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# Towards designing an aggregator to activate the energy flexibility of multi-zone buildings using a hierarchical model-based scheme

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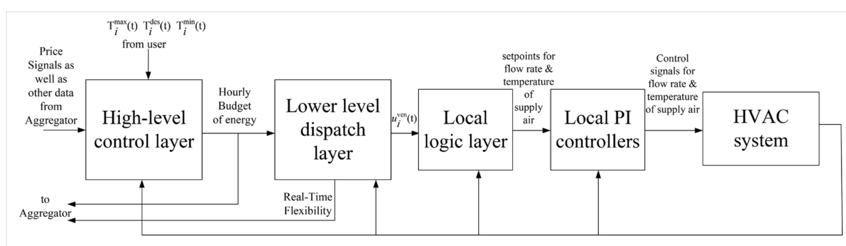
## HIGHLIGHTS

- Coupling HVAC systems with smart grids by a hierarchical model-based scheme.
- Keeping commitment to a pre-planned energy budget and satisfying comfort levels.
- Comparing the performance of a centralized model with a decentralized one.
- Analyzing available up and down regulating power for a typical building.

## GRAPHICAL ABSTRACT




## ARTICLE INFO

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Aggregator
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Market mechanism
Flexibility
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## ABSTRACT

Aggregators are emerging players in the future power markets which aggregate the flexibility of small consumers. This paper proposes a hierarchical model-based scheme to activate the energy flexibility of multi-zone buildings through a direct aggregation mechanism. The novelty lies in considering the power market mechanism in which consumers try to remain committed to their bids without violating their desired comfort levels. In the proposed approach, a high-level control layer determines an hourly energy budget for the whole building according to price signals and reports it to an aggregator. A lower-level dispatch layer then distributes the pre-planned hourly energy budget among different zones. At this level, the emphasis is on keeping the energy consumption as close to the pre-planned budget as possible while satisfying the comfort requirements. In addition, this layer computes the available real-time up and down regulating power and reports them to the aggregator. For comparison, we develop both a centralized and a decentralized model predictive control (MPC) scheme for the high-level control layer. Furthermore, a decentralized MPC with variable prediction horizon is designed for the lower-level dispatch layer. The proposed method is applied to a detailed multi zone building model developed in a high-fidelity simulation environment. The results show that the proposed scheme can keep its commitment to the aggregator to a large extent (by more than 93%) while maintaining the desired comfort levels. In addition, it is seen that the centralized model reduces energy costs and exhibits between 0.5% and 2.5% better commitment to the pre-planned budget in comparison with the decentralized one at the cost of sacrificing comfort to some extent. Moreover, some preliminary results regarding available up and down regulating power for residential buildings are reported for the first time.

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**Nomenclature**

| | |
|---|---|
| $x_i$ | the $i^{\text{th}}$ element of the vector $x$ |
| $T_i^{air}$ | the measured temperature of interior air within the $i^{\text{th}}$ zone |
| $T_{i,j}^{env}$ | the temperature of the envelope between $i^{\text{th}}$ zone and $j^{\text{th}}$ zone |
| $C_i^{int}$ | the interior's thermal capacitance of the $i^{\text{th}}$ zone |
| $R_i^{int}$ | the interior's thermal resistance of the $i^{\text{th}}$ zone |
| $C_{i,j}^{env}$ | the thermal capacitance of the envelope between $i^{\text{th}}$ zone and $j^{\text{th}}$ zone |
| $R_{i,j}^{env}$ | the thermal resistance of the envelope between $i^{\text{th}}$ zone and $j^{\text{th}}$ zone |
| $R_{i,j}^{dir}$ | the direct thermal resistance between $i^{\text{th}}$ zone and $j^{\text{th}}$ zone |
| $Q_i^{ven}$ | flow rate of supply air to the $i^{\text{th}}$ zone |
| $T_i^{sup}$ | temperature of supply air to the $i^{\text{th}}$ zone |
| $T_i^{des}$ | desired temperature for the $i^{\text{th}}$ zone |
| $T_i^{max}$ | maximum allowed temperature for the $i^{\text{th}}$ zone |
| $T_i^{min}$ | minimum allowed temperature for the $i^{\text{th}}$ zone |
| $\widehat{T}_i^{air}$ | the estimated temperature of interior air within the $i^{\text{th}}$ zone by observer |
| $C_{air}$ | Specific heat capacitance of the air |
| $t_s$ | sampling time |
| $t_s^{llc}$ | sampling time for the lower-level control layer |
| $u_i^{ven}$ | power delivered to the $i^{\text{th}}$ zone by the HVAC system |
| $u_i^{int}$ | power delivered to the $i^{\text{th}}$ zone by internal sources as well as solar radiation |
| $u_i$ | total power delivered to the $i^{\text{th}}$ zone |
| $(Q_i^{ven})^{min}$ | the minimum allowed flowrate of supply air for the $i^{\text{th}}$ zone. |
| $(Q_i^{ven})^{max}$ | the maximum allowed flowrate of supply air for the $i^{\text{th}}$ zone. |
| $(T_i^{sup})^{min}$ | the minimum allowed temperature of supply air for the $i^{\text{th}}$ zone. |
| $(T_i^{sup})^{max}$ | the maximum allowed temperature of supply air for the $i^{\text{th}}$ zone. |

## 1. Introduction

The rising share of renewable energy sources in the electricity production, which are generally fluctuating and unpredictable, leads to increasing imbalances between demand and supply [1]. This inspires new initiatives to mitigate their impact on the stability of the power grid, in particular. Aggregating the flexibility of small electricity consumers is among the most promising suggested solutions [2]. For example, residential and commercial buildings can provide flexibility services by adjusting the amount and timing of power used by their heating, ventilation, and air conditioning (HVAC) systems, which are the most energy demanding services in many buildings [3].

Many researchers have investigated exploiting the flexibility of HVAC systems through different methods such as model predictive control (MPC) schemes [4,5]. In [6], the authors propose an MPC framework to coordinate HVAC, battery storage and renewable generation in multi-zone buildings. The objective is to lower peak load demand while maintaining thermal comfort within acceptable levels. Their results show that the average load can be reduced by 23 % through the proposed method. In [7] it is suggested to use a two-layer hierarchical model predictive control scheme to enhance the energy efficiency of a multi-zone building. The high-level MPC applies a low-resolution model to make decisions for the air handling unit (AHU). A lower-level controller converts the high-level MPC decisions into commands for the individual zones. Their simulations reveal that the proposed scheme reduces energy use approximately between 11 % and 68 % depending on weather conditions. In [8], it is proposed to deal with the uncertainties in actual systems by developing a two-layer tube-based robust model predictive control (MPC) strategy for demand-controlled ventilation of multi-zone buildings. The first layer MPC generates nominal state trajectories considering nominal systems without uncertainties, while the second layer MPC generates control actions to direct the states of the real-world uncertain system to follow the nominal trajectories. Their experiments show that the proposed scheme is able to reduce indoor air quality cost by 10 % and energy consumption by 14 % compared with the conventional feedback control strategy.

