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Contracted energy flexibility characteristics of communities: Analysis of a control strategy for demand response

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HIGHLIGHTS

- The proposed control strategy was able to deliver demand response by preheating.
- Demand response events increased overall community energy consumption.
- Naive decentralisation can lead to increased pre-peaks and energy consumption.
- Dynamic energy pricing reduced capability to deliver demand response.
- Flexibility potential is driven by systems, people, environment and contracts.

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ABSTRACT

Increasing energy system flexibility through demand-side measures will help meet challenges brought by the transition to a low-carbon energy system. Through participation in demand response programmes, buildings can act as sources of contracted flexibility. Contracted flexibility, in this work, is defined as energy flexibility that is supplied to fulfil a set of contractual terms that define when and how demand modifications are delivered and under which incentives or penalties. This paper identifies the factors affecting contracted energy flexibility potential of homes implemented with a model-predictive control strategy designed to deliver a simplified but yet generalisable incentive-based demand response scheme. The control strategy was implemented in centralised and naive-decentralised architectures using co-simulations to observe interaction of the controller with an English community of 30 homes fitted with air-source heat pumps. The results showed that the control strategy was able to deliver sustained demand reductions without violating comfort by preheating the homes prior to demand response periods, if conditions were suitable. Preheating the homes increased overall energy consumption and, in some cases, caused a peak in electricity demand prior to the DR period. Modifying factors of control operation, like the coordination strategy, magnitudes of penalties, control constraints and notice period between call for demand reduction and its delivery, were shown to affect the ability to deliver demand reductions. The contracted flexibility potential of the community was shown to be characterised by the buildings and their systems, the physical and contractual environment, and behaviour and preferences of the occupants.

1. Introduction

The current plan to achieve net-zero greenhouse gas emissions in the United Kingdom, and indeed climate action plans around the world, calls for decarbonisation of the electricity supply through the introduction of intermittent renewable energy sources and electrification of demand. Electrification in the buildings sector will be achieved through the incorporation of millions of heat pumps, replacing typical gas fired boilers [1]. However, this transition increases the need for services that ensure supply and demand are balanced at various timescales due to the variable nature of renewable energy production and increased peak and base load electricity demand from electrification [2].

This development has increased the recognition of energy flexibility, which on the demand-side means the capability to modify energy demand in response to changes in energy supply or markets [2]. Buildings together with their heating, ventilation and air conditioning (HVAC) systems provide an inherent source of flexibility with the capability to store energy in their external fabric [3]. By using this storage potential, buildings could possibly offer flexibility solely with

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Nomenclature

α	decision variable to penalise exceeding the reference profile during demand response
ϵ^{low}	slack variable for violations of lower temperature bound
ϵ^{hi}	slack variable for violations of upper temperature bound
γ	heat input into controlled space
γ^{proj}	projected heat input one time-step prior to call for demand response
γ^{ref}	reference shaped heat input used to request demand reductions during delivery of demand response
θ^{in}	indoor temperature of a home
A_j	ARX-model coefficient for indoor temperatures lagged by j timesteps
ARX	auto-regressive model with exogenous inputs
B_l	ARX-model coefficient for heat inputs lagged by l time-steps
C	ARX-model coefficient for lagged indoor temperature one hour ago
D	ARX-model coefficient for outdoor temperature
DR	demand response
E	ARX-model coefficient for global horizontal irradiation
F	ARX-model constant, the interception point
P	total cost over control horizon
Q^{rad}	global horizontal irradiation
R	demand modification request made during demand response calls to modify γ^{proj} for creating γ^{ref}
T^{hi}	upper temperature bound
T^{low}	lower temperature bound
T^{out}	outdoor temperature
f	cost for violating the reference profile γ_{ref}
i	index defining the number of time-steps in the control horizon
i_{DR}	time steps between m and o when demand response is delivered
j	index marking individual buildings
m	index marking start of demand response period
n	index marking the last control time-step in the control horizon
o	index marking the end of demand response period
p	price of energy
r	cost of violations to temperature bounds
u	index marking the last individual building

their HVAC systems and external fabric while maintaining acceptable levels of service [4]. The flexibility potential in electrically heated residential buildings could be significant as 28% of energy demand within the UK was for domestic energy demand in 2017 [5]. Flexibility implemented solely through HVAC system control would require limited changes to sensing, computation and communications infrastructure, making this type of flexibility a cost-effective alternative compared to other sources of energy storage [6][7].

In electricity markets, flexibility is typically realised through demand response (DR) or ancillary service schemes, where a contractual relationship between parties sets requirements for delivery of energy flexibility. DR schemes can be divided broadly into three categories: price-based, incentive-based and demand bidding [8,9]. Price-based DR would, for example, be a variable energy pricing scheme where the goal is to influence energy consumption by expecting actors to modify demand in response to pricing. In demand bidding, participants would engage in a trading process to determine market prices and availability for demand response. After trading is concluded, the actors would then operate in accordance with the prices and commitments settled during trading. In contrast to the former two types of DR, incentive-based DR is about driving consumers towards specific behaviour in exchange for a separate reward under a contract [8].

The term *contracted flexibility* is used here to refer to energy flexibility that is used *for fulfilling a contract which sets the form of required flexibility and the incentives or penalties depending on the success of delivering the flexibility*, in contrast to for example voluntary reactions in price-based DR schemes [8]. To allow granular, decentralised actors to offer contracted flexibility, the aggregator role has been established to enable a single entity to collectively manage small assets and aggregate their contributions in electricity markets [2,10]. DR, balancing and other markets for flexibility are gradually being opened to aggregators managing large volumes of demand-side resources [10]. However the traditional electricity markets were designed around generators, which provide a specific profile of demand reduction. There is a need to understand how collections of electrically heated buildings would respond to such demand response calls as their behaviour could exhibit a different response than that of a generator. Further, the response generated from a collection of buildings could potentially differ under changing environmental and market conditions.

1.1. Background

For buildings and communities to benefit from existing DR schemes, scalable approaches to aggregate contributions of collections of buildings are needed. Traditional rule-based controls (RBC) of HVAC systems are not typically capable of responding to calls by external parties and only operate to provide a predefined level of service [6]. Thus, model-predictive control (MPC) of HVAC systems presents an attractive framework for delivering contracted flexibility since it allows pursuing a range of objectives simultaneously, for example minimising energy consumption while delivering flexibility for DR. In MPC, optimised control decisions are calculated in real-time by minimising the value of an objective function, for example cost, subject to constraints like indoor temperature and HVAC system capacity. Compared to RBC, MPC hence allows more advanced and optimal control strategies while maintaining comfort [6,11,12].

MPC has been shown capable of providing savings in energy and cost whilst ensuring comfort both in simulation and experimental studies. For example, Sturzenegger et al. [13] employed MPC in a commercial building and through simulations estimated an energy and cost saving potential of 17% compared to a simulated RBC base case. In addition, a facility manager involved with the study expressed satisfaction with the MPC performance. However, difficulties encountered during practical implementation highlight issues that prevent the wide-scale adoption of MPC, such as the need for advanced sensing and communication infrastructure, significant amounts of commissioning work required for model and system identification and the lack of expertise and knowledge amongst building services engineers in working with MPC systems [11,13].

Another distinct goal in MPC strategies of communities has been to reduce or limit peak energy demand. Cole et al. [14] investigated use of submitting optimised individual peak pricing signals to a community to reduce peak demand. Simulations of 900 homes showed peak demand reduction of 8.8–10% but increases in energy consumption of 7.5–11.4%. Nghiem and Jones [15] used co-simulations, where the control strategy was simulated together with emulating the real building response to MPC. The results from co-simulating three commercial buildings demonstrated ability to make a reduction of 69 kW over four hours by tracking a reference power demand obtained from simulations.

In addition to cost reductions and peak-shaving, researchers have also demonstrated a range of ways to exploit building flexibility with MPC. Corbin and Henze [16] used MPC to shape energy demand of buildings by minimising difference to a smoothed reference profile to lower peak demand and reduce variability. Through simulations of three communities consisting of thousands of buildings, it was found that energy consumption of the communities increased approximately 1–3% and peak demand reduced 0.0–0.15 MW at feeder level. Tindemans et al. [17] developed a decentralised MPC strategy to deliver frequency regulation with thermostatic loads. Their approach was to use a MPC strategy to construct individual reference power curves based on frequency and follow that reference. Bittel et al. [18] developed a MPC strategy for a commercial building to participate in an incentive-based DR scheme and demonstrated its use with simulations. The results showed a minor increase in energy consumption and reduction in net energy cost when delivering the service. The building however had the capability to shed load through fuel-switching instead of relying solely on thermal inertia.

However, the majority of work to date in evaluating energy flexibility has been considered for specific building, energy system or occupant contexts. Therefore, a need arose to more generally evaluate the flexibility potential in buildings and characterise their general behaviour. The IEA EBC Annex 67 introduced flexibility functions which are meant to act as a description of building flexibility potential [2,19]. However, the characterisation presented by Junker et al. [19] assumed capability to adjust set-points in reaction to a penalty, which in the context of buildings would mean reduction in the service levels. This conceptualisation was extended by Vandermeulen et al. [20] with a description of the flexibility function for a predictive building, better corresponding to use of MPC. Whilst providing more insight into the characterisation of energy flexibility without changing the level of service, there are still open questions around the effects of different control structures, penalties and incentives, temperature set-point profiles, heterogeneity of the building stock, and the uncertainties that arise from errors in predicting energy demand.

1.2. Aim, contribution, and organisation

Therefore, the aim and major contribution of this paper is to identify the key characteristics that affect contracted energy flexibility potential of communities equipped with electric heating and MPC. This is done through a systematic analysis of the impacts of weather and seasonality, energy pricing, penalties and incentives, the physical characteristics, occupant behaviour, and MPC design. This work systematically describes and evaluates the flexibility behaviour of heat-pump driven residential communities, enabling the development of future DR programmes tailored to the specific behaviour of residential building energy systems.

The remainder of the paper is organised in the following way. First the methodology is discussed which includes a review of the MPC strategies, system identification approach of the MPC model, emulation test-bed, co-simulation strategy, and scenarios used to evaluate the energy flexibility potential. Then the results of the system identification, base case scenarios and extended scenarios are reviewed. The paper ends with a general discussion of the work and conclusions.

2. Methodology

The methodological approach consists of several elements that will be described in the following subsections. There are four key elements to the approach: the control strategy design rationale, the mathematical descriptions of the MPC strategies, the model selection process to identify the models used in the MPC strategies, and a description of the simulation test-bed used to demonstrate the implementation of the control strategy. The following subsections describe each aspect in detail. The last subsection describes the various scenarios evaluated to assess the performance of MPC under varying conditions.

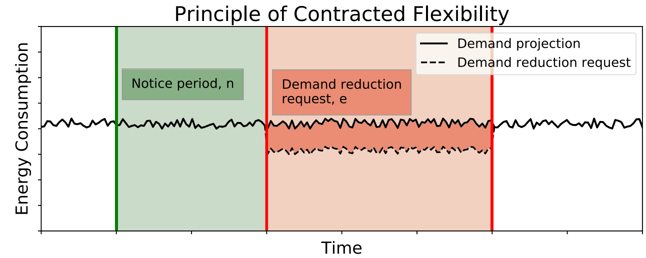

Fig. 1. Illustration of the basic principle of contracted flexibility when delivering demand reductions based on model-predictive control projections.

2.1. Control strategy design rationale

The contracted flexibility potential is explored through a simplified case of incentive-based DR which aims to capture the key requirements of most reserve capacity schemes. The contract is to deliver demand reductions at specific times of the day against a given baseline energy demand profile in response to requests by an aggregator. Fig. 1 illustrates the principle by plotting the anticipated demand profile and the requested demand reduction. A notice period is the time given to prepare for the delivery of a demand reduction, which can vary depending on the type of scheme. For example, the short-term operating reserve market in the UK requires that responses are made within 30 min from notification [21]. The baseline is modified to create a reference demand profile to follow at times when DR is needed.

