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Multi-market demand response using economic model predictive control of space heating in residential buildings

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ABSTRACT

Several studies have evaluated the potential for residential buildings participating in demand response programs based on the day-ahead electricity market prices. However, little is known about the benefits of residential buildings providing demand response by engaging in trading on the intraday market. This paper presents a simulation-based study of the performance of an economic model predictive control scheme used to enable demand response through parallel utilization of day-ahead market prices and intraday market trading. The performance of the control scheme was evaluated by simulating ten apartments in a residential building located in Denmark through a heating season (four months) using historical market data. The results showed that the addition of intraday trading to the more conventional day-ahead market price-based control problem increased the total cost savings from 2.9% to 5.6% in the existing buildings, and 13%–19% in retrofitted buildings with higher energy-efficiency. In the existing building the proposed control scheme traded on average 12.7 kWh/m^2 on the intraday market throughout the simulation corresponding to 21% of the reference consumption. For a retrofitted building the traded volume was 9.6 kWh/m^2 which corresponds to 52% of the reference consumption. These results suggest that the benefits of considering intraday market trading as a demand response incentive mechanism apply to a wide range of buildings.

1. Introduction

As the penetration of intermittent renewable energy sources (RES) such as wind power increases, so will the uncertainty associated with electricity production prognoses because of the inherent uncertainties of weather forecasts. This uncertainty complicates the task of maintaining an instantaneous balance between electricity supply and demand [1,2]. A commonly suggested way of addressing the issue of grid balancing under more volatile electricity production is the implementation of smart grids [3–6]. A characteristic of smart grids is effective utilization of Demand Response (DR) programs, where consumers are encouraged to adjust their demand to meet supply and thereby increase the overall efficiency of the energy system. Energy use in residential buildings constitutes a significant potential for DR as it accounts for 25% of the total energy consumption in the EU of which 67% is used for space heating in the North and West regions of EU [7]. This flexible consumption can be activated through different types of DR programs.

1.1. Demand response programs

DR programs are often divided into *direct* and *indirect* control programs [4,8,9]. In direct control programs, the consumer entrusts the energy planners and operators (PO) with direct control of their electrical loads; the PO can change consumption pattern directly. In indirect control programs, the consumer has full control of the electrical loads and the PO can only provide incentives for consumers to change their consumption pattern. One incentive from PO to consumers is to provide time-varying energy prices, which motivates consumers to reduce consumption in high price periods, e.g. by shifting consumption to periods with lower prices. This approach is referred to as *indirect price-based* DR programs. Previous studies have demonstrated that residential building owners may benefit from this type of DR programs. Halvgaard et al. [10] operated a residential-scale heat pump using Economic Model Predictive Control (E-MPC) with day-ahead prices and achieved 25–35% cost savings compared to traditional set point control dependent on comfort constraints. Avci et al. [11] used E-MPC to achieve a 13% cost reduction compared to a two-position thermostatic control of a residential heat pump, and Oldewurtel et al. [12] used MPC with a multi-objective cost-function to reduce consumption peaks by up to 39% and costs by 31.2%. Knudsen and Petersen [13] demonstrated that using E-MPC for space heating can enable cost savings, CO_2

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Nomenclature

Abbreviations

DR	Demand response
E-MPC	Economic model predictive control
RES	Renewable energy sources
PO	(Energy) Planners and operators
SSM	Supply-side management
TSO	Transmission system operator
BRP	Balance responsible party
MILP	Mixed integer linear problem
ITH	Intraday trading horizon
ID	Intraday (market)
DA	Day-ahead (market)

Symbols

x	State vector of the resistance-capacitance building model
p_{da}	Vector containing forecasted day-ahead market prices
u^{*}_{da}	Optimal sequence of control actions with respect to day-ahead prices
p_{id}	Vector containing prices from intraday market trades
u^{*}_{id}	Optimal sequence of control actions after intraday optimization
J^{*}	Cost of implementing the entire optimal control strategy

emission reductions, and shift consumption from periods of peak load to low load periods. The large spread in savings found in the above-mentioned studies may be caused by several factors including the magnitude of price fluctuations, how the reference case is defined as well as the inclusion of taxes. For example, Knudsen et al. [14] demonstrated that the economic incentive of performing DR using E-MPC of residential space heating strongly depends on the taxation mechanism of energy: a case study led to end-user energy cost savings between 2% and 9% depending on the taxation. Furthermore, Pedersen et al. [15] demonstrated that the cost savings of indirect price-based DR programs using E-MPC depends on the energy-efficiency of the building envelope and consequently the storage efficiency, which relates the amount of energy lost during the storage process to the amount of energy actually stored.

All of the mentioned studies use forecasts of energy prices and weather with durations upwards of days to prepare the building for DR by utilizing the inherent thermal inertia of the building as an energy storage. However, previous studies have demonstrated that buildings can also help solve grid balancing issues that arise on a shorter time scale. Oldewurtel et al. [16] used MPC with critical peak pricing to quantify the flexible consumption immediately available in buildings that have not been prepared to deliver flexibility, by introducing two performance metrics: Power Shifting Potential and Power Shifting Efficiency. De Coninck et al. [17] used MPC to derive cost curves describing the costs associated with deviation from optimal control strategies to activate flexibility. Both studies conclude that the availability and associated cost of flexibility in building space heating depend on several dynamic factors such as the current thermal state of the building and weather conditions, but they do not attempt to investigate whether the cost of the flexibility is aligned and compatible with the current electricity markets or incentive mechanisms. The following section describes the structure of wholesale electricity markets and clarifies why these may be suitable for activating the DR potential in residential space heating.

