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Smart Buildings (Predictive & Neuro-Fuzzy Control)

Handling thermal comfort in economic model predictive control schemes for demand response

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Abstract

Addressing thermal comfort is an important aspect of applying economic model predictive control (E-MPC) schemes with the objective to perform demand response (DR), e.g. minimize operational cost. This paper compares the performance of four E-MPC schemes using both single-objective and multi-objective formulations to address thermal comfort. It is difficult to proclaim the superior formulation as the notion of thermal comfort is a subjective matter. However, the single-objective problem formulation proposed in this paper contains a parameter, ε_{max}, which describes the maximum acceptable deviations from the preferred indoor air temperature. This parameter can be regarded as a user-defined indicator of the acceptable deviations from the preferred temperature or, in other words, their 'DR willingness'.

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Keywords: Themal comfort; Demand Response; Single objective optimization; Multi objective optimization; Economic model predictive control

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1. Introduction

Economic model predictive control (E-MPC) of building energy systems is an optimization based control scheme that uses a model of the building thermodynamics, forecasts of disturbances and measurements of the building state to determine a sequence of optimal control actions. Applying E-MPC together with time-varying energy prices to minimize the space heating operational cost and perform demand response (DR) have been investigated in several studies [1-4]. These E-MPC schemes achieve economic benefits by using the thermal capacity of the structural mass as storage by charging and discharging it with the room heating system in periods with low or high prices, respectively. The schemes therefore result in fluctuating indoor temperatures, and it is therefore necessary to ensure that economic benefits are not violating the thermal comfort of the occupants.

A simple E-MPC formulation in this regard is to assume that occupants are comfortable as long as temperatures are within a predefined comfort band, e.g. defined by a preferred temperature and an acceptable deviation from it. Using this comfort formulation, several studies have suggested significant cost savings and DR potentials. Halvgaard et al. [5] minimized the operational cost of a heat pump and achieved cost savings of 25% compared to traditional control. Pedersen et al. [4] optimized the space heating operation in a multi-apartment building which, compared to a conventional PI-controller, achieved cost savings of up to 6% and reduced energy consumption in peak-hours with up to 47%. Vrettos et al. [1] applied E-MPC for heat pump operation and achieved cost savings of 18.4% compared to a rule-based controller. However, an E-MPC scheme using this comfort formulation will often result in the controller tracking either the upper or the lower boundary of the comfort band [4]. This behavior means that the air temperature rarely is equal to the preferred temperature specified by the occupants. Another shortcoming of this formulation is that the building has no downward flexibility to offer in periods where the lower comfort bound is tracked, i.e. it is not possible to reduce the space heating demand if this service is requested by the supply side [6].

Another approach to ensure comfort is to formulate a multi-objective optimization (MOO) problem, i.e. simultaneously minimize operational costs and thermal comfort violations [2, 7-10]. Avci et al. [2] used an E-MPC scheme to minimize energy consumption and penalize temperature deviations from the preferred temperature, and introduced a discomfort tolerance index to weigh the objectives. Compared to a baseline controller, the E-MPC scheme reduced operational cost with 13% while increasing the mean temperature with 0.15°C. Morales-Valdés et al. [8] evaluated several MOO formulations and suggested to include Fanger's predicted mean vote (PMV) index or predicted percentage dissatisfied (PPD) index in the cost function which, however, led to a nonlinear optimization problem. Therefore, Cigler et al. [7] proposed a convex approximation of the PMV index in the cost function. However, including the PMV index in the cost function relies on assumptions regarding clothing level and metabolic rate, as well as measurement of air speed, relative humidity and the mean radiant temperature. Furthermore, the performance reported in the above-mentioned MOO studies depends on the selection of the assigned relative weights which essentially vary in time as they depend on the building conditions.

Current studies address thermal comfort in E-MPC formulations very differently, which may affect the reported DR potentials. This paper therefore reports on a simulation-based study, where the performance of an E-MPC scheme using both single-objective and multi-objective formulations to address thermal comfort violations is investigated. The aim is to provide a quantitative performance assessment of the different formulations in terms of comfort violations and operational cost, and to discuss their practical implications.