To analyse significance of the controller design in context of MPC and contracted flexibility in buildings, two MPC structures were considered: a centralised MPC and a naive-decentralised MPC approach. Fig. 2 illustrates how the two structures differ in their decision-making. With the centralised MPC, data is gathered from buildings and supplied to the aggregator which determines the control decisions and submits the control actions for the community to fulfil. Here, buildings would need to share information such as set-point profiles with the aggregator. In the decentralised case, this data would not be shared with the aggregator, or other buildings within the community, as each building makes control decisions based on individual pricing signals and individual requests for demand reduction from the aggregator. It is acknowledged that decomposition techniques using information exchange between the buildings might allow a more elaborate and close-to-

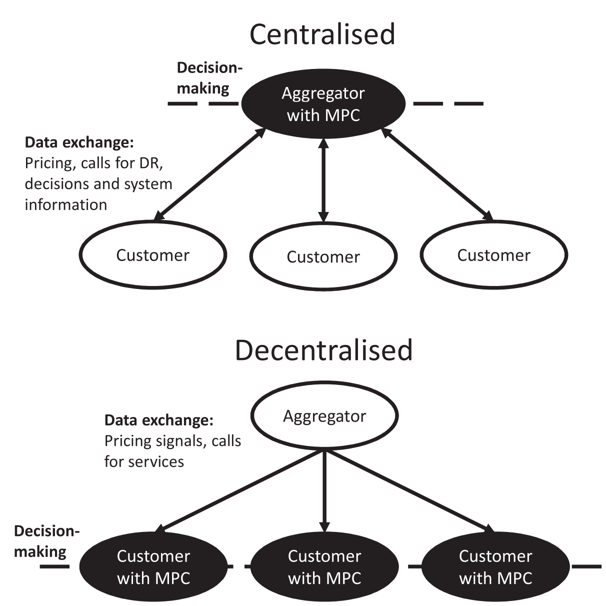

Fig. 2. Schematics illustrating the differences between centralised and decentralised model-predictive control (MPC) strategies.

optimal decentralised control design too [22–24]. However, the aim of this work is to demonstrate that the approach taken to determine how a community collectively achieves a demand reduction has implications for the delivery of energy flexibility. Therefore a naive approach is used since it provides the largest discrepancy to the centralised strategy.

An aspect important to note is that in this approach the collection of buildings is only responsible for delivering a pre-specified demand reduction. The work here does not evaluate how to decide the amount of demand reduction that should be delivered given specific market conditions. The aim is to see how the buildings behave under varying conditions when given a specific demand reduction request.

2.2. Model-predictive control formulations

Economic MPC objective functions for the centralised and naive-decentralised MPC strategies were formulated to investigate the contracted flexibility potential. In both strategies, the aggregation is instructed to keep its energy demand below a reference profile during the demand response period. This reference profile includes the demand reduction. Therefore any consumption above this profile results in not delivering the requested demand reduction and thus incurs a penalty. This can be framed contractually as a case where a community has committed to participate in a DR scheme implemented by an aggregator in exchange for incentives for participation and delivery. The mathematical formulation of the simpler naive-decentralised MPC is presented first, after which the centralised MPC is formulated.

2.2.1. Naive-decentralised control

The decentralised control problem solved by each individual controller is presented in Eqs. (1)–(5). P is the cost function which is minimised over n time steps which is the control horizon. γ is the heat input, a decision variable that is used to determine the compressor load of the heat pump in the buildings at each time step. p is the electricity price.

$$\min . P=\sum_{i=0}^{n}\left(\gamma_{i} p_{i}+\alpha_{i} f_{i}+\epsilon_{i}^{low} r+\epsilon_{i}^{hi} r\right) \tag{1}$$

$$\gamma_{i}-\alpha_{i} \leqslant \gamma_{i}^{ref}, \alpha_{i} \geqslant 0, \forall i=[0, \ldots, n] \tag{2}$$

$$\theta_{i}^{in}=\sum_{j=1}^{4} A_{j} \theta_{i-j}^{in}+\sum_{l=0}^{1} B_{l} \gamma_{i-l}+C \theta_{i-13}^{in}+ \tag{3}$$

$$D T_{i-1}^{out}+E Q_{i-1}^{rad}+F, \tag{4}$$

$$\forall i \in[1, \ldots, n]$$

$$\theta_{i}^{in}+\epsilon_{i}^{low} \geqslant T_{i}^{low}, \epsilon_{i}^{low} \geqslant 0, \forall i \tag{5}$$

$$\theta_{i}^{in}-\epsilon_{i}^{hi} \leqslant T_{i}^{hi}, \epsilon_{i}^{hi} \geqslant 0, \forall i \tag{6}$$

An aggregator is allowed to make calls for DR by using f to set a penalty for exceeding the reference profile γ^{ref} over the DR period. α is a decision variable defining the buildings' response to calls for DR. Eq. (2) lays out the basic principle. α becomes positive if the reference profile is exceeded and penalised at cost f in the objective function. By controlling f, the aggregator can define whether the buildings will be incentivised to avoid exceeding the reference profile. By setting the f zero, the MPC will operate to simply minimise costs.

To define γ^{ref} for demand reductions, a dynamic projection of demand by the MPC one time-step prior to a DR call, γ^{proj}, is used. γ^{proj} is modified with a fixed demand reduction R over the DR period, $i_{DR}=[m, o]$, which means $\gamma_i^{ref}=\gamma_i^{proj}-R, \forall i \in i_{DR}$. If $\gamma_i^{proj}-R \leqslant 0$, then $\gamma^{ref}=0$, corresponding to a situation where the demand reduction R could not be fully met based on the projected demand. Overall, this heuristic of defining a reference demand reflects the basic requirement that was illustrated in Fig. 1.

Eq. (3) lays out the thermal response model used to capture relationships between building indoor temperatures, θ^{in}, and heat input, γ. The exogenous terms are T^{out}, dry bulb temperature outdoors and Q^{rad}, global horizontal solar irradiation. Lagged values of indoor and outdoor temperatures are used. Coefficients A_j, B_k, C, D and E define relationships between the variables of the model and indoor temperature. F is the intercept of the model. The identification process of the models will be discussed further under Section 2.3.

Slack variables ϵ^{low} and ϵ^{hi} constraint indoor temperatures θ^{in} to stay within comfortable bounds as defined by T^{low} and T^{hi} in Eqs. 5 and 6. The cost for violations of temperature is set by r which, if comfort is of high importance, is set to a high value to ensure that the MPC delivers a set service level. r could also be a parameter that is tuned based on preferences of occupants in the building. For example in exchange for incentives, the magnitude of r could be reduced to provide more room for the MPC to operate above or below the temperature bounds during times of DR.

2.2.2. Centralised control

The formulation of the centralised MPC strategy is in principle the same as the naive-decentralised strategy. However, the optimisation is now done over the whole set of buildings in the community. The objective function and the flexibility constraints are shown in Eqs. (7)–(9).

$$\min . P=\sum_{i=0}^{n}\left(\sum_{j=0}^{u}\left(\gamma_{i, j} p_{i}+\epsilon_{i, j}^{low} r+\epsilon_{i, j}^{hi} r\right)++\alpha_{i} f_{i}\right) \tag{7}$$

$$\sum_{j=1}^{u} \gamma_{i, j}-\alpha_{i} \leqslant \sum_{j=0}^{u} \gamma_{i, j}^{ref} \tag{8}$$

$$\alpha_{i} \geqslant 0, \forall i \in[0, \ldots, n], j \in[0, \ldots, u] \tag{9}$$

The main difference to decentralised control is that penalties are not defined on the basis of individual homes but on aggregate for the whole community, where $j=[0, \ldots, u]$ marks the indices referring to individual buildings. This corresponds to the problem that an aggregator might face when delivering contracted flexibility: although individual buildings could comply and reduce demand, unless the whole cluster is able to meet the demand reduction request, the incentive would be lost or a penalty imposed. Such collective penalty could then be applied in retrospect to penalise non-compliant buildings or be bared by the whole community based on mutually agreed rules and regulations, similar to ones used in district heating and communal energy schemes, for example.

The penalty is associated with violating an aggregate reference profile which is defined by summing the demand projections of buildings from the MPC and then reduced by the community-wide reduction target. Since α is now defined as a flexibility parameter over the whole community, the contributions are allocated to individual buildings as seen most fit by the MPC, instead of aiming to deliver a set reduction from all buildings, like in the naive-decentralised MPC. The thermal response models and other constraints are defined for each building exactly the same as shown in Eqs. (3)–(6).

The formulations of both the naive-decentralised and centralised MPC strategies are continuous and linear, and can thus be solved by using linear programming. This model formulation was chosen for its simplicity. However, a misalignment between the simplistic MPC building models and the more detailed emulation test-bed exists. The effects of this discrepancy on the ability to deliver energy flexibility is discussed in Section 3 and brought up also in the limitations, under Section 4.2.

2.3. Identifying ARX-models

To capture the building thermal behaviour for MPC, a suitable model of the controlled system needs to be identified. In this work, AutoRegressive models with eXogenous inputs (ARX-models) were chosen. The aim of the identification is to select a single model structure that performs well for each of the thirty buildings across different seasons and times of day.

The parameters chosen for the identification were heat input, indoor temperatures, outdoor temperatures and solar irradiation. Use cases of ARX-models in community-scale MPC studies provide examples of such parameters configurations. For example, Cole et al. [25], Ma et al. [26], Perez et al. [27] and Gorecki et al. [28] used ARX-models with lagged indoor temperatures, outdoor temperatures, solar irradiation and heating or cooling input as predictors for MPC.

The models were identified with five days of five-minute training data and validated with three days of five-minute testing data. These two data-sets were created by using the community models described in the next subsection. Each data-set was produced by simulating the buildings with a pseudo-random control signal where heat input was off during the days and nights and randomly varied over morning and evening hours to simulate a traditional heating schedule. The identification of the models was done by using ordinary least squares (OLS) regression with the statsmodels package in Python [29].

Even having reduced the exogenous variables to the ones described above, there is still a need to determine which of the variables to include in the ARX model and how many lags to consider for both the autoregressive variable, indoor air temperature, and the exogenous variables. This is an infinitely large search space, therefore the following approach was taken to reduce the number of combinations evaluated.

First, the number of autoregressive indoor temperature terms was determined by plotting the partial autocorrelation and autocorrelation functions considering 40 lags (200 min). Variables exhibiting partial autocorrelation outside a 95% confidence interval were dropped from the model, following the Box–Jenkins approach [30].

Second, the pool of exogenous variables was chosen by performing initial OLS-regressions with the buildings by using all autoregressive terms and considering all exogenous variables lagged up to one hour. Then parameters that exhibited most correlation in relation to the current indoor temperature were chosen for the model identifications. The criterion for inclusion was that the confidence of correlation with indoor temperature was within a confidence interval of $p < 0.1$, calculated automatically by statsmodels for each parameter in the regression. The final exogenous variables considered in the model identification were outdoor temperature lagged by one timestep (5 min), global horizontal irradiation lagged by one time step, heat pump compressor power lagged by one time step and current heat pump compressor power.

Third, a final set of variable combinations was chosen by forward addition of exogenous variables to sets of lagged endogenous variables. The variables were added in the same order as they were introduced in the previous paragraph. The approach of forward addition was chosen to maintain the number of model evaluations reasonable, since focus was on finding models suitable for control rather than absolute model optimality. Performance of the models was evaluated using the Akaike Information Criterion (AIC) averaged over the thirty buildings and initial simulations with energy minimisation MPC. In case the energy minimisation MPC exhibited unacceptable performance in terms of comfort or energy demand, the control signal used in the system identification data was modified and the models re-evaluated. Identifications were performed for each simulation case day of the simulation studies: 7th of January, 1st of March and 11th of November. Overall 40 different ARX-model structures for each house were evaluated for each identification period.

