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Jiří Cigler

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Model Predictive Control for Buildings

Jiří Cigler

Czech Technical University in Prague,
Faculty of Electrical Engineering,
Department of Control Engineering

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Supervisor:	prof. Ing. Vladimír Kučera, DrSc., dr.h.c.
Supervisor specialist:	Doc. Ing. Lukáš Ferkl, Ph.D.
Ph.D. programme:	Electrical engineering and information technology
Study branch:	Control engineering and robotics

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Prague, June 2013 *Jiří Cigler*

Declaration

I declare that I worked out the presented thesis independently and I quoted all used sources of information in accord with Methodical instructions about ethical principles for writing academic thesis.

Abstract

Energy savings in buildings have gained a lot of attention in recent years. Most of the research is focused on the building construction or alternative energy sources in order to minimize primary energy consumption of buildings. By contrast, this thesis deals with an advanced process control technique called model predictive control (MPC) that can take advantage of the knowledge of a building model and estimations of future disturbances to operate the building in a more energy efficient way.

MPC for buildings has recently been studied intensively. It has been shown that energy savings potential of this technique reaches almost 40 % compared to conventional control strategies depending on the particular building type. Most of the research results are, however, based on simulation studies subject to number of assumptions. On the contrary, the objectives of this thesis are *i)* evaluate MPC energy savings potential on a real building, *ii)* develop and evaluate an alternative MPC formulation for buildings that is less sensitive to model mismatch and weather forecast errors, *iii)* develop and evaluate an alternative MPC formulation that takes into account mathematical formulas for thermal sensation of occupants.

First of all, this thesis deals with the implementation of the MPC controller on a pilot building of Czech Technical University (CTU) in Prague. The development of a grey-box thermodynamical model for control, the formulation of the underlying optimization problem and the development of the software platform for optimization problem solving and communication of the optimal control moves to the building automation system are topics treated in detail. Moreover, the evaluation of the energy savings potential is provided, showing that for the investigated building, the savings are between 15 % and 28 %, power peak demand was lowered by 50 %, while the thermal comfort in the building was kept on a higher level.

Then this thesis presents a tool that was used for the development of the MPC controller applied for the CTU building. The tool enables tuning and debugging of MPC controllers for buildings and allows users to explore controller behavior for different scenarios (e.g. weather conditions, occupancy profiles or comfort regimes).

Afterwards, based on the assessment of the long term operation of the MPC controller applied to the control of the building of the CTU, the main issues for practical applicability of MPC are pointed out and an alternative optimal control problem formulation tackling the issues is proposed showing a better closed-loop performance even in situations when there is a model mismatch or disturbance prediction errors when comparing the performance to the formulations presented in the literature.

Finally, this thesis deals with the development of a computationally tractable method for solving an alternative MPC problem formulation, which incorporates thermal comfort index predicted mean vote and which leads to a general constrained optimization problem. The advantage of this formulation is that it implicitly contains user perception of the thermal comfort in the cost function and thus it is possible to achieve better thermal comfort even with less input energy.

Keywords

Predictive control; Energy savings; Building control optimization; Thermal comfort

Abstrakt

Energetické úspory v budovách se v posledních letech staly častým předmětem výzkumu, který se v této oblasti zaměřuje zejména na možnosti využití lepších konstrukčních materiálů anebo alternativních a energeticky efektivnějších zdrojů energie s ohledem na to, aby byla minimalizována primární energie spotřebovaná v budově. Tato disertační práce se ale zabývá alternativní metodou, jak dosáhnout energetických úspor ve vytápění a chlazení budov. Metoda je založena na pokročilé technice procesního řízení zvané prediktivní řízení, jejíž předností je schopnost na základě modelu řízené soustavy a predikcí poruchových veličin ovlivňujících systém (v tomto případě se jedná například o počasí nebo obsazenost budovy) řídit budovu energeticky efektivnějším způsobem než tomu je u běžných řídicích strategií budov.

V posledních letech výzkum v oblasti prediktivního řízení budov ukázal, že prediktivní regulátor má potenciál až na 40 % úspory energie v porovnání s běžnými strategiemi řízení a to v závislosti na řadě faktorů. Většina výzkumných výsledků je ovšem založena na simulačních studiích opírajících se o celou řadu předpokladů. I proto je cílem práce ověřit potenciál energetických úspor díky MPC na reálné budově, dále vyvinout MPC formulaci, jenž sníží citlivost řízení na chyby v matematickém modelu budovy a nepřesnosti v předpovědi počasí a konečně vyvinout MPC formulaci, která bude přímo pracovat s vnímáním tepelné pohody v budově.

Nejdříve budou v práci uvedeny detaily o implementaci prediktivního regulátoru na budově ČVUT v Praze. Zejména se jedná o způsob získání parametrů matematického modelu s předdefinovanou strukturou, formulaci optimalizačního problému, který je jádrem každého prediktivního regulátoru, popis softwarové platformy pro řešení optimalizačního problému a komunikaci optimálních vstupů do řídicího systému budovy. Na základě analýzy kvality řízení je ukázáno, že prediktivní regulátor dosahuje 15 % až 28 % úspor v porovnání s dobře naladěným stávajícím regulátorem. Navíc prediktivní regulátor snižuje špičkový odběr energie na polovinu a udržuje v budově lepší tepelný komfort.

V další části se práce věnuje nástroji, který umožňuje ladit parametry prediktivního regulátoru pro budovy. Tento nástroj zejména umožňuje uživateli zkoumat chování regulátoru při různých podmínkách (například při různém počasí, obsazenosti budovy nebo různých požadavcích na teploty v místnostech).

Na základě analýzy dlouhodobého chování prediktivního regulátoru na budově ČVUT a poznatků z literatury k tématu byly stanoveny hlavní problémy, se kterými se při praktickém nasazení prediktivního regulátoru setkáváme. V práci jsou rozebrány tyto problémy a je navržena alternativní formulace optimalizačního problému, která do jisté míry problémy řeší a v uzavřené smyčce vykazuje lepší chování i v situacích, kdy nejsou přesné předpovědi poruchových veličin nebo existují nepřesnosti v matematickém modelu soustavy.

V neposlední řadě se práce zabývá návrhem výpočetně jednoduché metody pro řešení alternativní formulace problému prediktivního řízení, která v sobě zahrnuje index tepelného komfortu PMV a jenž svým zařazením spadá do skupiny obecného nelineárního programování. Výhodou této formulace je to, že přímo obsahuje matematický předpis pro vnímání tepelného komfortu a tak lze dosáhnout lepšího komfortu i za cenu menší spotřebované energie.

Klíčová slova

Prediktivní řízení; Energetické úspory; Optimalizace řízení budov; Tepelný komfort

Contents

Abbreviations

Here is a list of abbreviations that will further be used in the thesis.

CTU	Czech Technical University in Prague
FEE	Faculty of Electrical Engineering
EU	European Union
US	United States
MPC	Model Predictive Control: an advanced method for constrained optimal control, which originated in the late seventies and early eighties in process industries
SMPC	Stochastic Model Predictive Control: a subcategory of MPC techniques dealing with stochastic models of the controlled system
HVAC	Heating Ventilation and Air Conditioning: a technology of indoor and automotive environmental comfort
TABS	Thermally Activated Building Systems
BAS	Building Automation System: a control system of a building
BEPS	Building Energy Performance Simulation tools: simulation programs primarily used for long term energy calculations for buildings
SCADA	Supervisory Control and Data Acquisition: a type of industrial control system
PMV	Predicted Mean Vote index: a thermal comfort index that is used in various international standards for assessment of thermal comfort not only in buildings
LTI	Linear Time Invariant
4SID	Subspace State Space System Identification
DSPM	Deterministic Semi-Physical Modeling
RC	Resistance Capacitance
QP	Quadratic Programming

1. Introduction

1.1. Motivation

In recent years, there has been a growing concern to revert or at least diminish the effect of the climate changes or the climate changes themselves. Moreover, there is a permanent effort for energy savings in most of the developed countries. In addition, the European Union (EU) presented targets concerning energy cuts defining goals by 2020 [1]: *i)* Reduction in EU greenhouse gas emissions at least 20 % below the 1990 levels, *ii)* 20 % of EU energy consumption to come from renewable resources, *iii)* 20 % reduction in primary energy use compared to projected levels, to be achieved by improving energy efficiency. Similar goals, in some cases even more restrictive, have been stated by the US government with minor differences on the level of each state [2].

As buildings account for about 40 % of total final energy consumption and more than half of the end energy is consumed in heating, ventilation and air conditioning (HVAC) systems [3], an efficient building climate control can significantly contribute to the reduction of the power consumption as well as the greenhouse gas emissions.

It is also important to mention the current state of the building sector to find a way to achieve energy cuts. For instance in the US, there are about one to two million buildings newly constructed every year. However, there are approximately 110 million existing buildings consuming much more energy *per se* than new buildings constructed according to current standards. Even if each of the new buildings use net-zero-energy technology, it would take long time to achieve significant difference on the overall energy bill [4]. A much more productive approach for achieving the strict energy cuts would be to focus also on the retrofit of the existing buildings e.g by implementing energy efficient control algorithms into building automation systems (BAS), which can nowadays control HVAC systems, as well as the blind positioning and lighting systems [5, 6].

Besides sophisticated rule based control algorithms, there have emerged two main research trends in the field of advanced HVAC control recently [7]:

- Learning based approaches like neural networks [8, 9]; fuzzy and adaptive fuzzy neural networks [10, 11], genetic and evolutionary algorithms [12, 13], etc.
- Model based predictive control (MPC) techniques that are based on the principles of the classical control [14].

In this thesis, we will only focus on the latter techniques.

1.2. Model Predictive Control

MPC is a method for constrained optimal control, which originated in the late seventies and early eighties in the process industries (oil refineries, chemical plants, etc.) (see e.g. [15, 14, 16, 17]). MPC is not a single strategy, but a class of control methods with the model of the process explicitly expressed in order to obtain a control signal by minimizing an objective function subject to some constraints. In building control, one would aim at optimizing the energy delivered (or cost of the energy) subject to comfort constraints.

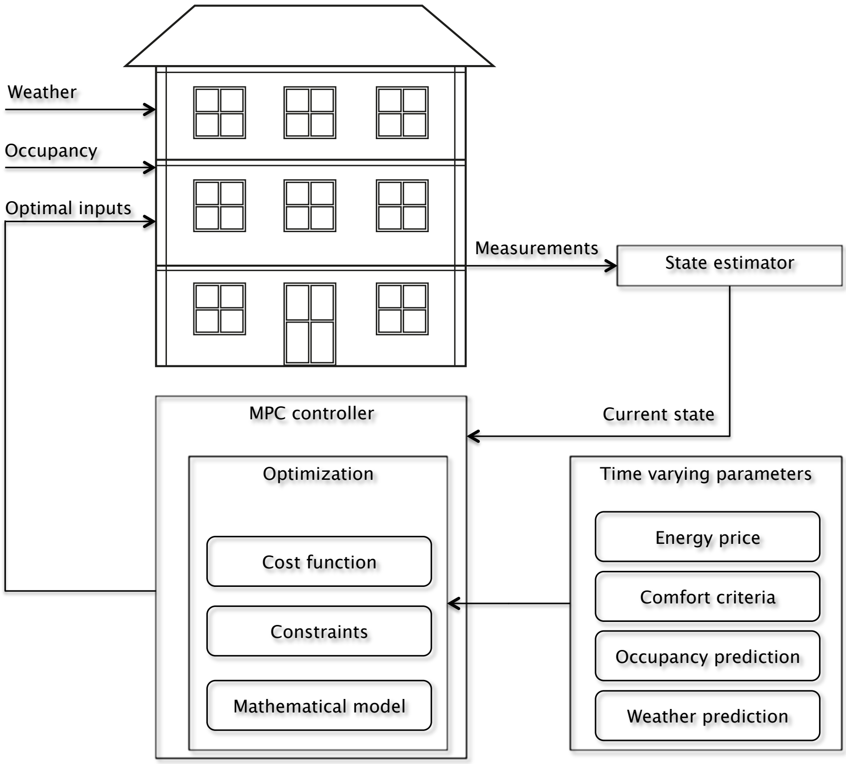

Fig. 1. Basic principle of MPC for buildings

During each sampling interval, a finite horizon optimal control problem is formulated and solved over a finite future window. The result is a trajectory of inputs and states into the future, respecting the dynamics and constraints of the building while optimizing some given criteria. In terms of building control, this means that at the current control step, a heating/cooling etc. plan is obtained for the next several hours or days, based on a weather forecast. Predictions of any other disturbances (e.g. internal gains), time-dependencies of the control costs (e.g. dynamic electricity prices), or of the constraints (e.g. thermal comfort range) can be readily included in the optimization.

The first step of the control plan is applied to the building, setting all the heating, cooling and ventilation elements, then the process moves one step forward and the procedure is repeated at the next time instant. This receding horizon approach is what introduces feedback into the system, since the new optimal control problem solved at the beginning of the next time interval will be a function of the new state at that point in time and hence of any disturbances that have acted on the building.

Figure 1 summarizes the basic principle of MPC for buildings. Time-varying parameters (i.e. the energy price, the comfort criteria, as well as predictions of weather and occupancy) are inputs to the MPC controller. One can see that the modeling and design effort consist of specifying a dynamic model of the building, as well as constraints of the control problem and a cost function that encapsulates the desired behavior. At each sampling interval, these components are combined and converted into an optimization problem depending on the MPC framework chosen. A generic framework is given by the following finite-horizon optimization problem:

$$\min_{u_0,\ldots,u_{N-1}} \quad \sum_{k=0}^{N-1} l_k(x_k, u_k) \qquad \text{Cost function} \tag{1}$$

subject to

$$x_0 = x \qquad \text{Current state} \tag{2}$$

$$x_{k+1} = f(x_k, u_k, w_k) \qquad \text{Dynamics – state update} \tag{3}$$

$$y_k = g(x_k, u_k, w_k) \qquad \text{Dynamics – system output} \tag{4}$$

$$(x_k, u_k) \in \mathcal{X}_k \times \mathcal{U}_k \qquad \text{Constraints} \tag{5}$$

where k is the discrete time step, N is the prediction horizon, $x_k \in \mathbb{R}^n$ is the system state, $u_k \in \mathbb{R}^m$ is the control input, $y_k \in \mathbb{R}^p$ is the system output, $w_k \in \mathbb{R}^l$ is the vector of known/estimated disturbances acting on the system, $\mathcal{X}_k$ and $\mathcal{U}_k$ denote the constraints sets of the state and inputs respectively and are explained below.

All of the components in the above MPC formulation are detailed below with the discussion how they affect the system and the resulting optimization problem. Please note that this is not a comprehensive overview of MPC formulations, but rather a collection of formulations, which are frequently used or reasonable in the field of building control. For a more comprehensive overview on MPC formulations, the reader is referred e.g. to [14].

Cost function

The cost function generally serves two purposes:

- **Stability.** It is common to choose the structure of the cost function such that the optimal cost forms a Lyapunov function for the closed loop system, and hence will guarantee stability. In practice, this requirement is generally relaxed for stable systems with slow dynamics, such as buildings, which leaves the designer free to select the cost strictly on a performance basis.

- **Performance target.** The cost is generally, but not always, used to specify a preference for one behavior over another, e.g., minimum energy or maximum comfort.

Generally, the main goal is to minimize energy cost while respecting comfort constraints, which can be formalized by the following cost function:

$$l_k(x_k, u_k) = (y_k - y_{r,k})^T Q_k (y_k - y_{r,k}) + R_k u_k, \tag{6}$$

where Q_k and R_k are time varying matrices of appropriate size and $y_{r,k}$ the reference signal at time k. The trade-off between precision of reference tracking and energy consumption is expressed by proportion of the matrices Q_k and R_k. The reference tracking is expressed as a quadratic form because it significantly penalizes larger deviations from the reference. The energy bill is usually an affine function of a total amount of consumed energy. Therefore, the control cost is weighted linearly.

Current state

The system model is initialized to the measured/estimated current state of the building and all future (control) predictions begin from this initial state x. Depending on what the state of the building is describing, it might not be possible to measure all of its components directly and e.g. Kalman filtering needs to be employed in order to obtain an estimate of the current state.

Dynamics

The controller model (i.e. the mathematical description of the building thermal dynamics) is a critical piece of the MPC controller. Typically, the linear dynamics is considered

$$x_{k+1} = Ax_k + Bu_k + Vw_k \tag{7}$$

$$y_k = Cx_k + Du_k + Ww_k. \tag{8}$$

Here the real matrices A, B, C, D, V, W are so called system matrices and are of appropriate dimensions. This is the most common model type and the only one that will result in a convex and easily solvable optimization problem.

Constraints

The ability to specify constraints in the MPC formulation and to have the optimization routine handle them directly is the key strength of the MPC approach. There can be constraints on the states or the output, as well as on the input. Linear constraints are the most common type of constraint, which are used to place upper/lower bounds on system variables

$$u_{min,k} \leq u_k \leq u_{max,k}, \tag{9}$$

or generally formulated as

$$G_k u_k \leq g_k. \tag{10}$$

The constraints can be similarly defined for system states and outputs.

1.3. Organization of the Thesis

This thesis is further structured as follows: Chapter 2 defines the goals to be achieved, Chapter 3 presents state-of-the-art in the area of MPC for buildings. The following Chapter 4 deals with the author's results. As this thesis is meant as a unifying text of author's published papers related to the topic of this doctoral thesis, the chapter contains four main papers with a brief description how the particular paper fits into the mosaic of this work. The main body of the text is concluded by Chapter 5 and a list of cited works.

2. Goals of the Thesis

Evaluation of MPC Energy Savings Potential on a Real Building

The objective here is to find a suitable pilot building for performing experiments with MPC controller, implement MPC controller and interconnect it with the building automation system of the building. Once the MPC controller is implemented, the objective is to evaluate the controller performance in terms of energy usage and satisfaction of thermal comfort. The performance is to be compared to a well-tuned state-of-the art control algorithm.

Development of a MPC Formulation Less Sensitive to Model Mismatch and Prediction Errors

Typically, the most common MPC formulation does not perform well in closed loop. Hence the second objective of this thesis is to develop and evaluate an alternative MPC formulation for buildings that is less sensitive to model mismatch and errors of weather prediction.

Development of a Computationally Tractable PMV Based MPC

Thermal comfort is a complicated quantity. According to the international standards defining requirements for thermal comfort in buildings, the thermal comfort can be expressed in two ways:

a) by a temperature range for operative temperature,

b) by a range for PMV index.

On the contrary to the first goal of the thesis, when a temperature range is used for the definition of the thermal comfort, the objective here is to use PMV index for representation of the thermal comfort directly in the MPC formulation. As the PMV is a nonlinear function of several quantities, the goal is to develop a computationally tractable MPC method solving this case.

3. State-of-the-Art

In this chapter, we present a literature overview of methods that are based on the formulation of the building control as an optimization problem. The building physics is formulated in a mathematical model that is used for the prediction of the future building behavior according to the selected operation strategy and weather and occupancy forecasts. The aim is mainly to design a control strategy that minimizes the energy consumption (or operational costs), while guaranteeing that all comfort requirements are met.

In the following, we will briefly mention related works in a structured way and we will start with early works dealing with MPC for buildings.

3.1. Early Works

A study presented by Grünenfelder and Tödtli [18] was among the first papers which formulated the control of the thermal storage as an optimization problem. The control of a simple solar domestic hot water system considering the weather forecast and two energy rates is discussed there. Some early papers [19, 20] deal with a least-cost cooling strategy using the building mass as a thermal storage.

An overview of the active use of thermal building mass is given by Braun [21], where a variable energy price and the cost of the power peak are considered in the formulation of the optimization problem.

Predictive control of radiant floor heating was studied by Chen [22], where the author first identified a model for MPC and then demonstrated on simulation results that the behavior of MPC is superior to the conventional controllers in terms of response speed, minimum offset and on-off cycling frequency.

Performance of MPC applied to the control of a radiant floor heating was later assessed by Cho [23] showing that the savings potential of MPC reaches 10 % during cold winter months and somewhat higher during mild weather conditions.

The Group around Tödli had been continuously developing MPC solution for Siemens company, which resulted in three patents [24, 25, 26] and a short conference paper [27]. In all these patents, a particular model structure is presented for the particular case, which of course restricts usage of this technique in these cases.

3.2. Energy Peak Reduction

Besides the energy minimization, predictive control can also contribute to energy peak reductions [28, 29]. Energy peak reduction can significantly lower the costs of the building operation and the initial cost of mechanical parts if considered in the building design. Grid thrifty control can also help to keep supplier–consumer balance in a grid.

Current grid load and energy peak reduction was considered in a simulation study of Oldewurtel et al. [30] dealing with power supply to several commercial buildings trying to find a trade-off between minimizing cost on side of building and flattening grid load profile.

Ma et al. [31] treated demand response control where MPC applied on cooling system of a multi-zone commercial building resulted in pre-cooling effects during the off-peak period and autonomous cooling discharging from the building thermal mass during the on-peak period.

3.3. Control Hierarchy

The hierarchy of the HVAC system controllers plays also an important role. MPC is generally suitable as a top-level controller only and the question always is, how to achieve a symbiosis between low-level control loops and the top-level MPC.

There have been couple of contributions on how to integrate MPC into the control hierarchy of the BAS [32]. Zhang and Hanby [33] addressed a building system with renewable energy sources which are generally of low intensity and temporally inconsistent. Supervisory control system is then responsible for deploying the energy directly into the building, storing for later use or rejecting to the environment.

The centralized MPC topology for multi-zone buildings is often undesirable and difficult to implement, as computational demands required to solve the centralized problem grows exponentially with the number of zones/subsystems. Another drawback of the centralized strategies is their poor flexibility and reliability, comparing to a decentralized or distributed control structure. In the case of the decentralized MPC, the large optimization problem is split into smaller ones (each with its own objective function and constraints) neglecting some interactions between building zones, while in the case of the distributed control structure, several MPC controllers minimize a global cost function. By using this technique, the overall computation time can be significantly reduced and, at the same time, the robustness of the whole control system can be increased. However, this solution comes at the cost of increased communication effort and sub-optimal performance.

Moroşan et al. [34] and later in [35] addressed heating of a multi-zone building with a decentralized and distributed MPC. While the performance of the decentralized one strongly depends on the level of interactions between subsystems, the distributed one, as each controller knows about control actions of its neighbors, keeps the same performance as the centralized one.

An alternative approach was presented by Ma, Anderson, and Borrelli [36] where the problem of distributed MPC is implemented using sequential quadratic program and dual decomposition.

3.4. Stochastic MPC

A stochastic model predictive control (SMPC) approach applied on a room temperature regulation problem is proposed in a pioneering work by Oldewurtel, Jones, and Morari [37]. The idea is to consider weather forecast (ambient temperature and solar radiation) to be a stochastic disturbance, therefore a weather prediction error model has to be constructed. Moreover, chance constraints are introduced into the optimization problem in order to meet hard constraints in at least 1-α % cases (because if the random distribution is unbounded, then the optimization problem with any hard constraint is infeasible).

A convex approximation technique outperforming the previous one and solving the same optimization problem was proposed by Korda and Cigler [38].

Later, Ma, Vichik, and Borrelli [39] presented an approach where the chance constraints are decoupled using Boole's inequality and for the resulting optimization problem, the authors proposed a tailored interior point method to explore the special structure of the resulting SMPC problem.