2. Method

A residential building consisting of ten apartments and five stairwells located in Aarhus, Denmark, was chosen as test case. A detailed EnergyPlus (EP) model was used to represent the building to be controlled; information on geometry and thermal characteristics of the building are provided in ref. [4] in which the building is denoted retrofit8. Furthermore, 100mm insulation was added to the partitioning walls to minimize the effect of inter-zonal heat exchange and thereby allow for a decentralized control principle [11]. The E-MPC scheme was implemented in MATLAB and used to operate the space heating of the EP model through co-simulation facilitated by the Building Controls Virtual Test Bed (BCVTB) [12]. The simulations were carried out for the period December 1, 2016 to February 28, 2017, which constitutes the coldest period of the heating season in Denmark, using an EP weather file based on on-site weather measurements. Historical day-ahead power market prices (cleared for Western Denmark, DK1 region) from the simulation period were used. To ease the interpretation of the results, internal gains originating from occupants and equipment were omitted, and perfect weather and price forecasts were assumed.

2.1. Economic model predictive control

At each time step the E-MPC scheme (eq. 1a-1g) determines a sequence of optimal space heating control actions which minimize temperature deviations from the preferred temperature (j_1) and the operational costs (j_2) for a finite prediction horizon N (set to 72 hours in this study).

$$
\begin{aligned}
&\underset{\varepsilon,u}{\text{minimize}} && \underbrace{\boldsymbol{\epsilon}^T\mathbf{Q}\,\boldsymbol{\epsilon}}_{j_1} + \underbrace{\boldsymbol{c}^T\boldsymbol{u}}_{j_2} && && \text{(1a)}\\
&\text{subject to} && x_{n+1} = \mathbf{A}x_n + \mathbf{B}u_n + \mathbf{E}d_n && \forall n = 0,\dots,N\text{-}1 && \text{(1b)}\\
& && y_{n+1} = \mathbf{C}x_{n+1} && \forall n = 0,\dots,N\text{-}1 && \text{(1c)}\\
& && \epsilon_{n+1} = T_{\text{preferred}} - y_{n+1} && \forall n = 0,\dots,N\text{-}1 && \text{(1d)}\\
& && 0 \le u_n \le P_{\max} && \forall n = 0,\dots,N\text{-}1 && \text{(1e)}\\
& && T_{\min} \le y_{n+1} \le T_{\max} && \forall n = 0,\dots,N\text{-}1 && \text{(1f)}\\
& && x_0 = x(0) && && \text{(1g)}
\end{aligned}
$$

where **Q** is a time-invariant symmetric matrix with main diagonal elements and $\boldsymbol{c}$ is the time-varying day-ahead prices. A state space representation of the building's thermodynamics is specified in eq. 1b and eq. 1c. The control actions are restricted by the maximum power $P_{\max}$ of the heating system (eq. 1e), and the defined thermal comfort band (eq. 1f), which may vary between the apartments as listed in Table1. Recent measurements of the air temperature are used to update the current state of the building in eq. 1g with a Kalman Filter.

Table 1. Input and state constraints

	Apt. 1	Apt. 2	Apt. 3	Apt. 4	Apt. 5	Apt. 6	Apt. 7	Apt. 8	Apt. 9	Apt. 10
$P_{\max}$	50 W/m^2	50 W/m^2	50 W/m^2	50 W/m^2	50 W/m^2	50 W/m^2	50 W/m^2	50 W/m^2	50 W/m^2	50 W/m^2
$T_{\text{preferred}}$	20.5 °C	22.0 °C	21.5 °C	22.0 °C	20.5 °C	21.5 °C	21.0 °C	20.0 °C	22.0 °C	21.5 °C
$T_{\min}$	19.5 °C	20.5 °C	20.5 °C	20.0 °C	19.0 °C	19.5 °C	19.0 °C	19.0 °C	20.5 °C	19.5 °C
$T_{\max}$	21.5 °C	23.5 °C	22.5 °C	24.0 °C	22.0 °C	23.5 °C	23.0 °C	21.0 °C	23.5 °C	23.5 °C