1.2. Electricity markets as DR platforms

This study evaluates an indirect price-based DR program utilizing two European-based wholesale electricity markets: the day-ahead market Elspot and the intraday market Elbas. Both markets are a part of the cross-border electricity market Nord Pool. Each participating country is divided into individual bidding areas that reflect geographical and grid characteristics. For example, Denmark consists of two bidding areas of which the Western Denmark region (DK1) is characterized by a high penetration of wind power production [18]. In 2015 the accumulated annual wind power production constituted approximately 55% of the total annual consumption of the DK1 region [19].

In DK1, the majority of electricity is traded on the day-ahead market Elspot, where electricity trades confirmed upon market closure is to be delivered the following day. The market closes each day at 12:00 CET and shortly thereafter the hourly day-ahead prices (p_{da}) for the following day are available to the public. The hourly price is settled through the pay-as-clear principle in which, for each hour, the price that balances supply and demand applies to all electricity traded across different market regions. However, in periods where transmission lines between bidding areas are congested (bottlenecks), a market split occurs resulting in different prices on each side of the congestion. The physical limitations of transmission lines thus lead to increased price fluctuations in regions with high shares of intermittent RES such as DK1. Fig. 1 shows how high wind power production within the region has a tendency to reduce the DK1 day-ahead clearing prices in 2015. Furthermore, the production from wind exceeded the regional consumption in 1442 h while negative prices were observed in 65 h. It is these day-ahead prices that have served as the sole price signal in many E-MPC or rule-based studies on DR for space heating in buildings [10,12,13,20–23].

The significance of wind power production in the region for the day-ahead market principle means that the trades depend strongly on the accuracy of production (and consumption) prognoses. The market therefore needs a way of correcting the already traded quantities on the day-ahead market to be consistent with updated production prognoses. Such corrections can be made through trading on the intraday electricity market (Elbas) which remains open from the day-ahead market closure up until one hour before the electricity is to be delivered. Despite the fact that trades can be made up to 33 h before delivery, over 50% of all intraday trades are made within the last three hours before intraday market closure as the accuracy of prognoses increase [18]. The total volumes traded on the Elbas market are currently small, constituting only approximately 3% of the annually sold and bought electricity on Elspot in 2015 [19]. However, Scharff et al. [18] identified high shares of intermittent production from RES to be a contributing factor towards increased intraday trading.

In conventional power systems grid balancing is achieved through supply-side management (SSM), where the transmission system operator (TSO) hires power plants that are able to adjust their power output to address any imbalanced operation from market actors. In all trades on the day-ahead electricity market, one of the actors involved with the trade assumes the role of the Balance Responsible Party (BRP). The BRP is committed to cover any expenses of the TSO to counteract any imbalance associated with the trade. The balancing power price is thus directly linked to the expenses associated with balancing carried out by the TSO. As the share of fluctuating renewable production increases, the task of balancing the grid becomes increasingly complicated which, consequently, increases the expenses resulting from imbalanced operation. As the balancing expenses increase, BRPs are expected to be more involved in intraday trading to ensure a balanced operation.

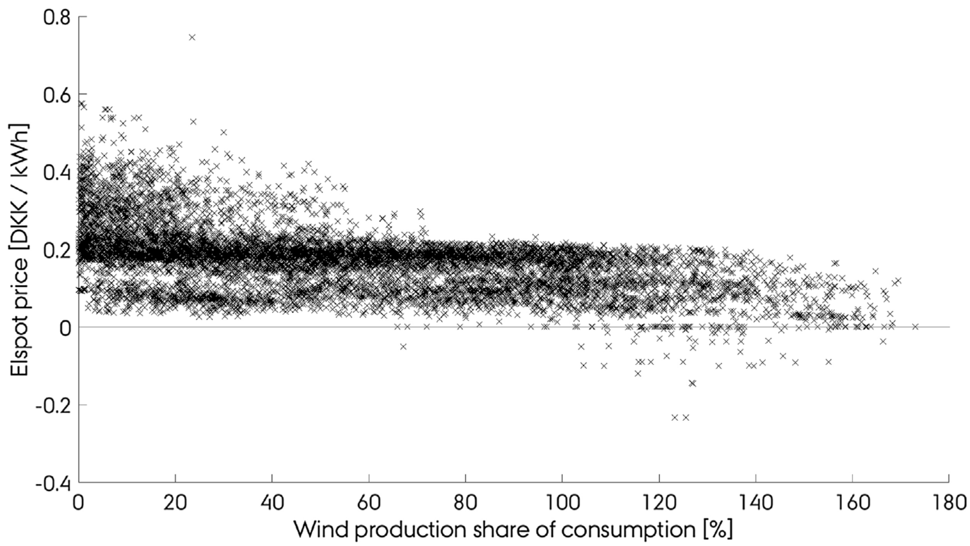

Fig. 1. The effect of wind power production on day-ahead electricity prices in the DK1 area. Source: Nord Pool, 2015 data.