3.5. Building Modeling

MPC inherently requires an appropriate model of the controlled plant, which is then used for the computation of the optimal control inputs. This model must be sufficiently precise, in order to yield valid predictions of the relevant variables (e.g. room temperatures), but at the same time, the model must be as simple as possible for the optimization task to be computationally tractable and numerically stable.

In the HVAC engineering community, building energy performance simulation (BEPS) tools (e.g., EnergyPlus, TRNSYS, ESP-r, etc.) are typically used for modeling of the building physics [40]. These tools contain numerous complex calculations, non-linearities, switches and iterative procedures that make their usage in online optimization prohibitive as the resulting models are in an implicit form[1]. An attempt to use a BEPS model within an optimization routine was reported by Coffey et al. [41], but generally, researchers seek models with lower complexity and computational demands. BEPS models can then be used for MPC algorithm evaluation when co-simulation scheme is used [42].

So-called linear time invariant (LTI) models are much more suitable for the use within an MPC framework. The usage of LTI models typically leads to a convex optimization problem that, in general, can be solved well by standard optimization software tools. Obtaining an appropriate LTI model of the controlled building is, however, a delicate and laborious task even for experienced and knowledgeable engineers. A brief review of methods that can be used for building modeling is mentioned by Prívara et al. [43]. Generally, following techniques can be used to obtain an LTI model:

a) *Black-box identification.* The model structure and parameters are identified in a statistical-empirical manner from on-site measurements or from signals generated from BEPS. Following identification methods are available options for buildings: *i)* Subspace state space system identification methods (4SID) [44]. *ii)* MPC relevant identification (MRI) (multi-step ahead prediction error is minimized) [45]. The black-box approach is conceptually simple, but technically tricky, and it crucially depends on the availability of appropriate input data sets that encompass sufficient long sequences of all relevant excitation-response signal pairs. These are very hard to obtain from a real building during normal operation.

a) *Grey-box modeling.* This approach describes a building's thermal dynamics based on a thermal resistance capacitance (RC) network [46, 47, 48, 49]. It presents an analogue to an electric circuitry, with temperature gradients and heat fluxes replacing electric potentials and currents. A plausible model structure (RC network topology) is first specified a priori, and then the model parameters are identified from measurements or BEPS simulations. The advantage of this approach is that basic knowledge of possible thermal interactions (e.g., neighbourship of building zones) can easily be introduced. However, the parameter identification is far from trivial.

a) *White-box modeling.* This approach also relies upon a thermal RC network. Here both the RC network's topology and its R and C elements (the model parameters) are derived directly from detailed geometry and construction data (see e.g. work by Sturzenegger et al. [50]). Compared to grey-box modeling, this approach has an even stronger physical basis. However, similarly to BEPS studies, it requires availability and processing of a large amount of building-specific information.

[1] In this context, we call a model explicit if there are mathematical formulas describing a state evolution, i.e. a set of differential or difference equations is available. Otherwise the model is called implicit.

3.6. Thermal Comfort Representation

Thermal comfort in buildings is usually evaluated using the operative temperature [51], which is, in the simplest way, defined as the average of the air temperature and the mean radiant temperature (i.e. usually computed as area weighted mean temperature of the surrounding surfaces [52]). However, the thermal comfort is a more complicated quantity and, in accordance with ISO 7730 [51] and ASHRAE 55 [53] international standards, it can be defined in a more general way as "*The condition of mind which expresses satisfaction with the thermal environment*", pointing out that it is a cognitive process influenced by various quantities, physical activity, physiological and psychological factors and typically, this process is described by the thermal comfort index called predicted mean vote (PMV).

The PMV index as a part of MPC cost function was presented by Freire, Oliveira, and Mendes [54], where the authors show that making use of PMV index, MPC can achieve even higher energy savings. On the other hand, the non linear character of the PMV index complicates the usage of this thermal comfort index. Several MPC problem formulations having PMV index in the cost function are compared by [55]. The comparison is carried out on a real building of a solar energy research centre.

In addition, there has been developed a direct relationship between PMV index and productivity rate of the occupants of the office buildings. As the cost of office laborers in the developed countries is much higher than the operational costs of a building, the fulfilment of thermal comfort (in terms of PMV) can result in a substantial economic benefit [56, 57].

3.7. Occupancy Predictions

Occupancy predictions can also be readily included into the MPC problem formulation. Investigation of the energy savings potential when using occupancy information to realize a more energy efficient building climate control is presented by Oldewurtel, Sturzenegger, and Morari [58]. The authors showed that this additional information can lead to significant energy savings (up to 50 % of energy required by HVAC system is saved depending on occupants' vacancy intervals).

3.8. Deployment of MPC

There have been several attempts to validate MPC technique by a real operation to prove energy savings potential.

Supervisory MPC controller was successfully tested by Henze et al. [59] on the control of an active and passive building thermal storage inventory in a test facility. The controller uses a three-step procedure consisting of *i)* short-term weather prediction, *ii)* optimization of control strategy over the next planning horizon using a calibrated building model, *iii)* post-processing of the optimal strategy to yield a control command for the current time step. The energy consumption was in this case reduced by about 10 % and costs were reduced by about 17 %.

Different MPC setups applied to a thermal storage of the building cooling system have been continuously tested in the campus of the University of California, Merced. A controller that minimizes cooling costs with respect to the time-varying electrical energy price is presented by Ma et al. [60]. The aim is to take advantage of night-time electricity rates and to lower the ambient temperature while pre-cooling the chilled water tank. Experimental results of pre-cooling are later presented in [61], where a more detailed building load model was used and where where MPC achieved up to 25 % energy savings. Later, the results were summarized in [47].

Last but not least, there are the results reported in [46], where the MPC applied to a heating system of a university building saves 30 % of energy in cross comparison with conventional control strategies like heating curve, lowers power demand peaks by 50 % and keeps thermal comfort in the building on a higher level.

3.9. Software Tools Dedicated to MPC for Buildings

In the literature, there have been reported several software tools capable of running MPC for buildings.

The development of a SCADA (Supervisory Control and Data Acquisition) system allowing MPC control for buildings is reported by e.g. Figueiredo and Costa [62]. The optimal control law is computed in MATLAB and the variables are transmitted into BAS via Dynamic Data Exchange protocol. The authors show the functionality on a real life example.

An alternative way to communicate optimal control moves is reported in [46]. Here, the optimization task is solved in Scilab environment and transmitted to BAS via a proprietary protocol.

These tools are dedicated mainly to interconnection of BAS and the computational core solving MPC optimization problem. On the other hand, there are two analyzation on-line tools *i)* `http://buildinglab.felk.cvut.cz`, *ii)* `http://bactool.ethz.ch/`. The former one is used for a design phase, allowing user to tune the controller performance, while the latter evaluates the mean behavior of the controlled system over a long time period in the order of months or a year and indicates whether the particular building is suitable for predictive control.

It is also important to mention the project GenOpt aiming at employing the predictive control framework directly without the need of a simple model. GenOpt rather uses detailed models developed in EnergyPlus or in other building performance simulation tools [41].

A similar project is MLE+, allowing users to easily interconnect simulation models developed in EnergyPlus with Matlab code and test algorithms for building automation systems [63].

4. Results

This chapter deals with authors' results related to the thesis. The chapter is not written in a common way but the core of it lies in the reviewed papers, which are included here with a short comment on how the particular paper contributes to the thesis. This format is approved by a directive issued by the Dean of Faculty of Electrical Engineering (FEE) of the Czech Technical University in Prague (CTU). This directive is called "Directive of the dean for dissertation theses defence at CTU FEE" and is available at `http://www.fel.cvut.cz/cz/vv/doktorandi/predpisy/SmobhDIS.pdf`, unfortunately only in Czech.

In the following, the three most important journal papers are presented accompanied by a conference paper that has recently been accepted for the conference Clima 2013 (`http://www.clima2013.org/`). This paper, however, presents important results related to the thesis and therefore it is included here aside the reviewed papers published in journals with impact factor.

4.1. Experimental Analysis of Model Predictive Control for an Energy Efficient Building Heating System

Full citation:
J. Široký, F. Oldewurtel, J. Cigler, and S. Prívara. “Experimental analysis of model predictive control for an energy efficient building heating system”. In: *Applied Energy* 88.9 (2011), pp. 3079–3087. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2011.03.009
Co-authorship: 25 %
Citations:

- Web of Science: 23 (out of which 5 are self citations)
- Google Scholar: 47 (out of which 12 are self citations)

Journal statistics according to the Journal Citation Report®

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Impact Factor:	5.106
5-Year Impact Factor:	4.456
Immediacy Index:	0.952
Citable Items:	558
Cited Half-life:	2.5
Citing Half-life:	5.7

Annotation:
This paper follows the previously published work dealing with the identification of a thermodynamical model of the CTU university building and first experience with deployed MPC [64]. This paper deals mainly with the description of the implementation of the MPC controller (development of a grey-box model, the formulation of the optimization problem to be solved, the development of the software platform for the optimization problem solving and the communication of optimal control moves to the BAS), validation of the MPC controller functionality (in terms of reasonable predictions the model gives and comfort violations the controller produces in closed-loop) and the evaluation of the energy savings (based on a cross comparison with well tuned state-of-the-art control strategy).
Contribution to the thesis:
This paper contributes mainly to the first goal of the thesis, i.e. it describes the implementation of the MPC controller on a pilot building and at the same time, the evaluation of the controller performance is presented.

In this paper, it is shown that the energy savings potential for using MPC with weather predictions for the investigated building heating system are between 15 % and 28 %, depending on various factors, mainly the insulation level and the outside temperature. Moreover, the power peak demand is lowered by 50 % and the thermal comfort in the building is kept on a higher level.

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Experimental analysis of model predictive control for an energy efficient building heating system

Jan Široký [a,*], Frauke Oldewurtel [b], Jiří Cigler [c], Samuel Prívara [c]

[a] Department of Cybernetics, Faculty of Applied Sciences, University of West Bohemia in Pilsen, Czech Republic
[b] Automatic Control Laboratory, Department of Electrical Engineering, Swiss Federal Institute of Technology in Zurich (ETHZ), Switzerland
[c] Department of Control Engineering, Faculty of Electrical Engineering, Czech Technical University in Prague, Czech Republic

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A B S T R A C T

Low energy buildings have attracted lots of attention in recent years. Most of the research is focused on the building construction or alternative energy sources. In contrary, this paper presents a general methodology of minimizing energy consumption using current energy sources and minimal retrofitting, but instead making use of advanced control techniques. We focus on the analysis of energy savings that can be achieved in a building heating system by applying model predictive control (MPC) and using weather predictions. The basic formulation of MPC is described with emphasis on the building control application and tested in a two months experiment performed on a real building in Prague, Czech Republic.

1. Introduction

Buildings account for 20–40% of the total final energy consumption and its amount has been increasing at a rate 0.5–5% *per annum* in developed countries [1]. Thanks to developments in the field of mechanical and civil engineering, building energy demands can be reduced significantly. Unfortunately, most of the conventional energy reduction solutions require considerable additional investments. In contrast, energy savings with minimal additional cost can be achieved by improvement of building automation system (BAS). In today's buildings not only heating, ventilation and air conditioning (HVAC) systems can be automatically controlled but also blind positioning and lighting systems can be operated by the BAS [2,3].

The paper focuses on methods that are based on the formulation of the building control as an optimization problem. The building physics are formulated in a mathematical model that is used for the prediction of the future building behavior according to the selected operation strategy and the weather and occupancy forecasts. The aim is to design a control strategy, that minimizes the energy consumption (or operational costs) while guaranteeing that all comfort requirements are met. An advanced control technique usually denoted as Model Predictive Control (MPC) is described in the paper.

A comprehensive overview of the literature related to predictive building control can be found on the web site of the OptiControl project[1]. The key principle of MPC used for building control is the efficient use of the thermal mass or thermal storage of a building. A study presented in [4] was among the first papers which formulated the control of the thermal storage as an optimization problem. The control of a simple solar domestic hot water system considering the weather forecast and two energy rates are discussed there. Some early papers [5,6] deal with a least-cost cooling strategy using the building mass as a thermal storage. An overview of the active use of thermal building mass is given in [7], where a variable energy price and the cost of the peak power are considered in the formulation of the optimization problem. The controller that minimizes cooling costs with respect to the time-varying electrical energy price is presented also in [8]. The aim is to take advantage of night-time electricity rates and to lower the ambient temperature while precooling the chilled water tank. Experimental results of precooling are presented in [9] where a more detailed building load model was used. Predictive control of heating using the thermal mass is discussed in, e.g. [10,11]. Energy savings making use of MPC in relation to different thermal comfort criteria is discussed in [12].

* Corresponding author. Address: Department of Cybernetics, Faculty of Applied Sciences, University of West Bohemia in Pilsen, Univerzitní 8, 306 14 Pilsen, Czech Republic. Tel.: +420 724 030 150.

E-mail addresses: jan.siroky@rcware.eu (J. Široký), oldewurtel@control.ee.ethz.ch (F. Oldewurtel), jiri.cigler@fel.cvut.cz (J. Cigler), samuel.privara@fel.cvut.cz (S. Prívara).

1 www.opticontrol.ethz.ch.

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Besides the energy minimization, predictive control can also contribute to energy peak reductions [13,14]. Energy peak reduction can significantly lower the costs of the building operation and initial cost of mechanical parts if considered in the building design. Current grid load and energy peak reduction was considered in [15]. Predictive control used for the sizing of heating systems for discontinuously occupied buildings is discussed in [16], where the model is decoupled into four simple RC models which enable modeling of the contribution of outdoor air temperature, solar radiation, and internal gains separately.

As mentioned, MPC is not the only technique that can be used for optimal building control. There were numerous attempts to utilize advanced control techniques that are well-known in industrial process control also for building control [17]. We briefly mention some of recently published alternative solutions to optimal building control. The general dynamic programming problem for the control of a borehole thermal energy storage system is solved in [18]. The aim was to guarantee the delivery of heat or cold all-year-around while minimizing the operational costs. A reinforcement learning technique used for a building thermal storage control is outlined in [19,20]. The real building experiment provided only 8.3% cost savings because the thermal storage has been only partially utilized by the learning control strategy. In [21], a set of fuzzy rules was used to cut down the time needed for tuning the supervisory controller. Genetic algorithms and simulated annealing were used for optimal control of cooling in [22]. The objective was to design economically optimal the use of natural ventilation, fan-driven ventilation, and mechanical air conditioning with respect to indoor temperature requirements. The unmanageable number of possible control sequences is reduced by consideration of practical issues based on physical insight.

The increased popularity of MPC usage for building control in recent years is indisputable, however, most of the results are based on the simulations or short time experiments. In this paper, we provide a detailed description of an MPC implementation on a real building and we analyze results from two months of operation. The paper is organized as follows. The predictive control strategy is presented in Section 2. Section 3 is devoted to modeling with stress on statistical modeling. A detailed case-study is discussed in Section 4. The Section 5 concludes the paper.

2. Model predictive control

The Building Automation System (BAS) aims at controlling heating, cooling, ventilation, blind positioning, and electric lighting, of a building such that the temperature, CO_2 and luminance levels in rooms or building zones stay within the desired comfort ranges. One typically divides the control hierarchy into two levels: the low-level controller which typically operates at the room-level and is used to track a specified setpoint, and a high-level controller which is done for the whole building and determines the setpoints for the low-level controllers. The article focuses on the usage of Model Predictive Control (MPC), which is used as high-level controller.

2.1. MPC strategy

MPC is a method for constrained control which originated in the late seventies and early eighties in the process industries (oil refineries, chemical plants, etc.) (see, e.g. [23–26]). MPC is not a single strategy, but a class of control methods with the model of the process explicitly expressed in order to obtain a control signal by minimizing an objective function subject to some constraints. In building control one would aim at optimizing the energy use or cost subject to comfort constraints.

During each sampling interval, a finite-horizon optimal control problem is formulated and solved over a finite future window. The result is a trajectory of inputs and states into the future satisfying the dynamics and constraints of the building while optimizing some given criteria. In terms of building control, this means that at the current point in time, a heating/cooling, etc. plan is formulated for the next several hours to days, based on predictions of the upcoming weather conditions. Predictions of any other disturbances (e.g., internal gains), time-dependencies of the control costs (e.g., dynamic electricity prices), or of the constraints (e.g., thermal comfort range) can be readily included in the optimization.

The first step of the control plan is applied to the building, setting all the heating, cooling and ventilation elements, then the process moves one step forward and the procedure is repeated at the next time instant. This receding horizon approach is what introduces feedback into the system, since the new optimal control problem solved at the beginning of the next time interval will be a function of the new state at that point in time and hence of any disturbances that have acted on the building.

Fig. 1 summarizes the basic MPC control scheme. As time-varying design parameters, the energy price, the comfort criteria, as well as predictions of the weather and occupancy are input to the MPC controller. One can see that the modeling and design effort consist of specifying a dynamic model of the building, as well as constraints of the control problem and a cost function that encapsulates the desired behavior. In each sampling interval, these components are combined and converted into an optimization problem depending on the MPC framework chosen. A generic framework is given by the following finite-horizon optimization problem:

Problem 1.

$$\min_{u_0,\dots,u_{N-1}} \sum_{k=0}^{N-1} l_k(x_k, u_k) \quad \text{Cost function} \tag{1}$$

s.t.

$$x_0 = x \quad \text{Current state} \tag{2}$$

$$x_{k+1} = f(x_k, u_k) \quad \text{Dynamics} \tag{3}$$

$$(x_k, u_k) \in \mathscr{X}_k \times \mathscr{U}_k \quad \text{Constraints} \tag{4}$$

where $x_k \in \mathbb{R}^n$ is the state, $u_k \in \mathbb{R}^m$ is the control input, k is the time step, $\mathscr{X}_k$ and $\mathscr{U}_k$ denote the constraints sets of the state and inputs respectively and are explained below. We now detail each of the four components in the above MPC formulation and discuss how they affect the system and the resulting optimization problem. Please note that this is not a comprehensive overview of MPC formulations, but rather a collection of formulations, which are frequently used or reasonable in the field of building control. For a more comprehensive overview on MPC formulations, the reader is referred, e.g. to [27].

2.1.1. Cost function

The cost function generally serves two purposes:

- **Stability.** It is common to choose the structure of the cost function such that the optimal cost forms a Lyapunov function for the closed loop system, and hence will guarantee stability. In practice, this requirement is generally relaxed for stable systems with slow dynamics, such as buildings, which leaves the designer free to select the cost strictly on a performance basis.
- **Performance target.** The cost is generally, but not always, used to specify a preference for one behavior over another, e.g., minimum energy or maximum comfort.

J. Široký et al. / Applied Energy 88 (2011) 3079–3087 3081

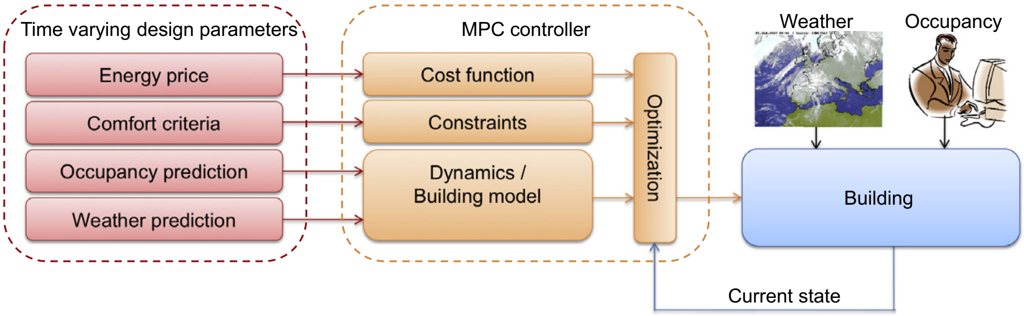

Fig. 1. Basic principle of model predictive control for buildings.

Generally, the main goal is to minimize energy cost while respecting comfort constraints, which can be formalized by the following cost function:

$$l_k(x_k, u_k) = (y_k - y_{r,k})^T Q_k (y_k - y_{r,k}) + R_k u_k, \tag{5}$$

where Q_k and R_k are time-varying matrices of appropriate size and $y_{r,k}$ the reference signal at time k. The trade-off between precision of reference tracking and energy consumption is expressed by proportion of the matrices Q_k and R_k. The reference tracking is expressed as a quadratic form because it significantly penalizes larger deviations from the reference. The energy bill is usually an affine function of a total amount of consumed energy. Therefore, the control cost is weighted linearly. The function Eq. (5) is not the only cost function applicable to building control. There could be, for example, peak energy demand penalization included in the energy bill that can be expressed by L^∞ norm of control inputs in the cost function. Detailed description of the cost function used in the Prague building is given in Section 4.3, for alternative formulations see [28].

2.1.2. Current state

The system model is initialized to the measured/estimated current state of the building and all future (control) predictions begin from this initial state x. Depending on what the state of the building is describing, it might not be possible to measure everything directly. In this case, a Kalman filter can be used to estimate the current state of the building and the estimate is used as initial state.

2.1.3. Dynamics

The controller model, i.e. the mathematical description of the building dynamics is a critical piece of the MPC controller. For the work presented in this paper we restrict ourselves to linear dynamics

$$x_{k+1} = Ax_k + Bu_k. \tag{6}$$

This is the most common model type and the only one that will result in a convex and easily solvable optimization problem.

2.1.4. Constraints

The ability to specify constraints in the MPC formulation and to have the optimization routine handle them directly is the key strength of the MPC approach. There can be constraints on the states or the output, as well as on the input. When explaining different forms of constraints in the following we will do it for input constraints only, but everything applies for state and output constraints alike. *Linear constraints* are the most common type of constraint, which are used to place upper/lower bounds on system variables

$$u_{\min,k} \leqslant u_k \leqslant u_{\max,k}, \tag{7}$$

or generally formulated as

$$G_k u_k \leqslant g_k. \tag{8}$$

The constraints can be constant, given by physical or logical limitations. For instance, valve cannot be open more that 100% or temperature of heating water cannot exceed some predefined level. The constraints can be also time-varying, e.g. to account for different comfort constraints during day-time and night-time. In general case, the constraints can be a function of state variables or inputs as discussed in Section 4.3. This class of constraints can also be used to approximate any convex constraint to an arbitrary degree of accuracy. Linear constraints also result in the simplest optimization problems. Furthermore, one might want to constrain the rate of change, which is done by imposing a constraint of the form

$$|u_k - u_{k-1}| \leqslant \Delta_{u_{\max}}. \tag{9}$$

3. Modeling

Modeling of the building requires insight both into control engineering as well as into HVAC engineering. Moreover, it is also the most time demanding part of designing the MPC setup.

Two approaches to building modeling are outlined in this section. Both of them come from so-called RC modeling. The aim is to provide insight into these techniques with emphasis on their applicability for MPC. Largely used computer aided modeling tools (e.g. TRNSYS, EnergyPlus, ESP-r, etc.) are not considered here, as they result in complex models which cannot be readily used for control purposes.

When large measurement data sets are available, a purely statistical approach for creation of a building model is preferred. A large number of System Identification methods exists (a survey is listed in, e.g. [29]), however, only a few of them have the capability of identification of multiple-input multiple-output (MIMO) systems, which are considered in case of building control. For identification of linear MIMO models, subspace identification methods are often used [29–31] and have been suggested for identification of building models as in [32].

Alternatively to the statistical approach, especially if there is a lack of data or some knowledge of building physics is present, the RC modeling can be used.