Despite the recent advances in exploiting the energy flexibility of buildings, there are still a few gaps preventing them from practical application. For instance, the power market mechanism is not reflected in the current proposed methods, which makes them impractical in most real cases. It is apparent that small consumers cannot take part in the electricity market directly because their consumption is too low to bid in the market. For this reason. aggregators are emerging players in the future power markets, which aggregate the flexibility of small consumers. In [9], authors demonstrate the role of aggregators in implementing and extending demand response (DR) in future smart grids. A literature review of mathematical modeling and optimization of DR algorithms can be found in [10]. Aggregators and small consumers must consider the market mechanism in their interaction. A hierarchical market model is presented in [11] to reduce the grid's operational costs by giving incentives to the aggregator and compensating the consumers. The aggregator and the consumers are considered as leader and followers respectively in [12] and a novel Stackelberg game approach is proposed to activate the demand response in a residential area.

Generally, the interaction between aggregator and small consumers could be direct or indirect [13]. In an indirect mechanism, the aggregator sends price signals to the consumers, which then they manage their consumption accordingly. The communication is unidirectional, and the consumers do not have any committed obligations to the aggregator. Implementation of indirect mechanisms is easier for aggregators but the uncertainty about consumers behavior makes it difficult for them to play in the electricity market. In case of direct mechanisms, on the other hand, communication is bidirectional. Small consumers send their demand and available flexibility to the aggregator, and they are committed to their bids once accepted. Implementation of the direct mechanism is more complicated for the consumer due to the trade-off between keeping commitment to the previous bids and satisfying the desired level of indoor climate at the same time. However, it makes it more practical for the aggregator to play in the electricity market.

This paper introduces a hierarchical consumer-side control scheme to activate the energy flexibility of a multi-zone building. The novelty lies in considering the power market mechanism within a direct control context. In the proposed scheme, a consumer tries to remain committed to its bid as much as possible without violating its desired comfort levels. To this end, a high-level control layer determines an hourly energy budget for the whole building and reports it to an aggregator. At this level, aggregator signals such as power price are considered as inputs. A lower-level dispatch layer then distributes the pre-planned hourly energy budget among different zones. At this level, the emphasis is on keeping the energy consumption as near as possible to the pre-planned budget while satisfying the comfort levels. Thus, the consumer tries to remain committed to its bids and satisfy the comfort levels at the same time. In addition, real-time available flexibility is computed and reported to the aggregator. Real-time available flexibility means how much the consumer can deviate from its pre-planned hourly energy budget within the current hour without violating its comfort levels (by reducing or increasing its consumption). Aggregator can exploit the real-time available flexibility to make a bid on electricity regulation market (See Section 2). Fig. 1 illustrates the idea.

A variety of models and methods can be used in the high-level control layer to predict the hourly energy budget. In this paper, we develop two candidate MPC schemes for the high-level control layer, a centralized and a decentralized one, and compare their performance. A decentralized MPC with variable prediction horizon is developed for the lower-level dispatch layer. For simulation purposes, a detailed model of a multi zone building is developed in the IDA ICE environment. Centralized and decentralized state space models are identified for the building, and the proposed hierarchical scheme is implemented in MATLAB environment. Communication between MATLAB and IDA ICE is established to take advantage of both environments at the same time via co-simulation. Finally, the results of co-simulations are presented and discussed. The main contributions of this paper can be summarized as follows:

A novel hierarchical MPC scheme is developed, which is suitable for coupling HVAC systems with smart grids using a direct control scheme. By the proposed approach, the consumers keep their commitment to the accepted bids by the aggregator while simultaneously satisfying the comfort levels.

Two different state space models, a centralized and a decentralized one, are developed for the case study building and their performances are compared in terms of keeping commitment to the pre-planned energy budget and satisfying comfort levels.

The rest of this paper is organized as follows. Section 2 provides a brief description of the power market mechanism. Section 3 discusses the case study building, the proposed models to capture its thermal dynamics and identification procedure. Section 4 presents the proposed hierarchical MPC approach. The co-simulations between MATLAB and IDA ICE and the results are presented in Section 5. In Section 6 we discuss the results. Finally, Section 7 concludes the paper.

## 2. A brief description of the power market mechanism

Modern electricity markets operate according to roughly the same principles. As a typical example, we review the Nordic electricity market (Nord Pool), which covers Sweden, Norway, Finland and Denmark [14]. The Nord Pool short-term electricity market includes three submarkets with different time scheduling for offering and clearing the bids. They are the Day-ahead market (Elspot), the Intraday market (Elbas) and the Regulation market, as depicted in Fig. 2.

The Day-ahead market (Elspot) is the prime Nord Pool submarket where a daily competitive auction establishes a price for each hour of the next day. All participants' bids are received before gate closure at 12:00, whereupon the system price and the area prices are calculated and revealed. Because the Day-ahead market is closed 12–36 h ahead of the actual operation hour, certain deviations are unavoidable. In order to deal with such deviations, electricity can be traded in the intraday market after the Elspot closure time up till 45 min prior to the operating hour via hourly contracts. Also, market players can bid for regulating power during this time span.

Transmission system operators (TSOs) maintain the network balancing during the hour of operation by activating some of the regulation bids as well as utilizing their reserved capacities. Accepted

