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Model predictive control for building active demand response systems

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Abstract

The Active Demand Response (ADR), integrated with the distributed energy generation and storage systems, is the most common strategy for the optimization of energy consumption and indoor comfort in buildings, considering the energy availability and the balancing of the energy production from renewable sources. In the paper an overview of basic requirements and applications of ADR management is presented. Specifically, the model predictive control (MPC) adopted in several applications as optimal control strategy in the ADR buildings context is analysed. Finally the research experience of the authors in this context is described.

Peer-review under responsibility of KES International

Keywords: Demand side management; Active demand response; Economic model predictive control; Energy market; Smart grid.

1. Introduction

Buildings are often characterized by a high simultaneous energy demand, that corresponds to a considerable peak demand effort in the energy distribution grid. Peak demand is a considerable issue for both suppliers and energy customers due to financial and capacity related aspects. Moreover, the profiles of users energy demand and energy produced from renewable sources typically do not match: the non-simultaneity between demand and supply causes

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Nomenclature

ADR	Active Demand Response
APL	Active Power Loss
ATC	Available Transmission Capacity
DSM	Demand Side Management
DR	Demand Response
ECMS	Energy and Comfort Management Systems
EENS	Expected Energy Not Supplied
EMPC	Economic Model Predictive Control
HVAC	Heating, ventilating and air conditioning
ICT	Information and Communication Technologies
MPC	Model Predictive Control
NSGA	Non-Dominated Sorting Genetic Algorithm
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
RTP	Real Time Pricing
SG	Smart Grid
TOU	Time of Use

imbalances in the electrical system, and the advantages that users can obtain are followed by drawbacks in the distribution grid [1].

To overcome these problems current solutions are represented by energy accumulators and storage elements. However, especially in the electric field, these technologies do not allow for a proper balance of powers required by the electricity grid and they undermine the reliability of the whole system. For this reason, in recent years the concept of Smart Grid (SG) was introduced: an electrical system able to exchange not only energy flows but also information between the various components of the grid. In this regard it becomes possible to optimize energy consumptions with respect to energy availability using algorithms for the control of the SG [2, 3]. Demand Side Management (DSM) is an approach that actively manage energy demand and supply in order to satisfy customers comfort requirements and in the meanwhile to achieve economics and consumptions savings. Active Demand Response (ADR) is a particular case of DSM: the focus is on the short-term load handling. In particular, the goal is to follow a daily short-term schedule (e.g. hourly) which is periodically adapted according to external conditions (e.g. users behavior, weather conditions, market energy price, energy production available) such that the day-ahead load curve constraint is met.

The DSM is aimed at modulating the shape of the load consumptions curve through direct and indirect operations affecting customers demand profile. Generally, the shape is modulated such that loads are shifted, peaks shaved or demand curve is flattened. DSM is an integrant part of SG and requires a proper ICT infrastructure (e.g. communication system, sensors, actuators, advanced processors, etc.) in order to achieve a dynamic control of the demand. DSM, by promoting the interaction and responsiveness of the customers, determines short-term impacts on the electricity markets, leading to economic benefits for both customers and utility. Moreover, by improving the reliability of the power plant and, in the long term, by lowering peak demand, this strategy allows reduction of the overall plant, capital cost investments and postpones the need of network upgrades.

Energy systems are generally divided into five main sectors: Generation, Distribution/Transmission, Trading, Retailing, Consumptions. Generation main actors consist of power plants, providing energy through fossils or renewable sources. Distribution phase is based on Distribution System Operators (DSOs) and Transmission System Operator (TSOs), which in some cases redistribute energy to retailers [4]. However, wiring and retailing can be separated in some scenarios. Aggregators are responsible of trading phase, they sell energy to final users on a retail or wholesale market. Finally, the main actors of the consumption phase are customers, mostly related to commercial and residential building sectors. In this scenario, DSM plays an important role on retail phase: aggregators trade energy according to dynamic deregulated markets in order to influence the demand curve by regulating customers'

behaviour through particular rates. Fig. 1 shows a scenario focused on a specific DSM application on buildings: the forecasted load curve can be used for adapting the daily buildings energy need in order to meet the required load hour by hour.
Demand Response (DR) is a specific tariff or program that allows end-use customers to change their normal patterns in order to respond to changes in price or availability of electricity on the markets [2].