3.1. RC modeling

The principle of the thermal dynamics modeling can easily be described by a small example as given in Fig. 2. The room can be thought of as a network of first-order systems, where the nodes

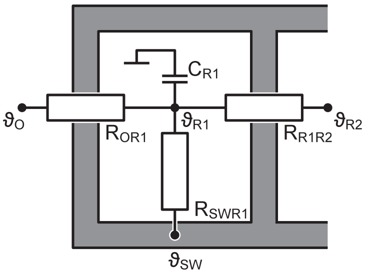

Fig. 2. RC modeling is based on the description of heat transmission between nodes that are representing temperatures. The figure captures example with two rooms where, ϑ_{R1} and ϑ_{R2} are the temperatures in the room $R1$ and $R2$, respectively, ϑ_0 is the outside temperature, ϑ_{SW} is the temperature of the supply water used for floor heating, C_{R1} denotes the thermal capacity of the room $R1$. Resistances are representing the thermal resistances between the nodes.

are the system states and these represent the room temperature or the temperatures in the walls, floor or ceiling. Then the heat transfer rate is given by

$$\frac{dQ}{dt} = K_{ie} \cdot (\vartheta_e - \vartheta_i)$$
$$\Rightarrow \underbrace{\frac{dQ}{d\vartheta_i}}_{C_i} \cdot \frac{d\vartheta_i}{dt} = K_{ie} \cdot (\vartheta_e - \vartheta_i), \tag{10}$$

where t denotes the time, ϑ_i and ϑ_e are the temperatures in nodes i and e, respectively, Q is thermal energy, and C_i denotes the thermal capacitance of node i. The total heat transmission coefficient K_{ie} is computed as

$$\frac{1}{K_{ie}} = \frac{1}{K_i} + \frac{1}{K_e}, \tag{11}$$

where the heat transmission coefficients K_i and K_e depend on the materials of i and e as well as on the cross sectional area of the heat transmission. For each node, i.e. state, such a differential equation as in Eq. (10) is formulated. The actuators are direct inputs to the node, which means that their input is added. The modeling of illumination and CO_2 concentration is omitted here for brevity, for more details on RC modeling see [28].

The model parameters (e.g. K_{ie} or C_i in Eq. (10)) can be determined in two ways: by reading from construction plans or by statistical estimation, which is described in the next sections.

3.1.1. Construction plan

Thermal capacities, resistances and other unknown parameters are determined from the construction plan according to the materials used and their tabular values. Simulations of the acquired model are then required to validate the model accuracy. If the model does not correspond to the measured data, parameter adjustment is necessary.

3.1.2. Statistical estimation

In this approach it is assumed that measurements are corrupted by noise, therefore, the model is extended by a stochastic component. The resulting stochastic differential or difference equations are used for estimation with Maximum Likelihood (ML) or Maximum a Posteriori (MAP) methods to get the desired parameters from a measured data set. Also in this case tabular values of the parameters can be used as initial guess, however, they do not need to be specified as accurately as in the previous case, because they will be updated. Software tools for dealing with statistical estimation are described for example in [33–35], some of them provide functionality to certify the resulting model validity using statistical hypothesis tests.

Following the statistical based estimation procedure is a special case of the ML method and can provide a fast way how to identify a discrete-time model of the continuous-time system $\dot{x}(t) = Ax(t) + Bu(t) + w(t)$ from input/output data where the full state is known (i.e. the state of the system corresponds to the system outputs); $A \in R^{n\times n}$, $B \in R^{n\times m}$, $u(t) \in R^m$ is considered to be the control input while $w(t) \in R^n \sim \mathcal{N}(0, \Sigma)$ is the process noise. The system model can be identified using following statistical procedure:

The first step is discretization of the continuous model as described above with sampling period T_s. Discrete-time model will be then the result from the identification procedure.

$$A_d = e^{AT_s} = I + AT_s + \frac{A^2T_s^2}{2} + \ldots \approx I + AT_s$$
$$B_d = \int_0^{T_s} e^{A\tau} \mathrm{d}\tau B \approx \int_0^{T_s} I \mathrm{d}\tau B = T_s B.$$

The presented discretization (in this case the simplest one – zero-order hold) preserves the structure of the system matrices A and B, so that an element of the discrete-time matrices (say, $a_{d_{i,j}}$) corresponds to the element of the continuous-time matrices at the same position ($a_{i,j}$). Therefore, we can then readily estimate the unknown parameters of the discrete-time model, as will be described below.

The data matrices for identification have the following structure:

$$X_k^{k+N} = (x_k, x_{k+1}, \ldots, x_{k+N})$$
$$U_k^{k+N} = (u_k, u_{k+1}, \ldots, u_{k+N})$$
$$E_k^{k+N} = (e_k, e_{k+1}, \ldots, e_{k+N}),$$

where e_k is white zero mean Gaussian noise with an approximate covariance $T_s^2\Sigma$. The estimation of the parameters θ_i within the system matrices (see Eq. (13)) then can be formulated into the least-squares framework as follows:

$$X_1^N = A_d X_0^{N-1} + B_d U_0^{N-1} + E_0^{N-1} = [A_d \ B_d] \begin{bmatrix} X_0^{N-1} \\ U_0^{N-1} \end{bmatrix} + E_0^{N-1}$$

$$\text{vec } X_1^N = \left(\begin{bmatrix} X_0^{N-1} \\ U_0^{N-1} \end{bmatrix} \otimes I_{n\times n} \right)^T \text{vec } [A_d \ B_d] + \text{vec } E_0^{N-1},$$

where (vec $\bullet$) is vectorization of a matrix and ($\bullet \otimes \bullet$) is a Kronecker product of two matrices. In this equation structure, we can add extra lines into the regressors matrix as well as the left-hand side vector for the structure of the matrices A and B to be preserved. Then, the unknown parameters are estimated using weighted least-squares with higher weights on the rows with constraints of the matrices structure.

4. Case study

The presented MPC scheme of Problem 1 was applied to the building heating system of the Czech Technical University (CTU) in Prague, see Fig. 3. MPC was applied there from January 2010 and was operational until the end of heating season in mid-March 2010.

4.1. Description of the building

As can be seen from Fig. 3, the CTU building is composed of four five-floor blocks, three eight-floors blocks and four-level intermediary parts among the respective blocks. All the blocks have the

(a) Sketch of the building. The insulated part comprises the building blocks B_1 and B_2, while the block B_3 is in non-insulated part of the building.

(b) The highest block in front is B_1, on the right from block B_1 are blocks B_2 and B_3.

Fig. 3. The building of CTU in Prague.

same construction and way of use. This provides us with the unique opportunity to compare different control techniques under the same weather conditions, since we can use different controllers in different blocks at the same time. The south part of the building was insulated two years ago and therefore we can evaluate effectiveness of MPC depending on the insulation level as well.

The CTU building uses a Crittall [36] type ceiling radiant heating and cooling system. In this system, the heating (or cooling) beams are embedded into the concrete ceiling that enables the utilization of the thermal capacity of the building. The heating system scheme of one building block is depicted in Fig. 4. The required temperature of supply water is achieved by mixing hot water from a heat exchanger with return water in a three point valve. The three point valve is operated by a low-level controller that maintains the supply water temperature at the setpoint determined by the high-level controller. In case of the CTU building, a PID controller was used as a low-level controller. For each heating circuit, there is one reference room temperature measurement. A detailed description of the heating system is given in [37].

4.2. Modeling of the building block

We consider a building with two heating circuits and two reference rooms, each related to one circuit as depicted above. The differential equations describing the system are as follows:

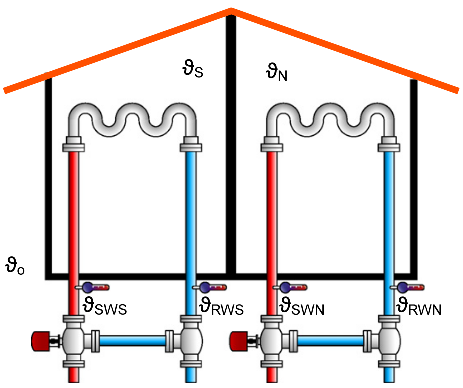

Fig. 4. Simplified scheme of the ceiling radiant heating system.

$$
\begin{aligned}
-\dot{\vartheta}_n &= \frac{1}{C_r R_w}(\vartheta_n - \vartheta_o) + \frac{1}{C_r R_r}(\vartheta_n - \vartheta_s) + \frac{1}{C_r R_{rwr}}(\vartheta_n - \vartheta_{rwn}) \\
-\dot{\vartheta}_s &= \frac{1}{C_r R_w}(\vartheta_s - \vartheta_o) + \frac{1}{C_r R_r}(\vartheta_s - \vartheta_n) + \frac{1}{C_r R_{rwr}}(\vartheta_s - \vartheta_{rws}) \\
-\dot{\vartheta}_{rwn} &= \frac{1}{C_{rw} R_{rwr}}(\vartheta_{rwn} - \vartheta_n) + \frac{1}{C_{rw} R_{rw}}(\vartheta_{rwn} - \vartheta_{swn}) \\
-\dot{\vartheta}_{rws} &= \frac{1}{C_{rw} R_{rwr}}(\vartheta_{rws} - \vartheta_s) + \frac{1}{C_{rw} R_{rw}}(\vartheta_{rws} - \vartheta_{sws})
\end{aligned}
\tag{12}
$$

The meaning of the variables and coefficients is explained in Table 1.

Considering the system state as $x^T = [\vartheta_s \vartheta_{rws} \vartheta_n \vartheta_{rwn}]^T$ and the input vector as $u^T = [\vartheta_o \vartheta_{sws} \vartheta_{swn}]^T$, the state-space model can be formulated in the following way:

$$
\begin{aligned}
\dot{x} = &\begin{bmatrix} -\frac{1}{C_r R_w} - \frac{1}{C_r R_r} - \frac{1}{C_r R_{rwr}} & \frac{1}{C_r R_{rwr}} & \frac{1}{C_r R_r} & 0 \\ \frac{1}{C_{rw} R_{rwr}} & -\frac{1}{C_{rw} R_{rw}} - \frac{1}{C_{rw} R_{rwr}} & 0 & 0 \\ \frac{1}{C_r R_r} & 0 & -\frac{1}{C_r R_w} - \frac{1}{C_r R_r} - \frac{1}{C_r R_{rwr}} & \frac{1}{C_r R_{rwr}} \\ 0 & 0 & \frac{1}{C_{rw} R_{rwr}} & -\frac{1}{C_{rw} R_{rwr}} - \frac{1}{C_r R_{rw}} \end{bmatrix} x \\
&+ \begin{bmatrix} \frac{1}{C_r R_w} & 0 & 0 \\ 0 & \frac{1}{C_{rw} Rz} & 0 \\ \frac{1}{C_r R_w} & 0 & 0 \\ 0 & 0 & \frac{1}{C_{rw} Rz} \end{bmatrix} u.
\end{aligned}
\tag{13}
$$

Finally, the parameters of this predefined system structure are estimated according to the procedure described in Section 3.1 whereas, in this case, the discrete-time system matrices have the following structure:

Table 1
Notation of the variables and coefficients used in the equations describing a building block.

Notation	Description
R_w	Outside wall heat resistance
R_{rwr}	Return water-to-room transition resistance
R_r	Room-to-room transition resistance
R_{rw}	Return water resistance
C_{rw}	Thermal capacity of return water
C_r	Thermal capacity of room
ϑ_o	Outside temperature (from weather forecast)
ϑ_n	Reference room temperature – north side
ϑ_s	Reference room temperature – south side
ϑ_{rwn}	Return water temperature – north side
ϑ_{rws}	Return water temperature – south side
ϑ_{swn}	Supply water temperature – north side
ϑ_{sws}	Supply water temperature – south side

$$A_d = \begin{bmatrix} \theta_1 & \theta_2 & \theta_3 & 0 \\ \theta_4 & \theta_5 & 0 & 0 \\ \theta_3 & 0 & \theta_1 & \theta_2 \\ 0 & 0 & \theta_4 & \theta_5 \end{bmatrix}, \quad B_d = \begin{bmatrix} \theta_6 & 0 & 0 \\ 0 & \theta_7 & 0 \\ \theta_6 & 0 & 0 \\ 0 & 0 & \theta_7 \end{bmatrix}$$

Validation of the identified model was carried out by comparison of open loop simulation with verification data set collected during Christmas 2009 (see Fig. 5). The merit of the proposed identification method can be especially seen in well identified trends of heating-up and cooling down.

4.3. Description of the controller

4.3.1. Control objectives

There are several requirements to be fulfilled:

4.3.1.1. Comfort requirements. The reference trajectory $y_{r,k}$, room temperature in our case, is known a priori, as a schedule. The major advantage of MPC is the ability of computing the outputs and corresponding input signals in advance, that is, it is possible to avoid sudden changes in the control signal and undesired effects of delays in the system response.

The schedule defines two minimal levels of the room temperature – during the day, the desired temperature is 22 °C while at night and during weekends there is a setback to 19 °C. One solution how to deal with minimal temperature requirement is to use reference tracking with dynamic cost which is difficult to tune and does not provide possibility for extension to more than two minimal temperature levels [16]. Another solution is to use it as a constraint. This can lead to infeasible problem in some situations. Moreover, there is a tolerance in proposed comfort criterion and therefore it can be useful to slightly violate comfort requirements if it results in considerable energy reduction. Thus, we proposed an alternative MPC problem formulation – the displacement below the reference trajectory is penalized in the criterion. Note, that the 2-norm was used for the weighting of the tracking error – for more accurate performance.

4.3.1.2. Minimization of energy consumption. As the return water circulates in the heating system (see Fig. 4), the energy consumed by the heating-up of the building is linearly dependent on the positive difference between heating ϑ_{sw} and return water ϑ_{rw} temperatures entering/exiting the three port valve in Fig. 4.

Thus, the 1-norm of weighted inputs is to be minimized.

4.3.2. MPC problem formulation

At first, the given system from Section 4.2 is partitioned as follows:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k \\ y_k &= Cx_k + Du_k \\ z_k &= Vx_k + Wu_k, \end{aligned}$$

where y_k stands for outputs with reference signal (e.g. $\vartheta_{in,k}$), whilst z_k represents the input-output differences – in our case $z_k = \vartheta_{sw,k} - \vartheta_{rw,k}$.

The requirements (see Section 4.3.1) for the weighting of the particular variables can be carried out by adding the slack variables a_k and b_k which are of same dimension as y_k and z_k, respectively. The resulting optimization problem can be written as follows:

$$J = \min_{a_k, b_k, u_k} \sum_{k=0}^{N-1} a_k^T Q a_k + R b_k$$

$$\begin{aligned} y_{r,k} - y_k - a_k \leqslant 0, &\quad a_k \geqslant 0 \\ z_k - b_k \leqslant 0, &\quad b_k \geqslant 0 \\ u_{\min} \leqslant u_k &\leqslant u_{\max} \\ |u_k - u_{k-1}| &\leqslant \Delta_{u_{\max}} \end{aligned} \tag{14}$$

$$y_k = CA^k x_0 + \sum_{i=0}^{k-1} CA^{k-i-1} Bu_i + Du_k$$

$$z_k = VA^k x_0 + \sum_{i=0}^{k-1} VA^{k-i-1} Bu_i + Wu_k.$$

Q and R stand for the weighting matrices of appropriate dimensions. The weighting matrices are constant because there is a flat rate for energy and the minimal room temperature defined by $y_{r,k}$ has to be maintained over whole the day with the same importance. Each building block requires different amount of energy for maintaining the same comfort therefore the proportion of the weighting matrices Q and R had to be tuned-up for each block separately. The physical limits of the heating system are expressed by constants $u_{\min}$, $u_{\max}$ and $\Delta_{u_{\max}}$. The lower limit for heating water temperature $u_{\min}$ was set to 20 °C, the upper limit for heating water temperature $u_{\max}$ was set to 55 °C and the maximum rate of change of the input signal $\Delta_{u_{\max}}$ that prevents the heating system from heat shocks was set to 20 °C/20 min. The temperature of supply water is controlled by the three point valve. Therefore, the lower limit $u_{\min}$ is not, in fact, a constant value but it is given as minimum of return water temperature and hot water from the heat exchanger. However, this can be neglected because just lower comfort limit is maintained and delivery of warmer supply water than predicted do not result in comfort criteria violation.

Eq. (14) can be readily rewritten into a quadratic programming (QP) problem and solved using a standard QP solver.

The prediction horizon N was chosen to be two days (the system was sampled with a sampling period of 20 min, i.e. N = 144) which is a trade-off between accuracy of the weather prediction and a sufficient length of the prediction horizon.

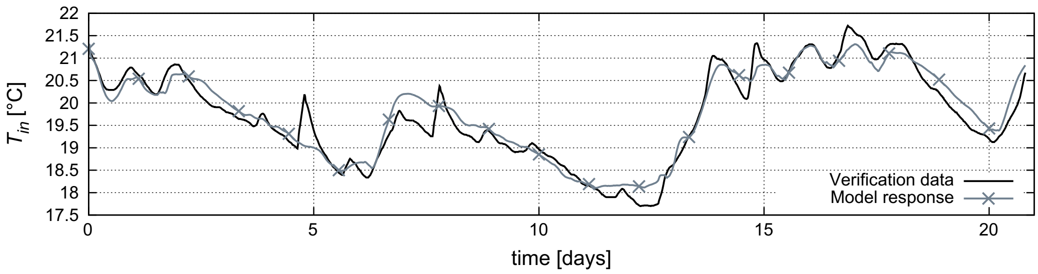

Fig. 5. Validation of model response against verification data set.

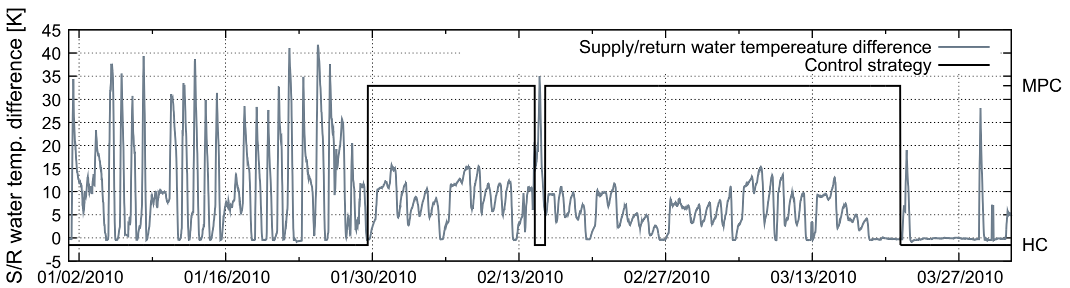

Fig. 6. Heating curve and MPC energy requirements profile.

4.4. Technical setup description

The building was operated by RcWare[2] BAS system. The RcWare system provides data from several weather forecasting servers. In case of the CTU building, weather forecast from National Oceanic and Atmospheric Administration[3] was used. The MPC was implemented in Scilab[4]. The optimization problem was solved by means of Scilab internal linear quadratic programming solver. The computation time was in average 21 s on a PC with Intel Core2 DUO CPU 2.5 GHz. Setpoints for supply water temperature were periodically computed by the following sequence

1. Retrieve the current state ϑ_{swn}, ϑ_{sws}, ϑ_{rwn}, ϑ_{rws}, ϑ_n, ϑ_s from BAS
2. Generate reference room temperature $y_{r,k}$, $k \in 0,\dots,N-1$ according to BAS setting
3. Download weather forecast $\vartheta_{o,k}$, $k \in 0,\dots,N-1$
4. Execute MPC scripts in Scilab
5. Apply new setpoints for ϑ_{swn}, ϑ_{sws} into BAS

Because of network communication and interaction between different environments, it was necessary to handle potential failures. In such cases, BAS switched to a backup strategy based on a heating curve and sent a SMS to the operator.

4.5. Investigations setup

Evaluation of the energy savings achieved by different control strategies is a complicated task. The weather conditions change all the time, as well as the number and behavior of the building occupants. Single comparisons of results are affected by these disturbances, therefore two independent comparisons of the real building experiment will be presented.

The first comparison denoted as cross comparison uses almost similar building blocks B_1 and B_2 [5]. The cross comparison had two phases, each lasted for a week. In the first week, block B_1 was controlled by the heating curve and block B_2 by MPC. The other week, the control strategies were switched. The advantage of the cross comparison is compensation of the majority of disturbances because both building blocks are exposed to the same weather conditions.

The second comparison is based on the utilization of so-called heating degree days (HDD) for the normalization of the building energy consumption. HDD is a quantitative index designed to reflect the demand for energy needed to heat a building. There are several methods of HDD computation. In this paper, the outside temperature is subtracted from the required room temperature and this number is summed over the analyzed time period

$$HDD = \sum_{k=T_{begin}}^{T_{end}} y_{r,k} - \vartheta_{o,k}, \tag{15}$$

where T_{begin}, T_{end} denote the beginning and the end of the measured period, respectively. The method is not precise, especially when outside weather conditions differ a lot. In order to minimize the negative effect of different weather conditions time periods with similar average outside temperature were selected for the comparison.

Because the heating water flow is constant, the sum of difference between the supply water temperature and the return water temperature can be used as energy consumption measure (denoted as E_{CM})

$$E_{CM} = \sum_{k=T_{begin}}^{T_{end}} (\vartheta_{sws,k} - \vartheta_{rws,k}) + (\vartheta_{swn,k} - \vartheta_{rwn,k}). \tag{16}$$

4.6. Results from real implementation

The Crittall heating system utilizes the building mass as a thermal storage. When the building was operated by a heating curve, the concrete construction was preheated during the night and the heating system was switched off in the morning. The strategy realized by MPC was different; the MPC preheated the concrete mainly at night but it did not switch off the heating during the day. The beneficial side effect of MPC strategy was a significant energy peak reduction as can be seen at Fig. 6. The aim of the energy peak reduction was not explicitly expressed in the problem formulation, it was just a result of the optimization process.

The cross comparison results are summarized in Table 2. According to this comparison, MPC saved approximately 16% of energy in both weeks.

The results from HDD based comparison are in Table 3. It can be seen, that the non-insulated block B_3 required nearly twice as much energy as the insulated blocks B_1 and B_2. The relative savings were more significant at insulated building blocks B_1 (28.74%) and B_2 (26.83%). Nevertheless, at the block $B_3$the relative savings were more than 17% even if there was a significant increase of the room temperature. The absolute MPC savings were larger at the non-insulated block B_3.

The average outside temperature during the cross comparison was −2.3 °C, while during the comparison based on HDD was 3.4 °C. In case of lower outside temperatures, the energy has to be continuously supplied to the building and the active usage of building heat accumulation is limited. This could be the reason why saving estimation based on the cross comparison is lower than savings estimation based on HDD.

[2] http://www.rcware.eu.
[3] http://www.noaa.gov.
[4] http://www.scilab.org.
[5] Block B_1 uses slightly more energy than block B_2, it can be seen in Table 3. This fact was considered in the cross comparison.

Table 2
Comparison of heating curve (HC) and model predictive control (MPC) strategies using similar building blocks B_1 and B_2.

		B_1		B_2		
	Mean ϑ_o (°C)	Control	Mean ϑ_s, ϑ_n (°C)	Control	Mean ϑ_s, ϑ_n (°C)	MPC savings (%)
1st week	−3.4	HC	21.4	MPC	21.1	15.54
2nd week	−1.3	MPC	21.4	HC	20.9	16.94

Table 3
Heating degree days based comparison. The ratio E_{CM}/HDDexpresses normalized energy demands for heating.