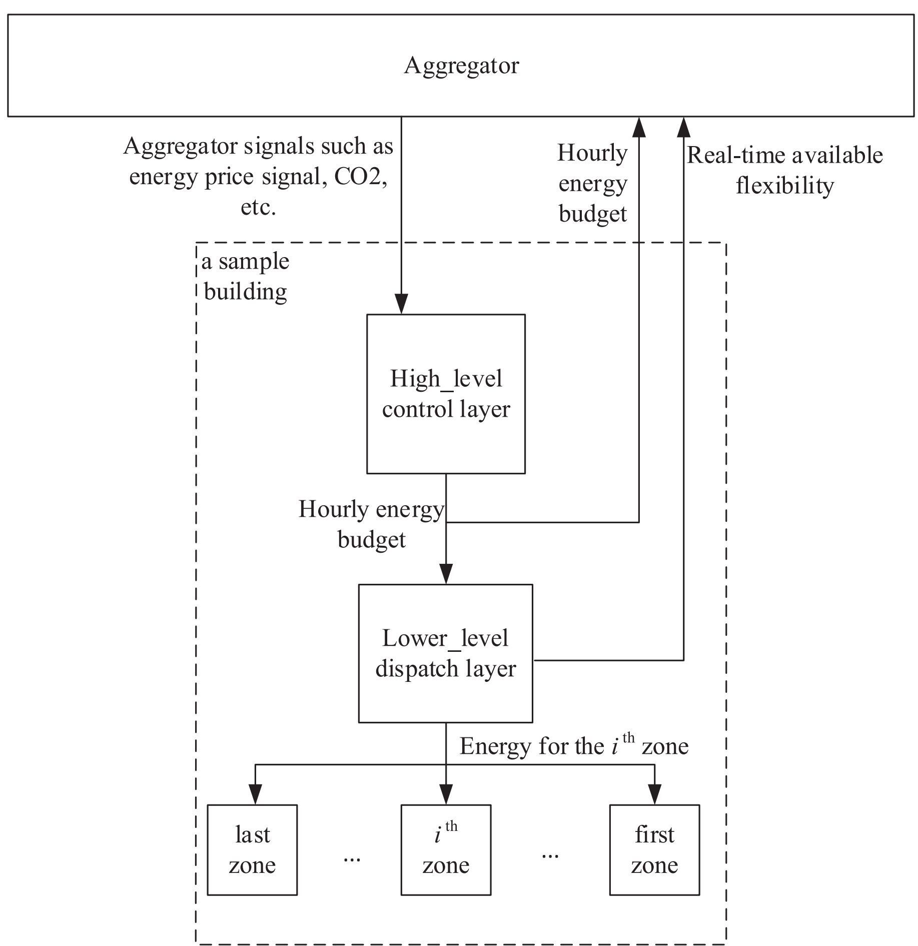


**Fig. 1.** Proposed hierarchical scheme for in-building control (delimited by the dashed rectangle).

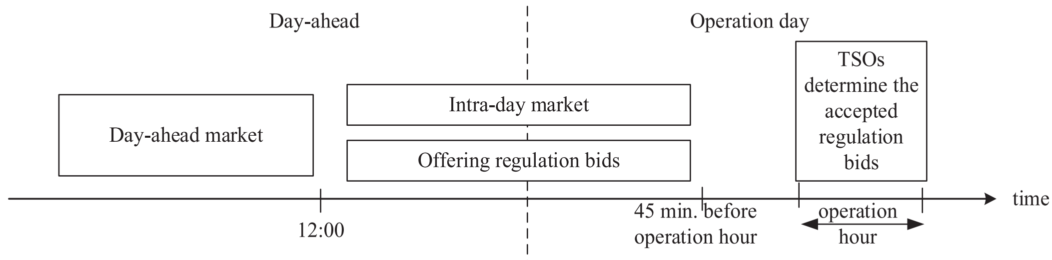


**Fig. 2.** The time schedule of Nord Pool.

regulation bids should be activated within 15 min and the duration may vary. There are two different types of regulating power: up-regulating and down-regulating.

In the up-regulation case, the electric power demand is higher than the planned production. Subsequently, the power price is higher than the day-ahead prices. In this situation, small consumers such as HVAC systems may reduce their heat production from the scheduled amount and an aggregator can sell the surplus power at a higher price. In the down-regulation case, the electric power demand is less than the planned production. Thus, the power price is lower than the day-ahead prices. In this condition, small consumers such as HVAC systems may increase their heat production from the scheduled amount. Accordingly, they contribute to the grid stability by increasing their power consumption. In the both cases, the consumers will be compensated for providing up and down-regulation services as well.

It is worthy of note that what we presented here is a “here and now” picture. The market is expected to evolve significantly in the coming years. In particular, markets at the local distribution level are also expected to become a part of the picture in order to support distribution system operators (DSOs).

## 3. Case study specifications, modeling and identification

The case study building consists of 11 zones. Fig. 3 illustrates a floor plan of the building. It is assumed only 6 zones can be controlled: Zone 1, Zone 2, Zone 6, Zone 9, Zone 10 and Zone 11.

For applications such as coupling HVAC systems with smart grids, we need models with different levels of complexity. They should be capable of capturing the thermal dynamics of each individual zone as well as the thermal interactions among adjacent zones. Furthermore, their time resolution should be high enough (e.g., sampling times on the order of a few minutes) to support real-time control. Moreover, since they are implemented in real-time, their computation burden should be low. In addition, they should be able to cope with real-time uncertainties and identifiable from a history of sensor data. It is evident that satisfying these all criteria is not practical by a single model. Accordingly, we investigate three different levels of modeling for the case study building in this paper.

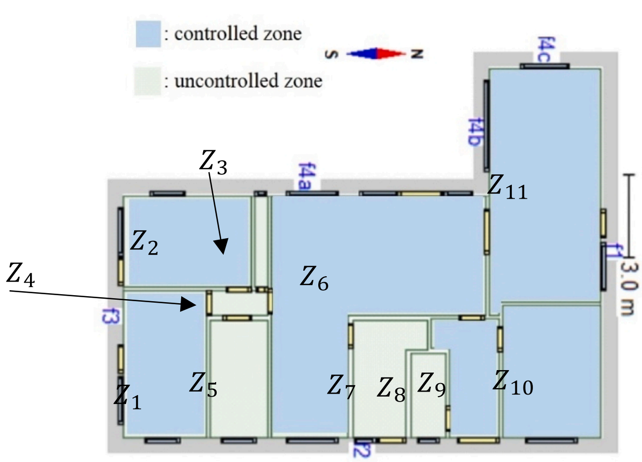


**Fig. 3.** Floor plan of the case study building.

Due to the presence of occupants, there are many limitations on conducting identification tests in the real-world buildings. As a result, the first level of our modeling is done in IDA ICE, a high-fidelity simulation environment that is very close to the reality [15]. It is capable of modeling the thermal dynamics of multi-zone buildings equipped with different HVAC systems and controllers in a highly accurate manner. A detailed model of the building is developed in the high-fidelity environment using the characteristics indicated in Table 1 and the effect of internal sources including equipment, occupants and light radiations are incorporated in the simulations. In addition, a detailed model of a state-of-the-art HVAC system is incorporated into the model (See Section 4.4). It is a complex model which is not suitable for control proposes but used as our reference model.

The second level of modeling is a central high order grey box resistor–capacitor (RC) model. Grey box RC models have been successfully applied to capture the thermal dynamics of a whole building [16]. In these approaches, the whole building is modelled with an equivalent RC model, i.e. a network of thermal resistors and capacitors (see Fig. 4). These models are suitable tools to investigate the heat demand of a building within relatively long-time horizons. In subsection 3.1, we utilize the grey box RC concept to model the multi-zone case study building and develop a central high order RC model that captures the thermal dynamics of individual zones as well as their thermal interactions. However, there are many parameters in the model, implying that identification is time consuming and cumbersome. Moreover, its computation burden in real-time is high. Consequently, in subsection 3.2 we develop a set of simpler decentralized data-driven models for real-time control. Subsection 3.3 illustrates the identification process and makes a brief comparison between the centralized and decentralized identified models. Subsection 3.4 discusses observer design and building predictive models.