The intraday electricity market prices (p_{id}) are settled according to the pay-as-bid principle, which means that individual trade prices are determined when market participants accept available offers. Therefore, prices may vary within any given hour [18]. Fig. 2 shows the marginal price of the day-ahead market and the interval for each hour in which trades settled on the intraday market over a three-day period in December 2015. The average intraday price and the day-ahead price are strongly correlated with a Pearson correlation factor of 0.91. However, as shown in Fig. 2, significant deviations between intraday and day-ahead prices occurred in several hours of the depicted period.

While the day-ahead price is a product of supply and demand, the intraday price is an indication of imbalances expected by the BRPs themselves. BRPs with flexible buildings in their own consumer portfolio may utilize this flexible demand to lower or avoid entirely the need for intraday trading. Similarly, other actors may use flexible consumption as a virtual power plant, offering energy on the intraday market.

1.3. Aim of this paper

Residential building owners or aggregators may increase their economic incentive to deliver DR to the electricity grid when multiple electricity markets are considered. A study by Ali et al. [24] demonstrated that the charging pattern of domestic hot water tanks can be planned taking both day-ahead market prices and (artificial) instantaneous balancing events into consideration. It therefore seems reasonable to assume that space heating can be planned in a similar manner. However, to the knowledge of the authors, there have been no reported studies on whether space heating of residential buildings can participate in multiple DR programs using day-ahead and intraday prices simultaneously. This study therefore investigates whether space heating can be operated to respond to both day-ahead and intraday market-driven DR programs in parallel without compromising thermal comfort.

2. Method

The following sections introduce the proposed control scheme capable of utilizing market conditions on the day-ahead and intraday market in parallel. First, Section 2.1 presents economic model predictive control in its more conventional configuration where only day-ahead prices are used to optimize operation of the building. Then, Section 2.2 expands upon the control scheme by introducing the expanded multi-market algorithm. Finally, Section

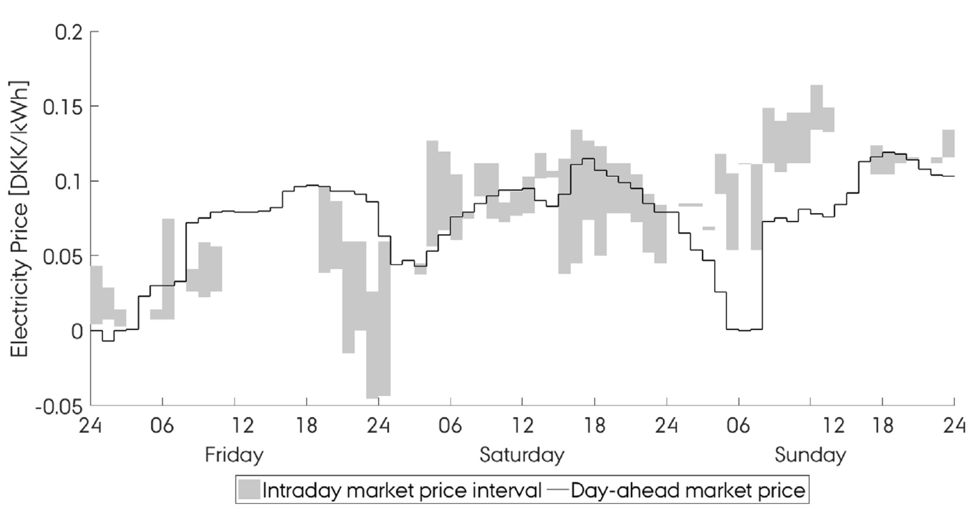

Fig. 2. Day-ahead clearing price and intraday market price-intervals (week 8, 2016).

2.3 presents the assumptions made for a case study used to illustrate the performance of the proposed control method.

2.1. Economic model predictive control

Economic model predictive control solves an optimization problem to determine the optimal sequence of control actions, u, for the space heating system by minimising the total operational cost for a finite prediction horizon N:

$$\underset{u}{\text{minimize}} \qquad \sum_{k=1}^{N} C_k^T \cdot u_k \tag{2a}$$

$$\text{subject to } x_k = \boldsymbol{A}x_{k-1} + \boldsymbol{B}u_{k-1} + \boldsymbol{E}d_{k-1} \tag{2b}$$

$$y_k. = \boldsymbol{C}x_k \tag{2c}$$

$$0 \leq u_k \leq P_{max} \tag{2d}$$

$$T_{min,k} \leq y_k \leq T_{max,k} \tag{2e}$$

$$\Delta T_{min,k} \leq \frac{\Delta y_k}{\Delta t} \leq \Delta T_{max,k} \tag{2f}$$

$$x_0 = x(0) \tag{2g}$$

where c_k is the time varying price associated with control action, u_k. The thermodynamics behaviour of the building to be controlled is described by Eqs. (2b) and (2c), and the control actions are constrained by the maximum design power of the space heating system by Eq. (2d). The controlled variable is the room air temperature, y_k, whose value and rate of change are constrained by Eqs. (2e) and (2f), respectively. Measurements are used to define the current state of the building in Eq. (2g), where the unobservable states are estimated using a Kalman Filter.