Block-control	E_{CM}/HDD	Mean ϑ_o(°C)	Mean ϑ_s, ϑ_n(°C)	Days compared	Relative MPC savings (%)
B_1-HC	0.906	3.8	21.6	84	28.74
B_1-MPC	0.645	3.2	21.8	49	
B_2-HC	0.813	4.0	21.7	85	26.83
B_2-MPC	0.595	3.0	21.7	49	
B_3-HC	1.532	3.8	20.9	84	17.67
B_3-MPC	1.262	3.2	21.9	49	

5. Conclusion

It was shown that the energy savings potential for using MPC with weather predictions for the investigated building heating system were between 15% and 28% depending on various factors, mainly insulation level and outside temperature. This is consistent with results achieved in large scale simulations done in scope of the Opticontrol project ([28] chapter 8). The real building application results are very encouraging, nevertheless, two issues have to be mentioned. First, each building is unique and the MPC saving potential is dependent on many factors as HVAC system, building construction or weather conditions to name a few. Second, the complete cost benefit analysis should not include just energy savings but also the cost of the MPC implementation, i.e. foremost the modeling effort, that presents the most time consuming part and MPC integration into a BAS. In contrast to the current building control techniques, MPC is based on a non trivial mathematical background that complicates its usage in practice. But its contribution to reduction of a building operation cost is so significant that it is expected that it will become a common solution for so-called intelligent buildings in a few years.

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4.2. BuildingLab: a Tool to Analyze Performance of Model Predictive Controllers for Buildings

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Annotation:
Further investigations of MPC performance applied to the control of the CTU building gave motivation for the development of a tool that would make MPC strategy for buildings easier to debug/tune and at the same time more understandable for wide public. Therefore we created a web application entitled BuildingLab (`http://buildinglab.felk.cvut.cz/`) and summarized all the features in the paper.

This tool enables users to explore the controller behavior, tune controllers by the means of displaying and comparing simulation results based on arbitrary disturbance profiles, validate mathematical models of the particular building, etc.
Contribution to the thesis:
This paper contributes to the first goal of this thesis. Having the web application that enables controller tuning makes the process of deployment of MPC on a real building faster and reliable (one can validate controller functionality in advance in different weather conditions, occupancy profiles or in different thermal comfort regimes).

The whole application is licensed under the terms of a permissive free MIT license, therefore it can easily be used by other research teams focused on MPC for buildings.

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BuildingLAB: A tool to analyze performance of model predictive controllers for buildings

Jiří Cigler[a,*], Pavel Tomáško[a], Jan Široký[b]

[a] Department of Control Engineering, Faculty of Electrical Engineering of Czech Technical University in Prague, Technická 2, 166 27 Praha 6, Czech Republic
[b] Department of Cybernetics, Faculty of Applied Sciences, University of West Bohemia in Pilsen, Pilsen, Czech Republic

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ABSTRACT

Model predictive control (MPC) for buildings has undergone an intensive research in the past years. The key principle of MPC is a trade-off between energy savings and user welfare making use of predictions of disturbances acting on the system (ambient temperature, solar radiation, occupancy, etc.). Several studies and experimental setups have shown the energy savings potential of MPC up to 30% compared to the conventional control strategies. Besides modeling of the buildings, the bottleneck of MPC wide-spreading is the understanding of the MPC paradigm from the HVAC engineers and managers. Therefore the objective is to develop a tool that would make MPC strategy for buildings more understandable for wide public. The application enable users to explore the controllers behavior, tune controllers with aid of displaying and comparing simulation results, validate mathematical models of the particular building, etc.

1. Introduction

1.1. Motivation for energy efficient building climate control

Recently, there has been a growing concern to achieve energy savings. As the building sector accounts for about 40% of total final energy consumption [1] and more than half is consumed in HVAC (heating, ventilation and air conditioning) systems, an energy efficient building climate control can significantly contribute to reduction of the power demands and lower thus the greenhouse gas emissions.

It is well known that building energy demands can be reduced significantly thanks to developments in the field of mechanical and civil engineering. However, considerable investments are usually required in order to achieve the energy cuts. In contrast, energy savings with minimal additional cost can be achieved by improvement of the algorithms of building automation system (BAS). The effort to implement advanced control algorithms in buildings has been shown by the activity of the leading academic and industrial teams in the area of HVAC control [2–6].

1.2. State-of-the-art in advanced control of HVAC systems

In recent years, there have arisen two main research trends in the field of advanced HVAC control

(i) learning based approaches coming from the area of artificial intelligence (mainly fuzzy techniques [6,7], genetic and evolutionary algorithms [8,9], etc.)
(ii) Model based predictive control (MPC) techniques that stand on the principles of the classical control and optimization techniques [10].

In this paper, we restrict ourselves only to MPC techniques.

The aim of MPC is to design control inputs that minimize the energy consumption while guaranteeing comfort requirements. From a wide variety of MPC properties and results, a few instances can be listed. The MPC controller:

(i) takes disturbance predictions (occupancy, weather etc.) into account, thus it adjusts control actions appropriately [11,12],
(ii) can utilize the thermal mass of a building in a better way compared to the conventional control strategies (e.g PID, weather compensated or rule based control) [13,14],
(iii) can be formulated with aid of thermal comfort indices instead of indoor operative temperature [15–17],
(iv) is able to deal with variable energy price that can be easily included into the formulation of the optimization problem [18,19],

* Corresponding author: Tel. +420 22435 7687.
E-mail address: jiri.cigler@fel.cvut.cz (J. Cigler).

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(v) can handle minimization of the energy peaks and thus shift energy loads within certain time frame [3,20,21] (beneficial because of both the possibility of tariff selection and lowering operational costs),
(vi) can take into account stochastic properties of random disturbance variables (e.g. weather forecast, occupancy profiles); convex approximation of a stochastic model predictive control problem for buildings is given in [12], etc.
(vii) can be formulated in a distributed manner and thus the computational load can be split among several solvers [22,23].

The conclusions are usually drawn from numerical simulations on detailed building models, e.g. EnergyPlus, Trnsys, etc. [24], however, there have also been reported some experimental setups of MPC which have shown the energy savings potential up to 30 % compared to conventional control strategies [3,11,25].

1.3. Understanding of MPC paradigm

Control engineering is quite an elusive discipline particularly when explained to people who have another profession. It is often difficult task to explain principles of feedback control, to create an insight into controller actions and to define the whole field of controller responsibilities.

The problem of understanding the feedback control starts to be even bigger when advanced control strategies are applied. In order to make not only the people working in HVAC branch but also managers to understand the whole process of control, it is needed to some way expound them the MPC strategy. Unless they check the idea themselves, they will not be willing to implement the strategy in practice even though the advanced MPC was proven to be capable of significant energy savings.

1.4. Goal of the work

Hence the ultimate goal of the work is to develop a tool that would make MPC strategy for buildings more understandable for wide public; the web application called BuildingLAB (http://buildinglab.felk.cvut.cz/, potential users can use username `eab` and password `eab`). Besides introduction to MPC framework, this tool will enable users to explore the controller behavior, tune controllers by means of displaying and comparing simulation results, validate mathematical models of the particular building, etc.

1.5. Related work

In literature, there have been reported several software tools capable of running MPC for buildings.

Development of a SCADA (supervisory control and data acquisition) system allowing MPC control for buildings is reported e.g. in [26]. The optimal control law is computed in MATLAB and the variables are transmitted into BAS via dynamic data exchange protocol. Moreover, the authors show the functionality on a real life example.

An alternative way to communicate optimal control moves is reported in [11]. Here, the optimization task is solved in Scilab environment and transmitted to BAS via a proprietary protocol.

It is also important to mention the project GenOpt aiming at employing a (predictive) control framework directly without the need of a simple linear model, rather it uses a detailed models developed in EnergyPlus or other building performance simulation tools [27].

These tools are dedicated mainly to interconnection of BAS and the computational core solving MPC optimization problem. Hence, the purpose of these tools is different from the purpose of BuildingLAB that is rather illustrative and educative.

Finally, there has recently appeared a tool called BACTool (http://bactool.ethz.ch/), which evaluate a mean behavior of the controlled system over a long time in order of months or a year and indicates whether the particular building is suitable for predictive control.

On the contrary to BACTool, the MPC simulations run in BuildingLAB are short term, covering the length of the prediction horizon. The short term predictions enable to analyze controller behavior in a detail in different scenarios (heating up after a weekend, day-night transition) with different weather data. Building operators and managers can see if the strategy computed by the predictive controller is reasonable and in accordance with their experience and common sense.

1.6. Organization of the paper

This paper is further structured as follows. The following Section 2 introduces to the typical MPC formulation for buildings. Section 3 deals with usage and design of BuildingLAB, which allows the user to simulate the MPC control strategy. Next in the Section 4, mathematical models of the building of the Czech Techical University (CTU) in Prague will be used for the demonstration of the application functionality. Section 5 concludes the paper.

2. Model predictive control for buildings

MPC is a method of advanced control originated in late seventies and early eighties in the process industries (oil refineries, chemical plants, etc.) [28]. MPC is not a single strategy, but a vast class of control methods with the model of the process explicitly expressed trying to obtain control signal by minimizing objective function subject to some constraints. The minimization is performed in an iterative manner on some finite optimization horizon to acquire N step ahead prediction of control signal that leads to minimum criterion subject to all constraints. This, however, carries lots of drawbacks such as no feedback, no robustness, no guarantee of stability, etc. Many of these drawbacks can be overcome by applying so-called receding horizon, i.e. at each iteration only the first step of the control strategy is implemented and the control signal is calculated again, thus, in fact, the prediction horizon keeps being shifted forward. Currently it is a well established control concept with guaranteed stability and recursive feasibility [10].

The technique heavily relies on the availability of a simple controlled plant model, which makes the process of plant model identification of a great importance. Building modeling is a delicate task as each building is unique and requires its own mathematical description. Therefore the building modeling have received much attention recently [29–32].

Mathematical formulation of the optimization problem of building HVAC MPC control can be:

$$
\begin{aligned}
&\min_{u} \quad \sum_{k=0}^{N-1} \left(\left| R_k u_k \right|_s + |Q_k (y_k - z_k)|_t \right) \\
&\text{subjectto}: \\
&F_k x_k + G_k u_k \leq h_k \\
&x_{k+1} = A x_k + B u_k + V v_k \\
&y_k = C x_k + D u_k + W v_k \\
&x_0 = x_{init} \\
&\underline{r}_k \leq z_k \leq \overline{r}_k
\end{aligned}
$$

where k is the discrete time, N is the prediction horizon length, $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$, $v \in \mathbb{R}^r$ and $y \in \mathbb{R}^p$ are vectors of the system states, inputs, disturbance inputs and system outputs respectively. Then A, B, C, D, V and W are system matrices of appropriate dimensions describing thermal dynamics of the controlled building. $z \in \mathbb{R}^p$ contains so called slack variables[1] on system outputs (usually zone temperature) meaning that the system output should be kept within the comfort range defined by lower and upper bounds $\underline{r}$ and $\overline{r}$ respectively (if the system output lies in the range interior then there is no penalization, otherwise the violation is appropriately penalized). Initial state $x_0 = x_{init}$ is a parameter of the optimization problem. Normally, the state is obtained either by full state measurement or by means of Kalman filtering.

F, G and h are the matrices and the vector defining a polytopic constraint on the system states and inputs (e.g. minimum or maximum input energy, etc.)

Finally, s and t specify the norm of the particular part of the cost function (it can be either one norm, two norm or infinity norm) and $Q \geq 0$, $R \geq 0$ are positive semidefinite weighting matrices of appropriate dimensions which express trade-off between reference tracking and energy consumption.

The proposed optimization problem is solved every control time-step in so called receding horizon fashion when the first control move is applied to the system only. In this application, open-loop optimal sequence will be presented to the user since it captures main controller properties.

3. Technical details about BuildingLAB

The application basically allows users to work with some MPC simulation – to set it up, launch it and explore its output. It can especially be used to iteratively run the same simulation, tune selected parameters and track results evolution.

3.1. Overall architecture

The cornerstone of the system is a web interface written in Django framework, expressing the simulation backend in a non-expert accessible way. Next noticeable part of the system is the task queue, making the application asynchronous. Task queue as well as disturbance profiles are backed by PostgreSQL relational database.

The optimal control problems solved by the system are typically quite time consuming with a need of a special software for solving optimization tasks (MATLAB environment with aid of YALMIP [33] in our case). This led to an establishment of a mechanism which in fact delivers the power of MATLAB to the user's web browser and in addition allows the user to run more tasks simultaneously. Tasks are temporarily stored in FIFO queue and are taken by one of computation cores as the core is free. User can then immediately continue by setting up the next task even though the first one has not yet ended.

All participants of the system (workers, web browsers) communicate with the application through HTTP, using only one web server (for the configuration, see Fig. 1). The web application connects to the database running on the same machine via the proprietary protocol of the database. Finally, software packages that are used by the application are mentioned in Table 1.

[1] The *slack variable* is artificially introduced variable, which serves for penalizing given variable, which is attached to, only when it escapes given interval. In our case, the slack variables are attached to system outputs.

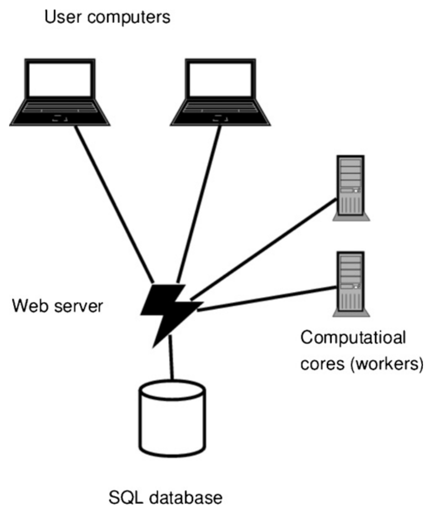


Fig. 1. Software architecture.

3.2. Templates and working copies

The system is built on the concept of templates and working copies. An administrator creates a set of templates and associates them to particular users who can then use them. The ordinary user can then take a look at the templates which have been associated to him or her, choose one, set its parameters and launch it. To use a template means that the user creates a working copy of the template. This copy becomes his or her private working place, where he or she can set various parameters, run the simulation using these parameters and finally explore the results produced by the simulation. The workflow is depicted in Fig. 2.

3.3. Simulation assignment presentations

The simulation assignment can be expressed to the user in several ways. Currently there are two:

3.3.1. Manager view

This one shows only user description, initial conditions and overall weights, see Fig. 3. It is meant for people without an expert knowledge of the building, just to see how the trade-off between comfort and cost influences system behavior. Overall weight from the slider is inserted into a mapping in order to create cost function weights – matrices Q and R. The mapping is automatically created at the time the simulation is inserted into the application. Other

Table 1
Software packages used in the project.

Package name	Version	Note
Python	2.7.2	Main programming language of the web-application
Django	1.3.1	High-level Python web framework
PostgreSQL	9.1.7	Database engine
Numpy	1.4.1	Python library; here used for data series cut-out, resampling, etc.
Apache HTTP server	2.2	web server software
MATLAB	7.13	Numerical computing environment
YALMIP	1.28	MATLAB toolbox for rapid prototyping of optimization problems
SnakeYAML	1.9	Java library for parsing YAML files
Java virtual machine	1.6.0-17	Virtual machine executing Java byte code; part of MATLAB

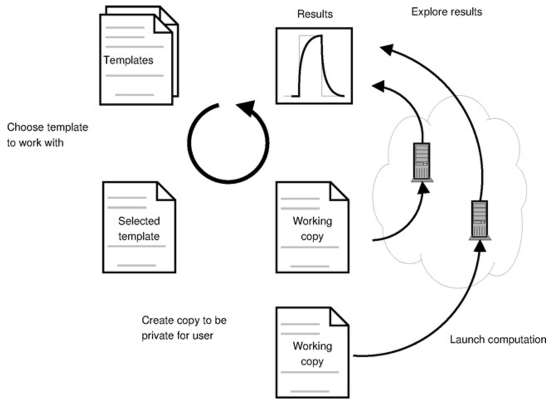


Fig. 2. Simplified application workflow.

settings, like reference trajectories, constraints, disturbance profiles, etc., are hidden, but are still present and serve as a predefined simulation settings.

3.3.2. Engineer view
This interface is more complex and allows user to change description, initial conditions, constraints, cost function items and disturbance profiles. This is a place for sophisticated experiments with the simulation. This view is depicted in Fig. 4.

3.4. Running the simulation

When all parameters are set to the desired values, the user can launch the computation. This action does not directly call some numerical routines. Instead, it enqueues the simulation into the queue, common for all users, where it waits for some free-for-use computation core. A log record is available for monitoring the simulation state. As long as the simulation is enqueued, the user can start setting up another simulation.

3.5. Displaying results

When the simulation finishes, results can be viewed. Results are presented in a form of charts, where related series are displayed in the same figure. The user can view only particular data series, and moreover, the user can compare two or more series, which are not related. The result view can show results of more than one simulation at the same time and allows to do these comparisons over more simulations.

4. Case study

Application functionality is demonstrated on mathematical models of the building of Czech Technical University (CTU) in Prague (see Fig. 5(a)). This building is a pilot application for various MPC experiments and MPC controllers with various settings (in terms of cost function forms, weights, constraints, etc.) have been in operation since 2009. First experiments with the building are reported in [25] and performance of the first MPC controller was evaluated in the following work [11]. A brief building description follows.

4.1. Description of the building

The CTU building is composed of four five-floor blocks, three eight-floors blocks and four-level intermediary parts among the respective blocks. All the blocks have the same construction and way of use. Each block can be divided into south and north part, each having its own heating circuit. The building uses Crittall [34] type ceiling radiant heating and cooling system. In this system, the heating (or cooling) beams are embedded into the concrete ceiling. A simplified scheme of the ceiling radiant heating system is illustrated in Fig. 5(b). The source of heat is a vapor-liquid heat exchanger, which supplies the heating water to the water container. A mixing occurs here, and the water is supplied to the respective heating circuits. An accurate temperature control of the heating water for respective circuits is achieved by a three-port valve with a servo drive. The heating water is then supplied to the respective ceiling beams. There is one measurement point in a reference room for every circuit. The set-point of the control valve is therefore the control variable for the ceiling radiant heating system in each circuit.

Mathematical models of each building block were obtained using a gray-box technique from the on-site measurements. The procedure is based on a reformulation of the estimation problem to a least-squares problem and it is described in detail in [11].

4.2. Description of the experiment

As an example of the application abilities, a small example follows. The example is based on the simple manager view (see Fig. 3)

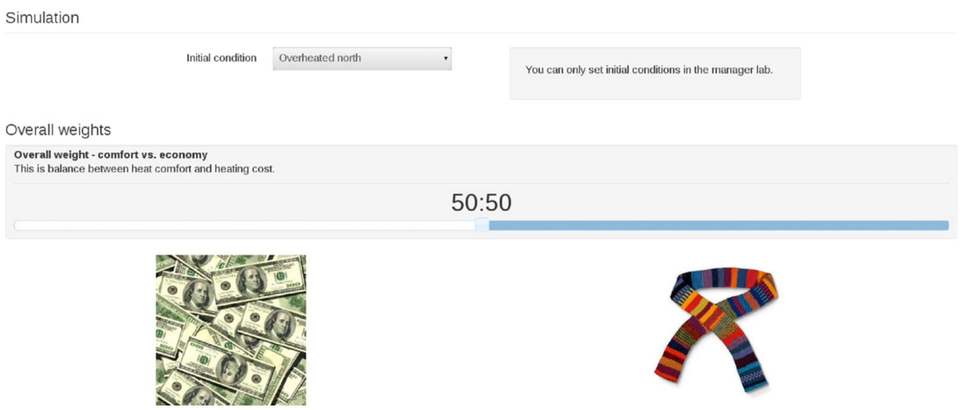


Fig. 3. The manager view.

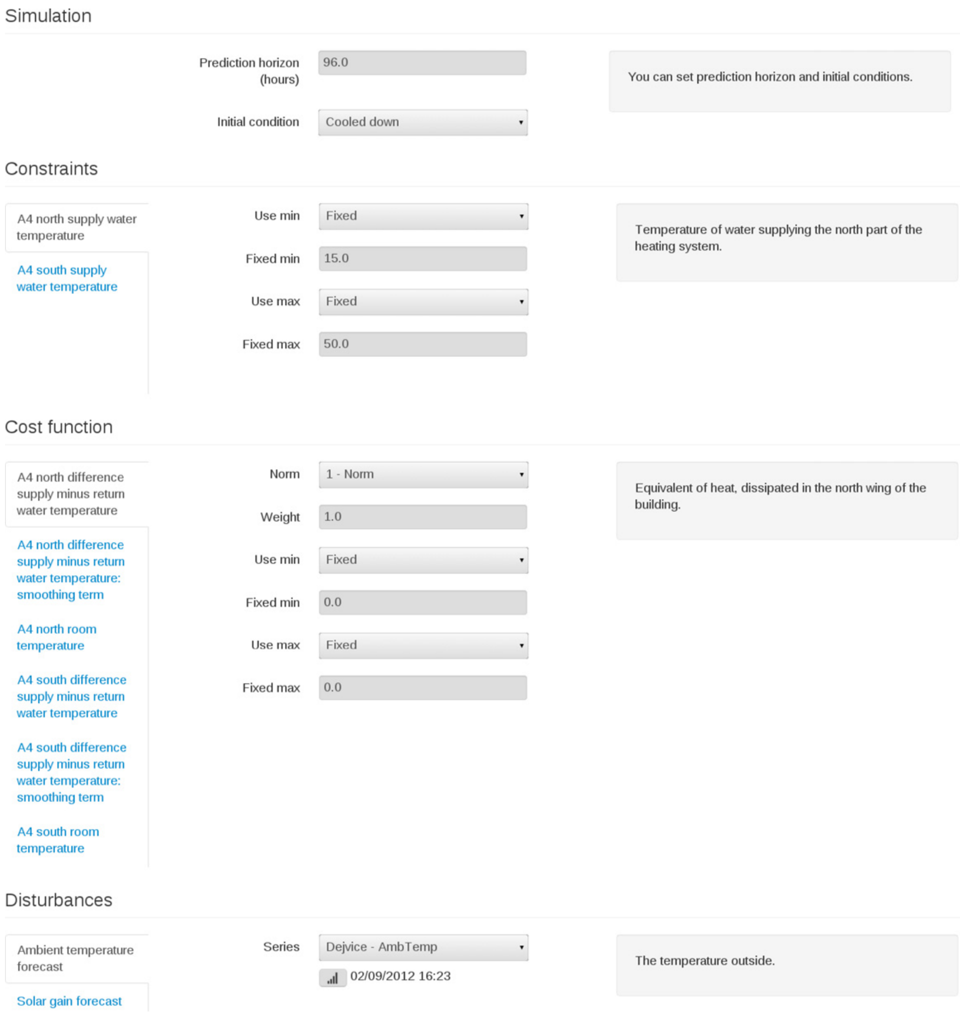
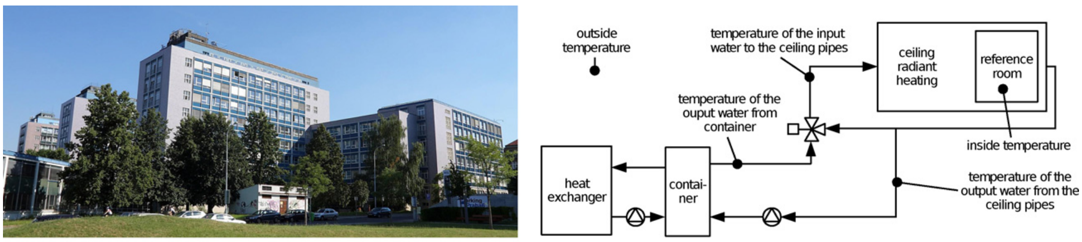


Fig. 4. The engineer view.

for one building block where a user can specify preferences whether the objective is:

(i) mainly to save energy and ignore the complains of the occupants that they have to wear scarves, the ratio is 1:99;
(ii) both comfort and economy is an objective, the ratio is 50:50;
(iii) mainly to keep thermal comfort (represented by dollars on the picture), the ratio between comfort and economy is 99:1

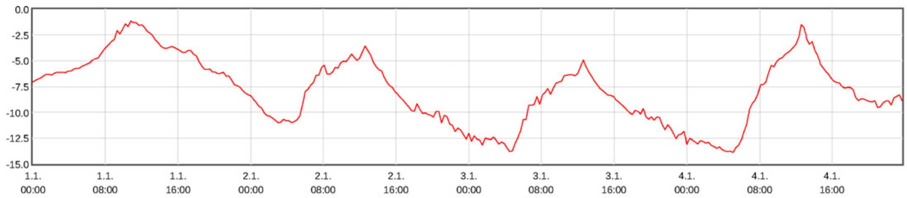
The ratio can be simply set using the slider in the manager view (note that when moving the slider, the underneath pictures are magnified accordingly to get better insight what is going on).