2.4. Community modelling and co-simulation approach

The developed MPC strategies were investigated with co-simulations where the MPC strategies were simulated together with emulation models that represented the response of real buildings to the controls. TEASER (Tool for Energy Analysis and Simulation for Efficient Retrofit) was used to create a set of 30 building models to emulate a community [31]. The models were third-order single-zone RC-models from the IBPSA building model library which have been validated according to standard VDI 6007 Part 1 [32].

The building geometries and material characteristics were based on standardised UK archetypes developed by Allen and Pinney [33]. The case community consisted of ten detached, twelve semi-detached and eight terraced houses to correspond with their respective portions in the UK housing stock [34]. The characteristics of houses, geometries and orientation, were varied within the community. Table A.5 under Appendix A summarises the geometries and basic thermal characteristics of the houses. For further details about the approach used in the community model creation the reader can refer to El Geneidy [35].

The reasons for choosing 30 houses to represent the community were practical: using 30 houses allowed creation of a community with representative shares of the three main house types in the UK housing stock. 30 houses were also found to demonstrate enough variability to compare different MPC structures and the co-simulations were computationally feasible with the computer used.

To model an electrified HVAC system, an air-to-water heat pump and a radiator were modelled in each house with the IBPSA building library [32]. The radiator was discretised as a single element with a nominal inlet temperature of 55 °C and outlet of 45 °C. A constant massflow was maintained in the system with an idealised pump, the energy consumption of this pump was omitted from the observed demand. The heat pump was connected to a boundary of outside air and had a nominal temperature change of 10 °C in both the evaporator and condenser. A first-order polynomial efficiency curve of the form $COP = COP_{nom} \times (a_0 + a_1\gamma_{pl})$ with 0.8 and 0.2 as coefficients, respectively, were used to account for changes in COP of the heat pump under part-load operation. Nominal COP (COP_{nom}) was 2.5 and compressor power capacity was 4.5 kW in detached and 3.0 kW in the semi-detached and terraced homes. The Modelica code of the building models and the Python scripts used in the simulations and identifications have been made publicly available in Github [36].

With the community model defined, the co-simulations were performed in the following step-wise manner: 1) the control problem was initialised with current internal temperatures of the house, 2) the optimisation problem was solved over the control horizon, and 3) the responses of each house to the resulting control sequences were emulated over one control time step. To run simulations and handle data exchange between the controller and emulation models, JModelica.org and MPCPy were used [37,38]. PuLP, a package for solving optimisation problems written in Python, was used to write and solve the optimisation problems [39]. The solver was Clp, an open-source simplex solver written in C++, maintained by the COIN-OR initiative [40].

In all simulation cases, the heat input profiles γ_i were constrained to change every 15 min in the simulations. This was done to ensure steady control of the heat pump avoiding frequent cycling, which has been found to improve COP, reduce malfunctions and spare equipment [41]. The constraints were tightened for the last 15 min of the optimisation horizon by forcing the slack variables ϵ^{low} and ϵ^{hi} to be zero. This constraint was implemented to make sure control projections were driving the systems towards a reasonable state ensuring comfort.

Set-point profiles were kept the same over all simulation cases. Control time-step of five minutes and control horizon of three hours was used with cases using MPC. All simulations were run with a Toshiba Satellite Pro laptop with a Windows 10 Enterprise 64-bit operating system, an Intel Core i5-6200U 2.3GH processor and 8 GB of RAM.

2.5. Energy flexibility evaluation scenarios

The aim of this work is to evaluate the ability of MPC strategies to deliver energy flexibility from collections of houses under a variety of conditions. To evaluate the operation, four base scenarios were considered: rule-based control (RBC), energy minimisation MPC, centralised DR MPC, and naive-decentralised DR MPC. The first two cases represent building performance in situations without DR. Table 1 summarises the main simulation inputs over all simulation scenarios. Table 2 summarises the main assumptions made in the base cases as well as the extended DR scenarios with MPC. The extended DR scenarios were used to evaluate how different factors affect the ability to deliver demand reductions. The elements and parameters that were varied compared to the base cases are highlighted in the table.

In RBC, a PI-controller (Proportional Integral) with hysteresis was set to meet the demand temperature in the homes. The energy minimisation MPC aimed to minimise energy demand in each building. These approaches were simulated to provide a comparison of how a typical home and an advanced home with MPC minimising energy consumption would operate. The latter two cases describe two approaches for delivering DR requests. The centralised MPC was considered due to its ability to achieve optimal solutions across the entire community as it has full knowledge of the collective system dynamics. A naive-decentralised control strategy was simulated to observe MPC operation in a case where each house was asked for the same demand reduction 0.2 kW rather than a community-wide reduction of 6 kW. This represents an aggregator with no information about the homes and defaults to a uniform request across all homes.

To evaluate the effect of intra-day variations, the scenarios were simulated over mornings and afternoons, 06:30–09:00 and 16:30–19:00, respectively. These times were chosen as they include the times when morning and evening peaks typically occur.

To investigate effects of different seasons and weather on the flexibility potential, the base case simulations were run over mornings and afternoons over three case days in Winter, Spring and Autumn. The case days were 7th of January (Winter), 1st of March (Spring) and 21st of November (Autumn). The case days were chosen from the weather file, a CIBSE typical reference year (TRY) for Nottingham, to represent typical conditions to the corresponding season [42]. In the afternoons, the temperature and solar irradiation reduced as time passed during all days. Days in March and November had similar temperature profiles but in March the solar irradiation was higher. January had the coldest average temperature and lowest solar irradiation of the case days. In the mornings temperature trends were stagnant or slightly decreasing over the simulation period, while solar irradiation was rising. Perfect predictions of weather were assumed in the simulations.

In the base cases with DR, a call to reduce demand for 30 min, from 07:30–08:00 and 18:00–18:30, was initiated by an aggregator at 07:00 and 17:00, respectively. The demand reduction request was 6 kW, 5.7% of the overall electric power capacity of the heat pumps. The incentive values for the DR base cases were set as follow: p was in the base cases set to 50 £/MWh, which is the approximate average wholesale electricity price in the UK [43]; r was 500 £/°C to heavily penalise comfort violations; and f was 100 £/MWh to represent a potential utilisation payment that an aggregator might lose or need to pay, if it would not meet the demand reduction request.

Occupancy started at 17:00 in the afternoons and 7:00 in the mornings; houses remained occupied throughout the simulation periods. Each occupied home had a demand temperature randomly allocated between 19 and 21 °C to reflect natural variation that one might expect in set-point temperatures within a community of houses. The MPC was able to operate within a bound of ±1 °C of the demand temperature set by the upper and lower temperature constraints (T^{hi}, T^{low} in Eq. (5) and (6)). When homes were unoccupied, the lower bound was set to 16 °C and upper bound to 25°C.

In addition to the base cases, a set of cases with DR was defined to find how introducing variations to the base case would affect delivery of contracted flexibility. First case under the extended DR scenarios with MPC in Table 2, “Occupancy”, is a case in which the home occupancy simultaneously ended at 8:00 to show how behavioural patterns of people might affect the flexibility potential. Pricing was varied from static to dynamic (”Pricing” in Table 2) to investigate how implementing DR calls under time-of-use pricing might affect ability to deliver demand reductions. A half-hourly price signal was used in these cases (p in Eq. (1) and (7)) with high cost hours occurring 18:00 onwards, a time when daily price peaks in the UK typically occur [43,44].

The following four cases in the table (“Increased reduction”, https://elsevier.proofcentral.com/en/landing-page.html?token=e6dfdc4719d9aeeacea440844d912752temp. bound”, “Cost of comfort” and “Cost of flexibility”) were created to observe how MPC would react to changes in contractual parameters. To ease analysis and presentation of the results these four cases were run with the same demand reductions requests of 9 kW. To investigate effect of temporal factors on the flexibility potential, cases where the notice period was reduced to 15 min (”Reduced notice period”) and delivery of DR was extended to one hour (“Extended DR period”) were also simulated.

The full set of the base case simulation cases and the extended DR scenarios with MPC thus covers a comprehensive exploration of the variables that affect operation of the developed MPC strategy and their effects on the contracted flexibility potential and its delivery.

3. Results

The results of analysing the co-simulation case studies will be discussed in the following subsections. The discussion will describe, in order, the results from the system identification, base case scenarios and the extended demand response scenarios.

3.1. System identification

The top-two models for January, March and November afternoons and the respective average AIC scores are shown in Table 3. The variables chosen for the final ARX-models were four lagged indoor temperatures, indoor temperature thirteen time-steps (one hour and five minutes) earlier, current and lagged heat pump compressor power, lagged outdoor temperature and global horizontal irradiation. This model structure was found best for November and January and second-best for March out of all model combinations. The formulation of the model is shown in Eq. (3) in Section 2.2.1.

The same model parameter values were used for mornings and afternoons, except in March, where two sets of ARX-model parameters were identified for morning and afternoon. This was because as part of the identification procedure the initial simulations with energy minimisation MPC demonstrated poor performance in March mornings when using the same range of heat inputs in the model identification data for both mornings and afternoons. Hence for March mornings the identification was done with a dataset that used higher heat input in the mornings. Values of the coefficients and results from the system identifications can be found in the tables under A.

3.2. Energy flexibility in base case scenarios

In the base case scenarios, the main aim was to achieve a 6 kW

Table 1
Main input parameters used in the co-simulation case studies with rule-based control (RBC) and model-predictive control (MPC).

Input Parameter	Value
RBC PI proportional gain	0.35
RBC PI integral time constant	1800
RBC PI hysteresis term	± 0.2
MPC time-step [min]	5
Control time-step [min]	15
Optimisation horizon length [h]	3

Table 2
Summary of all co-simulation cases with respective set ups, non-systematic elements compared to the base cases are highlighted in the table.

Simulation Case	MPC structure	Occupied during DR?	Pricing	R (kW)	T^{hi} change (°C)	$r\ (\frac{£}{°\mathrm{C\,h}})$	$f\ (\frac{£}{\mathrm{kWh}})$	DR notice period length (min)	DR call length (min)
Base Cases									
RBC	n/a	Yes	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Energy Minimisation MPC	Centralised	Yes	Static	6	0	500	n/a	n/a	n/a
Centralised DR MPC	Centralised	Yes	Static	6	0	500	100	60	30
Naive-decentralised DR MPC	**Decentralised**	Yes	Static	6	0	500	100	60	30
Extended Demand Response Scenarios with MPC									
Occupancy	Centralised	**No**	Static	6	0	500	100	60	30
Pricing	Centralised	Yes	**Dynamic**	6	0	500	100	60	30
Increased reduction	Centralised	Yes	Static	**9**	0	500	100	60	30
Upper temp. bound	Centralised	Yes	Static	**9**	**+ 1**	500	100	60	30
Cost of comfort	Centralised	Yes	Static	**9**	0	**75**	100	60	30
Cost of flexibility	Centralised	Yes	Static	**9**	0	500	**500**	60	30
Reduced notice period	Centralised	Yes	Static	6	0	500	100	**15**	30
Extended DR period	Centralised	Yes	Static	6	0	500	100	60	**60**

Table 3
Comparison of best performing ARX-model configurations for the afternoon case days in January, March and November.