The model of the building thermodynamics used in this study was a grey-box model formulated in state space form. Grey-box models are categorised by having a predefined structure of physically meaningful parameters such as heat loss coefficients and thermal capacities. These parameters are estimated from measurement data through methods from the field of System Identification. The model used in this study is a simple two-state model, where the two states represent the lumped thermal capacity of the zone air and the construction components, respectively. Forecasts of ambient temperature, solar heat gains and space heating are treated as inputs from which the model produces a prediction of the zone air temperature as output. A detailed description of the model structure used in this study is provided in Ref. [15].

At each discrete time step k, the states of the building model are updated and the optimization problem is solved using the MOSEK solver [25] resulting in a sequence of optimal space heating control inputs u^*. The output of the control scheme is thus the control strategy that, over a predefined prediction horizon N, satisfies the imposed constraints at the lowest operational cost. Only the first control action of each control sequence is implemented in the building after which a new sequence is computed at the start of the following time step – a control principle referred to as *receding horizon control* [26]. This approach allows for the control scheme to update weather and price forecasts continuously while enabling the use of building measurements to introduce feedback in the control loop.

2.2. Scenario-based optimization

The control scheme in Section 2.1 was expanded to enable the use of intraday price intervals in the optimization. A challenge in relation to this is to prevent the control scheme from purchasing and selling electricity within the same hour. One way of preventing such behaviour is to implement logic in the optimization problem that restricts the algorithm to be either in *selling-mode* or *buying-mode*. The resulting optimization problem would be a mixed integer linear problem (MILP) – an approach that was used in Bianchini et al. [27] to obtain on/off control of heaters. However, as the authors point out, MILPs are significantly more complex to solve than linear or quadratic programs, which limits the computationally tractable size of the problem. To avoid restricting the size of the optimization problem we chose a scenario-based approach instead, where optimization problems with different cost vectors corresponding to each relevant scenario were solved individually and then compared.

The decision making process including both the day-ahead and intraday market can be condensed to the principle described in Table 1. First, the optimal control strategy, u^*, is computed in each hour by solving the optimization problem defined in Eqs. (2a)–(2g) which only consider the day-ahead prices over a three day prediction horizon. While prices may not be available three days ahead, studies have shown E-MPC to be robust to simply repeating the price fluctuations from the first day [13]. This study assumes perfect price predictions for simplicity. Secondly, a shorter intraday trading horizon (ITH) is introduced – in this study ITHs of one and

Table 1
Breakdown of the new control algorithm.

```
Control Algorithm
for each timestep k = 1, 2, ... do
    for each zone i = 1:10 do
        measure zone states x_{0,i}
        obtain weather and price forecasts
        solve Eq. (2) using day-ahead prices, p_da, to obtain control strategy u*_da
        if intraday trading within ITH then
            for scenario j = 1, 2, ... do
                solve Eq. (2) using intraday market prices, p_{id,j}, within ITH to obtain control strategy, u*_{id,j}
            end
            find minimal objective value J*_j
            implement first control action of u*_{id,j}
        else
            implement first control action of u*_da
        end
    end
end
```

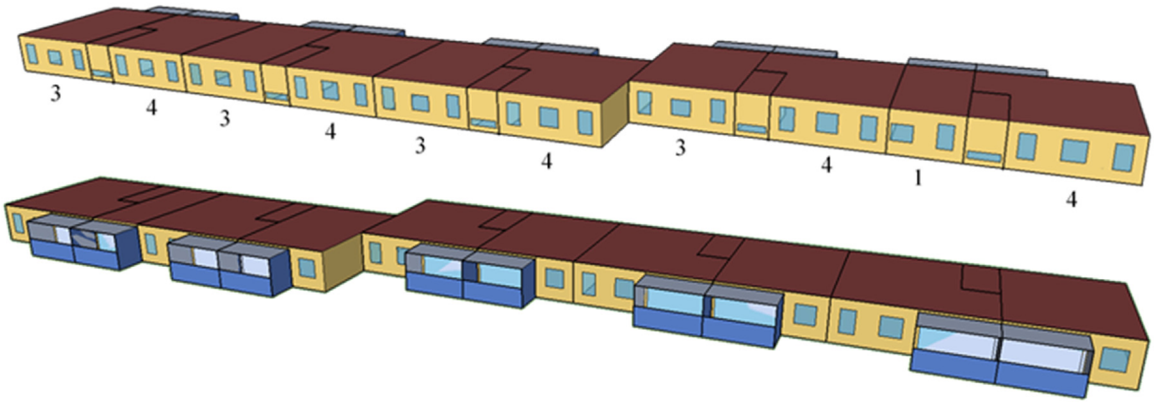

Fig. 3. Façades of case building with numbers indicating the apartments' number of rooms.

three hours were evaluated. Within the span of the ITH the algorithm evaluates currently available offers on the intraday market. If no offers are available, the intraday trading stage of the algorithm is not activated and the building is operated solely based on optimization using day-ahead prices. If trading offers are available inside the ITH, the algorithm treats the consumption procured on the day-ahead market as a trade commodity in the following intraday scenario optimization problems. These optimization problems evaluate all possible combinations of purchasing additional consumption or selling already procured consumption in each hour within the ITH. The controller then implements the intraday trading strategy that yields the highest profit, which may be to either store energy, sell part of the procured electricity back or stick to the original day-ahead optimized control sequence. In either case, the same comfort-related constraints used in the day-ahead optimization problem apply to all intraday scenarios, meaning that the algorithm will only sell energy in the extent that the thermal indoor climate remain within predefined comfort boundaries. To ensure compliance with the intraday market structure where the market closes one hour before delivery, each control strategy is computed one hour before implementation; hence, the strategy computed at time t = 8:00 is implemented in the building from t = 9:00 to 10:00.