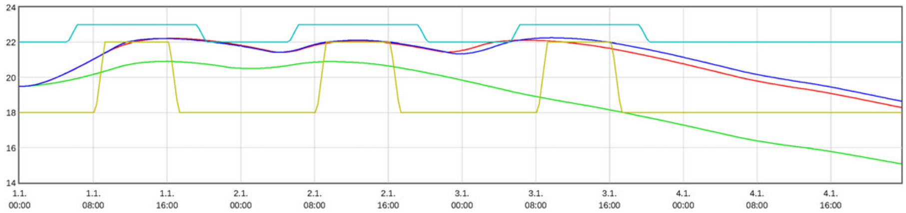
(a) A photo from the central park in Prague, Dejvice (b) Simplified scheme of the ceiling radiant heating system

Fig. 5. Building of Czech Technical University in Prague, Dejvice (a) A photo from the central park in Prague, Dejvice (b) Simplified scheme of the ceiling radiant heating system.

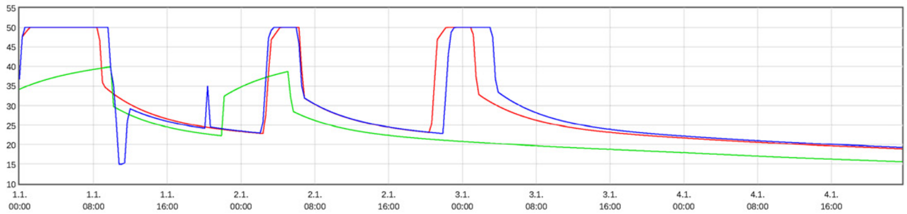
4. Results



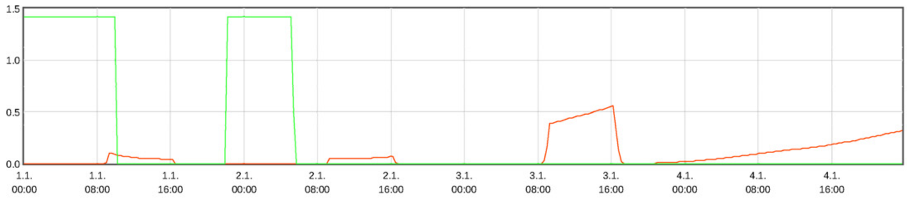
(a) Ambient temperature profile



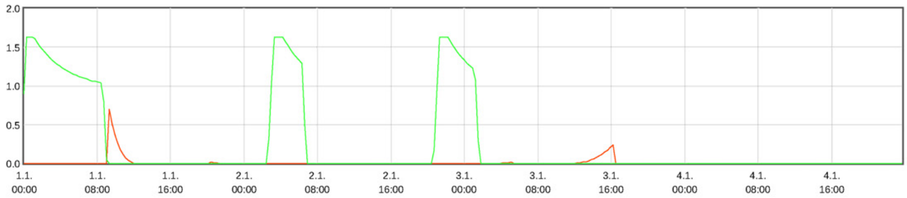
(b) South zone temperatures for all controller settings (blue 99:1, red 50:50, green 1:99, staircase signals delimit comfort range)



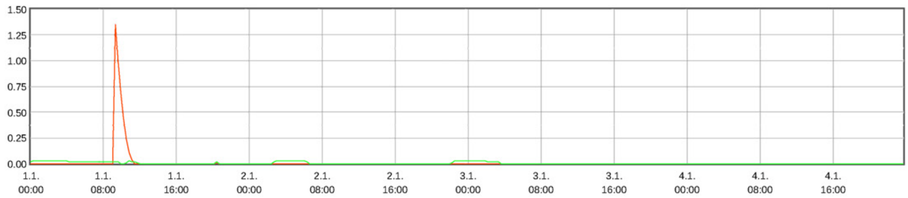
(c) South supply water temperatures for all controller settings (blue 99:1, red 50:50, green 1:99)



(d) Heating and comfort costs: weighting ratio 1:99 (green – heating cost, red – comfort violation cost)



(e) Heating and comfort costs: weighting ratio 50:50 (green – heating cost, red – comfort violation cost)



(f) Heating and comfort costs: weighting ratio 99:1 (green – heating cost, red – comfort violation cost)

Fig. 6. Comparison of simulation results, obtained using three different weight settings (a) Ambient temperature profile (b) South zone temperatures for all controller settings (blue 99:1, red 50:50, green 1:99, staircase signals delimit comfort range) (c) South supply water temperatures for all controller settings (blue 99:1, red 50:50, green 1:99) (d) Heating and comfort costs: weighting ratio 1:99 (green – heating cost, red – comfort violation cost) (e) Heating and comfort costs: weighting ratio 50:50 (green – heating cost, red – comfort violation cost) (f) Heating and comfort costs: weighting ratio 99:1 (green – heating cost, red – comfort violation cost). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

User can then select an initial state from the set of predefined ones – in this example we consider a cooled down building (this can happen for instance at the end of a weekend).

Having all simulations executed and computed, their solution can be compared using *series comparator*. It allows users to compare whatever signals from whatever simulations.

Weather profile that is used for all of the simulations is depicted in Fig. 6(a) – winter conditions were considered.

The following Fig. 6(b) shows a comparison of zone temperatures in the south part of the building block as well as the reference trajectories. It can be clearly seen that the higher stress on the *dollars* the better satisfaction of the thermal comfort. Especially in the case 1:99, the satisfaction of the thermal comfort is insufficient and such a setting could not be used in practice.

Similar trends can be observed also from Fig. 6 (c) where supply water temperature is depicted for all simulation settings. Note especially, that the strategy 99:1 results in an input sequence that heats up the building over the first 9 h (in order to rapidly increase the zone temperature) but then a cooling peak takes place for almost 2 h. This behavior is not economically beneficial – to deliver heat and then again cool – but it results in a better satisfaction of the upper thermal comfort limit. Last three Fig. 6(d–f) show heating and comfort costs for the particular controller settings. The first picture is related to the 1:99 setting and the heating cost dominates. The opposite situation happens for the setting 99:1.

This small example has shown a comparison of three settings of the manager view that is predefined by the administrator and results in a satisfactory performance at least for the setting 50:50. More complex experiments with controller settings can be done in the engineer view where the user can set more options and thus shape the system response *ad libitum*.

5. Conclusions

BuildingLAB allows user to familiarize with the MPC framework applied on buildings. Two interfaces (easy-to-use manager view and a more complicated engineering view) for defining a simulation assignment help users to see background of MPC for buildings.

Application functionality was demonstrated on a simple example in the Section 4. Moreover, it allows practitioners with an expert knowledge about building dynamics to assess a quality of the underlying mathematical models of the building by looking at the resulting system responses in some typical weather conditions.

The application is available at the web page of BuildingLAB i.e. http://buildinglab.felk.cvut.cz/. Some features are available only after logging into the application, therefore for the potential users we have prepared username `eab` with password `eab`. The application will be updated regularly when new features are added.

The application is maintained by CTU and licensed under the terms of MIT License. Full text of the license is included in the program release that is located on the title page of the application.

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4.3. Optimization of Predicted Mean Vote Index Within Model Predictive Control Framework: Computationally Tractable Solution

Full citation:
J. Cigler, S. Prívara, Z. Váňa, E. Žáčeková, and L. Ferkl. "Optimization of Predicted Mean Vote index within Model Predictive Control framework: Computationally tractable solution". In: *Energy and Buildings* 52 (2012), pp. 39–49. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2012.05.022
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Citing Half-life:	6.6

Annotation:
It was shown that by making use of PMV index in the MPC problem formulation, it is possible to achieve even higher energy savings [54, 67]. On the other hand, the price for the savings is the increased complexity of the resulting optimization problem that becomes a non convex constrained optimization problem. In this paper, PMV based formulation is stated at first, the main differences between typical MPC problem formulation and PMV based formulation are outlined, a computationally tractable approximation of the nonlinear optimal control problem is presented and its accuracy is validated.
Contribution to the thesis:
This paper contributes to the last point of the goals of this thesis, i.e. a computationally tractable MPC methods solving PMV based MPC problem is proposed and validated on a detailed BEPS model.

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Optimization of Predicted Mean Vote index within Model Predictive Control framework: Computationally tractable solution

Jiří Cigler*, Samuel Prívara, Zdeněk Váňa, Eva Žáčeková, Lukáš Ferkl

Department of Control Engineering, Faculty of Electrical Engineering of Czech Technical University in Prague, Technická 2, 166 27 Praha 6, Czech Republic

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ABSTRACT

Recently, there has been an intensive research in the area of Model Predictive Control (MPC) for buildings. The key principle of MPC is a trade-off between energy savings and user welfare making use of predictions of disturbances acting on the system (ambient temperature, solar radiation, occupancy, etc.). Usually, according to international standards, the thermal comfort is represented by a static range for the operative temperature. By contrast, this paper is devoted to the optimization of the Predicted Mean Vote (PMV) index which, opposed to the static temperature range, describes user comfort directly. PMV index is, however, a nonlinear function of various quantities, which limits the applicability and scalability of the control problem formulation. At first, PMV-based formulation is stated, the main differences between typical MPC problem formulation and PMV based formulation are outlined, a computationally tractable approximation of the nonlinear optimal control problem is presented and its accuracy is validated. Finally, control performance is compared both to a conventional and predictive control strategies and it turns out that the proposed optimal control problem formulation shifts the savings potential of typical MPC by additional 10–15% while keeping the comfort within levels defined by standards.

1. Introduction

1.1. Motivation

In recent years, there has been a growing concern to achieve energy savings. This has been demonstrated by the governments of many developed countries. For instance, the European Union (EU) presented targets concerning energy cuts defining goals until 2020 [1]: (i) Reduction in EU greenhouse gas emissions at least 20% below the 1990 levels, (ii) 20% of EU energy consumption to come from renewable resources, (iii) 20% reduction in primary energy use compared to projected levels to be achieved by improving energy efficiency. The similar goals, in some cases even more restrictive, have been stated by the U.S. government with minor differences on the level of each state [2].

As the buildings account for about 40% of total final energy consumption [3] and more than half is consumed in HVAC (heating, ventilation and air conditioning) systems, an efficient building climate control can significantly contribute to reduction of the power demands and lower thus the greenhouse gas emissions.

In addition, for instance in the U.S., there are about one to two million buildings being newly constructed every year. However, there are approximately 110 million existing buildings consuming much more energy *per se* than new buildings constructed according to current standards. Even when each of the new buildings would use net-zero-energy technology, it will take a long time to achieve significant difference on the overall energy bill [4]. Therefore, a much more productive approach for achieving the strict energy cuts would be to focus on the retrofitting of the existing buildings or by improvements of Building Automation Systems (BAS) and their algorithms that can be achieved with minimal additional cost. In this paper, we restrict ourselves only to improvements in BAS algorithms. The effort to implement advanced control algorithms in buildings has been shown by the activity of the leading academic and industrial teams in the area of HVAC control [5–9].

1.2. State-of-the-art in advanced control of HVAC systems

Recently, there have emerged two main research trends in the field of advanced HVAC control (i) learning based approaches like artificial intelligence; neural networks; fuzzy and adaptive fuzzy neural networks; etc. (ii) Model based Predictive Control (MPC) techniques that stand on the principles of the classical control.

The approaches from the former group are used in HVAC systems for their capability in dealing with nonlinearities as well as their capabilities to handle Multi-Input Multi-Output (MIMO) systems. These approaches can be for instance used to cut down the time needed for tuning the supervisory controller [10], to control

* Corresponding author. Tel.: +420 22435 7687.
E-mail address: jiri.cigler@fel.cvut.cz (J. Cigler).

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cooling system with several types of cooling strategies [11] or to optimize occupants' thermal comfort making use of ventilation control [9].

The latter technique can handle MIMO systems from its very nature and usually relies on the physically based mathematical model of the HVAC system and building dynamics. The aim of MPC is to design control inputs that minimize the energy consumption while guaranteeing that comfort requirements are met. A comprehensive and up-to-date overview of the literature related to the predictive control of buildings can be found on the website of the OptiControl project (www.opticontrol.ethz.ch). From the wide variety of results, a few instances can be listed. The controller (i) takes disturbance predictions (occupancy, weather, etc.) into account, thus it adjusts control actions appropriately [12,13], (ii) can utilize the thermal mass of a building in a better way compared to the conventional control strategies (e.g. PID, weather compensated or rule based control) [14,15], (iii) is able to deal with variable energy price that can be easily included into the formulation of the optimization problem [16,17], (iv) can handle minimization of the energy peaks and thus shift energy loads within certain time frame [6,18–20] (beneficial because of both the possibility of tariff selection and lowering operational costs), (v) can take into account stochastic properties of random disturbance variables (e.g. weather forecast, occupancy profiles); convex approximation of a stochastic Model Predictive Control problem for buildings is given in [21], (vi) can be realized using sampling algorithms [22] – typically for buildings, the shape of an input sequence does not differ a lot through the year (repeating day–night cycle) therefore the optimization can be carried out using appropriate signal selection from a bank of predefined signals, (vii) can be formulated in a distributed manner and thus the computational load can be split among several solvers [23–25]. There have also been reported some experimental setups of MPC which have shown the energy savings potential [6,12,26,27] (15–30% compared to conventional control strategies).

1.3. Representation of thermal comfort in MPC formulation

As already stated, the focus of MPC is not only on the minimization of costs or consumed energy, but it also aims at the fulfillment of comfort requirements, which have, so far, been defined by an operative or air temperature band that is derived from more general thermal comfort indices (according to the international standards [28–30]). From the analysis of MPC performance, it turns out that the control strategy always tries to track the lower/upper boundary of the reference trajectory, which may, however, deteriorate the comfort quality from a longer perspective or, on the other hand, keep a distance from the boundaries of the thermal comfort index. The first aim posed in this study is to quantify the level of deterioration/reserves, in sense of the thermal comfort index, caused by the tracking of the temperature band boundaries. To do so, the most widely used thermal comfort index Predicted Mean Vote (PMV) is selected [31].

PMV was developed by Fanger in the early seventies and includes parameters that influence thermal comfort. Among others, these are air velocity, relative humidity, metabolic rate, etc. Furthermore the Fanger's model has been accepted as a general standard since the eighties [29,30].

In addition, there has been developed direct relationship between PMV index and productivity rate of the occupants of the office buildings. As the cost of office laborers in the developed countries is much higher than the operational costs of a building, the fulfilment of thermal comfort can result in a substantial economic benefit [32,33].

In this study, PMV index will be explicitly implemented into MPC cost function which, however, results in a nonlinear optimization problem. Thus, the second aim of this work is to develop a sufficiently precise approximation strategy that solves the given nonlinear problem effectively. Performance of the controllers will be studied on a two zone office building which is for this purpose modeled using TRNSYS environment [34].

This work is inspired by two pioneering works in which the authors explicitly included PMV index into optimization problem [35,36]. To the author's best knowledge, there are no other works dealing with PMV optimization within MPC framework. The results of the authors are extended by:

- Development of an approximation strategy based on linearization of nonlinear terms in PMV formulation. Such an approximation is very close to the general formulation, however, it makes the problem computationally tractable even for long prediction horizons. Note that in the cited studies, prediction horizon $N = 10$ used to be a computational burden which is not sufficient for buildings as they have slow dynamics.
- The assessment of the comfort quality for various control strategies as well as considering more decision variables in the optimization problem (i.e. mean radiant temperature is taken into account as it is one of the main factors affecting the thermal comfort [37,38]).

Note also that PMV index is intensively studied in the other areas of the advanced building control. Takagi–Sugeno fuzzy forward controller tracking PMV set-point is presented in [9] to control air handling unit of a building. Moreover, PID-fuzzy controller is presented and compared with a classic ON–OFF controller in [39]. Both controllers have the objective to track the comfort range defined by PMV index and it is shown that the PID-fuzzy controller leads to the lower energy costs while keeping the comfort within desired range.

1.4. Organization of the paper

The paper is further organized as follows. Section 2 introduces the thermal comfort measures. Section 3 describes the setup that was used for validation of the proposed algorithms. Section 4 presents the investigated control strategies while Section 5 proposes approximations for handling nonlinearities in optimization problem. Section 6 has two objectives (i) to show that a short prediction horizon is inapplicable for thermal comfort regulation – thus the need for a computationally tractable solution will be validated, (ii) to assess energy consumption and comfort quality for various control setups. Finally, Section 7 draws conclusions and states possibilities for future work.

2. Thermal comfort

Thermal comfort in buildings is usually evaluated using the operative temperature [29], which is, in the simplest way, defined as the average of the air temperature and the mean radiant temperature (i.e. usually computed as area weighted mean temperature of the surrounding surfaces [40]). However, the thermal comfort is a more complicated quantity and, in accordance with ISO 7730 [29] and ASHRAE 55 [30] international standards, it can be defined in a more general way as "*The condition of mind which expresses satisfaction with the thermal environment*", pointing out that it is a cognitive process influenced by various quantities, physical activity, physiological and psychological factors.

There have been a lot of studies on the calculation of the thermal comfort conditions and the most widely used thermal comfort index is PMV that is described by a set of Eqs. (6)–(10) which includes parameters that influence thermal comfort of a human being. The PMV index predicts the mean value of the votes of a large group of people based on the heat balance of a human

Table 1
Quantities defining the thermal comfort (notation adopted from [29]).

Symbol	Quantity	Typical values	Units	Values considered further in the study
M	Metabolic rate	46–232	W/m^2	70 W/m^2 = 1.2 met, i.e sedentary activity (office, dwelling, etc.)
W	Effective mechanical power	≥0	W/m^2	0 W/m^2
I_{cl}	Clothing insulation	0–0.31	m^2 K/W	0.155 m^2 K/W = 1 clo for heating season, otherwise 0.75 clo
f_{cl}	Clothing surface area factor	0–1	–	Depends on I_{cl} (see (10))
t_a	Air temperature	10–30	°C	Decision variable
$\bar{t}_r$	Mean radiant temperature	10–40	°C	Decision variable
v_{ar}	Relative air velocity	0–1	m/s	0.1 m/s, i.e. typical for offices
p_a	Water vapor partial pressure	0–2700	Pa	Relative humidity assumed to be fixed at Φ = 50%
h_c	Convective heat transfer coefficient	0–12.1	W/m^2 K	Depends on the air and cloth temperatures according to (9)
t_{cl}	Clothing surface temperature	10–30	°C	Depends on multiple quantities, see (8)

Table 2
Design criteria for office spaces during heating and cooling seasons.

ISO 7730	Operative temperature range [°C]		PMV range [–]	PPD [%]
	Cooling season	Heating season		
Class A	24.5 ± 1	22 ± 1	0 ± 0.2	<6
Class B	24.5 ± 1.5	22 ± 1.5	0 ± 0.5	<10
Class C	24.5 ± 2.5	22 ± 2.5	0 ± 0.7	<15

body. The quantities arising in the equations are listed in Table 1. Note that most of the quantities/parameters can be obtained in a rather straightforward way, e.g. air temperature, velocity as well as humidity can be obtained by direct measurement, while clothing parameters and human activity can be estimated from the prior knowledge about the workload of the occupants. Mean radiant temperature is a more complicated quantity that depends not only on temperature of surrounding surfaces but also on solar radiation intensity [41,42]. In this paper, the motivation is to obtain a convex optimal control problem therefore the mean radiant temperature will assumed to be equal to area weighted average of the surfaces, i.e. linear combination of system states.

Thermal balance is achieved when the heat losses to the environment are equal to the heat produced by the human body. Hence, PMV consists of all heat transfers related to the human body. In Eq. (6) for PMV index, the symbol L stands for the thermal load of the body (in W/m^2) which can be further decomposed (according to the rows in (7)) to (i) difference between internal and external work, (ii) heat loss caused by the evaporation from the skin, (iii) respiration heat losses, (iv) radiation and convection from the body to the environment.

The PMV index is defined on a 7-level thermal sensation scale: 0 neutral, ±1 slightly warm/cool, ±2 warm/cool, ±3 hot/cold. Then the objective of indoor climate control in the office buildings is to keep PMV index or operative temperature within ranges defined in Table 2 [29].

Then quantitative measure of the thermal comfort of a group of people is defined by Predicted Percentage Dissatisfied (PPD) index

$$PPD = 100 - 95\exp(-0.034 \cdot PMV^4 - 0.22 \cdot PMV^2). \quad (1)$$

Note that even if PMV index is zero, there is 5% of dissatisfied occupants.

3. Simulation setup

In this section, the simulation environment that is used for validation of the studied algorithms is presented. The environment is schematically sketched in Fig. 1. In the core, there is a detailed TRNSYS model sharing the same disturbance profiles (occupancy and weather) as the MPC part which is composed of an optimization block that uses linear time-invariant (LTI) model for performing the numerical optimization. Time varying parameters (e.g. variable energy price or reference trajectories, etc.) are required by the MPC block. Detailed description of the individual blocks is given below.

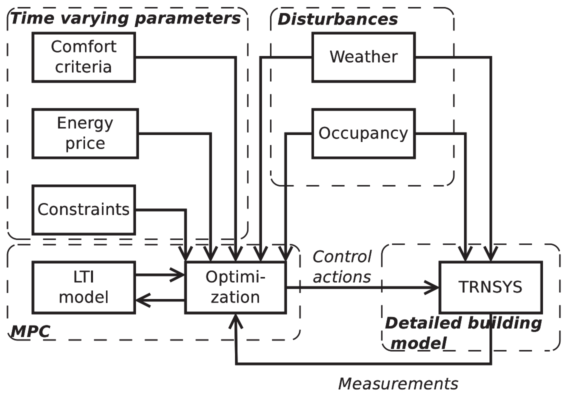


Fig. 1. Simulation environment.

3.1. Building simulator

The studied building, schematically outlined in Fig. 2, was constructed in TRNSYS environment using Type56 [34]. It is a medium weight office building with two zones separated by a concrete wall.