### 3.1. Centralized high order model

First, a relatively detailed RC model for each zone and its associated envelopes is proposed (Fig. 4). Then, we try to tune its parameters by conventional identification methods. For the case study building, this

**Table 1**
The characteristics used in the IDA ICE model.

| | | | |
|---|---|---|---|
| Floor area | 160 $m^2$ | U-value of roof | 0.2 $W/m^2K$ |
| Volume | 460 $m^3$ | U-value of slabs towards the ground | 0.3 $W/m^2K$ |
| Window/Envelope | 6.6 % | U-value of windows | 2.9 $W/m^2K$ |
| U-value of external walls | 0.4 $W/m^2K$ | U-value of doors | 2.9 $W/m^2K$ |

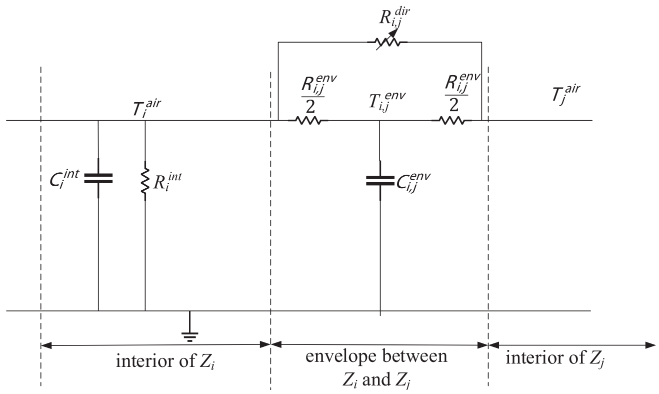


**Fig. 4.** A relatively detailed RC model for each zone.

procedure results in the following state-space model with 62 states, which we refer to as centralized high order model.

$$\dot{x}(t) = Ax(t) + Bu(t) + Ed(t) \tag{1}$$

$$y(t) = Cx(t) \tag{2}$$

In our centralized high order model, $x(t)$ comprised of $\left[ T_i^{air}(t) \quad T_{i,j}^{env}(t) \right], i,j \in \{1, 2, \cdots, 11\}$, is the state space vector, $u(t)$ is the control input vector of length 6 involving the thermal power delivered to the controlled zones, $d(t)$ is the measurable disturbance vector of length 5 indicating the thermal power delivered to the uncontrolled zones and $y(t)$ is the output of our model, comprising the temperature of all the 11 zones. $A$, $B$ and $E$ are constant matrices with appropriate dimensions that should be identified through conventional identification methods.

### 3.2. Decentralized second order models

In this subsection, we propose a second order single-input single-output (SISO) model with a slow and a fast mode for each zone as follows.

$$\dot{x}_{1,i}(t) = \lambda_{1,i}x_{1,i}(t) + b_{1,i}u_i(t) \tag{3}$$

$$\dot{x}_{2,i}(t) = \lambda_{2,i}x_{2,i}(t) + b_{2,i}u_i(t) \tag{4}$$

$$y_i(t) = x_{1,i}(t) + x_{2,i}(t) \tag{5}$$

Here, $x_{1,i}(t)$ and $x_{2,i}(t)$ are the two slow and fast states corresponding to the $i^{\text{th}}$ zone, $u_i(t)$ is the delivered thermal power to the $i^{\text{th}}$ zone and $y_i(t)$ is the temperature of the $i^{\text{th}}$ zone. $\lambda_{1,i}$, $\lambda_{2,i}$, $b_{1,i}$ and $b_{2,i}$ are four scalar parameters that should be identified through conventional identification methods for each zone.

The physical interpretation is that there are two thermal capacitances in each zone. The fast one corresponds to the heat capacitance of the indoor air and the slow one corresponds to the heat capacitance of the thermal mass of the zone.

### 3.3. Identification and comparison of the models

For identification purpose, a simulation is run for one sample day with arbitrary boundary conditions in IDA ICE environment. The simulation data are used to identify the unknown parameters of the models as well as the initial conditions by exploiting the "ssest" command from the System Identification Toolbox of MATLAB [17].

Fig. 5 and Fig. 6 compare the response of the first zone derived from the IDA ICE with the response of the identified centralized high order model as well as the response of the decentralized model. The sampling time for the identified models is one hour in Figs. 5 and 5 min in Fig. 6. The responses of other zones are more or less similar and are ignored for the sake of brevity.

As seen, there is a good agreement between the response of both centralized and decentralized identified models and the derived data from IDA ICE. Both centralized and decentralized models can predict the future responses within acceptable tolerance considering the sampling time. However, the computation burden of the distributed second order models is much less than the centralized high order one when considering optimization process. In addition, identification is much easier owing to fewer unknown parameters. On the other hand, the thermal interaction between zones can only be modeled in the centralized high order one. As a conclusion, the centralized high order model is suitable only for long-term optimizations e.g. hourly scale, while the distributed second order models can be utilized for short and long-term optimizations. In this study, we use the decentralized second order models in our lower-level dispatch layer due to their low computation burden. In the high-level control layer, we exploit both centralized and decentralized models and compare their performance.

### 3.4. Observer design and building predictive models

Both proposed centralized and decentralized models are in state space form. However, the states are not measurable directly. To build a predictive model, we use the prediction error as a feedback signal and design a Luenberger observer (see Fig. 7) [18]. Standard methods such as Kalman filtering techniques can be applied to compute the gain of the Luenberger observer [19].

## 4. Hierarchical control scheme

The proposed hierarchical control scheme is illustrated in Fig. 8. Each block is described in details in the subsequent subsections.

### 4.1. High-level control layer

This layer essentially is the one optimizing energy demand according to the market, and thereby links the building and the energy market (aggregator). It receives price signals as well as other data such as weather predictions from the aggregator and computes the hourly budget of energy for the whole building according to user adjustments. User settings include:

$T_i^{max}(t)$(maximum allowed air temperature for the $i^{\text{th}}$ zone).

$T_i^{min}(t)$(minimum allowed air temperature for the $i^{\text{th}}$ zone).

$T_i^{des}(t)$(desirable air temperature for the $i^{\text{th}}$ zone).

A variety of models and methods can be used in this layer to predict the hourly energy budget. In this paper, we utilize both the centralized and the decentralized models described in the previous section and compare their performance. Both models are discretized and updated with a sampling time of 15 min. However, MPC optimization runs every 1 h to reduce computation burden, while still matching the market timesteps. The prediction horizon of this layer should be 24 h or more. The exact optimization problem in this layer, depends on our objective, e.g. cost minimization, comfort level maximization, etc. Two different criteria are explored in this paper:

Maximizing comfort level.

This objective aims to minimize the difference between the desired temperatures (provided by the user) and the estimated temperatures (derived from the models).

Minimizing the energy cost.

This objective aims to minimize energy cost considering a time-varying price signal while keeping the temperature between the allowed minimum and maximum levels (provided by the user).