An ITH of one hour results in three optimization problems to be solved: the initial *day-ahead problem*, a *sell-scenario* and a *buy-scenario*. Expanding the ITH by one hour introduces, in addition to the three previous scenarios, the two scenarios where electricity is bought in the first hour and sold in the second hour, and vice-versa. The number of scenarios and thereby optimization problems $n_{scenario} = 1 + 2^{ITH}$ to be solved in each time step increases exponentially with the ITH and is consequently

However, as mentioned in Section 1.2, approximately half of all trades are made within the last three hours before intraday market closure. Therefore, in order to limit the number of scenarios to evaluate, a maximum ITH of three hours was chosen in this study.

2.3. Case study

This section presents the simulation-based case study used for demonstrating the performance of the proposed control scheme. The building to be controlled is a four-story apartment block built in 1978 and located in Aarhus, Denmark. An EnergyPlus [28] model of the building serves as a representation of the actual building. The apartment block has east-west oriented window configurations and west-oriented open balconies, see Fig. 3. To simplify the modelling and simulation process, only the third floor was investigated which is comprised of ten differently sized apartments. All apartments were modelled as individual thermal zones with all horizontal zone boundaries (ceiling, floor) assumed adiabatic. All thermal zones were modelled with electrical baseboard heating systems operated by the E-MPC control algorithm implemented in MATLAB [29]. The maximum allowed temperature increase of Eq. (2e) was chosen as four degrees above the set point in all apartments. Furthermore, the maximum rate of change in Eq. (2f) was specified as 2.1 ° per hour in accordance with ASHRAE's recommendations [30]. The link between MATLAB and EnergyPlus was facilitated with the Building Controls Virtual Test Bed (BCVTB) [31].

The simulation period was chosen as November 1 to February 28 corresponding to the main heating season in Denmark using the standard EnergyPlus weather data file of Copenhagen, Denmark [32]. Historical market data of electricity production, trading and prices (2015/16) from the day-ahead and intraday markets were used in the simulation as forecasts for operational planning of the building. The data was acquired through the Danish TSO, Energinet.dk [22] and Nord Pool [33,34]. Taxation of electricity was omitted in this study for the sake of simplicity in interpretation of results. Consequently, results presented in absolute values cannot be directly compared to the actual price paid by building owners. The case study does not investigate how weather and price forecast uncertainties affect the performance of the proposed control scheme.

Detailed information on the intraday trading was not available. The only data publicly available was the minimum, average and maximum prices of settled intraday trades for each hour. Because of this, optimal trading conditions were assumed, meaning that the algorithm achieves the lowest intraday price observed while energy is being purchased and highest when energy is sold back to the market. Another piece of information that was unavailable was the period during which a trade offer was available on the intraday market. Because of this, all trades settled during the ITH were assumed to be available at the beginning of the ITH. To reduce the significance of this assumption the ITH was limited to a maximum of three hours in this study. Finally, day-ahead prices were assumed outside the ITH interval.

Previous studies have indicated that the energy efficiency of the building envelope is an important factor in relation to DR quantity and duration [15,35]. The performance of the proposed control scheme was therefore also tested on two retrofitted versions of the existing building to investigate how increased energy-efficiency affected the potential for residential multi-market DR. Both retrofits involve more energy-efficient windows, additional external facade insulation, reduced infiltration rate, and a mechanical constant air volume ventilation rate of 0.5 h^{-1} with 80% heat recovery efficiency as listed in Table 2. The table also lists the reference consumption for space heating over the four months sim-

Table 2
Specification of retrofit scenarios and reference consumption in the simulated period.

	Additional façade insulation	Infiltration rate	Window configuration	Reference consumption
Existing	–	0.50 [h^{-1}]	existing	59.9 kWh/m^2
Retrofit1	0.125 m	0.18 [h^{-1}]	2-layer glazing	28.1 kWh/m^2
Retrofit2	0.205 m	0.10 [h^{-1}]	3-layer glazing	18.6 kWh/m^2

ulated for each respective building controlled with a PI-controller with constant set point. A more detailed description of the building model and the retrofit scenarios can be found in ref. [15].

3. Results

The following sections present the results from the simulations of the case building. The mechanism of the proposed control scheme is illustrated and evaluated on its impact on energy consumption, overall cost savings, utilization of the intraday market, and the fraction of trades that contributed towards grid balance.