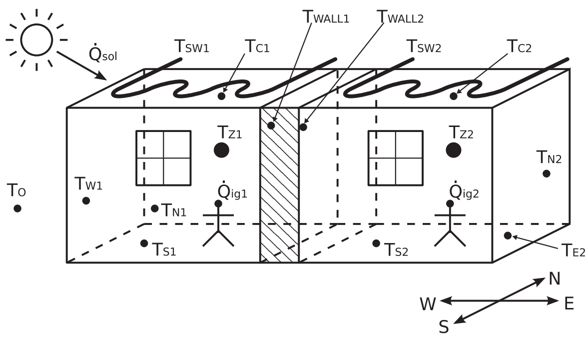


Fig. 2. A scheme of the modeled building.

Both zones have the same dimensions (5 m × 5 m × 3 m) and the south oriented walls of the zones include a window (3.75 m^2). Such a system structure was chosen because it also involves transitional properties between zones.

The HVAC system used in the building is of a thermo-active building system (TABS) type. Technically, it consists of a water-carrying tube systems integrated into the ceiling distributing supply water which then enables thermal exchange with the concrete core of the modeled building. Both zones are equipped with a separate heating circuit where the mass flow rate of the supply water is held constant and then, the supply water temperature is the only manipulated variable in a particular heating circuit. Internal gains are considered to have a standard profile of working days (typical for office buildings) while outside environmental conditions (involving ambient temperature, outside air relative humidity and solar characteristic) are simulated using TRNSYS Type15 with the year weather profile corresponding to Prague, Czech Republic.

Given the fact that a medium-weight building is studied, the timebase T_b = 1/4 h for Type56 was chosen. Note that the accuracy of the simulation results strongly depends on the ratio between the timebase and TRNSYS simulation time-step, which must be an integer multiple of the timebase. The objective is usually to have the longest possible time-step (in order to decrease simulation time) but it is important to keep in mind that a longer time-step may deteriorate simulation accuracy. Therefore the time-step was selected equal to the timebase to guarantee proper convergence of TRNSYS internal algorithms.

For the purposes of model identification and subsequent predictive control, the link between TRNSYS and Matlab was established based on TRNSYS Type155. All temperatures, solar radiation and internal gains depicted in Fig. 2 are assumed to be perfectly measured as they are passed through the communication link or precomputed in case of the disturbances. The meaning of the quantities is explained in Table 3.

3.2. Model for control

A model in the TRNSYS environment captures internal workings in a building very well, however, the model is in an implicit form that is not suitable for numerical optimization within MPC framework. Therefore simpler LTI models are usually identified in order to carry out MPC routines.

Table 3
Notation of the quantities in the system.

Notation	Description
T_o	Ambient temperature
T_{sw1}	Supply water temperature, zone 1
T_{sw2}	Supply water temperature, zone 2
$\dot{Q}_{sol}$	Total solar radiation
$\dot{Q}_{ig1}$	Internal gains, zone 1
$\dot{Q}_{ig2}$	Internal gains, zone 2
T_{c1}	Ceiling core temperature, zone 1
T_{s1}	Core temperature measured on south side, zone 1
T_{w1}	Core temperature measured on west side, zone 1
T_{n1}	Core temperature measured on north side, zone 1
T_{z1}	Zone temperature, zone 1
T_{c2}	Ceiling core temperature, zone 2
T_{s2}	Core temperature measured on south side, zone 2
T_{e2}	Core temperature measured on east side, zone 2
T_{n2}	Core temperature measured on north side, zone 2
T_{z2}	Zone temperature, zone 2
T_{wall1}	Core temperature measured on common wall, zone 1
T_{wall2}	Core temperature measured on common wall, zone 2

The LTI model of the system was identified using grey box technique[1] adopted from [12, Section 3.1.2]. Pseudorandom binary sequence was used as the excitation input signal and the resulting model has the structure

$$x(k+1) = Ax(k) + Bu(k) + Ww(k), \tag{2}$$

where k is the discrete time, $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$, $w \in \mathbb{R}^v$ and A, B, W are the matrices of appropriate dimensions. The vector of system states is composed as $x = [T_{c1}, T_{wall1}, T_{s1}, T_{w1}, T_{n1}, T_{z1}, T_{c2}, T_{wall2}, T_{s2}, T_{e2}, T_{n2}, T_{z2}]^T$, inputs $u = [T_{sw1},\ T_{sw2}]^T$ and disturbances $w = [T_o, \dot{Q}_{sol}, \dot{Q}_{ig1}, \dot{Q}_{ig2}]^T$. The sampling period of the model is twice as long as the time-step of TRNSYS simulation, i.e. T_s = 1/2 h. Note that t_a is equivalent to the zone temperature T_z while $\bar{t}_r$ is the area weighted mean temperature of the walls (the rest of system state).

4. Control strategies

Having a LTI model and a building simulator at hand, we can (i) formulate a control strategy which directly optimizes thermal comfort index violations, (ii) draw conclusions about the amount of required energy and comfort violations (in terms of PMV index) of conventional, predictive and proposed control strategies. To do so, controllers will be validated for three different office building comfort requirements defined by ISO 7730, i.e. Classes A–C (see Table 2). Some of the quantities influencing the thermal comfort will be assumed to be constant, for values see Table 1.

4.1. Conventional control strategy

From conventional strategies, the weather compensated control has been selected, because it is commonly used in the buildings of our interest [7,12]. It is a feedforward control strategy where the temperature of the supply water T_{sw} is set according to the ambient temperature T_o and desired zone operative temperature $T_{z,desired}$ by means of predetermined heating/cooling curves f_{wc}, that is

$$T_{sw} = f_{wc}(T_o, T_{z,desired}). \tag{3}$$

4.2. Typical MPC formulation for buildings

There exists a wide variety of MPC problem formulations for buildings (refer to the citations in Section 1). In this study, a typical formulation is used and the following optimization problem is solved in a receding horizon fashion:

$$\begin{aligned} \min_{u_0^{N-1}, z_0^{N-1}} \ & \sum_{k=0}^{N-1}\sum_{i=1}^{2} \underbrace{\left|(T_{sw,i}(k) - T_{c,i}(k))R\right|_2^2}_{\text{Energy minimization}} + \underbrace{\left|(T_{z,i}(k) - z_i(k))Q\right|_2^2}_{\text{Reference tracking}} \\ \text{subject to:} \ & \text{linear dynamics (2)}, \\ & x(0) = x_0, \\ & T_{sw,min} \le T_{sw,i}(k) \le T_{sw,max}, \\ & T_{z,min}(k) \le z_i(k) \le T_{z,max}(k). \end{aligned} \tag{4}$$

Here N is prediction horizon, Q, $R \geq 0$ are weighting matrices of appropriate size for tuning the algorithm while $T_{z,min}(k)$ and $T_{z,max}(k)$ are time varying limits defined by the particular class of ISO 7730 standard when occupants are present, otherwise the night setback is considered (lower limit at 18 °C). The term z_i refers to the

[1] The prior knowledge of the system structure can be included into identification algorithm, which at the end results in a better model for control compared to pure black box techniques [12].

J. Cigler et al. / Energy and Buildings 52 (2012) 39–49 43

slack variable on the zone temperature and expresses that the cost increases only if there is a violation of the reference band.

Decision variables are collectively denoted as u_0^{N-1}, z_0^{N-1} where e.g. $u_0^{N-1} = [u(0), u(1), \ldots, u(N-1)]$.

The energy minimization term is commensurate with the consumed energy as the constant mass flow rate is considered. Despite that fact, square of the energy term is minimized as the minimization of one norm leads to oscillatory behavior and deteriorates the overall closed loop behavior [43]. YALMIP optimization toolbox [44] with `quadprog` routine from Optimization toolbox for Matlab were used to define and solve the optimization problem.

Note that to isolate the impact of the particular control strategy, perfect knowledge of the disturbances is assumed on the prediction horizon as well as full system state measurement x_0. Concerning the accuracy of the disturbance predictions, our assumption is meaningful at least for comparing two predictive control strategies. Then in practice, the quantitative results of a predictive controller cannot achieve the theoretical numbers (so called *performance bound*) as the controller performance depends on the quality of the disturbance predictions. This issue was studied in [45] where the authors studied impact of the imperfect predictions on the performance of MPC controller for various types of buildings.

4.3. PMV index in MPC cost function

The last approach is to include optimization of the thermal comfort index PMV directly into the cost function, i.e. to minimize PMV or to keep PMV in a certain range and to penalize only violations, which leads to the following formulation with the aid of slack variables p_i:

$$\begin{aligned}
\min_{u_0^{N-1}, p_0^{N-1}} \; & \sum_{k=0}^{N-1} \sum_{i=1}^{2} \underbrace{\left|(T_{sw,i}(k) - T_{c,i}(k))R\right|_2^2}_{\text{Energy minimization}} + \underbrace{\left|(PMV_i(k) - p_i(k))Q\right|_2^2}_{\text{PMV minimization}}, \\
\text{subject to:} \; & \text{linear dynamics (2)}, \\
& x(0) = x_0, \qquad (5) \\
& T_{sw,min} \le T_{sw,i}(k) \le T_{sw,max}, \\
& PMV_{min}(k) \le p_i(k) \le PMV_{max}(k), \\
& PMV \text{ Eqs. (6)–(10)}.
\end{aligned}$$

$PMV_{min}(k)$ and $PMV_{max}(k)$ are time varying bounds defined by the particular class of ISO 7730 norm when occupants are present, otherwise the night setback is employed (lower limit of PMV is set to -1). The same assumptions as for the typical MPC formulation hold here.

5. Approximation of PMV computation

The optimization problem (5) is non-convex in the cost function as well as nonlinear in the constraints. It is caused mainly by: (i) the term representing water vapour partial pressure which depends on the air temperature according to Clausius–Clapeyron equation as

$$p_a = \Phi \cdot 6.1094 \exp\left(\frac{17.625 t_a}{t_a + 243.04}\right),$$

where Φ is the relative humidity, (ii) occurrence of the if–else conditions in the computation of convective heat transfer coefficient (9), (iii) radiant heat transfer between zone surfaces and human body. In the following, all the aforementioned terms will be treated such that the approximated optimization problem will be computationally tractable and, at the same time, the approximation will be sufficiently accurate.

$$PMV = (0.303 \cdot \exp(-0.036 \cdot M) + 0.028) \cdot L, \qquad (6)$$

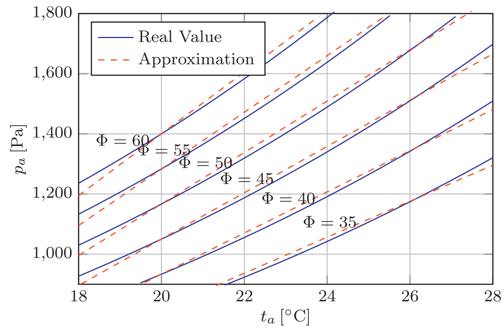


Fig. 3. Affine approximation of the nonlinear term for the computation of water vapor partial pressure.

$$\begin{aligned}
L = {} & (M - W) - 3.05 \cdot 10^{-3} \cdot (5733 - 6.99 \cdot (M - W) - p_a) \\
& - 0.42 \cdot ((M - W) - 58.15) - 1.7 \cdot 10^{-5} \cdot M \cdot (5867 - p_a) \\
& - 0.0014 \cdot M \cdot (34 - t_a) - 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot ((t_{cl} + 273.16)^4 \\
& - (\bar{t}_r + 273.16)^4) - f_{cl} \cdot h_c \cdot (t_{cl} - t_a), \qquad (7)
\end{aligned}$$

$$\begin{aligned}
t_{cl} = {} & 35.7 - 0.028 \cdot (M - W) - I_{cl} \cdot (3.96 \cdot 10^{-8} \cdot f_{cl} \cdot ((t_{cl} + 273.16)^4 \\
& - (\bar{t}_r + 273.16)^4) + f_{cl} \cdot h_c \cdot (t_{cl} - t_a)), \qquad (8)
\end{aligned}$$

$$h_c = \begin{cases} 2.38 \cdot |t_{cl} - t_a|^{0.25} & \text{if } 2.38 \cdot |t_{cl} - t_a|^{0.25} \ge 12.1 \cdot \sqrt{v_{ar}} \\ 12.1 \cdot \sqrt{v_{ar}} & \text{if } 2.38 \cdot |t_{cl} - t_a|^{0.25} < 12.1 \cdot \sqrt{v_{ar}} \end{cases}, \qquad (9)$$

$$f_{cl} = \begin{cases} 1.00 + 1.290 \cdot I_{cl} & \text{if } I_{cl} \le 0.078 \\ 1.05 + 0.645 \cdot I_{cl} & \text{if } I_{cl} > 0.078 \end{cases}. \qquad (10)$$

5.1. PMV convexification

5.1.1. Water vapor partial pressure

Analyzing the function dependence between zone air temperature t_a and water vapor partial pressure p_a for given relative humidity, almost affine dependence can be seen even though the phenomena is described by a complicated exponential function. The dependence is depicted in Fig. 3 and for particular value of relative humidity Φ can be read as

$$p_a = k_{pa} \cdot t_a + q_{pa},$$

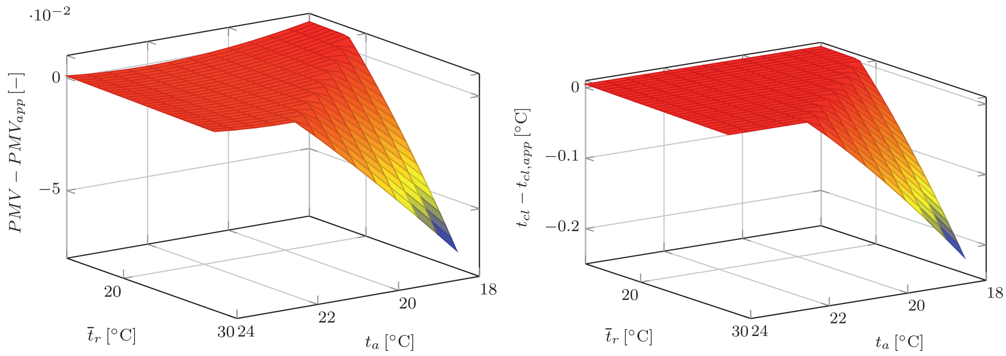
where k_{pa} and q_{pa} are appropriate constants.

5.1.2. Convective heat transfer coefficient

Computation of convective heat transfer coefficient is driven by formula (9). For small difference between cloth and zone temperatures, the constant value can be considered (in our case $|t_{cl} - t_a| \le 6$), but if the difference is higher, the nonlinear term should be used. The dependence on $|t_{cl} - t_a|^{0.25}$ will be however neglected and the consequences will be discussed later on.

5.1.3. Radiation between surfaces

Radiation between surfaces is the last factor causing a non-convexity of the original problem. If the two above mentioned approximations are implemented, the optimization problem becomes polynomial in decision variables. Such type of a problem can be solved globally by recently developed moment method [46].



(a) Absolute error in PMV approximation

(b) Absolute error in t_{cl} approximation

Fig. 4. Approximation error caused by the linearization of the formula for computation of PMV index. *PMV* is a value computed according to (6) while PMV_{app} using the approximations described in Section 5. Cloth temperature t_{cl} is a side product of these computations. Typical values for mean radiant temperature and zone air temperature are considered.

The original problem can be then restated into a form of semidefinite programming. This method is however suitable only for small classes of polynomial optimization problems and thus cannot be used for MPC-like problems, where the complexity quickly grows with the prediction horizon (in our case, the problem became intractable even for prediction horizon $N = 2$). From that reason, the radiant part was linearized around operating point at each MPC time-step which resulted in a Quadratic Programming problem at the end.

5.2. Convex approximation of PMV-based MPC problem

Putting all the aforementioned approximations together, the optimization problem (11) is yielded. The optimization problem becomes convex and a general nonlinear solver is not required anymore.

$$\min_{u_0^{N-1}, p_0^{N-1}} \sum_{k=0}^{N-1} \sum_{i=1}^{2} \underbrace{\left|(T_{sw,i}(k) - T_{c,i}(k))R\right|_2^2}_{\text{Energy minimization}} + \underbrace{\left|(PMV_i(k) - p_i(k))Q\right|_2^2}_{\text{PMV minimization}}, \tag{11}$$

subject to:linear dynamics (2),

$x(0) = x_0$, Current state

$T_{sw,min} \leq T_{sw,i}(k) \leq T_{sw,max}$, Min–Max constraints

$PMV_{min}(k) \leq p_i(k) \leq PMV_{max}(k)$,

$p_{a,i}(k) = k_{pa} \cdot t_{a,i}(k) + q_{pa}$ Approximation of p_a

$$PMV_i(k) = (0.303 \cdot \exp(-0.036 \cdot M) + 0.028) \cdot L_i(k),$$

$$\begin{aligned} L_i(k) = (M - W) &- 3.05 \cdot 10^{-3} \cdot (5733 - 6.99 \cdot (M - W) - p_{a,i}(k)) \\ &- 0.42 \cdot ((M - W) - 58.15) - 1.7 \cdot 10^{-5} \cdot M \cdot (5867 - p_{a,i}(k)) \\ &- 0.0014 \cdot M \cdot (34 - t_{a,i}(k)) - t_{x,i}(k), \end{aligned}$$

$$t_{x,i}(k) = 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot (t'_{cl,i}(k) - \bar{t}'_{r,i}(k)) + f_{cl} \cdot h_c \cdot (t_{cl,i}(k) - t_{a,i}(k)),$$

$$t'_{cl,i}(k) = t_{cl,i,0} + 273.16 + 4 \cdot (t_{cl,i,0} + 273.16)^3 \cdot (t_{cl,i}(k) - t_{cl,i,0})$$

Linearization of t_{cl}^4

$$\bar{t}'_{r,i}(k) = \bar{t}_{r,i,0} + 273.16 + 4 \cdot (\bar{t}_{r,i,0} + 273.16)^3 \cdot (\bar{t}_{r,i}(k) - \bar{t}_{r,i,0})$$

Linearization of $\bar{t}_r^4$

$$t_{cl,i}(k) = 35.7 - 0.028 \cdot (M - W) - I_{cl} t_{x,i}(k),$$

$h_c = 12.1 \cdot \sqrt{v_{ar}}$ Approximation of h_c

$$f_{cl} = \begin{cases} 1.00 + 1.290 \cdot I_{cl} & \text{if } I_{cl} \leq 0.078 \\ 1.05 + 0.645 \cdot I_{cl} & \text{if } I_{cl} > 0.078 \end{cases}.$$

Note that the terms with explicit specification of discrete time dependence are decision variables or variables that depends on u_0^{N-1} or p_0^{N-1} affinely (except of PMV_{min} and PMV_{max} that are time varying constraints). Furthermore, the terms with subscript $\bullet_0$ denote current value of the particular quantity (i.e. define the operation point in which the functions are linearized) while the terms with superscript $\bullet'$ stand for the linearized quantity derived from a more complicated quantity.

5.3. Evaluation of the approximation accuracy

Approximation errors in PMV and t_{cl} calculations caused by all simplifications are depicted in Fig. 4. The picture shows the dependence of the error on two decision variables that directly influence PMV and t_{cl} (the rest of variables have indirect impact) and it can be seen that the quality of approximation is sufficient. The bigger approximation error happens only in situations when there is a big difference between mean radiant temperature and zone air temperature because in such a case, the more complicated term for convective heat transfer coefficient comes to play (i.e. $h_c = 2.38 \cdot |t_{cl} - t_a|^{0.25}$). This is, however, not very usual thermal condition.

6. Analysis of control performance

This section has two main objectives. Firstly, it shows that a short prediction horizon is inapplicable for a thermal comfort regulation. This is done using a simple comparison of two MPC runs with different prediction horizons. Secondly, the assessment of energy consumption and comfort quality is addressed for various control setups.

6.1. Importance of prediction horizon length

So far, PMV-based MPC formulations have used very short prediction horizon [35,36] and general nonlinear solvers had to be employed in order to obtain optimal control moves. To show the importance of the proposed approximation technique, a small experiment devoted to a comparison of the computational time needed to solve the respective optimization problem has been performed and the results for different prediction horizons are summarized in Table 4. The computational time needed to solve the general nonlinear problem (5) – in our case solved using `fmincon` function from the Optimization toolbox for Matlab – quickly grows with the prediction horizon and would grow with the problem dimension, hence the scalability of the nonlinear problem is not guaranteed at all.

J. Cigler et al. / Energy and Buildings 52 (2012) 39–49

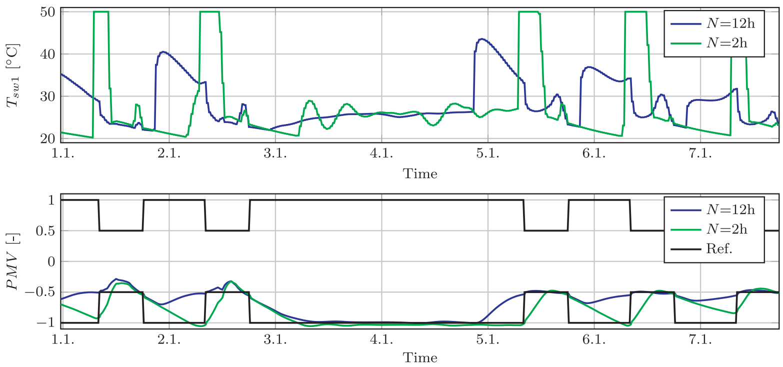


Fig. 5. Time-series for PMV-based MPC formulations for different setting of prediction horizon length.

In addition, the sufficiently long prediction horizon is unavoidable as the buildings possess slow dynamics and for some control actions it takes long time until they become evident on the system response (in terms of both response of the building envelope and adaptation of people).

A comparison of time-series is presented in Fig. 5 where two prediction horizons are considered for formulation (5). It is evident that the formulation with the shorter horizon ($N = 2/T_s = 4$) starts heating-up the zone too late and two hours are not sufficient for the controller to satisfy thermal comfort at the beginning of the

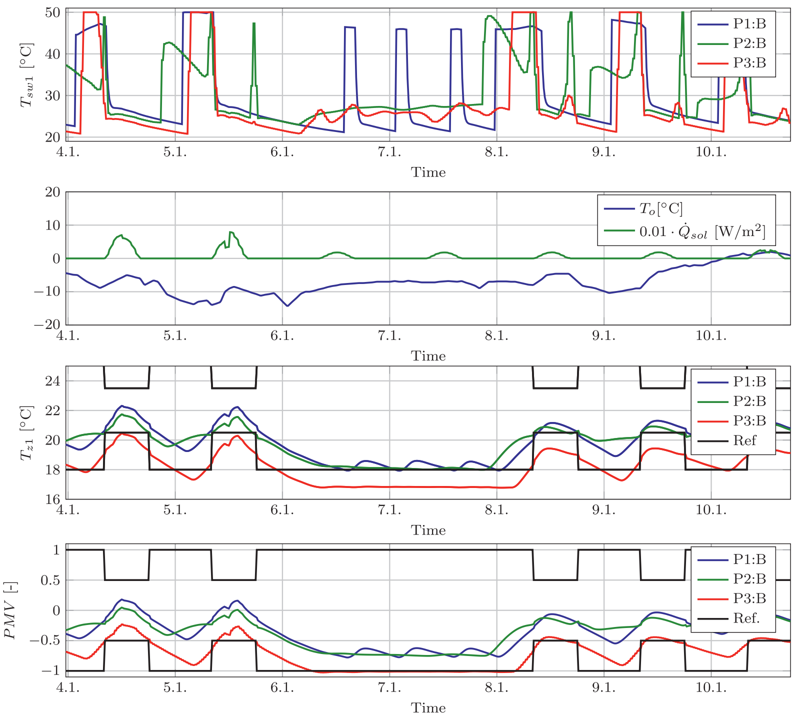


Fig. 6. Time-series for all control strategies, thermal comfort class B, signals for the first zone only.