Model structure, (θ_{in} lag, exogenous variables)	Average AIC
Winter - January	
$lag = 4,\ T^{out}_{i-1},\ Q^{rad}_{i-1},\ \gamma_i,\ \gamma_{i-1},\ \theta^{in}_{i-13}$	−3767
$lag = 5,\ T^{out}_{i-1},\ Q^{rad}_{i-1},\ \gamma_i,\ \gamma_{i-1},\ \theta^{in}_{i-13}$	−3766
Spring - March	
$lag = 5,\ T^{out}_{i-1},\ Q^{rad}_{i-1},\ \gamma_i,\ \gamma_{i-1},\ \theta^{in}_{i-13}$	−2905
$lag = 4,\ T^{out}_{i-1},\ Q^{rad}_{i-1},\ \gamma_i,\ \gamma_{i-1},\ \theta^{in}_{i-13}$	−2903
Autumn - November	
$lag = 4,\ T^{out}_{i-1},\ Q^{rad}_{i-1},\ \gamma_i,\ \gamma_{i-1},\ \theta^{in}_{i-13}$	−4871
$lag = 5,\ T^{out}_{i-1},\ Q^{rad}_{i-1},\ \gamma_i,\ \gamma_{i-1},\ \theta^{in}_{i-13}$	−4870

demand reduction. This was evaluated for the base cases with DR, for each season, mornings and afternoons. Fig. 3 shows how DR calls influenced the demand profile compared to the baseline projection in the base cases with DR. In all cases a peak in energy consumption occurred prior to DR period, typically 15 min before the DR call. This peak was due to preheating as the controller aimed to reduce demand over the DR period. A sustained reduction of 6 kW over the full DR period could not always be reached or even requested in periods of low demand. For example, in March morning, after an initial reduction, the heat demand exceeded the baseline projection over the DR period. In November afternoon, the MPC was able to deliver a sustained reduction of 6 kW compared to the baseline projection. In January and March afternoons, a sustained reduction could be delivered, but not the full 6 kW. In the mornings, meeting the request was difficult for the MPC, and demand could in most cases only be reduced for short periods of time after preheating in the beginning of the DR period compared to the baseline demand.

The external weather conditions can explain the variation in the ability to deliver demand reductions. The morning periods had much colder temperatures than the afternoon periods. This meant that after preheating, the temperatures reduced quickly to the lower temperature bound. This required an increase in demand and therefore the home was no longer able to deliver demand reductions. This can be seen in Fig. 4 where in the morning scenario many buildings return to the lower temperature bound within 10 min. This same phenomenon was observed across the seasons as well but the effect was not as acute.

On the Winter case day the outdoor temperature during the simulation period degraded from 0.0 to −2.5 °C, while for the Autumn case day this variation was between 4.0 and 2.2 °C. At 15:00 global horizontal irradiation was 100 $\frac{\mathrm{W}}{\mathrm{m}^2}$ on the Autumn case day but only 30 $\frac{\mathrm{W}}{\mathrm{m}^2}$ on the Winter case day. The difference in overall energy demand between these two days was 62.9 kWh. This led to high demand but also difficulty in delivering a full reduction throughout the whole DR period on the Winter case day.

In contrast, March afternoon had low heat demand due to higher indoor and outdoor temperatures and solar radiation which reduced the overall potential for demand reductions and hence to provide contracted flexibility. In the spring cases, the 6 kW reduction was equivalent to a 89.6% reduction to the average power demand projected over the DR period. Therefore the optimal solution required all systems to turn down during the DR period which was not sustainable for 30 min. This also indicates why the centralised and decentralised approaches in this scenario resulted in similar profiles. The optimal solution was the same as the decentralised solution which was asking each building to turn down their heating.

In the other cases however, there are large differences in performance between the centralised and decentralised approaches. Table 4 reports the energy consumption, comfort violations, and peak power demands for all base case scenarios to numerically highlight the differences. The implementation of DR with the centralised and decentralised approaches always increased energy consumption when compared to the energy minimisation case. This increase in energy consumption due to the implementation of DR has also been found by other researchers [14,16,27]. The increases in cases with DR were in the range of 2.17–7.90 kWh, or 3.31–25.11%, compared to energy minimisation cases. Energy consumption increased due to the preheating, effectively corresponding to a storage loss.

A major difference between the centralised and decentralised approaches was in the magnitude of the pre-peak experienced before the DR call. As shown in Fig. 3, the pre-peak for the decentralised cases was much higher than that of the centralised case. This is explained by the effect of intelligent selection and coordination. In the decentralised case, each home was asked to make a demand reduction, resulting in each home preheating to respond to the DR call. However in the centralised case, only the homes with the highest thermal mass and lowest heat loss were chosen to provide the demand reduction. This also means that the homes that can most efficiently provide the demand reduction

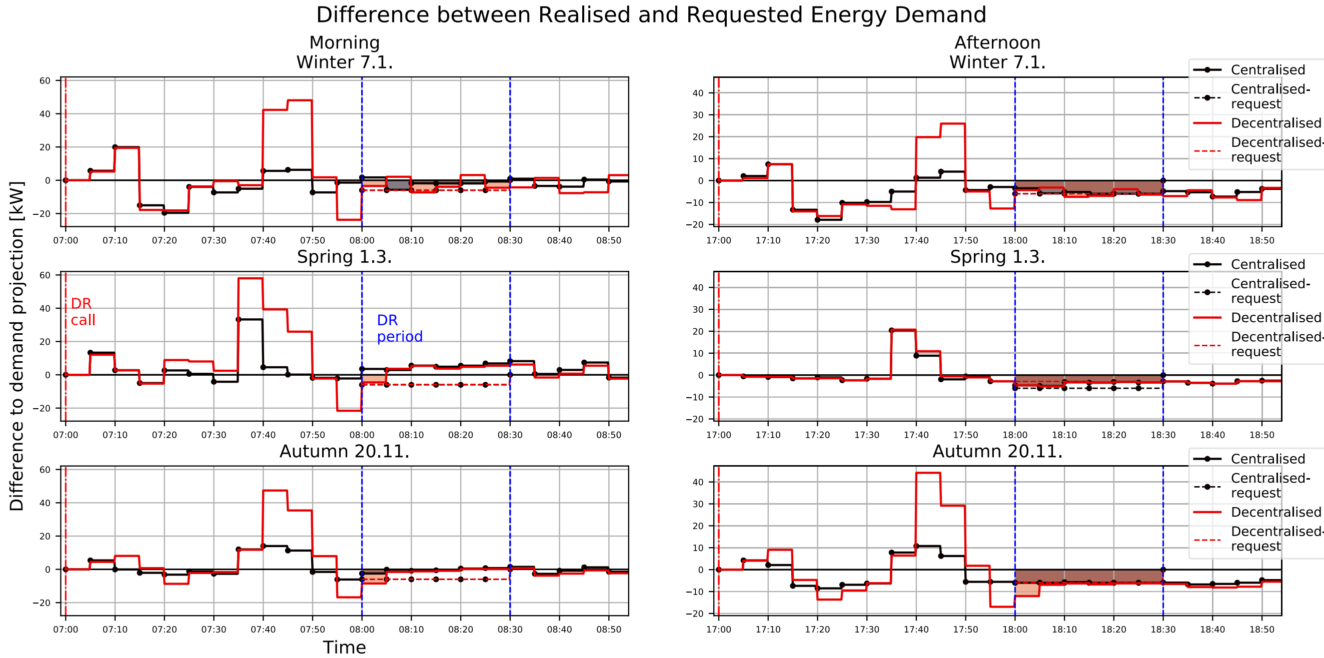

Fig. 3. Differences between realised demand and the demand projections by the model-predictive controller acting as the baseline. The dashed lines illustrate the reduction request made with load-shaping in each case. Coloured areas indicate when the community operated below the projected baseline.

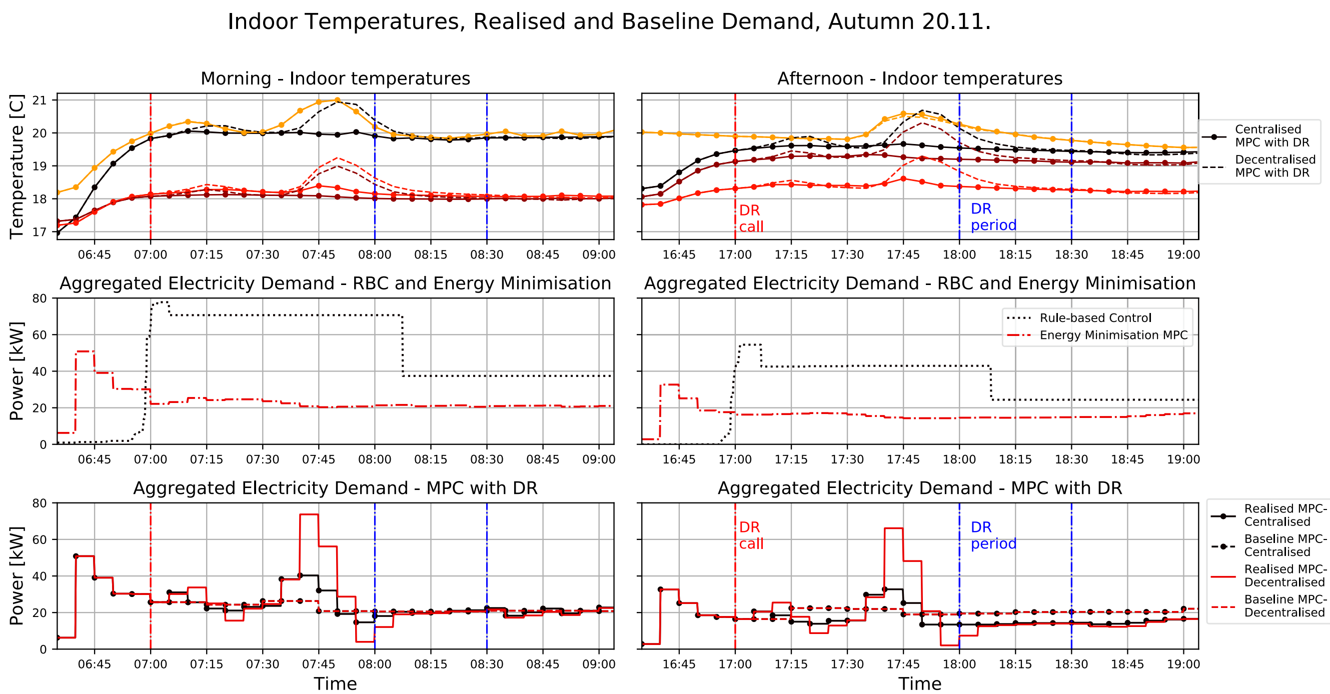

Fig. 4. Realised indoor temperatures in a sub-set of the homes in the community, aggregated power demand of the rule-based controller and energy minimisation model-predictive controller; and power demands in the base case scenarios with DR together with the demand baseline projection made before the DR call at 16:55.

are used. This behaviour is well illustrated in the indoor temperature plots of Fig. 4 where all houses in the centralised MPC with DR are not preheated in response to the call. This energy efficiency benefit is also demonstrated in Table 4, which shows that the centralised approach used less energy to deliver the demand reductions than the decentralised approach in all cases.

However, the analysis indicates that the introduction of DR through the MPC approach can lead to a new and increased peak power demand compared to the energy minimisation cases due to the pre-peak just before the DR call. As shown in the power plots in Fig. 4, for the autumn cases, the decentralised approach created a new overall peak at 07:30 and 17:30 in the morning and afternoon cases, respectively. Table 4 shows this effect for all cases considered. With the energy minimisation MPC, peak demands occurred before start of occupancy to bring the homes to their desired temperature in time. The decentralised approach introduced a new peak power demand in all cases except winter afternoon, where the high peak demand was caused by simultaneous start of occupancy. The centralised approach only created new peaks in the spring and autumn afternoon cases but the magnitude of the increase was small. In the base cases with DR, the peak caused by DR calls

Table 4
Results for energy consumption, set point violations and peak power for the base case scenarios.