3.1. The mechanism

The air temperature and heating rate in a three-room apartment using a conventional PI-control scheme with a constant set point, E-MPC using only day-ahead prices, and the proposed multi-market control scheme are shown in Fig. 4 to illustrate the mechanism of the controller. The intraday action (Fig. 4 bottom) shows how the control scheme interacted with the intraday market in each time step. As a guide to the remaining figures of this article, it should be noted that any control scheme that involve intraday trading (marked ITH) also includes day-ahead trading.

It is not possible to compare results from the two E-MPC-based control schedules directly because they are outcomes of separate simulations where the state of the building may deviate significantly at any given time. However, on multiple occasions the effects of intraday trading are easily distinguishable. For example on Friday where the intraday trading resulted in additional temperature boosting before noon and again in the evening compared to the E-MPC based on only day-ahead prices. On Sunday the opposite happened, where extended periods of temperature boosting were cancelled since selling the procured energy was more profitable.

3.2. Energy consumption and cost savings

The extension of the E-MPC scheme to include intraday trading enables the building to participate in grid balancing while also increasing the potential for cost savings. Fig. 5 shows the performance of three E-MPC schemes when implemented in the case building and the two retrofit scenarios. For transparency, results are presented both in absolute and relative terms compared to a PI-controlled baseline of each building case (origo).

The results from the E-MPC based on day-ahead prices indicated that the retrofitted buildings (R1 and R2) only achieved moderately higher absolute cost savings compared to the existing building (R0). The reason is that, although the E-MPC scheme in the retrofitted buildings tended to load shift more often, the magnitude of load shifts in the existing building is larger due to the higher reference consumption, as also seen in [15]. The introduction of intraday trading reduces the difference in absolute cost savings achieved in the three buildings. This can be explained by relatively low fluctuations in the day-ahead prices that were only sufficient to make utilization of flexibility profitable in the retrofitted buildings, but not in the existing building where a higher loss is associated with the storage process. Since the prices on the two markets, as mentioned in Section 1.2, are strongly correlated, this often resulted in the energy-efficient buildings having already utilized all the available flexibility before trading on the intraday market, whereas this was not the case with the existing building. Ali et al. [24] addressed this issue by reserving part of the flexibility by using more restrictive comfort constraints in the initial day-ahead optimization than the following intraday optimization problems. However, the authors argued that reserving flexibility may just as well influence the economic potential negatively as positively since the benefits and viability of reserving flexibility depend strongly on the frequency of DR-events, the size of the economic incentives offered, and the risk-willingness of the consumer.

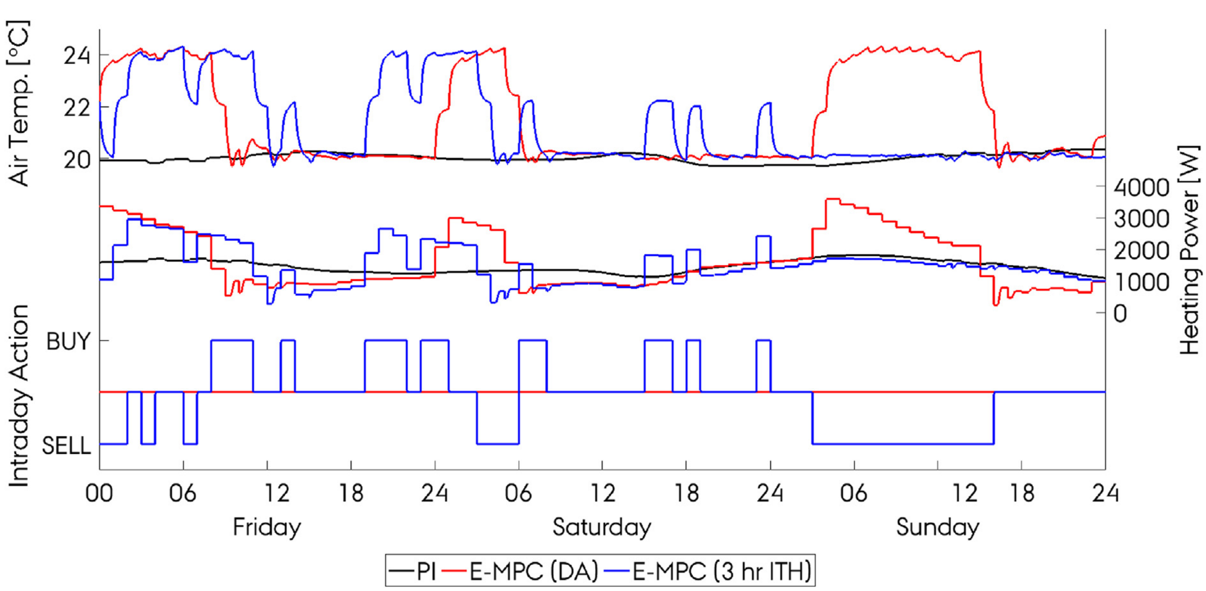

Fig. 4. Example period of both upward and downward regulation in the Retrofit2 building.