### 4.2. Lower-level dispatch layer

A real-time controller with an update rate of 5 min, dispatches the

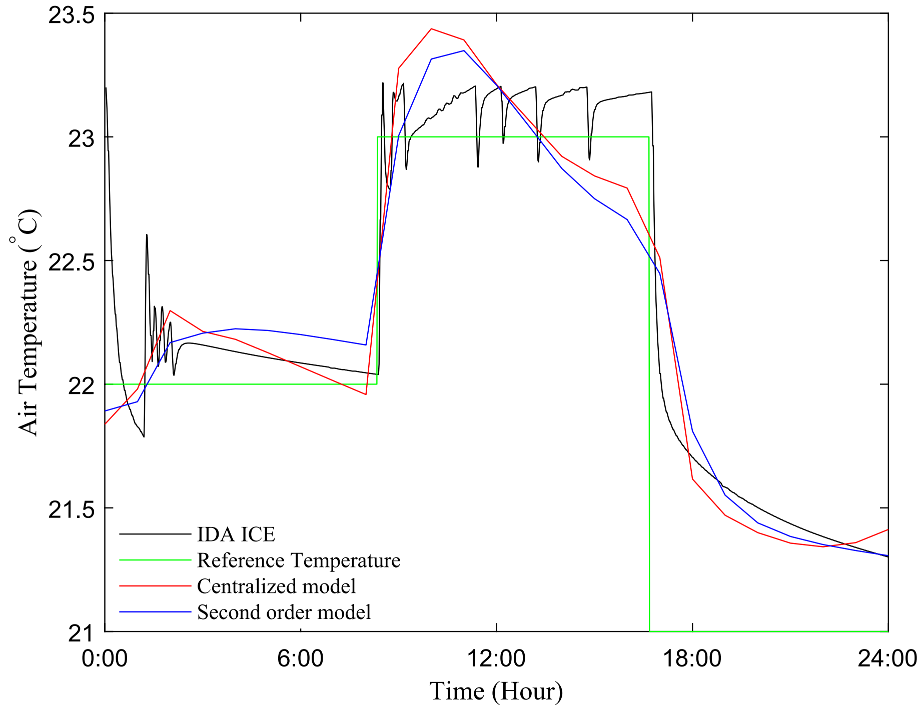


**Fig. 5.** Comparison the response of identified models against IDA ICE for the first zone ($t_s = 1$ h).

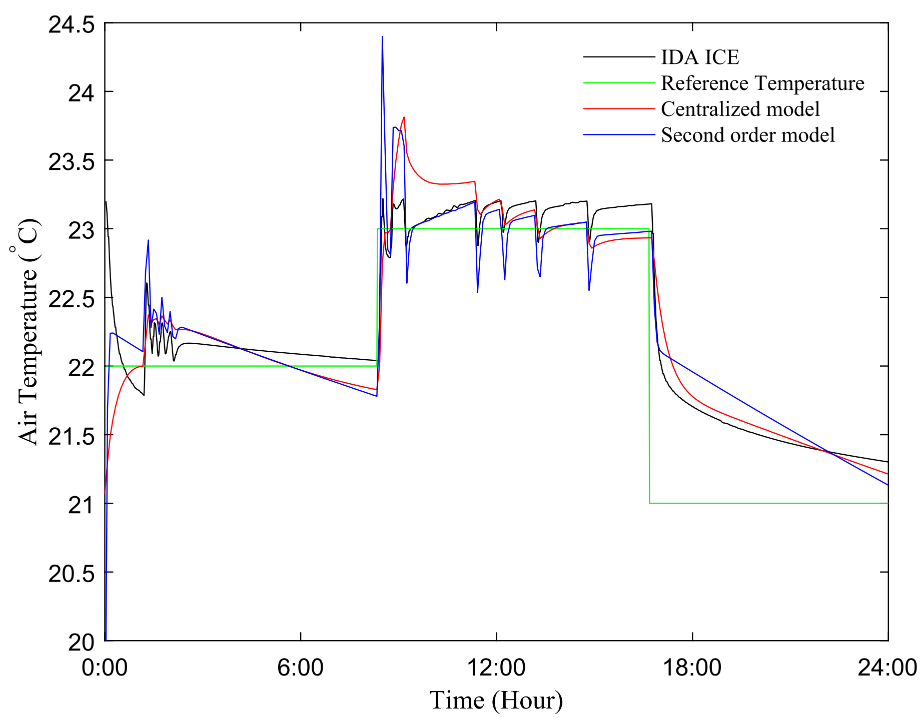


**Fig. 6.** Comparison the response of identified models against IDA ICE for the first zone ($t_s = 5$ min.).

pre-planned energy budget among different zones. Two conflicting objectives should be addressed in this layer. The first one is keeping the commitment to the pre-planned energy budget provided by the high-level controller and the second objective is keeping the temperatures as close to the desired ones as possible. At the first, we try to satisfy both objectives. If the problem was infeasible or we are at the last minutes of the current hour (e.g., the last quarter), the emphasis is on maintaining the commitment to the pre-planned energy budget while keeping the temperatures only within the allowed maximum and minimum levels.

Due to their low computation burden, the second order models are discretized with a sampling time of 5 min in this layer and exploited in an MPC scheme with variable prediction horizon. Assume we are at the moment $t = kt_s^{llc}$ of the current hour, (where $t_s^{llc} = 300$ seconds and $k = 0, 1, \cdots, 11$). The following subroutine is run 12 times each hour (every 5 min):

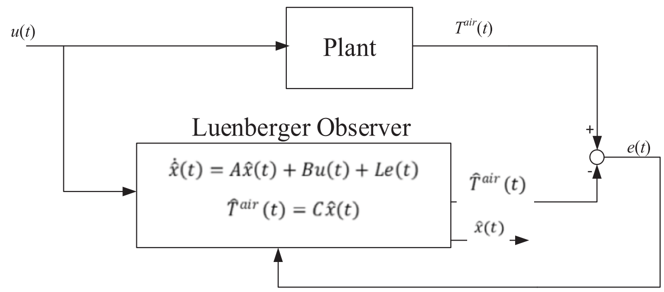


**Fig. 7.** Luenberger observer.

1. Calculate the remaining budget of energy for the rest of the current hour ($E_{bud}(k)$).
2. At the beginning (e.g., $k \le 8$), solve the following optimization problem corresponding to satisfying both the objectives.

$$\min_{u_i^{ven}(k+j)} \sum_{i=1}^{N_z} \sum_{j=1}^{12-k} \left(T_i^{des}(k+j) - \hat{T}_i^{air}(k+j)\right)^2 \tag{6}$$

s.t.

