuss related work on DDMPC for building energy systems. Afterwards, the methodology is explained and an evaluation of its performance is conducted.

1.1. Related Work

Typically buildings are modeled by using a resistor capacitor (RC) approach where aggregated thermal masses of a building are connected via heat transfer resistances. This leads to a linear set of equations well suited for model predictive control. The building HVAC system is then represented by energy balances. [5, 6] Since physically-based models mostly use simplifications and neglect certain aspects, they can be outperformed by well-trained black box models [7]. Black box modeling techniques often used in combination with model predictive control for buildings are for example linear system identification methods like ARX, ARMAX or 4SID [4, 6], Gaussian Process Regression [8], Random Forests [9] and Artificial Neural Networks (ANN) [10]. At this point especially ANN show high accuracy when it comes to building modeling [11]. Yang et al. [12] presented a real life DDMPC algorithm for an office building and a lecture hall leading to reduction in cooling energy consumption of 58 % and 36 % respectively. Mugnini et al. [13] investigated the performance of an ANN based MPC compared to a very simplified RC-model based MPC when controlling a building simulated in TRNSYS. In this study, both the DDMPC and the physically-based MPC lead to large violations of the comfort constraints. In summary, DDMPC showed promising results in recent years but lacks comparability due to the highly diverse use cases and methods [4]. DDMPC in literature also lacks comparison to well-tuned, state of the art MPC algorithms. Additionally, both DDMPC and physically based MPC algorithms presented in literature work on a set point level and rely on subsystem controllers to reach these. The development and tuning of these subsystem controllers adds additional costs to the implementation of advanced control strategies. The contribution of the present work includes the benchmark of a DDMPC versus a well tuned physically-based MPC with focus on robustness and controller performance. In comparison to other publications, the DDMPC also directly controls actuator valves and thus reduces the need to accurately tune subsystem controllers like PIDs.

2. Methodology

In the following we will present the considered use case, the physically-based MPC and its process model as well as the data driven controller and its training strategy.

2.1. Use Case

The control strategies presented in this work are tested on a detailed office thermal zone model (see figure 1) including an air-handling unit (AHU) and a concrete core activation (CCA) combining fast and slow system dynamics. The system is modeled in Modelica using the AixLib library [14] and parametrised based on the ASHRAE140 testcase 900 [15]. The thermal zone itself is modeled using the linear RC approach. The AHU and CCA consider non-linearities like the pressure losses of hydraulics as well as the valve characteristics and the heat transfers in the cooling and heating coils. The influence of solar radiation depends on the time of the year and is calculated based on VDI 6007-3 [16]. Other disturbances considered are the internal gains by electrical devices inside the zone, humans and lights which are calculated based on the office profiles presented in [17]. The system can either be controlled by temperature set points for the AHU and power set points for the CCA or by setting four valve positions (heating and cooling coils of the AHU and CCA respectively).
2.2. Physically-Based Model Predictive Control

The physically-based MPC uses a linear system model with six states $x$, two inputs $u$ and eight disturbances $d$.

\[
\begin{align*}
x &= [T_{\text{Air}}, T_{\text{Wall,int}}, T_{\text{Wall,ext}}, T_{\text{Roof}}, T_{\text{Win}}, T_{\text{CCA}}] \\
u &= [T_{\text{AHU.set}}, \dot{Q}_{\text{CCA}}] \\
d &= [T_{\text{amb}}, T_{\text{amb,Roof,corr}}, T_{\text{amb,Win,corr}}, T_{\text{amb,Walls,corr}}, S_{\text{humans}}, S_{\text{lights}}, S_{\text{devices}}, \dot{Q}_{\text{sol}}]
\end{align*}
\]

The states are the temperatures of the air, roof, internal and external walls, concrete core activation and windows, which are connected by 13 unique heat transfer resistances. As inputs the temperatures set point of the AHU and the power of the CCA are used. The disturbances are the ambient temperature, radiation corrected ambient temperatures on windows, external walls and roof, schedules for internal gains by humans, lights and electrical devices and the heat input by solar radiation transmitted through the window. All these disturbances are precalculated and perfectly known. The radiant internal gains and the transmitted solar radiation are distributed on the thermal masses by geometrical split factors. The model predictive controller is implemented as an economic controller with comfort constraints using the slack variable $\epsilon$. Thus, the violation $\epsilon$ of the room temperature constraints is penalized with the factor $Q$. The energy consumption and the change of inputs $\Delta u_k$ are penalized by $R$ and $\dot{R}$ respectively, resulting in the cost function 2a with the constraints 2b-2e.