Since the two objectives j_1 and j_2 are conflicting, there is generally no unique solution that optimizes both objectives simultaneously, which suggests that a useful approach to solving the MOO is that of Pareto optimality [13]. The set of Pareto optimal solutions, which from a mathematically point of view is equally acceptable, forms a Pareto front. The simplest method to obtain Pareto optimal solutions is convex combination of j_1 and j_2, e.g. the weighted sum approach (as used in ref. [2, 7, 8]): $J = \lambda \cdot j_1 + (1-\lambda) \cdot j_2$, where $\lambda \in [0,1]$. Note that if $\lambda=1$ the control scheme is a traditional reference tracking control problem, whereas if $\lambda=0$ the control scheme is similar to the ones used in ref. [1, 4, 5]. However, as mentioned in the introduction, the performance of this approach depends significantly on the assigned relative weights which are difficult to choose when the Pareto front is steep or if the objective functions have very different ranges [13, 14]. Furthermore, thermal discomfort can be difficult to quantify since thermal comfort has no direct economic translation. To overcome this, Das and Dennis [13] proposed a normal boundary intersection (NBI) method to approximate the Pareto front with evenly distributed discrete solutions that are independent of weights between objectives (see Figure 1).

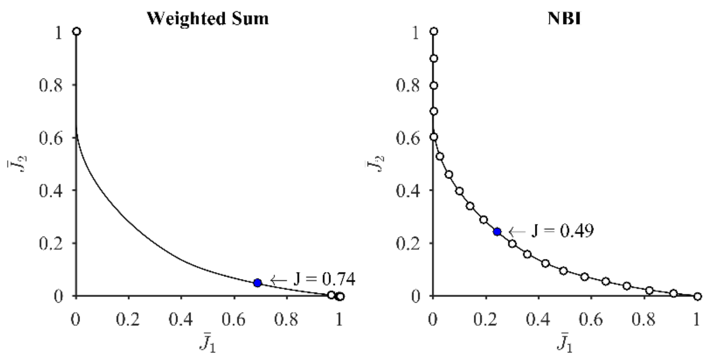

Figure 1. Normalized optimal Pareto solutions with λ increments of 0.05.

When the set of discrete Pareto solutions has been determined, several approaches exist to select and implement an agreeable trade-off between j_1 and j_2 [15]. In this study, the compromise solution is selected, which corresponds to the solution with the shortest Euclidean distance to the utopia point. The utopia point is, as the name suggests, an ideal solution when minimizing each objective independently. Figure 1 displays the results of the weighted sum and NBI methods for a scenario with two objectives with different ranges, and indicates that NBI is more resistant to ill-conditioned problems. The utopia point is origin, the solid line is the continuous Pareto front and the black and blue circles mark the obtained discrete Pareto solutions and the compromise solution, respectively.

Since an MOO problem is computationally demanding to solve compared to a single-objective optimization (SOO) problem, a SOO formulation is proposed which aims at imitating the behavior of MOO. The formulation builds on eq. 2a-2g. However, **Q** is an appropriate sized matrix of zeros (i.e. only objective j_2 is effective). Furthermore, additional state constraints are specified as illustrated in Figure 2, describing the maximum acceptable temperature deviations within the prediction horizon using the parameter ε_{max} [°Ch] which is then a tuning parameter to indicate preference between thermal discomfort and operational cost minimization.