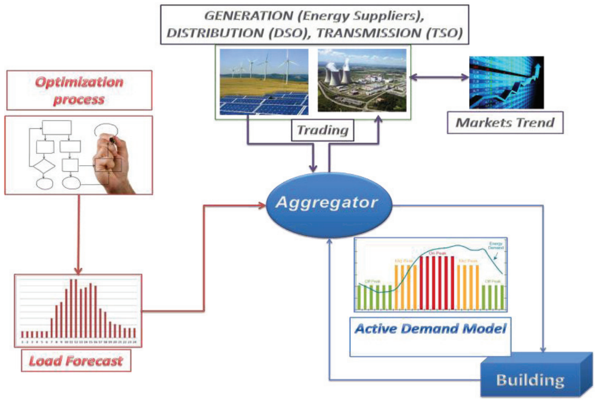


Fig.1 Example of an application scenario of DSM on residential and tertiary buildings.

End users can be directly or indirectly involved into the DR strategy. In the former scenario, they can perform load curtailment (e.g. dimming lights level, decreasing thermostat setpoints, etc.), consumptions shifting, for example by shifting heating/cooling phases into lower price time windows, or storage utilization (e.g. renewables). In the latter case, intermediary agents are involved, such as curtailment service providers, aggregators of retail customers or DR providers [5].
The paper is organized as follows. Section 2 explains how the DSM acts in the energy distribution systems through the DR policies. In Section 3 some applications in the buildings context of the ADR management by reviewing related literature, including applications of the MPC as optimal control strategy are described. In Section 4 some preliminary results of the authors research activities in progress in this perspective are presented. Finally in Section 5 the findings and conclusions are summarized.

2. Demand Response policies

DR policies can be divided into dispatchable, namely reactive policies that enable to provide energy when actually needed, and non-dispatchable, whose policies are proactive based and need to be properly scheduled. Among these two categories, different approaches were summarized in [3, 4]:

- Non-Dispatchable:

  – *Dynamic Pricing*. In this category, the approach is to influence the demand by driving customers behaviour according to global load requirements, through a dynamic price of the energy. Prices can vary on an hourly, daily or even a monthly basis. Lower fares during off-peaks periods encourage users to reschedule their activities. Most common dynamic pricings are:

    - Time of Use (TOU): it is a very diffused tariff, generally daily changing with fixed blocks of pricing rates;
    - Critical Peak Pricing: employed for commercial and industrial customers, it is an event-based tariff that triggers when critical peaks occur, and apply very high energy rates;
    - Real Time Pricing (RTP): the rates change very fast, generally with hourly basis, depending to wholesale market prices.

- Dispatchable:
  - *Incentive Based*. Such approach is event based: a reward is guaranteed to customers for providing load reduction when particular events occur such as emergency, ancillary services or even interruptions. In Direct Load Control, customers allow a degree of control on their own equipment. Such approaches are very reliable, as the response of the users to events is fast and can overcome problems at system level.
  - *Demand Reduction Bids*. Customers actively propose a bid of a remunerated load reduction to aggregators.

A DSM approach could lead to several benefits involving many aspects:

- Reducing generation margin. The total capacity of installed generation is generally larger than the system maximum demand in order to ensure the security of supply in case of exceptional events. It is estimated by Central Electricity Generating Board that margins account to 25%. Strbac [6] investigated the magnitude of shortages and their frequency in UK using a simplified generation model. According to his study, instead of dealing with such shortages by installing generation surplus systems that would be used very infrequently, it may be possible to identify house- holds that would be willing (for a fee) to forgo consumption relatively infrequently.
- Improving transmission system. Transmission infrastructures historically are designed for supporting large scale generation technologies. Moreover, for avoiding overloads due to circuit fails, they are based on a redundant network structure. A DSM approach can overcome those failures through load curtailing, allowing a proper design of the network.
- The non-dispatchable and non completely predictable nature of renewable sources as wind and solar power has somehow limited their penetration in energy markets and distribution supply. DSM can improve their usefulness, rescheduling load peaks during high renewable supply and, on the other hand, decreasing demand during low renewable production.

Despite those advantages, also some drawbacks arise [1]. The current markets structure is centralized and homogeneous, thus does not suit properly the flexibility required by DSM. Moreover, since benefits of DSM affect a considerable amount of different entities, it is challenging to identify a business model that justifies the investments [7]. Customers, especially in residential sector, do not always behave in economically rational manner: a study of Thorsnes et al. [8] demonstrated that price changes are not linearly related to consumptions changes, as the bill is not always the first concern of the customers.