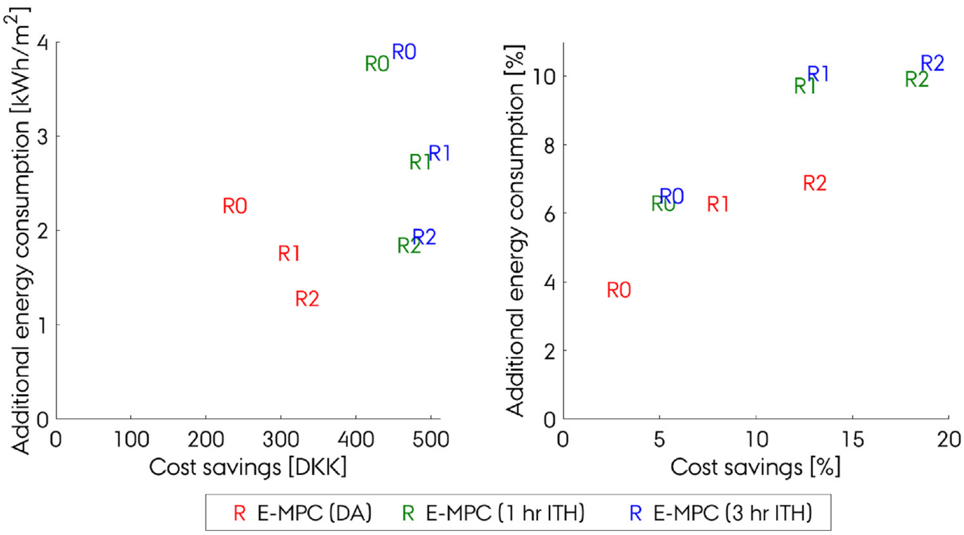

Fig. 5. Economic performance of the algorithm and effect on consumption aggregated for all apartments. Left (a) absolute differences from reference, right (b) relative to the reference.

Fig. 5b, which shows the cost savings in relative terms, indicates a significant difference in the achieved cost savings between the three buildings, suggesting that a higher fraction of the consumption can be made flexible in retrofitted buildings. Furthermore, the effect of enabling the control scheme to trade on the intraday market is seen to positively influence the potential in all cases significantly. The increase in consumed energy seen in Fig. 5 happens since heat is stored by increasing the air temperature. This increase in temperature naturally results in a higher heat loss to the surroundings, and thereby a higher overall consumption. The control algorithm determined when market conditions were sufficiently profitable to make up for the heat lost in the storage process. Finally, Fig. 5 suggest that the economic potential gained by increasing the ITH from one to three hours is marginal.

3.3. Interaction with the intraday market

This section presents how the proposed control scheme interacts with the two electricity markets. The electricity volumes traded by the E-MPC using day-ahead only and the proposed multimarket E-MPC are displayed in Fig. 6.

The results indicate that extending the ITH leads to a moderate increase in intraday trading activity. The reason is that this allows the control scheme to use more elaborate trading patterns including scenarios where electricity was bought in one hour in order to sell procured electricity in the next hour. Furthermore, the share of electricity procured through intraday trading increased for the retrofitted scenarios. This suggests that energy-efficient buildings, retrofitted or new, could on an aggregated level be considered assets in terms of short-notice residential DR.

As described in Section 1.2, BRPs with imbalanced operation are motivated to engage in intraday trading to avoid paying balancing prices. This suggests a certain correlation between the intraday trading and the expected grid balance. The philosophy behind the proposed control scheme is that, by contributing to the balance of individual market actors, the resulting DR will on average have contributed more to overall grid balance than imbalance. However, since balancing out a single BRP does not necessarily equate to increased grid balance, it is necessary to evaluate whether the performed DR actually contributed to balancing the grid.

This was done by labelling all intraday trades carried out by the control scheme based on whether it contributed to balancing

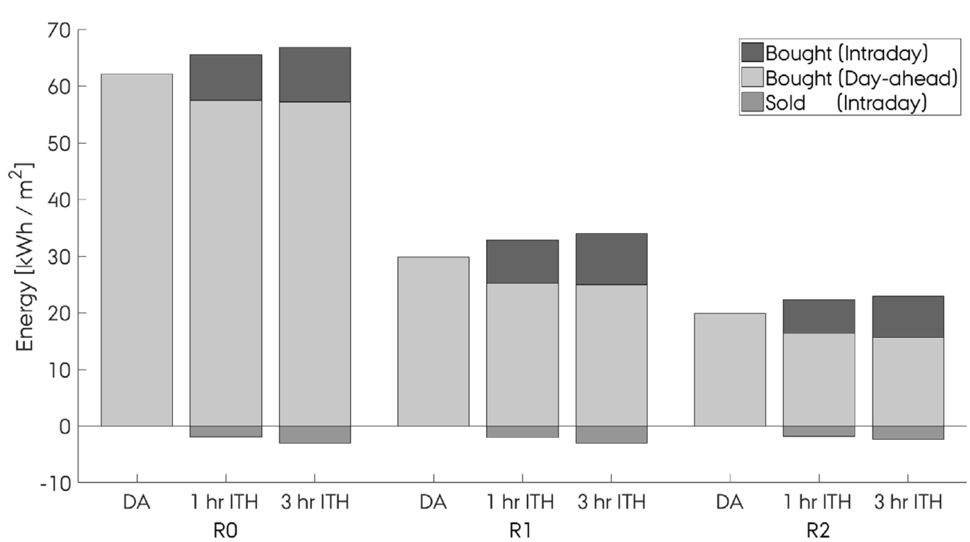

Fig. 6. Electricity traded on the day-ahead and intraday markets (mean of all zones).