$$\sum_{i=1}^{N_z} \sum_{j=1}^{12-k} u_i^{ven}(k+j) = \frac{E_{bud}(k)}{t_s^{llc}} \tag{7}$$

$$u_i(k+j) = u_i^{ven}(k+j) + u_i^{int}(k+j) \tag{8}$$

$$\hat{x}_{1,i}(k+j) = \lambda_{1,i}\hat{x}_{1,i}(k+j-1) + b_{1,i}u_i(k+j-1) + l_{1,i}e_i(k+j-1), \tag{9}$$

$$\hat{x}_{2,i}(k+j) = \lambda_{2,i}\hat{x}_{2,i}(k+j-1) + b_{2,i}u_i(k+j-1) + l_{2,i}e_i(k+j-1), \tag{10}$$

$$\hat{T}_i^{air}(k+j) = \hat{x}_{1,i}(k+j) + \hat{x}_{2,i}(k+j), \tag{11}$$

$$e_i(k+j-1) = \begin{cases} T_i^{air}(k) - \hat{T}_i^{air}(k) & j = 1 \\ 0 & j > 1 \end{cases} \tag{12}$$

$$T_i^{min}(k+j) \le \hat{T}_i^{air}(k+j) \le T_i^{max}(k+j) \tag{13}$$

$$0 \le u_i^{ven}(k+j) \le P_i^{max} \tag{14}$$

where $u_i^{int}$ denotes the thermal power rate of internal sources, including occupants, equipment as well as light and sun radiations within the $i^{th}$ zone and $N_z$ is the number of zones.

3. Satisfying the equality constraint (7) is the most challenging part of the proposed scheme. So, if the optimization problem was infeasible or it was the last minutes of the current hour (e.g., $k \ge 9$), solve the following optimization problem. Now, the emphasis is on keeping the commitment to the pre-planned energy budget while keeping the temperatures only within the allowed maximum and minimum levels.

$$\min_{u_i^{ven}(k+j)} \sum_{i=1}^{N_z} \sum_{j=1}^{12-k} \left(\frac{E_{bud}(k)}{t_s^{llc}} - \sum_{i=1}^{N_z} \sum_{j=1}^{12-k} u_i^{ven}(k+j)\right)^2 \tag{15}$$

s.t. (8)–(14).

The outcome of optimization (6) or (15), is the delivered power to each zone within the next 5-minute intervals.

Solve the following optimization problem.

$$\min_{u_i^{ven}(k+j)} \sum_{i=1}^{N_z} \sum_{j=1}^{12-k} \left(T_i^{min}(k+j) - \hat{T}_i^{air}(k+j)\right)^2$$

s.t. (8)–(14).

The outcome of this optimization would be $\frac{E_{bud}(k)}{t_s^{llc}} - \left(\sum_{i=1}^{N_z}\sum_{j=1}^{12-k} u_i^{ven}(k+j)\right)$ that is delivered to the aggregator as the available (real-time) up regulating power.

Solve the following optimization problem.

$$\min_{u_i^{ven}(k+j)} \sum_{i=1}^{N_z} \sum_{j=1}^{12-k} \left(T_i^{max}(k+j) - \hat{T}_i^{air}(k+j)\right)^2 \tag{16}$$

s.t. (8)–(14).

The outcome of this optimization would be $\left(\sum_{i=1}^{N_z}\sum_{j=1}^{12-k} u_i^{ven}(k+j)\right) - \frac{E_{bud}(k)}{t_s^{llc}}$ that is delivered to the aggregator as the available (real-time) down regulating power.

### 4.3. Control logic layer

The output of this layer is the reference setpoints for the local PID controllers to regulate the temperature and flowrate of supply air. The control logic layer translates $u_i^{ven}(k)$ into the temperature and flowrate of the supply air ($T_i^{sup}(k)$ and $Q_i^{ven}(k)$) and then sends them to the local PI controllers. In this research we apply minimum air flow rate strategy to reduce the system's acoustic noise [20]. In this strategy, we manipulate both temperature and flowrate of the supply air to control the delivered energy. For this purpose, first we set

$$Q_i^{ven}(k) = \left(Q_i^{ven}\right)^{min} \tag{17}$$

$$T_i^{sup}(k) = \frac{u_i^{ven}(k)}{C_{air}Q_i^{ven}(k)} + T_i^{air}(k) \tag{18}$$

where $\left(Q_i^{ven}\right)^{min}$ is the minimum allowed flowrate of supply air for the $i^{th}$ zone.

If $T_i^{sup}(k) < \left(T_i^{sup}\right)^{min}$, then we set

$$T_i^{sup}(k) = \left(T_i^{sup}\right)^{min} \tag{19}$$

where $\left(T_i^{sup}\right)^{min}$ is the minimum allowed temperature of supply air for

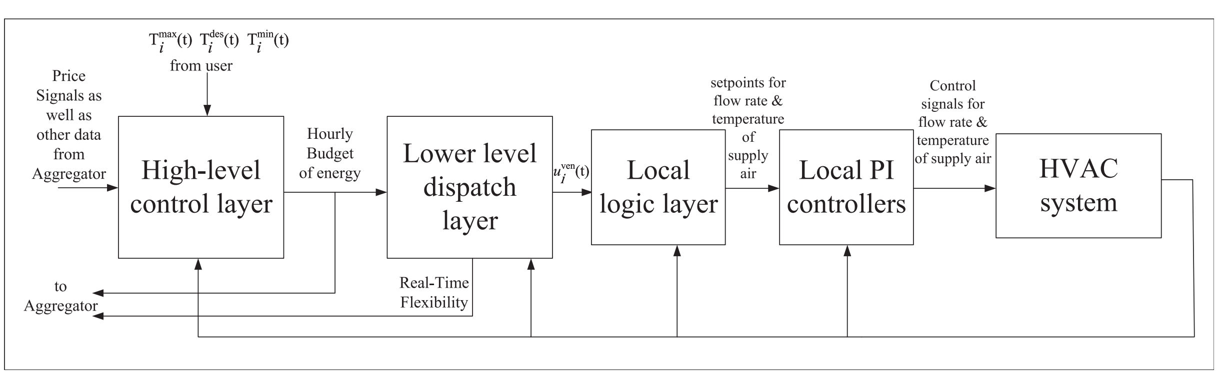


**Fig. 8.** Hierarchical control scheme.

the $i^{th}$ zone.

If $T_i^{sup}(k) > (T_i^{sup})^{max}$, then we set

$$T_i^{sup}(k) = (T_i^{sup})^{max} \tag{20}$$

$$Q_i^{ven}(k) = \frac{u_i^{ven}(k)}{C_{air}(T_i^{sup}(k) - T_i^{air}(k))} \tag{21}$$

where $(T_i^{sup})^{max}$ is the maximum allowed temperature of supply air for the $i^{th}$ zone.

If $Q_i^{ven}(k) > (Q_i^{ven})^{max}$, we set

$$Q_i^{ven}(k) = (Q_i^{ven})^{max} \tag{22}$$

where $(Q_i^{ven})^{max}$ is the maximum allowed flowrate of supply air for the $i^{th}$ zone.