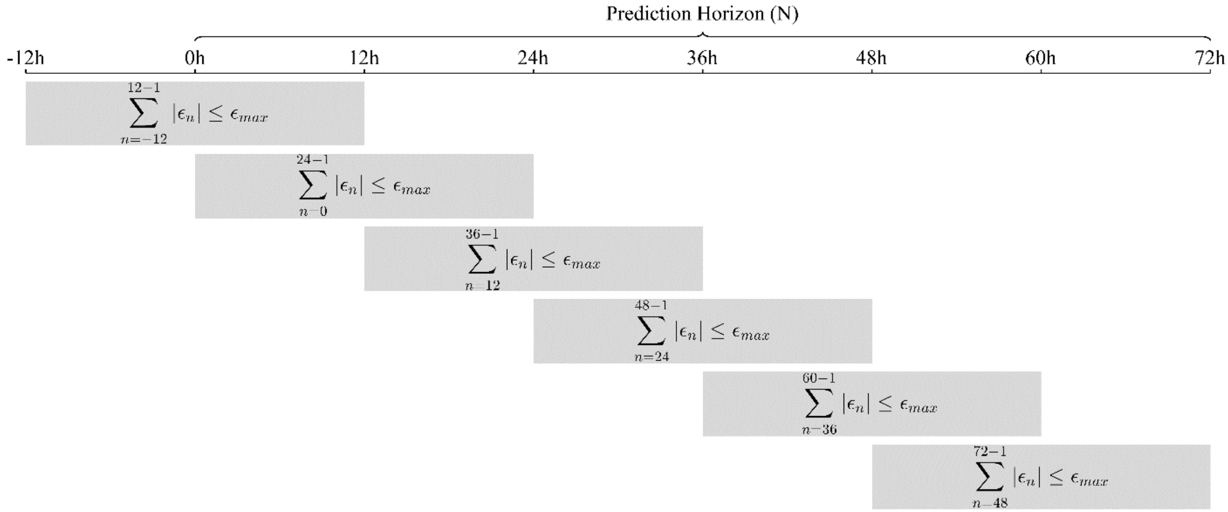

Figure 2. Principle of proposed additional six state constraints

3. Results and discussion

Simulation results obtained using the following four different E-MPC formulations have been evaluated with regard to their ability to reduce deviations from the preferred temperature (see Table 1) and to minimize operational costs:

a) Single objective: Minimize temperature deviations from the preferred temperature.
b) Single objective: Minimize operational costs.
c) Multi objective: Compromise solution (see Figure 1) between temperature deviations and cost.
d) Single objective: Minimize operational costs, but with additional state constraints (see Figure 2).

The objectives and constraints imposed in the four different control schemes vary as a result of the different formulations, thus rendering any direct comparison of results unfair from a mathematical point of view. The evaluation is therefore based on quantification of the four problem formulations on the achieved results. Figures 3a-d depict the indoor air temperature for a one week period in apartment 3 using the four E-MPC schemes with the time-varying energy prices ***c*** depicted at the bottom of Figure 3. Formulation a) ensured a temperature (solid line) close to the preferred temperature at all times, whereas the three other formulations utilized the thermal comfort band (dashed lines) to minimize operational cost. Formulation b) caused the E-MPC scheme to mainly track the lower and upper comfort bounds in order to exploit price fluctuations by charging and discharging the thermal capacity of the building. Formulation c) tracked the preferred temperature for the majority of the time, allowing deviations in temperature when prices encouraged it. The proposed formulation d) with $\varepsilon_{max} = 9$ °Ch exhibited similar behavior and DR-potential as c).