3. Optimal control strategies in the ADR building context

An efficient building energy management is essential for the reduction of power demands and greenhouse gas emissions [9, 10]. Buildings sector accounts for about 40% of total final energy consumption and more than 50% is due to heating, ventilation and air conditioning (HVAC) systems [11, 12, 13]. Thus, the challenge concerning building control systems is to find a compromise between user comfort and energy consumption. In particular, with regards to the ADR scenario, the energy and comfort management systems (ECMS) have the main objective to accomplish the comfort of occupants and reducing energy consumption, taking into account the energy market price variation. The ECMSs base their operations on intelligent control systems (ICS),which use ICT infrastructure [14]. They commonly require functions including indoor comfort parameters (as for example thermal, humidity, indoor air quality and illumination levels), occupant preferences and energy control [14]. The following Subsections illustrate some literature examples of optimal control strategies provided by ECMSs in the ADR building context, with particular attention to MPC applications. Then, in the next Section, the first research experiences gained by the authors in this regard are described.

3.1. Demand side management applications

Several approaches have been proposed recently for DSM. Faria et al. [15] used a simulation based analysis for minimizing the final users energy cost in a DR scenario. Simulator developed is based on Power System CAD for the network modeling and on MATLAB for DR plan management and users' behavior modeling. Customers have been divided into 5 categories (domestic, small commerce, medium commerce, large commerce and industrial). Each one has its proper tariff plans and demand curve characterization. The simulator has been used for fitness evaluation of a Particle Swarm based optimization.

Nguyen et al. [16] proposed a multi-objective optimization approach based on NSGA-II. He tried to optimize a 4 objective functions problem: maximizing Available Transmission Capacity (ATC), while minimizing Expected Energy Not Supplied (EENS), Active Power Loss (APL) and DR programs capacity. ATC is a measure of the transfer capability in the physical transmission network for future commercial activities over already committed uses. Adequate ATC is needed to ensure all economic transactions to be achieved. EENS index evaluates composite system reliability for the power system [17]. APL provides an evaluation on the idle-time of the slack node in a transmission system. Finally, DR programs capacity represents the total power capacity available through DR plans. For the optimization phase, a binary coded parameterization has been used, since problem described is discretized.

Schibuola et al. [18] showed how control strategies aimed at DR management within dynamic price-driven electricity markets may ensure good performances. A typical apartment with HVAC system was simulated, and actual prices and weather conditions were considered. The HVAC consists of a heat pump coupled with a solar thermal plant and a photovoltaic (PV) system. In particular, three control strategies were applied, whose action is based on the cost of electricity (absolute and relative to the following 12 h) and on the level of the local electricity generation from PV. The simulations showed that through proper control strategies is possible to achieve relevant money savings and high degrees of energy self-consumption.

Gelazanskas [2] proposed a model predictive control (MPC) aiming at keeping actual load curve as close as possible to desired one, and is based on a Neural Network model predicting future price to be used for achieving desired load amount. Input variables are time, weather conditions, desired and actual load.

Since most promising improvements on DR context can be achieved through fast changing dynamics such as RTP, an MPC approach can be suitable for such problems. Moreover inputs constrained and known disturbances simplify its application.

3.2. Model predictive control applications

The MPC [19] is an optimal control technique that at each time step uses the measurements of the state and a mathematical model of the system in order to predict the system evolution; moreover, the optimization of an objective function allows to reach the desired system behavior. MPC can take into account the possible operational constraints that have to be satisfied and the predictions of the possible disturbances affecting the system. MPC strategies, in addition to the need of system modeling, usually have high computational requirements. Although these issues have to be overcome, this model-based approach does not need large amounts of data from specific buildings, as data- driven models do, and from its application high energy savings can be reached.

In literature, the mainly employed control systems for building ECMS are MPC [14, 20]. MPC is also one of the most adopted DR modeling approach [1, 14, 20] based on the perfect knowledge of the system (i.e. the responsive appliances). Significant peak demand reduction were shown by several studies of model-based DR control with a time-varying rate [21]: Economic MPC (EMPC) is gradually becoming popular for managing energy consumption in buildings subject to variable energy prices, such as TOU prices or RTP. These energy prices are employed directly in the objective function of the EMPC problem. The model considers how energy prices can be designed in order to achieve a specific objective, which often is the minimization of peak energy demand. EMPC is a useful tool for managing building energy systems (e.g. HVAC) and it is effective for both the operating systems based on a variable pricing structure and the determination of the optimal variable prices for a given system [22]. Using these techniques, in a closed loop control scheme is possible to exploit the dynamic effects of the system to properly match the supply.