### 4.4. HVAC system

The proposed approach can be applied to a verity kind of HVAC systems. In this study, we apply it to a novel multi-zone air heating and ventilation (MZHV) system which is capable of regulating both the supply airflow rate and the supply air temperature to the rooms independently of each other. A detailed model of the HVAC system is implemented in the IDA ICE environment and then it is coupled with the model of our case study building. Interested readers in the modelling of the novel HVAC system and its energy consumption are referred to [20].

## 5. Co-simulation and results

After identification procedure, we run a few co-simulations involving IDA ICE (HVAC and building simulation) and MATLAB (control) to investigate the performance of the proposed method. In this study, we only investigate air heating systems and four different scenarios are investigated according to Table 2.

The simulations are done for two sample days of autumn and winter, namely 2nd January and 6th October 2020. It is assumed we have a perfect knowledge about the supplied energy from internal sources, including lighting, occupants, solar irradiation as well as in-house equipment. Fig. 9 shows the profile of internal loads for the simulation period. In addition, Fig. 10 and Fig. 11 show the ambient temperature and spot electricity prices within the simulation period respectively.

The desired temperature ($T_i^{des}(t)$) profile for all zones are considered as depicted in Fig. 12 where $\alpha$ is set to 24 for the first two zones and it is set to 23 for the 4 remaining zones. $T_i^{max}(t)$ and $T_i^{min}(t)$ are set 1℃ above and below $T_i^{des}(t)$), respectively.

We define six indexes for comparison.

The relative differences between hourly consumed energy and the pre-planned budget are computed and their mean is defined as an index to show how precisely the building is keeping its commitment. We denote this index as “mean commitment violation”.

The mean absolute difference between the desired and simulated temperature responses at each zone is computed and then their mean is defined as an index for the comfort violation, denoted as “mean comfort violation”.

Another index is the “daily energy cost”. For this index, the real spot

**Table 2**
Investigated scenarios.

| | Centralized high order model | decentralized second order models |
|---|---|---|
| Maximizing comfort | Scenario 1 (Centralized/ Comfort) | Scenario 2 (Decentralized/ Comfort) |
| Minimizing energy cost | Scenario 3 (Centralized/Cost) | Scenario 4 (Decentralized/ Cost) |

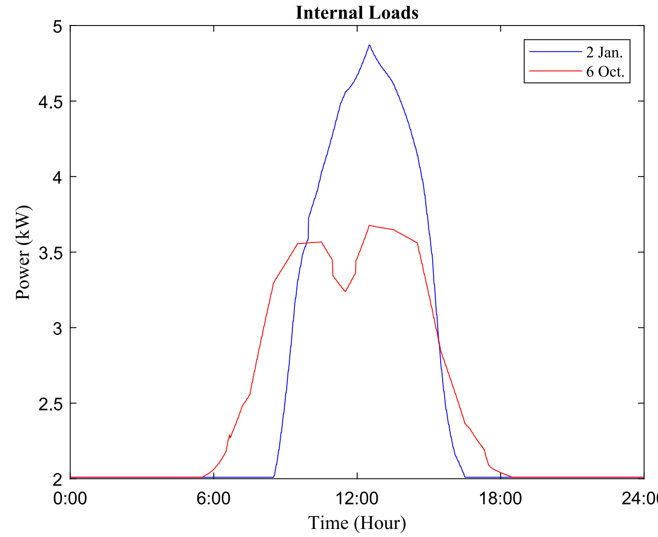


**Fig. 9.** Internal loads for the simulation period including solar radiations.

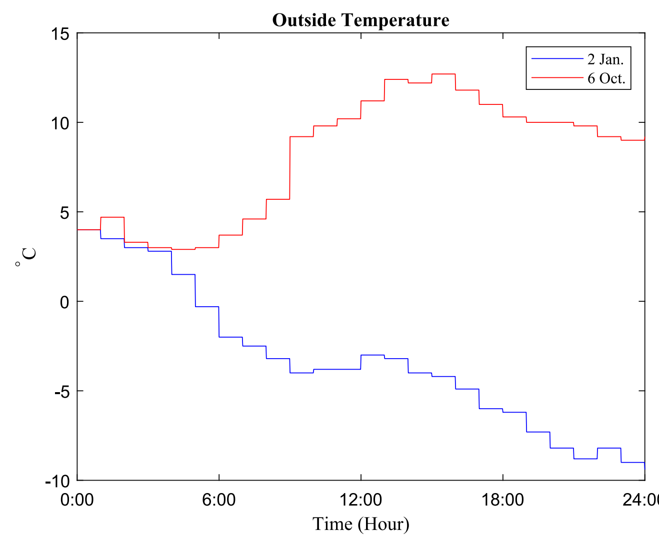


**Fig. 10.** Ambient temperature for the simulation period.

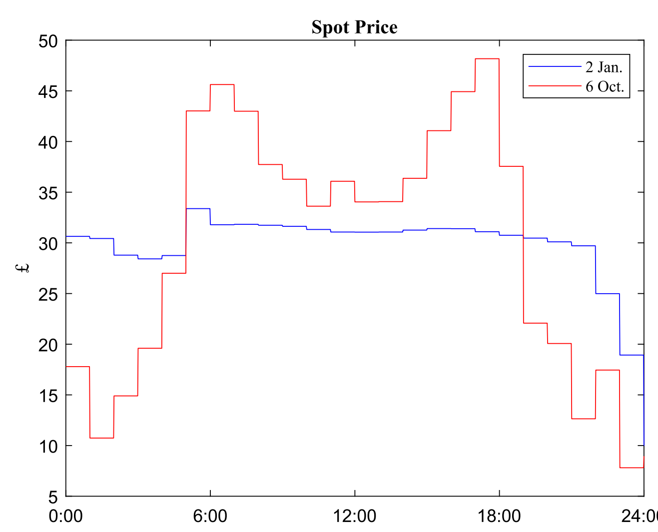


**Fig. 11.** Spot electricity prices for the simulation period.

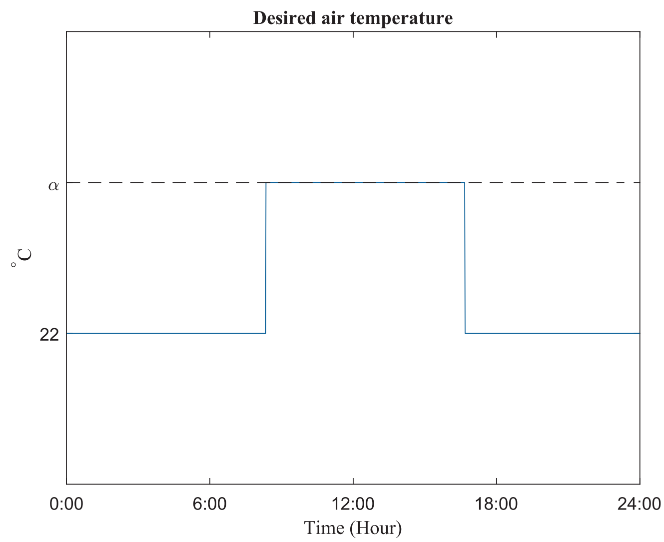


**Fig. 12.** Profile of desired air temperature.

price of electricity is applied (see Fig. 11).