Case	Consumption [kWh]		Comfort Violation [Ch]		Peak Power [kW]	
Winter - January						
	Morning	Afternoon	Morning	Afternoon	Morning	Afternoon
RBC	153.53	148.84	7.45	8.90	82.60	80.27
Energy Min.	116.09	104.84	0.92	0.17	87.60	80.81
Centralised DR MPC	118.25	107.21	1.07	0.16	86.10	80.81
Naive-decentralised DR MPC	123.05	108.31	0.80	0.17	95.48	80.81
Spring - March						
	Morning	Afternoon	Morning	Afternoon	Morning	Afternoon
RBC	153.79	22.59	8.59	0.98	87.74	12.62
Energy Min.	92.84	8.64	3.92	1.01	88.75	5.46
Centralised DR MPC	95.39	10.63	3.62	0.92	88.46	25.14
Naive-decentralised DR MPC	100.74	10.81	3.38	0.92	96.00	25.48
Autumn - November						
	Morning	Afternoon	Morning	Afternoon	Morning	Afternoon
RBC	121.06	75.82	6.15	1.86	77.74	54.47
Energy Min.	60.23	41.73	1.99	0.02	50.83	32.67
Centralised DR MPC	63.31	44.33	1.27	0.00	50.84	32.73
Naive-decentralised DR MPC	67.03	47.49	1.03	0.01	73.69	66.13

occurred 15 min before start of the DR period. The differences in peak demand between the cases with DR and the energy minimisation MPC varied between 0–33.46 kW. DR calls did not affect the comfort violations negatively, but rather reduced them compared to energy minimisation MPC because operation close to the lower temperature bound was reduced.

The scenarios can also be compared to the RBC approach. Table 4 shows that all of the MPC approaches, even those that implemented DR calls, used less energy to maintain temperature and most often had less, or practically the same, thermal comfort violations. The peak power in the RBC can be lower or higher than the MPC approaches. This variation is due to how the PI controller responded across the varied conditions. This does indicate however that a home switching from a RBC to a predictive controller capable of implementing DR would still receive reductions in energy demand and reduced thermal comfort violations, but might in the meantime experience higher peak demands at different times of the day.

3.3. Extended scenarios with demand response

This section presents the results for the extended scenarios with DR and MPC, which provide further insights on the MPC operation and implications of changes to the base case set up on ability to deliver contracted flexibility from the community.

3.3.1. Occupancy

Fig. 5 shows how a simultaneous change in occupancy during the DR period affected the ability to deliver demand reductions. With occupancy ending at 8:00 in all houses, there was effectively no energy demand and hence no flexibility to request or to offer during DR. This outcome follows intuitively from the MPC framework where energy minimisation baseline projections are used. When the home changes from occupied to unoccupied, the upper and lower temperature bands are widened, effectively enabling a lower temperature to be maintained in the home. In the energy minimisation case, the case defining the baseline energy demand, the energy for heating reduced because no additional energy was needed during the transition to the lower set point. Since there was no demand for heating during this time, the DR calls can not reduce demand any further resulting to inability to provide demand reductions.

3.3.2. Pricing

Fig. 6 illustrates how the realised energy demand compared with the baseline projections under dynamic and static pricing. As the figure shows, the 6 kW reductions could not be delivered in the dynamic pricing scenario. The high price periods in the dynamic price scenario coincided with the DR periods. Dynamic pricing made the MPC "pre-

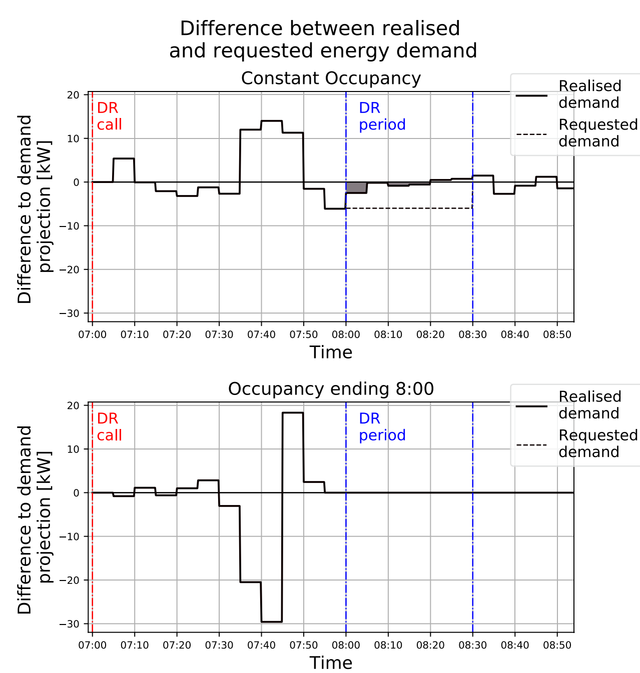

Fig. 5. Differences between the realised energy demand and projected energy demand by the model-predictive controller in two cases: with occupancy persisting throughout the demand response period, and occupancy ending during the demand response period.

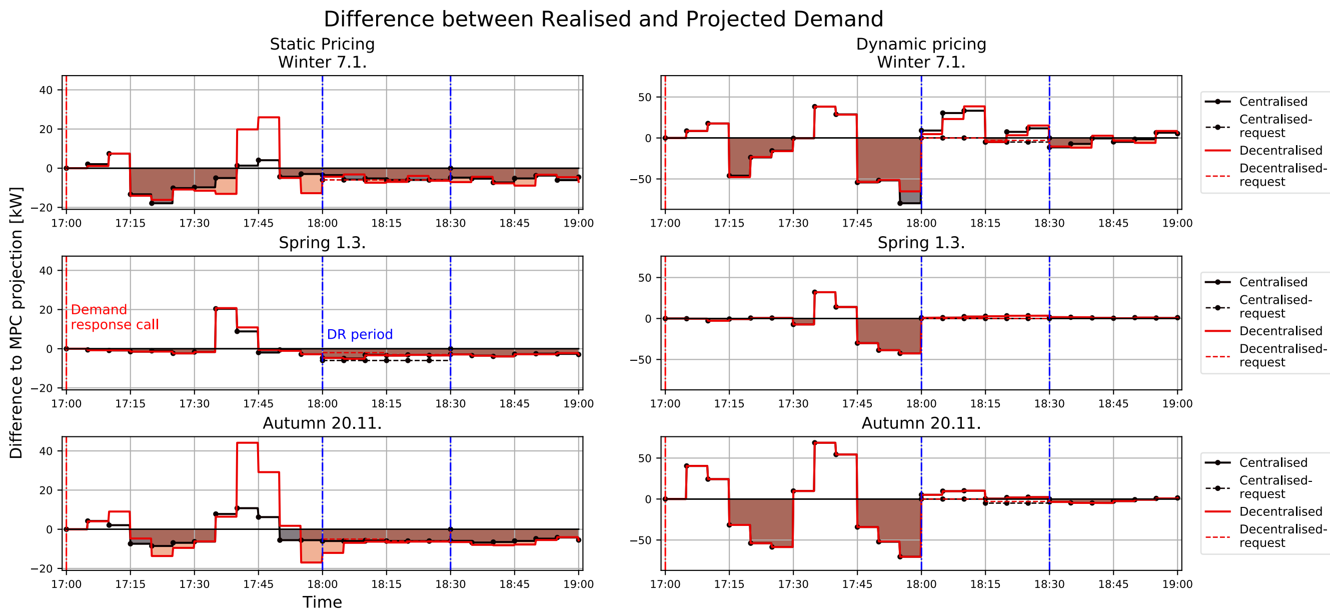

Fig. 6. Differences between realised demand and baseline projections under static and dynamic pricing over afternoons in January, March and November.

emptively" reduce demand over the DR period because of high prices making the baseline projections already low during the DR period. Thus, further reductions in demand could not be attained, reducing the contracted flexibility potential. This was true irrespective of the co-ordination strategy.

3.3.3. Demand reduction request, penalties and constraints

To understand the effects of increasing the demand reduction request and the potential trade-offs a MPC would face when varying preferences over comfort and flexibility, scenarios with increased demand reduction, adjusted values of r (the cost of violating comfort), f (the costs of not delivering the DR request), and an increase in the upper temperature bound were analysed. A 9 kW demand reduction request was made in all of these scenarios to ease presentation and interpretation of the results.

Fig. 7 plots results from the four cases. Increasing the reduction request led to a preheating pattern and a reduction of 9 kW, which was exceeded at the end of the DR period. The peak demand in this case was 46.4 kW.

By reducing r, the indoor temperature was allowed to violate the lower temperature bound to meet the demand reduction. Reducing r also led to a rebound where the reference was exceeded to bring the temperature back within the comfort bounds and to avoid further violations at the end of the DR period. Reducing r made the controller violate comfort during the DR period, decreased energy consumption but did not significantly affect the peak demand, the peak demand was 45.6 kW.

Increasing f, the penalty for not providing a demand reduction, made the MPC use more preheating and led to a higher indoor temperature before the DR period and peak demand. With high f, the rebound at the end of the DR period took place as well but was slightly lower compared to the case where the cost of comfort was low. Increasing f also had the affect of increasing the overall energy consumption to 49.9 kWh (12.6%) and significantly increasing peak demand from 46.4 kW to 75.1 kW. This indicates that there is a trade-off between the increased cost of energy consumption to deliver the demand reductions and the magnitude of the penalty for not delivering the demand reduction. This is apparent in the results of increasing the upper temperature bound. This alone did not lead to materially different operation compared to changing the penalties, since the amount of preheating is governed by the relative magnitude of the energy price and flexibility price and not strictly the upper temperature bound.

3.3.4. Demand response and notice period

Fig. 8 plots indoor temperatures and energy demand to show how changing the length of the DR period and the notice period affected flexibility potential. A sustained 6 kW reduction for a full hour could not be delivered as the requested profile was slightly exceeded during the DR period. The reason for these slight exceedances was found to be at least partly due to model inaccuracies in the baseline predictions, which led the MPC to perform corrective actions during the DR period. In contrast, a very short notice period led to very little preheating and a smaller peak demand, which in practice led to the MPC not being able to deliver the requested demand reduction. The MPC still however managed to reduce demand compared to the baseline projection over the DR period.

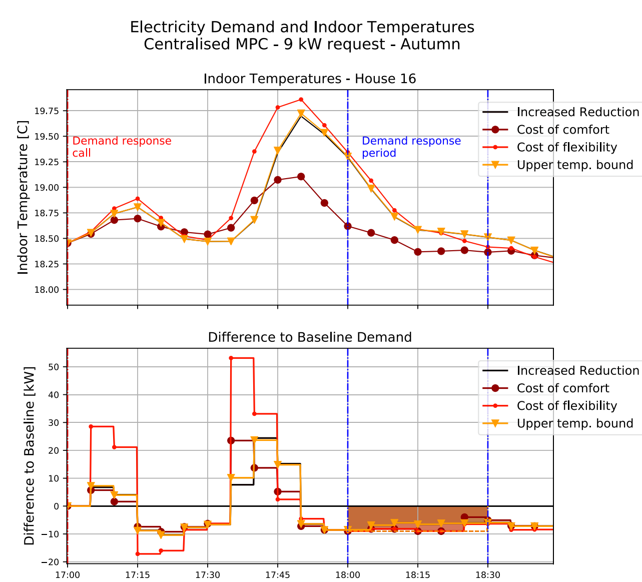

Fig. 7. Emulated temperatures of a building from the community and differences between energy demand and projected baseline demand by the model-predictive controller in cases with varying values of r and f and increased upper temperature bound.