Table 4
Computational times needed to solve the optimization problems.[a]

Prediction horizon	Typical MPC formulation (4)	PMV formulation (5)	PMV formulation (11)
$N = 8$	0.38 s	3.07 s	1.24 s
$N = 16$	1.07 s	61.06 s	3.22 s
$N = 24$	1.18 s	324.72 s	8.08 s
$N = 32$	2.05 s	969.63 s	15.26 s

[a] Recorded on Debian Linux 6.0.3 machine with two processor cores, @2.60 GHz.

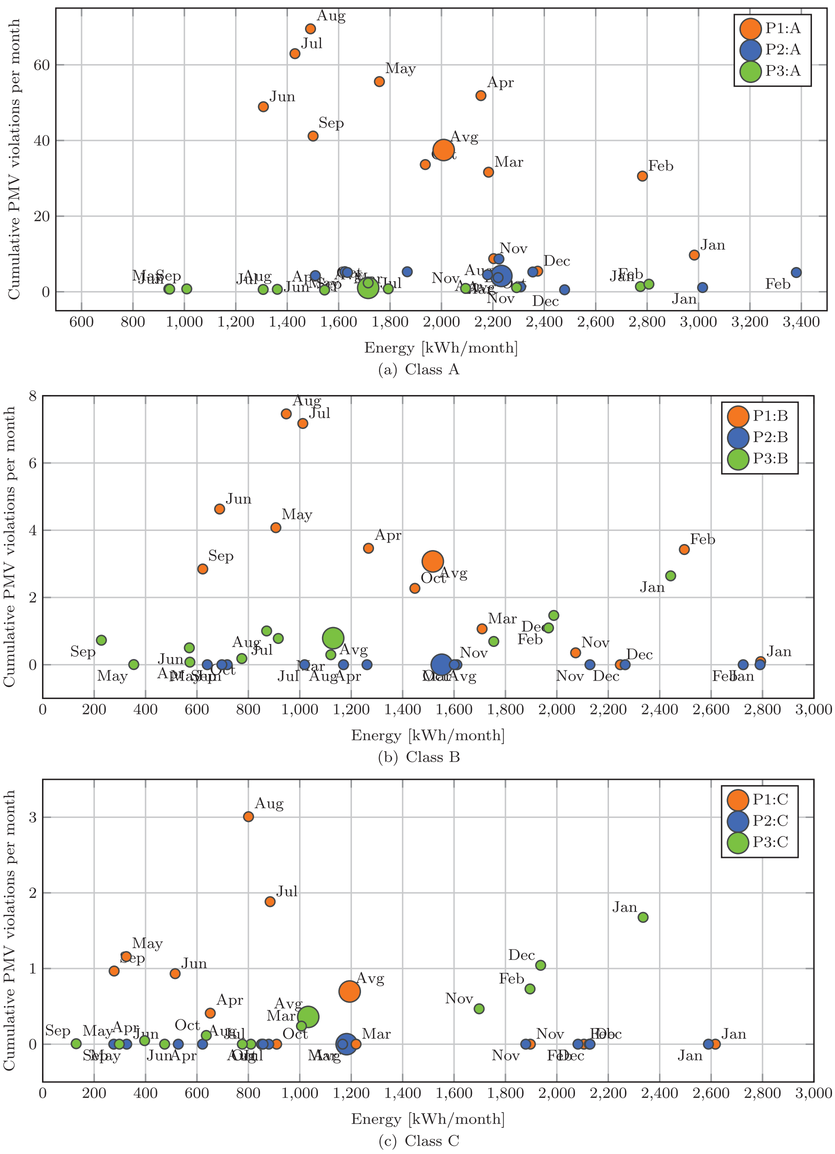


Fig. 7. Consumed energy and comfort violations in terms of the average of PMV range violation.

working hours. With the longer prediction horizon ($N = 12/T_s = 24$) the controller can react sufficiently in advance and thus satisfy thermal comfort in almost all time instants.

6.2. Control performance

Yearly simulations for all thermal comfort classes and controllers were compared and the summary is shown in Figs. 6–8. In the following discussion, the control strategies will be referred to as

- P1: weather compensated control according to (3)
- P2: typical MPC formulation, i.e. problem (4)
- P3: MPC formulation with PMV index approximation explicitly specified in the cost function, i.e. Eq. (11).

For both of the predictive control strategies, the prediction horizon set $N = 12/T_s = 24$. In addition, the predictive strategies were tuned such that there was high stress on the comfort satisfaction, i.e. Q was selected much higher than R.

Time-series for the particular control strategies and ISO 7730 Class B are depicted in Fig. 6. Because of the similarity of the signals for the first and the second zone, only the signals for the first zone are depicted. Data for one week are shown only.

Supply water temperatures are shown in the upper part of the figure and one can see that P1 and P2 are characterized by a similar

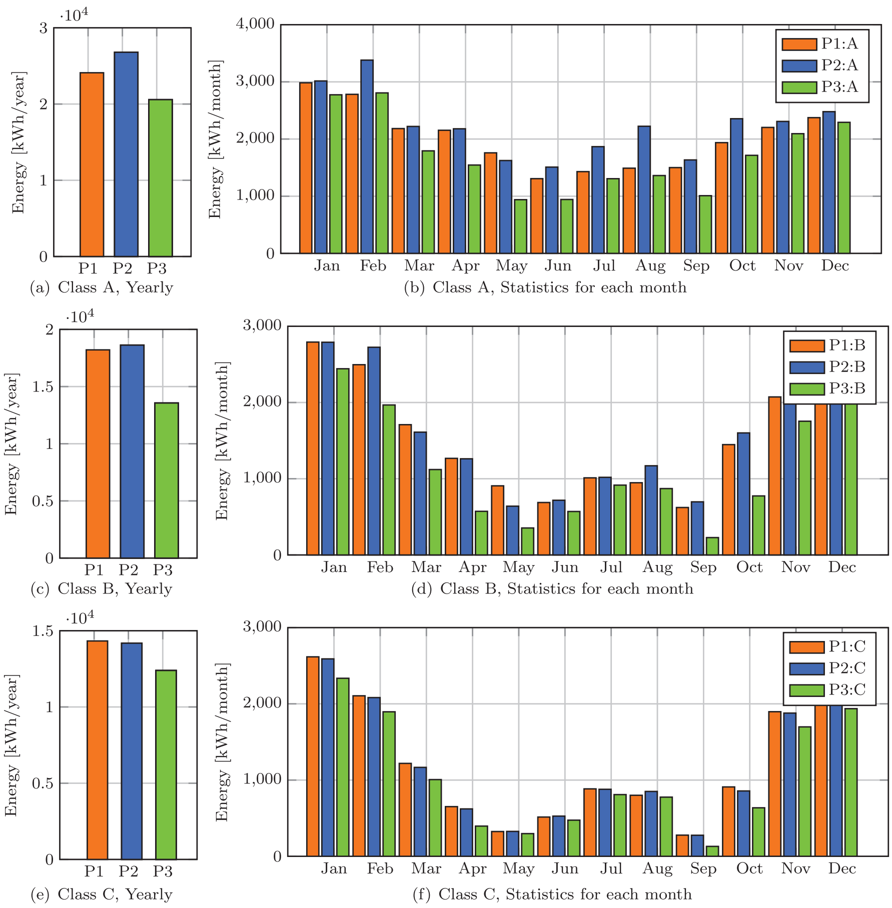


Fig. 8. Energy consumption comparison.

behavior while P3 results in lower values. Similarity between P1 and P2 is caused by the fact that weather compensated controller was tuned based on the prior knowledge about typical MPC control actions. In all cases the controllers preheat the building in advance in order to satisfy the thermal comfort during the daytime, and moreover, P2 and P3 are capable to compensate to abrupt changes in solar radiation (the second part of the figure). Note that PMV in the lower part of the figure is computed using (6)–(10).

In case P3, even the temperatures of walls and air are lower, which can be seen in the third part of the figure. Although the temperatures in case P3 are lower than in P2, the thermal conditions fulfill the thermal comfort requirements defined by the standard. This is the place where the formulation of P3 can bring further energy savings as the solution to problem P2 keeps a distance from the PMV boundaries.

Further conclusions can be observed from Fig. 7 (consumed energy vs. cumulative PMV comfort range violations). We can see that there are no thermal comfort violations in case P2, whilst in cases P1 and P3 certain violations occur which are in case P3 in the 5% tolerance range defined by the norm [29].

As far as energy consumption is concerned, the control strategy P3 performs by 10–15% better than the rest of control strategies (see Fig. 8 where cumulative as well as month-by-month energy consumption for particular comfort class are presented). P1 and P2 recorded comparable results in terms of energy consumption but small amount of comfort violations in case of P1 have to be taken into account. Comparable results should not be surprising although lot of authors claims that MPC strategies have a huge saving potential compared to conventional control strategy (see discussion in Section 1 and citations therein). This phenomenon has been initially observed by [47] where the authors compare three control strategies (manual, MPC, manual operation with knowledge how MPC operates building) and draw conclusions that knowledge of MPC control actions can contribute to energy savings, thus the total energy consumption of manual operation approaches the MPC results. In [48], the idea was extended by introducing a complementary statistical technique that allows for the extraction of the of logistic decision models from the optimal control results. In addition, it has been shown that MPC strategy can be sufficiently precise approximated by a set of rules guaranteeing control performance comparable to MPC as well as a closed loop stability [49]. In addition, the set of rules is more comprehensible for the operators of the building compared to the complicated optimization problem setup.

7. Conclusions and future works

7.1. Conclusions

In this paper, a computationally tractable approach for solving PMV-based predictive control optimization problem was proposed. In order to prove the applicability and scalability to bigger problems, accuracy and significant speed-up compared to the general nonlinear solution were shown. Moreover, further possibilities for energy cuts were outline. As PMV index directly describes user thermal comfort, the "allowed" temperatures are not so conservative as in common MPC formulation for buildings. By optimizing the thermal comfort index PMV directly, predictive control approach can save further 10–15% energy compared to the typical MPC formulation while keeping the comfort within the range defined by standards. We also showed that the conventional control strategy can perform in a very similar way as typical MPC.

Inclusion of PMV into the cost function and constraints, however, brings about some issues:

- The prior knowledge of the activity of the occupants, clothing, etc. is assumed. That is one of the reasons why the temperature range in the standards is more conservative than PMV range. However, air and mean radiant temperature belong among the dominant factors influencing the comfort index. The rest of the quantities in the PMV formula does not have such a huge impact and thus an expert estimate is sufficient.
- The resulting optimization problem is nonlinear and therefore, for large setups, difficult to solve (see Table 4). It was demonstrated on the office building example that sufficiently long prediction horizon is crucial in order to satisfy thermal comfort requirements and thus an approximative solution for the general nonlinear optimization problem was proposed. Accuracy and computational efficiency has been studied and successfully validated.

7.2. Future works

Next research will focus on application of the proposed technique on a real building and evaluation of energy saving potential based on a long time operation.

Moreover, assumptions about the constant value of relative humidity do not hold generally and the PMV based MPC formulation needs to be extended by another optimization variable.

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4.4. On the Selection of the Most Appropriate MPC Problem Formulation for Buildings

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Annotation:
Based on *i)* observations from the long term MPC operation on the CTU building and *ii)* literature dealing with MPC for buildings, we specified four main issues that engineers are facing when formulating MPC optimization problem for a real building. These issues are described in detail in this paper and an alternative practical aspects motivated optimal control problem formulation is proposed there. It is shown that this formulation behaves in a better way especially in situations when there is some model mismatch (i.e. always except for MPC simulations), disturbance prediction errors, etc.
Contribution to the thesis:
This paper contributes to the second point of the goals of this thesis. The proposed optimal control problem formulation helps to achieve even better controller performance because the resulting performance *i)* is not oscillatory (in both open- and closed-loop operation) due to smoothing terms introduced in the cost function, *ii)* is sufficiently robust to disturbance predictions and model inaccuracies, *iii)* guarantees recursive feasibility of the optimization problem, *iv)* respects user-defined comfort limits in such a way that it is high probable that high comfort violations do not occur, *v)* does not increase significantly the energy consumption, *vi)* does not increase the numerical complexity of the problem significantly – the problem stays in the same class of convex optimization problems.

On the Selection of the Most Appropriate MPC Problem Formulation for Buildings

Jiří Cigler*[1], Jan Široký#, Milan Korda⋆, Colin N. Jones⋆

*University Centre for Energy Efficient Buildings, Czech Technical University in Prague, Czech Republic
[1]jiri.cigler@uceeb.cz
#University of West Bohemia in Pilsen, Czech Republic
⋆École Polytechnique Fédérale de Lausanne, Switzerland

Abstract
Model Predictive Control (MPC) for buildings has gained a lot of attention recently. It has been shown that MPC can achieve significant energy savings in the range between 15-30% compared to a conventional control strategy, e.g., to a rule-based controller. However, there exist several reports showing that the performance of MPC can be inferior to that of a well-tuned conventional controller. Possible reasons are at hand: i) minimization is typically not performed over energy but instead over some input quantity that has a different meaning ii) a model mismatch and inaccuracies in weather predictions can cause wrong predictions of future behavior which can result in undesirable behavior of the control signal (e.g. oscillations) and, as a consequence, in increase in energy consumption. This behavior has been observed when applying one of the widely used economic MPC formulation to the building of Czech Technical University in Prague. These oscillations are not an issue for buildings only, but also for every economic MPC that minimizes the absolute value of the control action. In this paper, we discuss all the these aspects of the implementation of MPC on a real building, show and analyze data from MPC operation on the university building and finally propose and validate an MPC formulation that alleviates the sensitivity to model mismatch and inaccuracies in weather predictions.

Keywords – Energy Savings; Model Predictive Control; Optimization

1. Motivation

It is a well known fact that in developed countries the energy consumption in buildings accounts for around 40 % of the total final energy and more than half of this amount is consumed in HVAC (Heating, Ventilation and Air Conditioning) systems [1]. Therefore, improvements in algorithms for Building Automation Systems (BAS) can significantly contribute to desired energy savings.

In recent years, there have appeared a lot of simulation or real case studies evaluating advanced control algorithms applied to BAS showing savings potential of these strategies ranging up to 40 %. One of the intensively studied control techniques for BAS is the Model Predictive Control (MPC) [2, 3, 4, 5]. The objective of the MPC algorithm is to optimally select control inputs in such a way that the energy consumption is minimized and, at the same time, comfort requirements are met. In the following, we assume basic familiarity with the MPC control technique (i.e., the notions of objective function, constraints, decision and slack variables, etc.; for details please refers to, e.g., [6]).

Recently, there has been presented a wide variety of papers dealing with MPC applied to control of BAS with the following properties: *i)* The MPC controller takes disturbance predictions (occupancy, weather etc.) into account, adjusting control actions appropriately [2, 3]. *ii)* The thermal mass of the building can be utilized in a better way compared to conventional control strategies [7]. *iii)* Thermal comfort indices can be easily included into the formulation of MPC problem and therefore the performance of MPC can result in a better subjective thermal comfort [8, 9, 10]. *iv)* Variable energy prices can easily be included into the formulation of the optimization problem [11, 12]. *v)* Minimization of the energy peaks can be handled by MPC and thus energy loads can be shifted within certain time frame [3, 13, 14] (beneficial because of both the possibility of tariff selection and lowering operational costs). In the above-mentioned papers, the conclusions are usually drawn from numerical simulations on detailed building models, e.g., EnergyPlus, Trnsys, etc.; however, experimental setups of MPC have also been reported, showing energy savings potential of up to 30 % compared to conventional control strategies [3, 15, 16].

The objective of this paper is, however, slightly different from the objective of the aforementioned ones. Based on the experience from four heating-seasons of MPC deployment on a real pilot building [15], we point out main challenges that mar the idealistic world of MPC encountered in most academic studies. In addition, we propose a new MPC formulation that tries to circumvent these problems.

2. Problem Description

From the analysis of a long-term behavior, we can point out the following three main issues that need to be tackled in order to obtain a robust and reliable control strategy:

Oscillatory behavior: The objective of MPC for buildings is to minimize energy consumption and thus reduce the energy bill. As the energy cost is an affine function of energy consumption[1], the MPC problem cost function is typically of the form

$$J = \sum_{k=0}^{N_u-1} |R_k u_k|_1 + \sum_{k=0}^{N_y-1} |Q_k(y_k - y_k^r)|_2^2, \tag{1}$$

where k is the discrete time, N_u and N_y are the control and prediction horizon respectively, $u \in \mathbb{R}^m$ and $y \in \mathbb{R}^p$ are the vectors of system inputs and outputs respectively, y^r is the vector of the reference trajectories for the output signals and finally, R_k and Q_k are (possibly time-varying) weighting matrices. In this cost function, 1-norm (i.e., the sum of absolute values) of the input energy is to be minimized. However, 1-norm MPC, which can be cast as a Linear Program (LP), always activates some of the constraints as the solution lies on one of the vertices of the constraint polytope and hence such an optimization problem results in a bang-bang-type deadbeat or idle control that is undesirable

[1] The constant term in the affine function represents especially maintenance costs

for buildings [17, 18]. In addition, MPC works in a receding horizon fashion when at every time-step, a finite-horizon optimal control problem (FHOCP) is solved and only the first control move is applied to the system. In the following time step, the next FHOCP is solved with updated measurements, disturbance predictions and comfort requirements. A small change in these parameters may cause an abrupt change in the optimal solution. Sensitivity of the optimal solution to the LP to a parameter change is case-dependent and difficult to assess a priory. Although in general, this sensitivity is higher for 1-norm control problems (leading to LPs) than for problems with a quadratic cost function leading to quadratic programs (QPs). Note that the quadratic norm for the comfort only does not significantly change the 1-norm-like behavior especially when there are few comfort violations (the slack variables are not active and the 1-norm-like behavior dominates). On the contrary, weighting of energy using a quadratic norm leads to a smooth input profile; the problem, of course, is that the energy bill is not proportional to the square of energy.

Robustness to model inaccuracy and disturbance prediction errors: Buildings are complex systems, each is unique and therefore a detailed modeling of every building where MPC shall be applied is economically unjustifiable. Hence one has to expect that the model will always be inaccurate. Disturbance predictions are also subject to (sometimes significant) errors. These facts increase the importance of the two aforementioned issues.

Fig. 1 shows an example of the undesirable behavior recorded during ten days of a normal operation of MPC on our pilot building. Besides disturbances and room temperature that is to be kept at a certain comfort level, we can observe progress of supply water temperature, which is the only manipulated variable that is being computed by MPC. We can observe undesirable oscillatory behavior causing higher energy consumption towards the end of the data series. This behavior happens when a standard 1-norm-like MPC formulation considered in the majority of academic papers is used.

Recursive feasibility: In the literature, various MPC problem formulations for buildings have been proposed (a review will be given in Section 3.). Some of the problem formulations, however, do not guarantee recursive feasibility and therefore cannot be used as a long-term, reliable control strategy.

Small and high comfort violation: In practice, it is acceptable that BAS can cause small violation of comfort but major and/or persistent violations are unacceptable. Freezing occupants are not willing to hear anything about "inaccurate model" or "infeasible optimization problem".

During normal building operation, a reasonable tradeoff between energy consumption and comfort can be found using cost function weighting factors. However, during some special events, these settings can be inappropriate. An example of such event is the Christmas holiday that allows for a long-term setback in the case of university building. At the end of the setback there is a need for enormous amount of energy that has to be delivered into the building

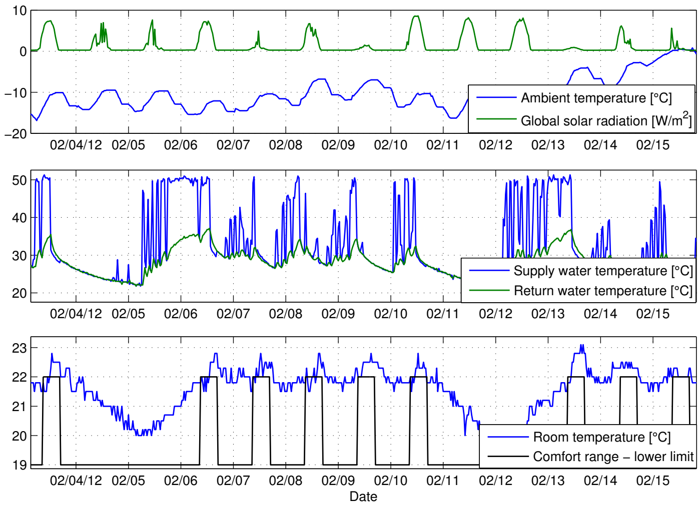


Fig. 1: Oscillations of supply water temperature recorded during MPC operation

in order to return to a "normal operation" of the building. Unfortunately, in the case of our pilot building, the optimal solution that was exercised caused major comfort violations during the first day after the Christmas holiday. Hence, there is a need for definition of comfort requirements that have to fulfilled at any cost.

The paper is further structured as follows: *i)* Section 3. analyzes state-of-the art, what FHOCP formulations are typically used for buildings. These formulations are assessed from the point of view of recursive feasibility, sensitivity to oscillations, etc. *ii)* Section 4. proposes a new FHOCP formulation that addresses the aforementioned issues. *iii)* Section 5. presents a case study where the proposed FHOCP is validated. *iv)* Finally, Section 6. outlines other directions for designing practically robust FHOCP.

3. Existing Model Predictive Control Formulations for Buildings

In this section, we present some of the typical optimal control problem formulations for buildings. We restrict ourselves to deterministic, non-hybrid and centralized MPC formulations because such formulations are the most widely used ones in practice. More advanced variants of MPC (e.g. stochastic or distributed) are far more complex to analyze and are left for future investigations.

We assume that the models of the buildings are linear time invariant (LTI) with heat fluxes as inputs and zone temperatures as outputs. The models have the following form:

$$x_{k+1} = Ax_k + Bu_k + Vv_k, \qquad y_k = Cx_k + Du_k + Wv_k, \tag{2}$$

where $v_k \in \mathbb{R}^s$ is the vector of disturbances, $y_k \in \mathbb{R}^p$ is the vector of system outputs and , $x_k \in \mathbb{R}^n$ is the vector of system states. Real matrices A, B, C, D, V, W are so called system matrices and are of appropriate dimensions.

We will start from the formulations that have appeared in the literature. Pros and cons for each of the formulation will be given. Each formulation eliminates some drawbacks of the previous one. In the next section, we then present a new formulation that we deem to be so far the most suitable formulation for buildings (both from the point of view of the quantities being optimized and a practical viewpoint).