\[
\begin{align*}
\min_{u,x,\epsilon} \sum_{k=0}^{N-1} \left( \epsilon_k^2 \cdot Q + \dot{Q}_{\text{AHU,k}} \cdot R + \dot{Q}_{\text{CCA,k}} \cdot R + \Delta u_k^2 \cdot \dot{R} \right) \\
\text{s.t.} \quad &x_{k+1} = f(x_k, u_k, d_k) \\
&u_{\text{min}} \leq u_k \leq u_{\text{max}} \\
&T_{\text{Air, min}} - \epsilon_k \leq T_{\text{Air,k}} \leq T_{\text{Air, max}} + \epsilon_k \\
&x_0 = \hat{x}_0 \\
&\forall k \in [0, ..., N - 1]
\end{align*}
\]

Furthermore, the comfort constraints 2d are chosen to be wider outside working hours to exploit larger energy saving potentials. The control horizon for the physically-based linear MPC is chosen to 3 h with a step size of 10 min. The resulting linear optimization problem is solved in less than 50 ms for all time steps.
2.3. Neural Network based Model Predictive Control

The data driven model predictive controller uses an artificial neural network to recursively predict the next state. Since we are solely interested in controlling the air temperature, we replace the dynamic constraint with

\[ T_{\text{Air},k+1} = f_{\text{ANN}}(T_{\text{Air},k}, \ldots, T_{\text{Air},k-n}, u_{k}, \ldots, u_{k-n}, d_{k}, \ldots, d_{k-n}) \]  

At this point we introduce the previous time steps which considers former system states and thus accounts for slow system dynamics. The inputs \( u \) are the four valve positions while the disturbances \( d \) are the ambient temperature, global and diffuse radiation and the occupancy schedule. In total 20 days of training are used to generate the model. The training is conducted by providing random temperature set points within the comfort constraints as well as random control signals. Here, Keras is used to generate and train the ANN. After an initial training the controller model is continuously updated with new measurements on a weekly basis. It was found that a neural network with one layer and 16 neurons using the sigmoid activation function approximates the system accurately enough. The controller itself is designed in CasADi using the interior point solver IPOPT to efficiently solve the nonlinear optimization problem. The control horizon of the non linear, data driven MPC is 3 h with a step size of 15 min resulting in 48 optimization variables. To reduce the computational load, the time step size is increased compared to the physical controller. The maximum solution time of the non linear optimization problem is less than 1.5 s on a desktop PC providing real-time feasibility.

3. Results

In order to compare both controllers a one year simulation was conducted. For the data driven controller, the first 20 days where used for the initial training. Figure 2 shows an exemplary week of operation in April with both cooling and heating demand. Both controllers manage to keep the room temperature within constraints while reducing energy consumption through anticipatory heating and cooling respectively. Since the black box model is continuously updated, the controller adapts to changing environmental characteristics like the increased influence of solar radiation in summer compared to the initial training in January. From February to December the physically-based controller violates the constraints over a period of 73 h by more than 0.05 K. The mean violation is 0.1 K and the maximum violation of 0.24 K respectively. The data driven controller has a constraint violation greater than 0.05 K for 13 h with a maximum of 0.16 K and a mean of 0.08 K, showing better performance than the physically-based controller. The physically-based MPC has a higher constraint violation, since it relies on subsystem controllers which cannot always provide perfect set point tracking. At the same time, the data driven MPC increases the energy consumption by 3.5 %. The latter is due to minimizing the valve openings instead of a minimized energy consumption as it is the case for the white box controller. In the data driven controller the valve positions are minimized since the energy consumption is not learned yet. All in all, the data driven model predictive controller provides a similar performance as the white box approach while providing the option to directly compute actuator signals.

4. Conclusion

In this work, we presented an ANN-based MPC and a physically-based MPC applied to a detailed thermal zone simulation. We show that data driven MPC is a promising approach to overcome the time consuming model development necessary to develop model predictive controllers for buildings. The black box process model learns the influence of all relevant disturbances and also the characteristics of an air-handling unit and a concrete core activation. The data driven controller shows a similar performance as the white box controller with perfect knowledge while ensuring real-time feasibility. The data driven controller results in less constraint violation
but increases the energy consumption slightly. Furthermore, the data driven controller directly interacts with the actuators, reducing the need to tune accurate subsystem set point controllers which are necessary for a physically-based MPC. Additionally, we employ sequential online learning to continuously improve our process model after an initial training of 20 days. Thus, in a real life application changing usage patterns or system characteristics can easily be considered by the controller.

In our future work we will focus on making this approach more scalable by reducing the training effort and testing it on real life applications with imperfect disturbance information.

Acknowledgments
We gratefully acknowledge the financial support provided by the BMWi (Federal Ministry for Economic Affairs and Energy), promotional reference 03ETW006A.