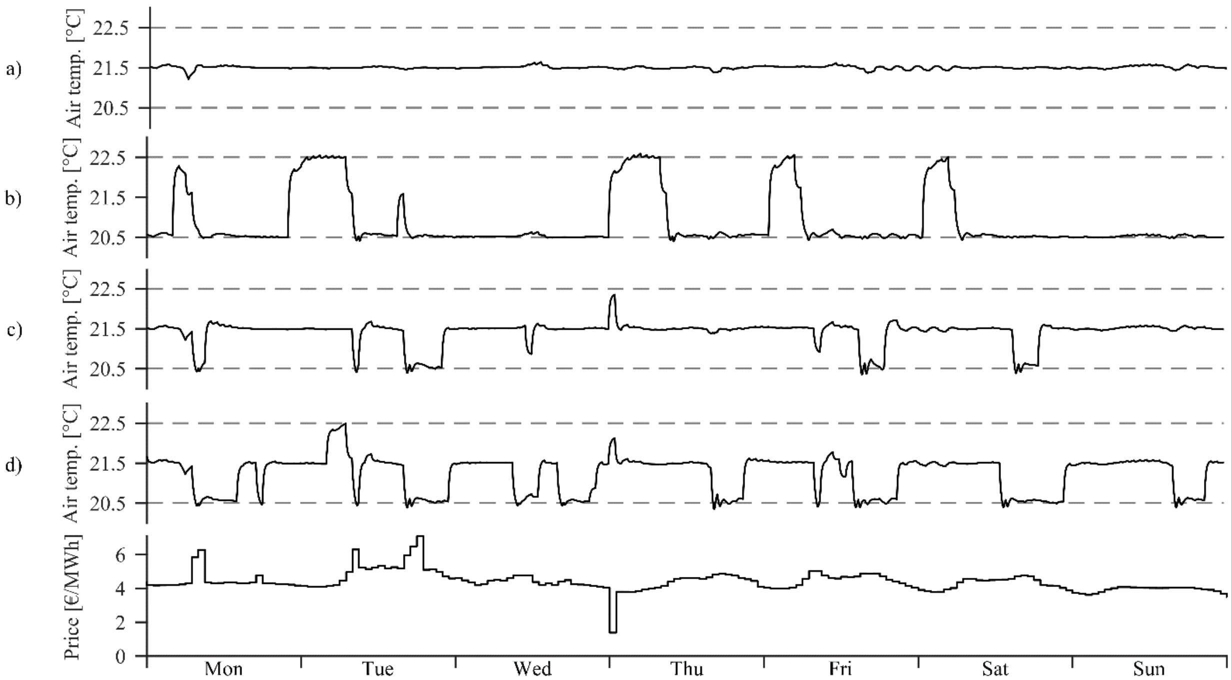

Figure 3. Mechanism of the four E-MPC schemes and the energy price during one week.

The normalized total operational cost during the entire 90-day simulation period as a function of the normalized average root-mean-square-error (RMSE) across the ten apartments is displayed in Figure 4 for the four formulations. The solutions obtained using problem formulations a), b) and c), respectively, are marked with "x" while solutions for formulation d) with different ε_{max} values are illustrated with "o" (displayed numbers are ε_{max}). Formulation a), which was a traditional set point tracking control problem, resulted in the lowest deviations from the preferred set point temperature but also the highest operational cost. Formulation b) achieved the lowest operational cost but also the highest RMSE. Formulation b) may therefore have overestimated the DR potential since occupants, in reality, may experience uncomfortable thermal conditions when tracking the lower comfort bound for long consecutive periods. Formulation c) demonstrated an acceptable compromise between the two objectives while formulation d) achieved similar performance as formulation c). Figure 4 indicates an almost convex combination of the two solutions a) and b) when choosing different values for ε_{max}, which could not be achieved by convex combination of the objectives (e.g. using the weighted sum approach) because of the different ranges of the objectives. Furthermore, formulation c) and d) enable downward flexibility, i.e. it is possible to reduce space heating if this service is sought by the grid.

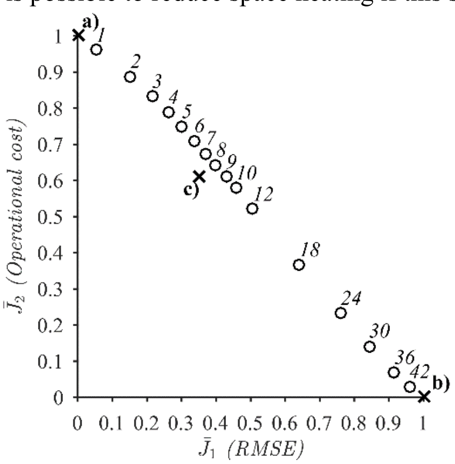

Figure 4. Normalized mean RMSE and total operational cost for all ten apartments.

4. Conclusion

This paper reports on a simulation-based study aimed at quantifying the performance of an E-MPC scheme using four different optimization problem formulations that handle thermal comfort in different ways. It is difficult to conclude which of the four formulations is preferable as it depends on whether – and how much – the occupants are willing to deviate from their preferred indoor air temperature to minimize operational cost through demand responses. However, the parameter ε_{max} in the proposed single-objective problem formulation – a parameter describing the maximum acceptable deviations from the preferred indoor air temperature – could be communicated to occupants as a personal indicator for the acceptable tradeoff between deviations from the preferred temperature and cost savings or, in other words, their 'DR willingness'.

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