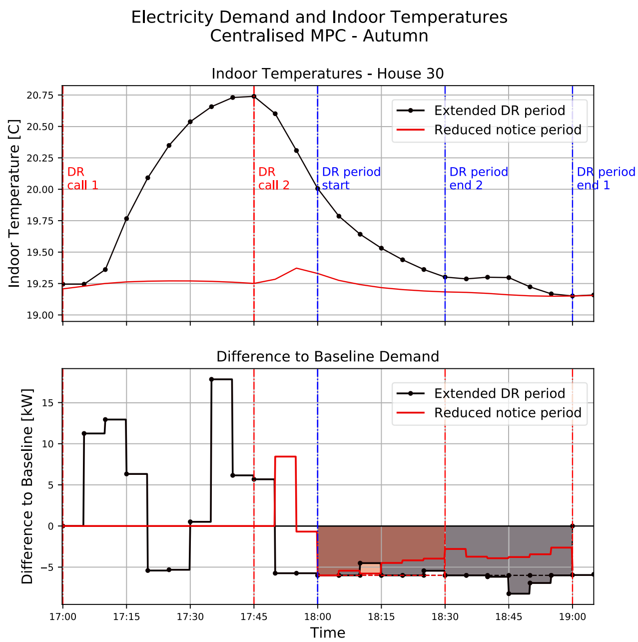

Fig. 8. Emulated temperatures of a building from the community and differences between projected baseline and realised energy demands in cases with reduced notice period and an extended demand response period.

4. Discussion

4.1. Factors of flexibility

The results show how the energy flexibility potential of a group of homes depends on the following factors: the weather, building dynamics, occupant preferences and behaviour, the contractual environment and the community-scale implementation strategy.

The weather was shown to greatly affect the ability to deliver demand reductions. The colder temperatures in the morning and during the winter periods limited how long demand reductions could be sustained. In a country like the UK, where weather conditions are relatively homogeneous across the country, the flexibility potential harnessed strictly from the home's thermal mass will be limited in the very cold winter months and mornings.

The building thermal dynamics and the heating systems determine the magnitude and duration of the demand reduction request as well. The building thermal dynamics, in conjunction with the weather conditions, determine the rate of decay of the internal temperature which governs how long demand reductions can be maintained without violating thermal comfort. They also contribute to how quickly the home will be able to heat up, affecting how quickly the pre-heating required for the demand reductions can occur. The HVAC system capacity affects the baseline energy demand and the operational regime of a control strategy. For example, increasing the capacity of the heat pump systems would allow more rapid changes in indoor temperatures and potentially higher preheating potential. In addition, possible constraints on ramping or cycling of HVAC systems, indoor temperature and the control time-step together effectively determine how quickly responses can be made to calls for DR.

Occupant set point preferences and the comfort band tolerances define the amount of energy flexibility that would be available. As shown in the simulation studies, the set point profiles which were defined by the demand temperature and the operational bound, define flexibility potential together with outdoor temperature. The demand and outdoor temperatures create the baseline heating demand which is modified for DR. Without baseline heating demand, no flexibility is available for fulfilling the contract. The upper and lower temperature bounds determine the operational regime available for modifying demand in response to requests.

In addition to the magnitude of the temperatures bounds, their change over time as a function of occupancy also affects the ability to deliver demand reductions. As demonstrated in the results, a change in occupancy, which increased the temperature bounds, completely removed any demand reduction capability. In the UK, the demand for domestic space heating typically peaks in the mornings and evenings, indicating that most homes have different demand temperatures for occupied and unoccupied periods [45]. However scenarios in which the temperature bounds are decoupled from occupancy could result in more consistent availability to conduct preheating. More continuous space heating patterns could thus better support the availability of buildings for providing contracted flexibility. But again a trade-off with energy efficiency emerges. The sensibility of maintaining heat demand solely for the purpose of flexibility could be questionable.

The contractual and market environment which determines the magnitude of the incentives and penalties, how quickly the demand reductions must be delivered and the underlying price for electricity, also affected the energy flexibility potential. Depending on preferences of the home owners, modifying penalties and incentives can be used to capture trade-offs in comfort, energy consumption and delivery of flexibility for the contract. With an adequate incentive or penalty, it could be acceptable to effectively reduce the lower temperature bound to allow a longer-term demand reduction. The trade-off in the cost of energy and the penalty for not delivering a demand reduction determine how aggressively the demand reductions would be sought. Also, the length of the notice period before the DR period along with operational constraints affect the response potential to modify demand for DR. The length of the DR period and the modification request determine the optimum actions before and after the DR period. The simulation studies showed how a short notice period in conjunction with a long and large DR request resulted in limited ability to preheat and thus inability to deliver the demand reduction.

Lastly, how the homes are coordinated to deliver the sustained demand reduction affects the flexibility potential and the power profile of the response. With communities having variability in their use patterns and thermal characteristics, centralisation is needed to achieve efficient delivery of sustained demand reductions. Centralisation also led to less changes to the demand profile, which affected the magnitude of the appearance of new peak demands. However, increasing the community size to the scale needed for participation in today's markets could cause problems in computational feasibility since the size of the optimisation problem would increase. Therefore decentralised approaches will be needed but the losses from the lack of shared information, as demonstrated through the naive-decentralised MPC scenarios, could lead to less efficient delivery of demand reductions and increases in peak power demand.

In addition to illustrating the factors above that affect energy flexibility, the simulations also demonstrated the importance of the baseline energy demand for contracted flexibility and how uncertainties, errors and disturbances affect this baseline and its interpretation. The baseline fundamentally determines the foreseeable modification potential which is also affected by the control strategy itself and its implementation. The co-simulation case studies showed that convergence to the baseline demand projection after response to DR varied, in some of the cases the MPC continued to operate below the baseline even after the DR period. There are several reasons for why the projected baseline might not be fully accurate. For example, during occupancy, homes had internal gains heating the spaces, which the ARX-models did not account for. Also, since the control horizon was constantly moving, the future decisions were affected by new knowledge of the upcoming weather conditions.

Uncertainties in predicting energy demand complicate establishing accurate baselines which poses a challenge for creating justifiable penalties or incentives for buildings participating in demand response.

Should a consumer with large energy consumption be entitled to a higher incentive for reducing energy demand in comparison to a frugal user providing less flexibility potential? Or would people be willing to trade-off certain amount of comfort to achieve financial rewards? These are questions that need to be considered during the design of future energy markets.

Overall, for DR schemes to be successful in harnessing the contracted flexibility potential of groups of electrically heated homes, the characteristics highlighted previously should be comprehensively accounted for when designing relationships between aggregating parties and consumers or communities. This could be achieved through contracts, policy and/or regulation that encourage developing control techniques that maintain cyber-security while ensuring optimality or in the design of penalty and incentive schemes that avoid unreasonable reductions in levels of service, for example. The challenge for aggregators or grid-operators would be to find the most acceptable combinations which allow effective use of buildings for DR, potentially together with other assets, to form a profitable asset portfolio to participate in the energy market or maintain technical stability. Individuals in communities need to find balance between getting adequate incentives while maintaining an acceptable level of service.

4.2. Limitations

As in any simulation study, the results of the study depend on the numerous assumptions made and limit the generalisations that can be made. In practice a heat pump might not provide the possibility to be controlled continuously over the power range of the compressor as was assumed in this study. Further, the heat pump COP in the emulated buildings was assumed to have a linear relationship with the part-load of the compressor when in practice, heat pumps' performance varies as a function of outdoor temperature as well. These assumptions enabled the MPC to perform better control than what might in practice be possible. This could make conclusions about the ability to deliver flexibility more optimistic than what would happen in practice.

This work also did not explicitly consider the range of uncertainties that would be encountered in an experimental study, including affects of inaccurate weather forecasts, inaccurate baseline demand forecasts and measurement uncertainty. Depending on how these effects interact with each other, the uncertainties could lead to less ability to deliver demand reductions making the current results optimistic.

The methodology also did not consider varying the range of aggregations from tens to hundreds or even thousands of buildings, using buildings of varying use-types or operating buildings in conjunction with other flexible resources, representing the complexities a real-life aggregator would be dealing with. Considering more buildings could decrease the overall variability in occupancy behaviour and set-point preferences making it easier to deliver demand reductions from an aggregation of houses.

Lastly, the current MPC formulation was chosen to be linear and continuous which ultimately limits the generality of the results. Different incentive and penalty structures could be implemented to extend the current MPC formulation. For example, a quadratic penalty could be included in the objective function, which would undoubtedly lead to a different response when changing the penalty.

This work has highlighted the various factors that can affect the ability to deliver contracted flexibility but the limitations outlined here demonstrate the need for further research that could be done to fully understand how the contracted flexibility potential can be harnessed in real-world environments and under a variety of potential control strategies.

5. Conclusions

The aim of this paper was to identify the key characteristics that affect the contracted energy flexibility potential of communities equipped with electric heating and model-predictive control (MPC). This was done through a systematic analysis of weather, energy pricing, penalties and incentives, the physical characteristics, occupant behaviour, and MPC design on the flexibility potential.

Centralised and naive-decentralised MPC strategies were implemented to fulfil a simple flexibility contract, where a fixed demand reduction was provided over a set period of time based on a baseline energy demand prediction made by the MPC. To observe operation of the controller, in total twelve base case co-simulations were run through three case days in the mornings and afternoons to investigate the factors defining the contracted flexibility potential of a community consisting of 30 English homes. Results from the co-simulations showed that the homes had flexibility to offer for a simple, but generalisable incentive-based demand response (DR) scheme while operating within a comfort band solely by using their thermal mass. This flexibility was delivered by first preheating the homes before the DR call and subsequently reducing the magnitude of demand.

Overall, five categories of characteristics were found to define the contracted flexibility potential of the homes: the weather, building dynamics, occupant preferences & behaviour, the contractual & market environment and the community-scale implementation strategy. The weather affected the seasonal and time-of-day demand reduction potential. The building thermal and energy system dynamics determined the duration and magnitude of the demand reductions, as well as how quickly a building was able to respond to a call to reduce demand. The occupant thermal comfort preferences contributed to the magnitude of the DR request. Sudden changes in set point temperatures due to occupancy could reduce the availability of energy flexibility.

The contractual and market environment determined the value of the trade-off between the cost of the additional energy required to deliver the demand reductions and the penalty for not delivering the demand reduction. They also determined how willing a home would be to violate thermal comfort bounds. The trade-offs between energy consumption, incentives and penalties affected how aggressively the controller would preheat the home, changing the delivery of flexibility. Lastly, the strategy for aggregating the demand reductions across the homes affected the ability to deliver sustained demand reductions. A naive decentralised MPC approach reduced the ability to deliver contractual demand reductions, even though the energy required as well as the magnitude of the preheating peaks increased.

Understanding the effects of these factors is important for developing future schemes that can make use of the dynamic nature of energy flexibility. Outcomes of this work can aid stakeholders concerned with managing energy demand, such as aggregators and network operators, to design acceptable DR schemes that reflect the unique character of building energy flexibility.

Declaration of Competing Interest

None.

Acknowledgment

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Appendix A. Complementary Tables

Table A.5,A.6,A.7,A.8, A.9, A.10

Table A.5
Geometries of the houses included in the case community for simulations.