Night pre-cooling or pre-heating in buildings was an important way to shift energy demand for decades. The EMPC technique was successfully used to reduce further more peak demand through a more accurate adjusting of temperature set-points in HVAC systems, as described in [21]. In this work [21] the authors propose a closed-loop control system based on an EMPC technique to reduce energy and demand costs for HVAC systems of commercial buildings considering real-time uncertainties and constraints. The economic objective function in MPC accounts for the daily electricity costs and the optimization problem aimed at minimizing them. It was shown by a weekly simulation that under the TOU electrical pricing structure, EMPC brings substantial cost savings by automatically triggering pre-cooling effect and shifting the peak demand away from on-peak hours.

Oldewurtel et al. [23] showed that in the building HVAC control the peak electricity demand relative to a given reference load curve can effectively be reduced by incorporating an appropriate electricity RTP tariff directly into the cost function of a MPC strategy. They proposed an hourly-based electricity tariff for end-consumers, designed to reflect costs of electricity provision, based on spot market prices as well as on electricity grid load levels. They used least-squares support vector machines for electricity tariff price forecasting, and thus provide the MPC controller with the necessary estimated time-varying costs for the whole prediction horizon. In the given context, the hourly pricing provides an economic incentive for a building controller to react sensitively with respect to high spot market electricity prices and high grid loading, respectively. By simulations it was shown that a grid-friendly behavior was rewarded.

Zong et al. [24] presented an example of a MPC for electrical heaters control to maximize the use of local generation (e.g. solar power) in an intelligent building. The MPC is based on dynamic power price and weather forecast, considering an optimization objective such as minimum cost and minimum reference temperature error. The authors demonstrated that this MPC strategy can realize load shifting in periods with low prices and maximize the PV self-consumption in the residential sector. They expect that this demand side control study can considerably save energy, as the end users can avoid high electricity price charge at peak time, and improve grid reliability, when there is a high penetration of Renewable Energy Sources in the power system.

In [22] an EMPC problem is presented to determine optimal prices that minimize the peak electricity demand. The system was a simulated community of 900 residential homes where thermostat set-points could be automatically controlled. The key feature of this formulation considers a centralized problem (e.g., minimizing peak electricity demand) and implements it in a decentralized framework using pricing. For the presented cluster of homes, the optimal pricing profiles were relatively low prices for every hour except for the peak hour. This pricing structure was able to reduce peak demand by 9.6% when implemented in a decentralized control considering the minimum cost EMPC formulation, compared to the 10% peak reduction with the centralized control and minimum peak demand formulation.

In their work, Mendoza-Serrano and Chmielewski [25] discussed the effect of thermal energy storage in reducing operating costs related to HVAC systems for building temperature control. In particular they used the EMPC in combination with thermal energy storage to time-shift power consumption away from periods of high demand to periods of low energy cost. Dynamic electricity pricing and weather condition forecasts were incorporated within the methodology. The authors also considered the capital costs associated with thermal energy storage and proposed an optimization framework aimed at providing the proper balance between equipment costs and operational savings.

The paper of Ma et al. [26] presents an EMPC for the optimization of the set-points in HVAC systems for load shifting and cost minimization under the TOU price policy. In order to ensure the proper building operations, the economic objective function accounted for: the combination of energy and demand costs with a TOU rate structure; a dynamic thermal process and power model of the building thermal mass dynamics; a set of constraints. The effectiveness of EMPC in energy cost savings was demonstrated using simulation: the EMPC strategy was capable of shifting the peak demand in off-peak hours and reducing energy costs compared to a baseline case for the building.

4. The experience of the Smart Village

Since 2012, the authors are involved in a research project aimed at developing a small prototype of a Smart City, called Smart Village, inside ENEA Casaccia Research Centre (Rome). Several buildings located in the Centre are equipped with an advanced monitoring system aimed at collecting energy consumption (electrical and thermal) and the environmental conditions. One relevant activity carried on concerns the optimal control of a building located in the Smart Village considering HVAC consumption and users comfort requirements through a DR approach. Then first results related to a research experience in the context of MPC of indoor temperatures are presented.