Table 3
Percentage of time the DR contributed to balance and imbalance, respectively.

Grid state	Building	R0		R1		R2	
	Control action	1 h ITH	3 h ITH	1 h ITH	3 h ITH	1 h ITH	3 h ITH
Downregulation (48% of time)	Correct	33.1%	39.8%	36.9%	42.7%	35.0%	41.4%
	Incorrect	2.5%	8.1%	3.9%	8.8%	4.4%	7.7%
	No action	64.4%	52.1%	59.2%	48.5%	60.6%	50.9%
Upregulation (28% of time)	Correct	9.6%	17.8%	11.8%	18.6%	14.6%	17.4%
	Incorrect	17.4%	24.6%	17.4%	23.9%	15.6%	21.7%
	No action	72.9%	57.6%	70.9%	57.6%	69.8%	60.9%

the grid or introduced further imbalance. The terminology used in the following takes offset in the grid point of view. This means that buildings can provide *upward regulation* to the grid by lowering the consumption and, conversely, *downward regulation* by increasing consumption. According to Table 3, the grid was in need of downregulation 48% of the time and upregulation 28% of the time during the simulation period [19].

Furthermore, Table 3 indicates how the algorithm operated during these hours by dividing control actions into 'correct' ones that aided the grid and 'incorrect' ones that would have negatively impacted grid balance. As such, the following is an evaluation of both the proposed control scheme and the historical market conditions in relation to the needs of the electricity grid. Periods where the grid was not in need of balancing power was left out of this analysis.

It is seen that the control scheme, in a relatively large fraction of the time where the grid was in need of regulation, did not engage in intraday trading, but merely implemented the control action optimized with respect to day-ahead prices. Depending on the specific simulation, this tendency was observed between 48% and 73% of the time, which can be caused by e.g. poor price conditions or a lack of available flexibility.

The results in Table 3 also indicate that the algorithm performed well during times where the grid was in need of downregulation during which the actions carried out by the controller mostly favoured the grid. During these periods, the controller increased the consumption of the building to store energy between 33% and 43% of the time. On the other hand, it is seen that the control scheme was less efficient at providing services to a grid in need of upregulation. In these periods, more incorrect actions than correct were carried out. Inspecting the historical data revealed that the intraday prices often did not reflect the state of the grid correctly. When the grid needed downregulation, the prices indicated the opposite 22% of the time while in the upregulation scenario this was the case 47% of the time.

4. Discussion

The case results presented in Section 3.2 indicate that the majority of the economic benefits of including intraday trading can be achieved with a one-hour ITH, and thereby – compared to three-hour ITH – reduce the complexity of the planning phase. This implies that simple *one-way* trading patterns (i.e. buy-only or sell-only strategies) were sufficient. However, in real-world application, the ability to consider multiple offers at the same time may allow for easier integration with the market, where offers may be placed at any time throughout the trading window corresponding to the relevant hour. Longer trading horizons allowing utilization of offers entering the intraday market early may therefore be more practical, also bearing in mind that the computational time of the three-hour ITH control problem including both the day-ahead and all eight intraday scenarios for all ten zones was approximately 1.2 s. Rule-based logic could potentially speed this up further by ruling out scenarios that are unlikely to produce optimal solutions based on price characteristics.

The economic optimization in the E-MPC control scheme will often result in the control scheme tracking the lower temperature set point to minimise the energy consumption – only raising the temperature when prices encourage it. During periods of set point tracking the building has, due to the zero-tolerance for comfort violations, no negative flexibility to offer to the intraday market. Consequently, the controller was only able to sell electricity when temperature boosting had occurred as a result of the day-ahead optimization. This relationship can be found in Fig. 4 where it is clear that electricity was only sold in periods where the day-ahead algorithm was performing temperature boosting. This limitation, in combination with misleading prices, is seen to impact the results of Section 3.3, where the control scheme is less efficient at reducing consumption (i.e. providing upward regulation) than increasing consumption (downward regulation). Enabling buildings to provide upward regulation could be done by allowing temperature violations based on either the profitability of prices or simply a certain fraction of time could to some extent address this limitation.

5. Conclusion

This simulation-based study indicates that consumers may increase their economic incentive to invest in economic predictive control of residential space heating by engaging in trades on the intraday electricity market in parallel with the day-ahead electricity market. Especially buildings that do not provide sufficient storage-efficiency to frequently exploit day-ahead price fluctuations through load shifting benefited from the multi-market approach; here, cost savings were approx. doubled compared to the single-market approach. The results also indicated that increasing the energy efficiency of the building, despite the reduction in overall consumption, only had a small negative impact on the quantities of energy traded on the intraday market. This suggests that also new or recently retrofitted buildings may benefit from participating in intraday market-driven demand response.

Finally, future work should investigate how an alternative formulation of comfort constraints that allows temporary set point violations increases the potential for buildings to provide services to electricity grids in need of upward regulation.

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