Also, we compute the total daily used energy.

Finally, we compute the total available daily up and down regulating energy.

Table 3 and Table 4 summarize the results.

## 6. Discussion

The "mean commitment violation" index in the first column of Table 3 and Table 4, reveal that the violation from the pre-planned energy budget is between 3 % and 7 % in all the scenarios. It is worthy of note that we are trying to keep the comfort for all the controlled zones in the simulations. The "commitment violation" index could even be improved further by sacrificing the comfort of a zone with less importance i.e., the excess or lack of energy can be transferred to that zone in order to keep full commitment to the pre-planned energy budget.

On the other hand, the "mean comfort violation" index in the second column of Table 3 and Table 4 demonstrate that the mean violation from desired temperatures is less than 1 ℃ in all scenarios, which is within the maximum allowed deviation (It was set to 1℃ in the simulations).

Generally, it is seen that the proposed method can keep a good commitment to its pre-planned budget while mostly satisfying the comfort levels in all scenarios.

Furthermore, the centralized high order model demonstrates better commitment and lower energy cost in comparison with the decentralized models. The "mean commitment violation" index is up to 5 % for the centralized method while it is up to 7 % for the decentralized models. In addition, it is seen that the centralized model reduces energy costs to some extent. On the other hand, the decentralized models provide better comfort for the user.

Considering available daily up and down regulating power, it is seen minimizing energy cost, instead of maximizing comfort will increase available up regulating power while decrease the available down regulating power, as expected. In addition, it is seen there is generally a direct relationship between available regulating power and the total energy use. For example, on the 2nd of January the energy consumption is higher than 6th of October and consequently the available regulating power is also higher.

It should be highlighted that our results are among the first investigations in this field. The simulation results depend significantly on the boundary conditions such as price signals, ambient temperature, desired temperature, sun radiation, etc. Thus, giving a complete picture regarding the available up and down regulating power for residential buildings requires more studies.

The main limitation of the proposed method is the lack of suitable models for real-world buildings and HVAC systems. It is one reason that we exploited a white-box model such as IDA ICE to validate the proposed method. The thermal dynamics of buildings are nonlinear and time-varying. Moreover, the uncertainty associated with disturbance and noise in practical applications is considerable. It makes the development of appropriate models challenging and cumbersome. In addition, there are many limitations for carrying out identification tests in occupied buildings which intensify the problem. Implementing the proposed method on the real-word case studies are subject of our ongoing research projects.

## 7. Conclusion

Aggregating the flexibility of small electricity consumers by new players in the future energy markets is among the most appealing suggested solutions to attenuate the impact of fluctuating and unpredictable renewable energies on the stability of power grid. The market mechanism should be considered in the interaction between aggregators and small consumers. This paper proposes a hierarchical model-based scheme to exploit the energy flexibility of a multi-zone building through a direct control mechanism by aggregators. The novelty lies in considering the power market mechanism and dealing with the tradeoff between keeping commitment to the pre-planned energy budget and keeping comfort levels for the consumers. In the proposed approach, a high-level control layer determines hourly budget of energy for the whole building and proclaim it to an aggregator. At this level, aggregator signals such as power price are considered. A lower-level dispatch layer then distributes the pre-planned hourly energy budget among different zones. At this level, the emphasize is on keeping the energy consumption as near as possible to the pre-planned budget. In this study, a decentralized MPC with variable prediction horizon is developed for the lower-level dispatch layer. A centralized and a decentralized model predictive control (MPC) schemes for the high-level control layer are suggested and their performances are compared regarding keeping commitment and satisfying comfort levels. For simulation purpose, a detailed model of a multi zone building is developed in the IDA ICE

**Table 3**
Simulation results for 2nd Jan. 2020.

| Scenarios | mean commitment violation (%) | mean comfort violation (℃) | daily energy cost (€) | total daily used energy (kWh) | total available daily up-regulating energy (kWh) | total available daily down-regulating energy(kWh) |
|---|---|---|---|---|---|---|
| Centralized/ Comfort | 2.9 | 0.7 | 1.62 | 54.67 | 34.30 | 15.85 |
| Decentralized/ Comfort | 3.7 | 0.5 | 1.71 | 57.10 | 33.31 | 14.03 |
| Centralized/ Cost | 3.2 | 1.0 | 1.42 | 48.25 | 33.77 | 9.43 |
| Decentralized/Cost | 4.7 | 0.9 | 1.44 | 48.07 | 38.20 | 6.05 |

**Table 4**
Simulation results for 6th Oct. 2020.

| Scenarios | mean commitment violation (%) | mean comfort violation (°C) | daily energy cost (€) | total daily used energy (kWh) | total available daily up-regulating energy (kWh) | total available daily down-regulating energy(kWh) |
|---|---|---|---|---|---|---|
| Centralized/ Comfort | 4.4 | 0.5 | 0.68 | 20.52 | 34.05 | 5.85 |
| Decentralized/ Comfort | 6.9 | 0.4 | 0.96 | 29.69 | 25.56 | 12.32 |
| Centralized/ Cost | 4.6 | 0.6 | 0.67 | 19.69 | 35.46 | 4.97 |
| Decentralized/Cost | 4.0 | 0.4 | 0.83 | 24.57 | 33.32 | 9.33 |

environment along with a detailed model of HVAC system. The centralized and decentralized state space models are identified for the building and then the proposed hierarchical scheme is implemented in MATLAB environment. The communication between MATLAB and IDA ICE is stablished and co-simulations (MATLAB and IDA ICE) are done. The results show that the proposed scheme can keep its commitment to the aggregator to a large extent (by more than 93 %) while maintaining the comfort levels satisfactory. In addition, it is seen the centralized model demonstrates a better commitment to the pre-planned energy budget (between 0.5 % and 2.5 %) and reduces energy cost more at the cost of sacrificing comfort in comparison with the decentralized one. Moreover, some preliminary results regarding available up and down regulating power for residential buildings are reported for the first time that should be confirmed by future studies.

### CRediT authorship contribution statement

**Mahmood Khatibi:** Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft. **Samira Rahnama:** Conceptualization, Methodology, Software, Funding acquisition. **Pierre Vogler-Finck:** Conceptualization, Methodology. **Jan Dimon Bendtsen:** Conceptualization, Methodology, Supervision. **Alireza Afshari:** Conceptualization, Methodology, Funding acquisition, Project administration.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

### Data availability

Data will be made available on request.


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