4.1. Day-ahead demand response for a multi-zone building: experimental set up Casaccia Research Centre

In this activity, a genetic based multi-objective algorithm (NSGA-II) is used for optimizing the day-ahead setpoints of rooms thermostats and the water supply temperature of the thermal plant of building ‘F40’in the Smart Village, according to weather data and occupancy forecasting. In order to evaluate building performance in terms of consumptions and comfort, a white box approach was used based on a MATLAB Simulink simulator of the building. The goal of the optimization is to find optimal indoor set-points of different zones and optimal thermal plant supply water in order to minimize thermal consumptions and maximize users comfort. Thermal comfort was formulated in terms of Percentage of Person Dissatisfied (PPD) and PMV (Predictive Mean Vote). PMV is a comfort index introduced by Fanger [27] and is based on variables depending on environment and user subjective factors.
As baseline, the setting parameters used before the remote control installation are:

- Supply Water Temperature: 65°C;
- Supply Water Flow: 42000 kg/h;
- Indoor Air Temperature: 21 °C.

Since an online daily optimization in a continuous research space based on a simulator would be unlikely to be applied, and a too small change on thermostats set-points would not affect actuators, the research space was discretized. The bounds of the design variables are shown in Table 1.

Table 1.Parameters bounds.

Variable	Lower Bound	Upper Bound	Step
Indoor Temperature [°C]	17.5	22.5	0.5
Supplied Water Temperature [°C]	30	80	1

As a first step, an exhaustive research on the entire space was performed: a comparison between the baseline and the obtained Pareto front has been carried out. As testing period, three months of heating period were considered. Fig. 2 shows the baseline solution compared with two Pareto fronts: one obtained simulating fan-coils always turned on, and another one where the fan-coils are turned on only 12 hours (07:00 – 19:00).

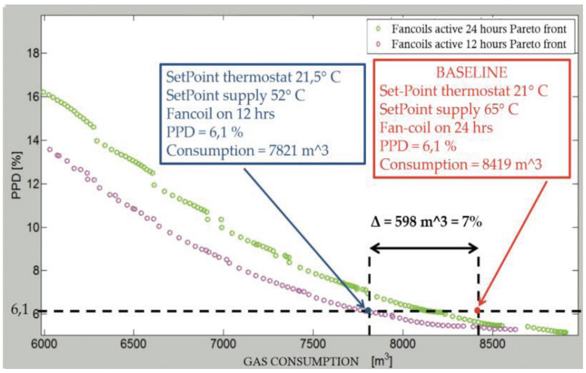


Fig. 2 Exhaustive Search.

The Pareto fronts obtained are seasonal, thus for the whole 89 days constant set-point temperatures of the rooms thermostats and water supply were set. As shown in Fig. 2, the baseline solution is dominated in both Pareto fronts, and 7% of energy saving can be obtained without affecting comfort level.

Successively, an optimization based on NSGA-II algorithm was performed. In order to investigate overall benefits of applying a daily approach over a seasonal approach, both tests using the same number of fitness performance evaluations were performed. Fig. 3 shows the front obtained through optimization and the best Pareto, namely the non-dominated set obtained over all 612 combinations. As trade-off between energy consumption savings and thermal comfort, a PPD threshold of 10%, according to UNI EN ISO 7330 requirements, was selected. The closest value obtained is 9.1%, which led to 18.7% total saving.

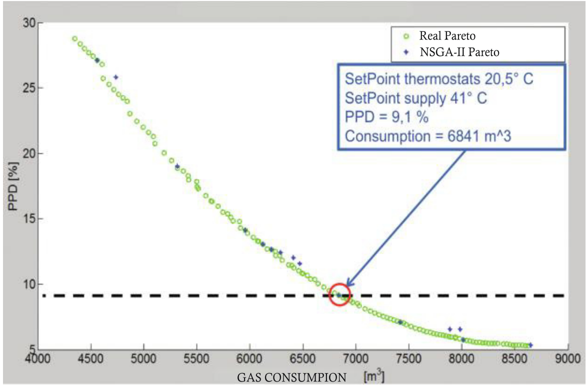


Fig. 3. Optimized Pareto front.

It is worth to highlight that although many application cases are based on electric consumption, remarkable results can be obtained on thermal consumptions too. Indeed, contour conditions as weather, pricing, stored resources and renewables availability influence the optimization results and then the best control strategy to be used.

This approach is going to be improved introducing the energy cost as a further objective function.