House nr.	Type	Element Area [m^2]					Vol-ume [m^3]	Orien-tation [°]
		Total	Ground Floor	Win-dow	Outer Wall + Roof	Inner Wall + Roof		
1	Detached	91.9	50.5	13.7	226.7	120.7	229.8	310.8
2	Detached	109.0	50.8	13.5	214.8	120.0	272.5	268.3
3	Detached	101.8	50.9	12.8	228.2	126.0	254.5	330.9
4	Detached	101.9	52.8	13.8	214.4	133.0	254.6	193.4
5	Detached	103.5	53.0	13.5	217.0	129.2	258.9	287.1
6	Detached	94.8	49.1	13.6	210.8	125.4	237.1	246.6
7	Detached	104.7	48.7	12.3	205.9	131.5	261.9	358.1
8	Detached	104.7	46.7	12.2	227.1	117.0	261.7	230.4
9	Detached	96.1	50.9	13.6	198.0	132.0	240.2	253.6
10	Detached	90.4	54.6	12.7	201.9	126.4	226.0	198.1
11	Semi-Detached	82.8	39.1	10.2	131.9	119.9	194.7	214.4
12	Semi-Detached	77.3	41.7	10.3	144.1	130.9	181.6	250.9
13	Semi-Detached	83.2	43.6	10.5	138.6	125.3	195.5	193.2
14	Semi-Detached	87.4	41.5	10.0	141.6	126.1	205.5	256.1
15	Semi-Detached	92.9	43.5	10.0	142.6	129.1	218.2	293.1
16	Semi-Detached	83.9	44.5	9.9	140.2	133.7	197.1	197.2
17	Semi-Detached	92.0	44.6	9.9	145.0	131.4	216.1	249.8
18	Semi-Detached	86.4	38.8	10.6	141.9	124.7	203.1	255.8
19	Semi-Detached	83.1	41.8	10.1	147.0	125.3	195.2	329.0
20	Semi-Detached	88.2	41.5	10.0	140.9	133.7	207.4	297.7
21	Semi-Detached	93.5	43.7	10.0	147.0	134.3	219.7	206.9
22	Semi-Detached	92.9	41.6	10.1	142.2	124.1	218.2	180.4
23	Terrace	82.8	41.4	10.3	93.7	189.3	190.3	324.6
24	Terrace	78.4	39.2	10.6	88.2	190.8	180.3	277.0
25	Terrace	82.4	41.2	10.5	85.6	186.6	189.6	200.7
26	Terrace	70.0	35.0	9.8	86.2	175.1	161.1	214.2
27	Terrace	78.3	39.1	9.7	94.4	178.4	180.0	295.5
28	Terrace	79.4	39.7	9.7	89.0	174.5	182.5	282.2
29	Terrace	81.5	40.7	9.8	80.5	170.6	187.4	269.9
30	Terrace	78.7	39.3	9.8	85.5	174.8	181.0	255.3

Table A.6
ARX-model parameters for January afternoon and morning.

House	$A_1(\theta^{in}_{i-1})$	$A_2(\theta^{in}_{i-2})$	$A_3(\theta^{in}_{i-3})$	$A_4(\theta^{in}_{i-4})$	$B_0(\gamma_i)$	$B_1(\gamma_{i-1})$	$C(\theta^{in}_{i-13})$	$D(T^{out}_{i-1})$	$E(Q^{rad}_{i-1})$	F
1	1.90	−1.43	0.64	−0.17	0.06	0.023	0.023	0.008	−0.00003	0.67
2	1.82	−1.28	0.52	−0.13	0.06	0.042	0.023	0.007	0.00028	0.75
3	1.90	−1.44	0.65	−0.17	0.06	0.029	0.023	0.008	0.00010	0.71
4	1.82	−1.28	0.52	−0.13	0.06	0.032	0.024	0.006	0.00009	0.76
5	1.81	−1.25	0.49	−0.12	0.05	0.038	0.024	0.008	0.00005	0.74
6	1.83	−1.28	0.51	−0.13	0.06	0.026	0.023	0.010	−0.00022	0.66
7	1.84	−1.30	0.53	−0.13	0.06	0.038	0.023	0.001	0.00032	0.77
8	1.91	−1.46	0.66	−0.17	0.05	0.031	0.022	0.006	0.00005	0.71
9	1.84	−1.29	0.50	−0.13	0.06	0.028	0.023	0.007	−0.00020	0.66
10	1.92	−1.45	0.63	−0.17	0.06	0.021	0.023	0.006	−0.00018	0.63
11	1.94	−1.48	0.65	−0.17	0.08	0.034	0.022	0.005	0.00005	0.65
12	1.83	−1.30	0.53	−0.13	0.08	0.043	0.024	0.004	0.00030	0.80
13	1.87	−1.32	0.52	−0.13	0.07	0.037	0.024	0.007	−0.00012	0.64
14	1.86	−1.30	0.51	−0.13	0.07	0.036	0.024	0.006	−0.00014	0.67
15	1.87	−1.33	0.52	−0.12	0.07	0.043	0.023	0.007	0.00004	0.68
16	1.91	−1.42	0.60	−0.15	0.07	0.026	0.023	0.006	−0.00011	0.65
17	1.90	−1.42	0.61	−0.15	0.07	0.043	0.023	0.006	0.00022	0.71
18	1.85	−1.32	0.52	−0.13	0.07	0.047	0.023	0.005	0.00032	0.74
19	1.90	−1.43	0.62	−0.15	0.07	0.038	0.023	0.006	0.00019	0.70
20	1.92	−1.44	0.61	−0.15	0.07	0.028	0.022	0.006	−0.00005	0.65
21	1.94	−1.47	0.63	−0.16	0.06	0.032	0.022	0.006	−0.00005	0.63
22	1.90	−1.38	0.55	−0.13	0.06	0.037	0.023	0.007	−0.00016	0.64
23	1.76	−1.07	0.33	−0.08	0.06	0.043	0.026	0.009	−0.00006	0.52
24	1.71	−1.06	0.36	−0.09	0.07	0.067	0.027	0.009	0.00011	0.74
25	1.93	−1.40	0.57	−0.14	0.06	0.031	0.023	0.007	−0.00005	0.46
26	1.67	−0.96	0.31	−0.08	0.07	0.072	0.028	0.010	0.00001	0.74
27	1.74	−1.09	0.38	−0.10	0.07	0.060	0.026	0.009	0.00002	0.68
28	1.88	−1.32	0.52	−0.14	0.07	0.036	0.024	0.007	−0.00009	0.50
29	1.86	−1.27	0.47	−0.12	0.06	0.042	0.025	0.007	−0.00011	0.48
30	1.80	−1.19	0.44	−0.11	0.07	0.065	0.025	0.005	0.00044	0.65

Table A.7
ARX-model parameters for March morning.

House	$A_1(\theta^{in}_{i-1})$	$A_2(\theta^{in}_{i-2})$	$A_3(\theta^{in}_{i-3})$	$A_4(\theta^{in}_{i-4})$	$B_0(\gamma_i)$	$B_1(\gamma_{i-1})$	$C(\theta^{in}_{i-13})$	$D(T^{out}_{i-1})$	$E(Q^{rad}_{i-1})$	F
1	1.38	−0.64	0.21	−0.05	0.056	0.11	0.03	0.00365	0.00048	1.03
2	1.57	−0.83	0.28	−0.07	0.031	0.08	0.02	−0.00162	0.00048	0.46
3	1.47	−0.73	0.25	−0.06	0.045	0.10	0.03	−0.00083	0.00052	0.82
4	1.51	−0.76	0.25	−0.07	0.033	0.08	0.03	−0.00022	0.00042	0.58
5	1.51	−0.76	0.25	−0.06	0.035	0.09	0.03	0.00000	0.00044	0.62
6	1.41	−0.65	0.21	−0.05	0.044	0.10	0.02	0.00403	0.00037	0.91
7	1.58	−0.84	0.29	−0.07	0.029	0.07	0.02	−0.00123	0.00040	0.41
8	1.46	−0.73	0.25	−0.06	0.047	0.10	0.03	0.00103	0.00045	0.89
9	1.46	−0.70	0.23	−0.05	0.041	0.09	0.02	0.00487	0.00032	0.79
10	1.41	−0.66	0.22	−0.05	0.053	0.11	0.03	0.00793	0.00033	0.97
11	1.51	−0.79	0.28	−0.07	0.055	0.13	0.03	0.00148	0.00039	0.70
12	1.55	−0.82	0.28	−0.07	0.043	0.09	0.02	−0.00285	0.00040	0.44
13	1.47	−0.72	0.24	−0.06	0.053	0.12	0.02	0.00316	0.00034	0.76
14	1.50	−0.75	0.24	−0.06	0.045	0.11	0.02	0.00169	0.00030	0.71
15	1.54	−0.81	0.26	−0.06	0.039	0.11	0.03	−0.00101	0.00036	0.57
16	1.45	−0.72	0.24	−0.05	0.055	0.13	0.02	0.00256	0.00034	0.85
17	1.59	−0.87	0.31	−0.08	0.038	0.10	0.02	−0.00262	0.00039	0.45
18	1.59	−0.86	0.30	−0.07	0.036	0.09	0.02	−0.00240	0.00038	0.37
19	1.54	−0.82	0.29	−0.07	0.049	0.10	0.03	−0.00238	0.00042	0.56
20	1.47	−0.73	0.24	−0.05	0.055	0.12	0.03	0.00135	0.00036	0.82
21	1.48	−0.75	0.25	−0.06	0.052	0.12	0.02	0.00138	0.00035	0.81
22	1.51	−0.77	0.25	−0.06	0.045	0.12	0.02	0.00235	0.00029	0.72
23	1.34	−0.57	0.21	−0.05	0.050	0.15	0.03	−0.00229	0.00027	0.71
24	1.36	−0.61	0.24	−0.07	0.051	0.15	0.04	−0.00341	0.00034	0.47
25	1.33	−0.59	0.27	−0.09	0.069	0.18	0.03	0.00037	0.00032	0.88
26	1.33	−0.56	0.21	−0.06	0.056	0.16	0.04	−0.00309	0.00032	0.56
27	1.36	−0.59	0.22	−0.06	0.053	0.15	0.04	−0.00328	0.00031	0.56
28	1.31	−0.58	0.25	−0.08	0.072	0.19	0.03	0.00078	0.00031	0.98
29	1.36	−0.61	0.26	−0.08	0.063	0.18	0.03	0.00094	0.00025	0.77
30	1.44	−0.70	0.32	−0.10	0.046	0.14	0.03	−0.00383	0.00035	0.22

Table A.8
ARX-model parameters for March afternoon.

House	$A_1(\theta^{in}_{i-1})$	$A_2(\theta^{in}_{i-2})$	$A_3(\theta^{in}_{i-3})$	$A_4(\theta^{in}_{i-4})$	$B_0(\gamma_i)$	$B_1(\gamma_{i-1})$	$C(\theta^{in}_{i-13})$	$D(T^{out}_{i-1})$	$E(Q^{rad}_{i-1})$	F
1	1.43	−0.54	0.08	0.00	0.041	0.12	0.00730	−0.00322	0.00037	0.38
2	1.56	−0.73	0.17	−0.03	0.027	0.11	0.01280	0.00243	0.00041	0.26
3	1.47	−0.60	0.10	0.00	0.036	0.12	0.01294	−0.00118	0.00039	0.33
4	1.46	−0.66	0.18	−0.04	0.041	0.13	0.02500	0.00962	0.00042	0.51
5	1.46	−0.67	0.19	−0.04	0.043	0.13	0.02515	0.01013	0.00043	0.52
6	1.42	−0.61	0.16	−0.02	0.052	0.14	0.01201	0.01263	0.00025	0.69
7	1.54	−0.71	0.16	−0.03	0.026	0.10	0.01501	0.00243	0.00039	0.25
8	1.48	−0.62	0.11	0.00	0.036	0.12	0.01038	−0.00209	0.00036	0.36
9	1.42	−0.61	0.14	−0.01	0.050	0.14	0.00871	0.01267	0.00023	0.72
10	1.43	−0.56	0.09	0.01	0.045	0.13	0.00650	0.00025	0.00032	0.50
11	1.51	−0.59	0.12	−0.05	0.038	0.17	−0.00394	−0.00224	0.00021	0.17
12	1.49	−0.56	0.13	−0.06	0.035	0.14	−0.00102	−0.00066	0.00023	0.14
13	1.50	−0.60	0.14	−0.05	0.043	0.17	−0.00670	−0.00019	0.00021	0.24
14	1.52	−0.68	0.19	−0.06	0.052	0.17	−0.00255	0.00340	0.00020	0.34
15	1.56	−0.77	0.26	−0.08	0.051	0.17	0.01339	0.00227	0.00028	0.25
16	1.49	−0.58	0.13	−0.05	0.041	0.16	−0.00562	−0.00081	0.00020	0.23
17	1.56	−0.66	0.16	−0.07	0.031	0.14	0.00000	−0.00068	0.00022	0.14
18	1.55	−0.66	0.17	−0.07	0.030	0.14	−0.00026	−0.00029	0.00023	0.13
19	1.50	−0.57	0.12	−0.06	0.037	0.15	−0.00089	−0.00171	0.00023	0.15
20	1.51	−0.60	0.13	−0.05	0.038	0.16	−0.00427	−0.00172	0.00019	0.19
21	1.52	−0.62	0.14	−0.05	0.035	0.15	−0.00423	−0.00167	0.00019	0.19
22	1.55	−0.68	0.18	−0.06	0.043	0.17	−0.00524	0.00146	0.00019	0.29
23	1.48	−0.66	0.22	−0.07	0.047	0.16	0.00367	0.00832	0.00011	0.56
24	1.51	−0.67	0.21	−0.07	0.031	0.14	0.01429	0.00220	0.00021	0.20
25	1.47	−0.53	0.10	−0.05	0.020	0.13	−0.00781	−0.00113	0.00013	0.18
26	1.46	−0.64	0.22	−0.08	0.049	0.17	0.01367	0.00896	0.00017	0.49
27	1.48	−0.68	0.23	−0.08	0.044	0.16	0.01641	0.00686	0.00019	0.43
28	1.47	−0.53	0.10	−0.04	0.025	0.14	−0.00838	0.00007	0.00013	0.26
29	1.49	−0.59	0.13	−0.04	0.031	0.16	−0.00903	0.00266	0.00013	0.37
30	1.52	−0.57	0.12	−0.07	0.013	0.11	0.00006	−0.00307	0.00017	0.03

Table A.9
ARX-model parameters for November.