References
[1] Drgoňa J, Picard D and Helsen L 2020 Journal of Process Control 88 63–77 ISSN 09591524 URL https://linkinghub.elsevier.com/retrieve/pii/S0959152419306857
[2] Freund S and Schmitz G 2021 Building and Environment 197 107830 ISSN 03601323 URL https://linkinghub.elsevier.com/retrieve/pii/S0360132321002365
[3] Sturzenegger D, Gyalistras D, Morari M and Smith R S 2016 IEEE Transactions on Control Systems Technology 24 1–12 ISSN 1063-6536, 1558-0865 URL http://ieeexplore.ieee.org/document/7087366/
[4] Kathirgamanathan A, De Rosa M, Mangina E and Finn D P 2021 *Renewable and Sustainable Energy Reviews* **135** 110120 ISSN 13640321 arXiv: 2007.14866 URL http://arxiv.org/abs/2007.14866

[5] Picard D, Drgoňa J, Kvasnica M and Helsen L 2017 *Energy and Buildings* **152** 739–751 ISSN 0378-7788 URL http://www.sciencedirect.com/science/article/pii/S0378778817302190

[6] Drgoňa J, Arroyo J, Cupeiro Figueroa I, Blum D, Arendt K, Kim D, Ollé E P, Oravec J, Wetter M, Vrabie D L and Helsen L 2020 *Annual Reviews in Control* **50** 190–232 ISSN 13675788 URL https://linkinghub.elsevier.com/retrieve/pii/S1367578820300584

[7] Arendt K, Jradi M, Shaker H R and Veje C 2018 Comparative Analysis of White-, Gray- and Black-box Models for Thermal Simulation of Indoor Environment: Teaching Building Case Study *Proceedings of the 2018 Building Performance Modeling Conference and SimBuild co-organized by ASHRAE and IBPSA-USA (ASHRAE)* pp 173–180

[8] Jain A, Nghiem T, Morari M and Mangharam R 2018 Learning and Control Using Gaussian Processes 2018 ACM/IEEE 9th International Conference on Cyber-Physical Systems (ICCPSS) (Porto: IEEE) pp 140–149 ISBN 978-1-5386-5301-2 URL https://ieeexplore.ieee.org/document/8443729/

[9] Smarra F, Di Girolamo G D, De Iulis V, Jain A, Mangharam R and D’Innocenzo A 2020 *Nonlinear Analysis: Hybrid Systems* **36** 100882 ISSN 1751570X URL https://linkinghub.elsevier.com/retrieve/pii/S1751570X20300297

[10] Jain A, Smarra F, Reticioli E, D’Innocenzo A and Morari M 2020 arXiv:2001.07831 [cs, eess] ArXiv: 2001.07831 URL http://arxiv.org/abs/2001.07831

[11] Afram A and Janabi-Sharifi F 2015 *Energy and Buildings* **94** 121–149 ISSN 03787788 URL https://linkinghub.elsevier.com/retrieve/pii/S0378778815001504

[12] Yang S, Wan M P, Chen W, Ng B F and Dubey S 2020 *Applied Energy* **271** 115147 ISSN 03062619 URL https://linkinghub.elsevier.com/retrieve/pii/S0306261920306590

[13] Muggini A, Coccia G, Polonara F and Arteconi A 2020 *Energies* **13** 3125 ISSN 1996-1073 URL https://www.mdpi.com/1996-1073/13/12/3125

[14] Müller D, Lauster M R, Constantin A, Fuchs M and Remmen P 2016 AixLib - An Open-Source Modelica Library within the IEA-EBC Annex60 Framework *BauSim* (Stuttgart: Fraunhofer IRB Verlag) pp 3–9 URL https://publications.rwth-aachen.de/record/681852

[15] Knebel D E, Lutz J D, Kennedy S D, Marriott C E, Beda M F and McBride e a 2007 *ASHRAE STANDARDS COMMITTEE 2006–2007* 269

[16] VDI 2012 VDI 6007-3 - Calculation of transient thermal response of rooms and buildings Modelling of solar radiation

[17] Kümpel A, Stinner F, Gauch B, Baranski M and Müller D 2019 A Representative Simulation Model for Benchmarking Building Control Strategies (Banff, AB, Canada) URL http://www.iaarc.org/publications/2019_proceedings_of_the_36th_isarc/a_representative_simulation_model_for_benchmarking_building_control_strategies.html

[18] Chollet F and others 2015 *Keras* URL https://keras.io

[19] Andersson J A E, Gillis J, Horn G, Rawlings J B and Diehl M 2019 *Mathematical Computation* **11** 1–36 ISSN 1867-2949, 1867-2957 URL http://link.springer.com/10.1007/s12532-018-0139-4

[20] Wächter A and Biegler L T 2006 *Mathematical Programming* **106** 25–57 ISSN 0025-5610, 1436-4646 URL http://link.springer.com/10.1007/s10107-004-0559-y