Minimization of delivered energy and satisfaction of the constraints: This formulation was reported by [19, 20, 5, 21]. The cost function contains a single term standing for the minimization of the delivered energy while the thermal comfort is guaranteed by means of hard constraints on the system outputs, i.e. zone temperatures.

$$\min_u \sum_{k=0}^{N_u-1} |R_k u_k|_1 \tag{MPC1}$$

$$\text{subject to: linear dynamics Eq. (2),} \qquad x_0 = x_{init},$$
$$G_k u_k \leq h, \qquad \underline{r}_k \leq y_k \leq \overline{r}_k.$$

The matrices G_k, h_k define time varying polytopic constraints on system inputs and states, while $\underline{r}_k$ and $\overline{r}_k$ stand for the time varying reference trajectory for the system outputs. Initial state x_{init} is a parameter of the optimization and is provided by means of Kalman filter or full state measurement at each time-step.

Although the presented control strategy was advertised as a "new control strategy suitable for MPC for buildings" [20], from our experience, this optimal control problem formulation as is cannot be used in the practice. The most obvious drawback is the lack of recursive feasibility: if the initial state implies any comfort violation, then the optimization problem will be infeasible and the controller cannot work anymore. Feasibility issues are usually handled with the aid of the so-called slack variables on system states and system outputs. Hard constraints are imposed only on the system inputs.

Trade-off between energy consumption and set-point tracking error: An alternative simple MPC formulation that tackles feasibility issues was presented in [4, 9, 22, 23, 24, 14] and has following form[2]:

$$\min \sum_{k=0}^{N_u-1} |R_k u_k|_1 + \sum_{k=0}^{N_y-1} |Q_k(y_k - r_k)|_2^2 \tag{MPC2}$$

$$\text{subject to: linear dynamics Eq. (2),} \qquad x_0 = x_{init}, \qquad G_k u_k \leq h,$$

Here, r is the set-point which is to be tracked. Although this formulation has the form that is typically used in process industry [6], it is not suitable for buildings. According to standards defining indoor thermal comfort, operative temperature[3] should lie within certain temperature range. Forcing the temperature to follow

[2] Some authors use without any reasoning quadratic norm for penalization of input energy instead of one norm

[3] Operative temperature is defined as the average of the air temperature and the mean radiant temperature (i.e. usually computed as area weighted mean temperature of the surrounding surfaces)

a single set-point curtails the freedom of the controller and may result in a higher energy consumption. In addition, typical effects of MPC regulation like a night-time pre-cooling or pre-heating are suppressed. A similar formulation with the aid of slack variables can add the desired freedom to the MPC controller.

Trade-off between energy consumption and comfort range violations: Slack variables are additional decision variables that are weighted only in situations when some quantity, which the slack variable is imposed on, reaches certain bound. They are useful especially in situations when the objective is to keep system outputs within a certain range and the slacks penalize the violation of the range. The following formulation was presented in [15, 16, 25, 2, 26].

$$\min \sum_{k=0}^{N_u-1} |R_k u_k|_1 + \sum_{k=0}^{N_y-1} |Q_k(y_k - z_k)|_2^2 \tag{MPC3}$$

$$\text{subject to: linear dynamics Eq. (2),} \qquad x_0 = x_{init},$$
$$G_k u_k \le h, \qquad \underline{r}_k \le z_k \le \overline{r}_k$$

In this optimal control problem setup $z_k \in \mathbb{R}^p$ is the slack variable on the zone temperature. The advantages of such a formulation has already been discussed; however, the use of the 1-norm to weight the system inputs is a major disadvantage. As it is well known, the solution of a linear program lies on a vertex of the polytopic constraint set. If the constraints are not very tight, a bang-bang control profile is obtained. This behavior is undesirable in closed loop operation in the presence of model mismatch because then the control actions can lead to a highly oscillatory behavior (see Fig. 1). Unpleasant oscillations can be suppressed by introducing hard constraints on the maximum rate of change of the input signals. But what if, accidentally, there is a strong need to heat up the building and to use the maximum capacity of the heating system immediately? This problem as well as other aforementioned issues are handled in the optimal control problem formulation given in the following section.

4. Practical Aspects Motivated Formulation

In this section, we introduce a new MPC formulation that is motivated by practical aspects. The aims of this formulation are (i) suppress oscillation appearing in receding horizon due to minimization of the 1-norm of the input signal, (ii) minimize sensitivity of the controller to the model mismatch and imperfect disturbance predictions while making use of minimal additional energy, (iii) guarantee recursive feasibility, (iv) respect thermal comfort limits defined by standard norms e.g. ISO 7730 and guarantee that significant comfort range violations do not occur, (v) does not increase the numerical complexity of the problem significantly.

The proposed formulation has the following form:

$$\min \sum_{k=0}^{N_u-1} \left(|R_k u_k|_1 + \delta \text{smooth}(k)\right) + \sum_{k=0}^{N_y-1} \left(|Q_k(y_k - z_k)|_2^2 + |Q_k^c(y_k - z_k^c)|_2^2\right) \tag{MPC4}$$

$$\text{subject to: linear dynamics Eq. (2),} \quad x_0 = x_{init}, \quad u_{last} = \{u_{-1}, u_{-2}, \dots\}$$
$$G_k u_k \le h, \qquad \underline{r}_k \le z_k \le \overline{r}_k, \qquad \underline{r}_k^c \le z_k^c \le \overline{r}_k^c$$

Here, $z_k \in \mathbb{R}^p$ and $z_k^c \in \mathbb{R}^p$ are slack variables and together with $\underline{r}_k, \overline{r}_k$ define comfort constraints that can be violated from time-to-time, while $\underline{r}_k^c, \overline{r}_k^c$ define comfort constraints that cannot be violated at any cost. These comfort constraints give the MPC controller sufficient freedom to operate the building in an energy-efficient way.

It is expected that system inputs and outputs are scaled to a similar range of values and that $\max(R_k, \delta_k, Q_k) \ll Q_k^c$.

Recursive feasibility of this formulation is guaranteed as there are no hard constraints imposed on system states nor system outputs.

Finally, the objective of the smoothing term is to suppress oscillations in receding horizon as well as on prediction horizon. Here it is important that there is the term u_{last} holding information about past system inputs that were computed by MPC. Based on these values, we can easily smooth the receding horizon progress of the input signal. We propose following variants of smoothing terms:

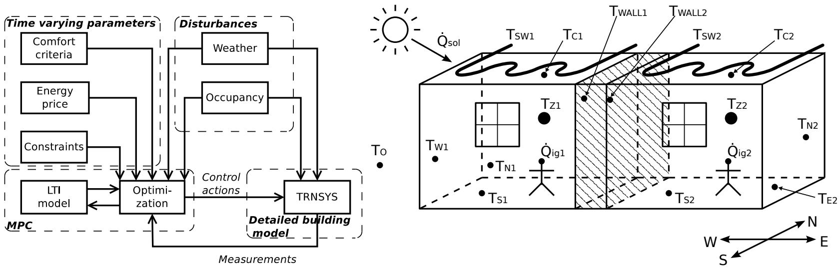
- MPC4a: $\text{smooth}(k) = |Zu_k|_2^2$, i.e. the problem is regularized in such a way that not only the one norm of the input signal is minimized, but also quadratic norm is minimized. Here, Z is an appropriate weighting matrix.
- MPC4b: $\text{smooth}(k) = |u_k - u_{k-1} - p_k|_2^2$ and one additional constraint is introduced $\underline{\Delta u} \le p_k \le \overline{\Delta u}$ for $k = 1 \dots N_u$. Here $\underline{\Delta u}, \overline{\Delta u}$ are minimum/maximum values allowed for the input change not to be penalized, p is a slack variable and thus the square of the inner term regularizes the optimization task.
- MPC4c: $\text{smooth}(k) = |u_{k-2} - 2u_{k-1} + u_k|_2^2$, i.e. minimization of curvature of the input signal. Here, it is required to know two of the past inputs.

In the following section, we will compare the three proposed smoothing terms to the presented MPC formulations without any smoothing term.

5. Case Study: Validation of the Proposed MPC Formulation

For validation of the proposed MPC formulation, we will use a TRNSYS simulation environment. Schematically, the simulation setup is depicted in Fig. 2a. In the core, there is a detailed TRNSYS model sharing the same disturbance profiles (occupancy and weather for Prague, Czech Republic) as the MPC part which is composed of an optimization block that uses linear time-invariant (LTI) model for performing the numerical optimization. Time-varying parameters (e.g. variable energy price or reference trajectories etc.) are required by the MPC block. The setup is designed in such a way that the problems with model mismatch causing oscillations may appear. Disturbance prediction errors are not considered here.

The building under investigation, schematically outlined in Fig. 2b, was constructed in TRNSYS environment using Type56. It is a medium weight office building with two zones separated by a concrete wall and with thermo-active building systems (TABS) controlled separately. Both zones have the same



(a) Simulation environment (b) A scheme of the modeled building

Fig. 2: Simulation setup

Table 1: Performance comparison of MPC formulations. In relative comparisons, the results are always compared to the MPC3.

	Delivered energy [kWh/month]		Comfort violations [Kh/month]	
	Aboslute	Relative	Absolute	Relative
MPC1	–	–	–	–
MPC2	5555	-111 %	0	-100 %
MPC3	2631	0 %	3.22	0 %
MPC4a	1946	26 %	3.43	6 %
MPC4b	2355	10 %	4.61	43 %
MPC4c	1885	28 %	4.45	38 %

dimensions ($5 \times 5 \times 3\,$m) and the south oriented walls of the zones include a window ($3.75\,\text{m}^2$). A detailed description of the building is given in [27].

The LTI model Eq. (2) of the system was identified using grey box technique adopted from [15, Section 3.1.2] and verification of its accuracy is given in [27].

The performance of the presented MPC formulations were validated on one month simulations within the simulation environment. For evaluation of thermal comfort, ISO 7730 class B was used. The results of all formulations are summarized in Table 1 and Fig. 3.

As already noted, MPC1 does not guarantee recursive feasibility. This was confirmed by a simulation that crashed at simulation time $T_s = 16\,$h. The state of the LTI model ended up out of the allowed range, and hence the optimization problem became infeasible.

The objective of MPC2 is to track a set point – in our case, the average of the lower and upper comfort limits. This fact caused a significant increase in energy consumption. In addition, oscillations described above were observed (due to space limitation, simulation results for MPC2 are not reported in Fig. 3).

Formulation MPC3 is taken as a baseline for all comparisons in the Table 1. From Fig. 3, it can be seen that the oscillations occurring on the CTU building appears also here and especially over the weekend (1/7 and 1/8) when there is a long setback. In such a situation, solution is either to heat at the maximum possible level or to do nothing. Such behavior naturally increases the long-term energy consumption.

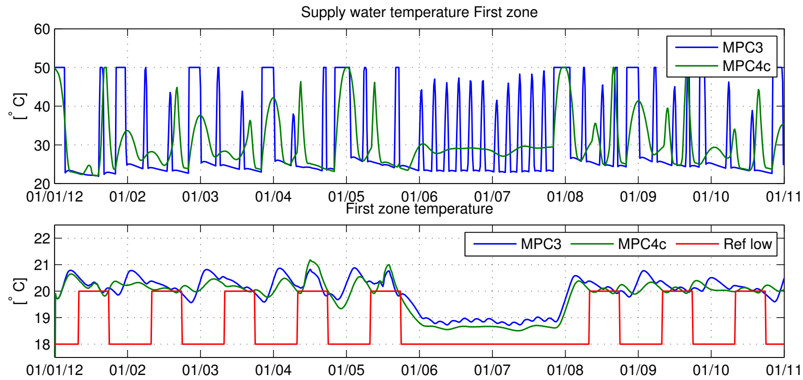


Fig. 3: Comparison of timeseries

On the contrary, MPC4 in all variants achieves better results in terms of energy consumption with comparable amount of comfort violations. MPC4b reaches a slightly higher consumption than the other formulations with smoothing terms. In this case, the amplitude of the oscillations is suppressed, not the oscillations as such.

6. Conclusions and Remarks

In this paper, we analyzed existing MPC problem formulations for buildings. We mentioned pros and cons for each of them and based on this analysis and past experience we proposed a new MPC formulation that (i) is not oscillatory (in both open- and closed-loop operation) due to smoothing terms introduced in the cost function, (ii) is sufficiently robust to disturbance predictions and model inaccuracies, (iii) guarantees recursive feasibility of the optimization problem, (iv) respects user-defined comfort limits in such a way that it is high probable that high comfort violations do not occur, (v) does not increase significantly the energy consumption, (vi) does not increase the numerical complexity of the problem significantly – the problem stays in the same class of convex optimization problems, (vii) is able to capture small and high comfort violations, thereby ensuring that high comfort violations do not occur at any cost. A disadvantage of the proposed algorithm is the increased number of tuning parameters. Typically, there are two weighting coefficients (the matrices Q and R); the proposed formulation has three. Tuning of the third, smoothing, variable is essential for achieving the benefits described above; an improperly tuned smoothing term can either lead to too oscillatory or too smooth (and hence energy-inefficient) behavior.

Finally, the proposed MPC problem formulations were validated within a TRNSYS simulation environment, showing that the introduced smoothing terms can significantly contribute to the robustness of the MPC for buildings.

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5. Conclusions

5.1. Summary and Contribution

Model predictive control for buildings is a very large research area and therefore in this thesis, we focused on three main goals only. Solving of the goals contributed to the state-of-the-art both from a theoretical and practical point of view. We briefly remind the main contributions of this thesis.

- The main practical achievement of this thesis is the implementation of MPC on a pilot building of the CTU in Prague. Assessing the energy savings potential, it was shown that the potential for using MPC with weather predictions for the investigated building heating system were between 15 % and 28 % depending on various factors, mainly insulation level and outside temperature. Moreover, the peak energy demand was lowered by 50 %.

  For tuning and testing of MPC controller applied for CTU building, we also developed a tool called BuildingLab. The tool is not limited for CTU building only, but can be used for any building described by a linear time invariant model.

  We did not implemented MPC only on the CTU building, but there are two other buildings that we have been dealing with.

  - The first one is a new office building in Munich, Germany. Performance of MPC was compared in simulations to the performance of a well-tuned rule-based controller very similar to the one currently deployed in the real building. MPC yielded similar energy usage (to within 5 %) as the reference controller at a comparable amount of thermal comfort violations. This result was mainly because of the building's relatively light construction (that provided little scope for predictive thermal storage management) and the high quality of the original control [69].
  - The other one is a new office building in Hasselt, Belgium. The building itself is a light façade but in the core, both the floors and the ceilings are equipped with so-called double layer Thermally Activated Building Systems (TABS), where water piping circuits are integrated into the concrete core itself. Our proposed two-level control algorithm reduces energy consumption by $15 - 30$ % in average (depending on the methodology used for the comparison) and simultaneously significantly reduces comfort violations, when compared with the previously applied non-predictive control strategy [70].

- The long term operation of MPC did not always go well. Therefore over the time, we had a chance to analyze MPC behavior and point out the main issues. Subsequently, we proposed an alternative MPC problem formulation that tackles these issues and results in a better performance in situations when there is some model mismatch, disturbance prediction errors, etc.

- Finally, we proposed a tractable method for solving PMV based MPC problem for buildings, which translates the original general constrained optimization problem into QP that can be solved in polynomial time. The accuracy of this approximation was analyzed, showing only a small difference between the real value and approximation that can be neglected for control purposes. The application of this control scheme requires, however, sensors that are not available in buildings we control, therefore this methods has not been tested on a real building yet.

The two above mentioned alternative MPC formulations are the main theoretical achievements of this thesis.

We showed that MPC application results are very encouraging, nevertheless, for commercial transferring of the technology, one has to keep two issues in mind. First, each building is unique and the MPC saving potential depends on many factors like HVAC system, building construction or weather conditions to name a few. Second, the complete cost benefit analysis should not include just energy savings but also the cost of the MPC implementation, i.e. the modeling effort in particular, that presents the most time consuming part and MPC integration into a BAS. These aspects are discussed in detail in the author's recent paper [69].

5.2. Future Research

The most recent work has been focused on the selection of the most suitable MPC formulation for buildings. This part can even be more extended by performing a sensitivity analysis of the resulting optimization task. Basically, two methods are at hand.

The first one is based on the techniques for sensitivity analysis in optimization, i.e. Lagrange coefficients associated with constraints can be analyzed. Then a high value of a Lagrange coefficient indicates a possible high increase of the overall cost and thus it should be related to the sensitivity of the particular equality/inequality constraint to e.g. model mismatch, prediction error and so on. Lagrange coefficients can be obtained for all typical initial states, reference trajectories and disturbances (either by means of a sampling of the state-space or by multi-parametric programming) and further compared. In addition, it can be extended and the structure of the dual problem can be studied in detail.

Moreover, with the computational power now available, we can run exhaustive large-scale Monte-Carlo MPC simulations with various MPC formulations, under various operating conditions and with models of various complexity for simulations setup where there is a model mismatch and/or a disturbance prediction error.

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Appendix A.

Contents of the Attached CD

`thesis/`
Directory containing the PDF versions of this document, doctoral thesis statement, list of author's publications and curriculum vitae.

`journal_papers/`
Directory containing all author's journal papers referenced in this thesis

`conference_papers/`
Directory containing all author's conference papers referenced in this thesis

Publications of the Author

Publications Related to the Thesis

Publications in Journals with Impact Factor

[Dis-A1] J. Cigler, S. Prívara, Z. Váňa, E. Žáčeková, and L. Ferkl. "Optimization of Predicted Mean Vote index within Model Predictive Control framework: Computationally tractable solution". In: *Energy and Buildings* 52 (2012). (co-authorship: 55%), pp. 39–49. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2012.05.022.

[Dis-A2] S. Prívara, J. Široký, L. Ferkl, and J. Cigler. "Model predictive control of a building heating system: The first experience". In: *Energy and Buildings* 43.2 (2011). (co-authorship: 30%), pp. 564–572. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2010.10.022.

[Dis-A3] J. Široký, F. Oldewurtel, J. Cigler, and S. Prívara. "Experimental analysis of model predictive control for an energy efficient building heating system". In: *Applied Energy* 88.9 (2011). (co-authorship: 25%), pp. 3079–3087. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2011.03.009.

[Dis-A4] S. Prívara, J. Cigler, Z. Váňa, F. Oldewurtel, C. Sagerschnig, and E. Žáčeková. "Building modeling as a crucial part for building predictive control". In: *Energy and Buildings* 56 (2013). (co-authorship: 20%), pp. 8–22. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2012.10.024.

[Dis-A5] J. Cigler, P. Tomáško, and J. Široký. "BuildingLab: a tool to analyze performance of model predictive controllers for buildings". In: *Energy and Buildings* 57 (2013). (co-authorship: 60%), pp. 34–41. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2012.10.042.

Publications in Reviewed Journals

[Dis-B1] J. Cigler, S. Prívara, Z. Váňa, E. Žáčeková, and L. Ferkl. "Optimization of Predicted Mean Vote index within Model Predictive Control framework: Computationally tractable solution". In: *Energy and Buildings* 52 (2012). (co-authorship: 55%), pp. 39–49. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2012.05.022.

[Dis-B2] S. Prívara, J. Široký, L. Ferkl, and J. Cigler. "Model predictive control of a building heating system: The first experience". In: *Energy and Buildings* 43.2 (2011). (co-authorship: 30%), pp. 564–572. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2010.10.022.

[Dis-B3] J. Široký, F. Oldewurtel, J. Cigler, and S. Prívara. "Experimental analysis of model predictive control for an energy efficient building heating system". In: *Applied Energy* 88.9 (2011). (co-authorship: 25%), pp. 3079–3087. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2011.03.009.

[Dis-B4] S. Prívara, J. Cigler, Z. Váňa, F. Oldewurtel, C. Sagerschnig, and E. Žáčeková. "Building modeling as a crucial part for building predictive control". In: *Energy and Buildings* 56 (2013). (co-authorship: 20%), pp. 8–22. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2012.10.024.

[Dis-B5] J. Cigler, P. Tomáško, and J. Široký. "BuildingLab: a tool to analyze performance of model predictive controllers for buildings". In: *Energy and Buildings* 57 (2013). (co-authorship: 60%), pp. 34–41. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2012.10.042.

Patents

There are no patents related to the thesis.

Publications indexed in WoS

[Dis-D1] J. Cigler, S. Prívara, Z. Váňa, E. Žáčeková, and L. Ferkl. "Optimization of Predicted Mean Vote index within Model Predictive Control framework: Computationally tractable solution". In: *Energy and Buildings* 52 (2012). (co-authorship: 55%), pp. 39–49. ISSN: 0378-7788. DOI: 10.1016/j.enbuild.2012.05.022.

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[Dis-E1] L. Ferkl, J. Cigler, and J. Rakušan. "Jak nastavit termostat na příjemně: Predicted Mean Vote". In: *TZB Haustechnik* 2 (2012). (co-authorship: 50%), pp. 44–46. ISSN: 1803-4802.

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[Dis-E4] J. Cigler, S. Prívara, Z. Váňa, D. Komárková, and M. Šebek. “Optimization of Predicted Mean Vote Thermal Comfort Index within Model Predictive Control Framework”. English. In: *Proceedings of the 51st IEEE Conference on Decision and Control*. (co-authorship: 50%). Maui, Hawaii, US: IEEE, 2012, pp. 3056–3061. ISBN: 978-1-4673-2064-1. DOI: `10.1109/CDC.2012.6427051`.

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[Dis-E6] J. Cigler, D. Gyalistras, J. Široký, V. N. Tiet, and L. Ferkl. “Beyond Theory: the Challenge of Implementing Model Predictive Control in Buildings”. In: *Proceedings of 11th Rehva World Congress, Clima 2013*. (co-authorship: 60%). Prague, Czech Republic, Accepted, to appear, 2013.

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[NonDis-A1] M. Korda and J. Cigler. “Nonquadratic stochastic model predictive control: A tractable approach”. In: *Automatica* 48.9 (2012). (co-authorship: 50%), pp. 2352–2358. ISSN: 0005-1098. DOI: `10.1016/j.automatica.2012.06.053`.

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Patents

There are no patents related to the thesis.

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Curriculum Vitae

Jiří Cigler was born in Pelhřimov, Czech Republic, in 1985. In 2007, he received the bachelors degree in the study branch of cybernetics and measurement at the Faculty of Electrical Engineering of the Czech Technical University in Prague. Two years later and at the same institution, he received a masters degree in the study branch of control engineering. Since 2009, he has been a Ph.D. student at the same university.

He has been involved in several research projects: before his Ph.D studies, he participated e.g. on *i)* the development of mobile robots for the international robot competition EUROBOT, *ii)* 3D reconstructions of photosynthetic activity of plants, *iii)* TORSCHE Scheduling toolbox. During his Ph.D. studies, he took part in the following projects: *i)* Research grant of the Czech Ministry of Industry "Integration of building systems, research and application of smart algorithms affecting energy consumption in buildings", *ii)* OptiPremier project, *iii)* European project GEOTABS (`http://geotabs.eu`), *iv)* Preseed project "MPC for buildings commercialization" of the University Centre for Energy Efficient Buildings of Czech Technical University in Prague.

His teaching activities at CTU cover courses on Theory of Dynamical Systems, Combinatorial Optimization and Mathematical Analysis. He has also supervised several students' projects and diploma theses.

During his Ph.D. studies, he stayed at the group of Prof. Morari at ETH Zurich for 5 month, where he participated on the OptiPremier project.

His scientific results were presented at several international conferences, mainly organized by IEEE. Among others, it was especially IEEE CDC 2010, 2011 and 2012, IEEE MSC 2011, IEEE ICARCV 2010, etc. The results were also published in multiple reviewed journal papers. Currently, he has 9 reviewed journal papers that have been cited by 41 publications indexed in the database of Web of Science.