House	$A_1(\theta^{in}_{i-1})$	$A_2(\theta^{in}_{i-2})$	$A_3(\theta^{in}_{i-3})$	$A_4(\theta^{in}_{i-4})$	$B_0(\gamma_i)$	$B_1(\gamma_{i-1})$	$C(\theta^{in}_{i-12})$	$D(T^{out}_{i-1})$	$E(Q^{rad}_{i-1})$	F
1	1.55	−0.89	0.37	−0.11	0.07	0.12	0.030	0.013	0.00002	0.87
2	1.44	−0.70	0.22	−0.07	0.07	0.15	0.030	0.013	0.00031	1.01
3	1.53	−0.85	0.33	−0.10	0.07	0.13	0.029	0.012	0.00012	0.93
4	1.40	−0.65	0.21	−0.06	0.07	0.15	0.031	0.014	0.00018	1.09
5	1.42	−0.68	0.22	−0.06	0.07	0.15	0.031	0.013	0.00016	1.04
6	1.43	−0.69	0.23	−0.07	0.07	0.14	0.031	0.015	0.00001	0.95
7	1.42	−0.67	0.22	−0.07	0.07	0.16	0.031	0.010	0.00029	1.13
8	1.55	−0.88	0.34	−0.10	0.07	0.13	0.028	0.012	0.00005	0.93
9	1.41	−0.66	0.21	−0.07	0.07	0.15	0.031	0.014	−0.00004	1.04
10	1.45	−0.76	0.30	−0.10	0.08	0.15	0.033	0.013	−0.00015	1.06
11	1.50	−0.82	0.32	−0.10	0.10	0.19	0.032	0.011	0.00004	0.99
12	1.41	−0.68	0.24	−0.08	0.10	0.20	0.034	0.010	0.00030	1.16
13	1.49	−0.79	0.29	−0.09	0.09	0.17	0.033	0.012	0.00001	0.93
14	1.46	−0.72	0.24	−0.07	0.08	0.18	0.032	0.012	0.00002	0.99
15	1.49	−0.77	0.26	−0.08	0.08	0.18	0.032	0.012	0.00015	0.91
16	1.53	−0.84	0.32	−0.10	0.08	0.16	0.032	0.012	0.00001	0.87
17	1.51	−0.82	0.30	−0.09	0.09	0.17	0.032	0.010	0.00025	0.96
18	1.47	−0.76	0.27	−0.09	0.09	0.19	0.033	0.011	0.00033	1.02
19	1.53	−0.85	0.33	−0.10	0.09	0.17	0.032	0.011	0.00021	0.93
20	1.56	−0.90	0.36	−0.11	0.08	0.16	0.031	0.011	0.00002	0.88
21	1.57	−0.90	0.35	−0.10	0.08	0.16	0.031	0.011	0.00002	0.87
22	1.50	−0.78	0.27	−0.08	0.08	0.18	0.031	0.012	−0.00001	0.95
23	1.37	−0.53	0.11	−0.02	0.05	0.23	0.043	0.007	0.00028	0.38
24	1.34	−0.53	0.13	−0.03	0.07	0.26	0.041	0.008	0.00030	0.66
25	1.50	−0.72	0.20	−0.04	0.04	0.21	0.037	0.006	0.00018	0.31
26	1.26	−0.43	0.11	−0.03	0.10	0.29	0.041	0.010	0.00026	0.84
27	1.33	−0.50	0.11	−0.02	0.08	0.26	0.040	0.009	0.00026	0.67
28	1.44	−0.65	0.18	−0.04	0.05	0.23	0.039	0.007	0.00015	0.49
29	1.39	−0.59	0.16	−0.04	0.07	0.26	0.040	0.009	0.00014	0.62
30	1.34	−0.54	0.16	−0.05	0.09	0.28	0.036	0.007	0.00045	0.86

Table A.10
Results from system identification and validation of the ARX-models, for March results are for the models identified for afternoons. R^2 metric is marked by R2 and mean squared errors by MSE in the table.

	January				March-Morning				March-Afternoon				November			
	Identification		Validation		Identification		Validation		Identification		Validation		Identification		Validation	
House	R2	MSE	R2	MSE	R2	MSE	R2	MSE	R2	MSE	R2	MSE	R2	MSE	R2	MSE
1	0.9992	0.0063	0.998	0.0137	0.9961	0.0121	0.9951	0.0190	0.9961	0.0121	0.9951	0.019	0.9985	0.0027	0.9886	0.0343
2	0.9993	0.0059	0.9981	0.0137	0.9985	0.0098	0.9982	0.0126	0.9985	0.0098	0.9982	0.0126	0.9988	0.0023	0.988	0.0354
3	0.9993	0.0055	0.9979	0.0137	0.9975	0.0090	0.9968	0.0143	0.9975	0.009	0.9968	0.0143	0.9987	0.0023	0.9879	0.0345
4	0.9992	0.0062	0.998	0.0135	0.9982	0.0069	0.9979	0.0095	0.9982	0.0069	0.9979	0.0095	0.9986	0.0025	0.986	0.0375
5	0.9992	0.0063	0.998	0.0144	0.9982	0.0069	0.9978	0.0097	0.9982	0.0069	0.9978	0.0097	0.9986	0.0026	0.9869	0.0369
6	0.9991	0.0076	0.998	0.0155	0.9969	0.0084	0.9962	0.0128	0.9969	0.0084	0.9962	0.0128	0.9984	0.0032	0.9877	0.0353
7	0.9993	0.0059	0.9984	0.0112	0.9986	0.0092	0.9981	0.0118	0.9986	0.0092	0.9981	0.0118	0.9988	0.0022	0.9875	0.0337
8	0.9993	0.0053	0.9981	0.0126	0.9971	0.0090	0.9962	0.0146	0.9971	0.009	0.9962	0.0146	0.9987	0.0022	0.9881	0.034
9	0.9992	0.0073	0.9982	0.0138	0.9968	0.0088	0.9954	0.0151	0.9968	0.0088	0.9954	0.0151	0.9986	0.0029	0.9869	0.0375
10	0.9992	0.0068	0.9983	0.0129	0.9956	0.0111	0.9943	0.0187	0.9956	0.0111	0.9943	0.0187	0.9987	0.0027	0.9861	0.0434
11	0.9993	0.0048	0.9982	0.0103	0.9976	0.0086	0.9967	0.0147	0.9976	0.0086	0.9967	0.0147	0.9987	0.0021	0.9875	0.0344
12	0.9991	0.0047	0.9978	0.0106	0.9986	0.0074	0.9981	0.0110	0.9986	0.0074	0.9981	0.011	0.9985	0.0019	0.9858	0.0322
13	0.9991	0.0054	0.998	0.0113	0.9964	0.0094	0.9957	0.0148	0.9964	0.0094	0.9957	0.0148	0.9985	0.0022	0.988	0.0309
14	0.9991	0.0052	0.9979	0.0114	0.9966	0.0063	0.9967	0.0086	0.9966	0.0063	0.9967	0.0086	0.9985	0.0021	0.9876	0.0289
15	0.9992	0.0045	0.998	0.0107	0.9984	0.0037	0.9989	0.0037	0.9984	0.0037	0.9989	0.0037	0.9986	0.0019	0.9892	0.0258
16	0.9992	0.0047	0.9979	0.0106	0.9966	0.0077	0.9959	0.0122	0.9966	0.0077	0.9959	0.0122	0.9985	0.0021	0.9891	0.0263
17	0.9993	0.0039	0.9979	0.0103	0.9988	0.0058	0.9983	0.0092	0.9988	0.0058	0.9983	0.0092	0.9987	0.0017	0.9889	0.0266
18	0.9992	0.0046	0.998	0.01	0.9988	0.0074	0.9984	0.0108	0.9988	0.0074	0.9984	0.0108	0.9986	0.002	0.9889	0.0263
19	0.9992	0.0043	0.9979	0.0108	0.9983	0.0071	0.9977	0.0119	0.9983	0.0071	0.9977	0.0119	0.9986	0.0019	0.9885	0.0283
20	0.9992	0.0044	0.9979	0.0103	0.9972	0.0071	0.9964	0.0119	0.9972	0.0071	0.9964	0.0119	0.9986	0.0019	0.989	0.0268
21	0.9992	0.0041	0.9979	0.0098	0.9973	0.0069	0.9964	0.0116	0.9973	0.0069	0.9964	0.0116	0.9987	0.0018	0.9894	0.0256
22	0.9992	0.0047	0.998	0.0106	0.9964	0.0071	0.9961	0.0107	0.9964	0.0071	0.9961	0.0107	0.9986	0.0019	0.9881	0.0284
23	0.999	0.0024	0.9968	0.0064	0.9976	0.0034	0.9969	0.0052	0.9976	0.0034	0.9969	0.0052	0.9979	0.0015	0.9968	0.0042
24	0.999	0.002	0.996	0.0074	0.9990	0.0029	0.9989	0.0034	0.999	0.0029	0.9989	0.0034	0.9977	0.0012	0.9936	0.0081
25	0.9991	0.002	0.9972	0.0052	0.9968	0.0081	0.9952	0.0138	0.9968	0.0081	0.9952	0.0138	0.9982	0.0013	0.9974	0.0039
26	0.9989	0.0025	0.9959	0.0086	0.9983	0.0035	0.9976	0.0053	0.9983	0.0035	0.9976	0.0053	0.9973	0.0015	0.9903	0.0122
27	0.999	0.0022	0.9962	0.0075	0.9986	0.0028	0.9982	0.0039	0.9986	0.0028	0.9982	0.0039	0.9976	0.0013	0.993	0.0092
28	0.9991	0.0022	0.9971	0.0054	0.9961	0.0074	0.9945	0.0123	0.9961	0.0074	0.9945	0.0123	0.9979	0.0013	0.9954	0.0065
29	0.9991	0.0023	0.9974	0.0055	0.9961	0.0065	0.9944	0.0109	0.9961	0.0065	0.9944	0.0109	0.9976	0.0015	0.9933	0.0096
30	0.999	0.002	0.998	0.0038	0.9994	0.0073	0.9987	0.0110	0.9994	0.0073	0.9987	0.011	0.9981	0.0011	0.9927	0.0097

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