4.2. Adaptive model predictive control of the indoor temperatures of a multi-zone building

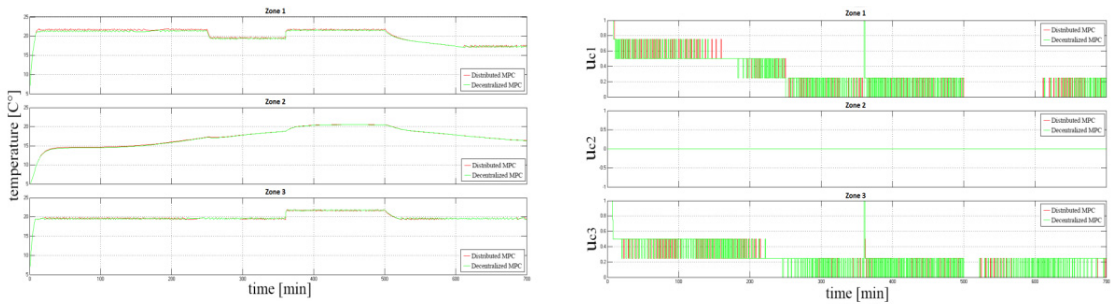
In a latter approach, an adaptive MPC of the indoor temperatures of a three-zones office building is proposed [28]. In order to reduce the energy consumption, at each simulation step the information about the occupancy level of each zone (four different occupancy levels ranging between 0 and 1 were considered) was used for calculating the proper control action with a prediction horizon of 10 minutes. In particular, two adaptive strategies were adopted: dynamic temperature set-points and dynamic weighting coefficients of the objective function. The experimentation was carried out first considering the thermal coupling between the zones implementing a distributed MPC architecture. Then a decentralized MPC architecture (without the thermal coupling between the zones) was also analysed. The results were evaluated in terms of energy consumption and comfort level defined by the indoor operative temperatures. In the experimentation an entire working day with four different time periods, correspondent to different occupancy levels for each zone, was considered. For the results evaluation, two performance indices were adopted: for the comfort, when the occupancy level is maximum, the daily average distance of actual indoor temperatures from set-points temperatures in the whole building, MAE_{TOT}; for the consumption, the total air mass flow rate through fan-coil units in the whole building, M_{tot}.

Both adaptive (that take in account the occupancy level of each zone) and non-adaptive (that do not take in account the occupancy level of each zone) MPC strategies followed very well the temperature set-points profiles in each time period of the day. This is also evident from MAE_{TOT} results reported in Table 2: each configuration reports small temperature errors and distributed MPC presents smaller errors than decentralized one. Looking at Table 2, the great advantage of using an adaptive MPC strategy is evident: the results related to M_{tot} confirm that the control effort, and then the energy consumption, of an adaptive MPC configuration is much lower than non-adaptive strategy. The adaptive strategies take in account the occupancy level of each zone in order to control the indoor temperatures. In particular, the distributed MPC strategy with dynamic weighting coefficients offers the best performances in terms of comfort and consumptions, but on the other hand it requires a preliminary tuning phase very accurate and not so immediate of the coefficients.

Table 2. Adaptive and non-adaptive MPC results comparison.

Dynamic Temperature Setpoints	MAE_{TOT} [°C]	M_{tot} [kg]
Distributed	0.084	3029
Decentralized	0.130	2954
Dynamic Weighting Coefficients	MAE_{TOT} [°C]	M_{tot} [kg]
Distributed	0.035	2148
Decentralized	0.051	2187
Non-adaptive MPC	MAE_{TOT} [°C]	M_{tot} [kg]
Distributed	0.073	4223
Decentralized	0.105	4117

In Fig. 4(a) the temperature evolutions in each zone of the building during the experimentation day, resulting from the application of dynamic temperature set-points MPC strategy, are shown. In this case, when a zone is fully occupied, the set-point temperature is 22°C. It can be observed that the central zone, characterized by occupation 0 for the whole day, reaches anyway temperatures of about 20 °C due to the thermal exchanges with zone 1 and zone 3. The control action evolutions in each zone of the building, resulting from the application of dynamic temperature set-points MPC strategy, are shown in Fig. 4(b). The fan-coil of the zone *i* supplies hot air at temperature and an air mass flow rate depending on the MPC control signal $u_{c,i}$ ranging between 0 and 1. For a more realistic simulation, only 5 possible values between 0 and 1 with a step of 0.25 were defined for the control signals. In Fig. 4(b) it can be observed that the control signal for the second zone is always 0 because this zone is unoccupied for the whole day.



(a) (b)

Figure 4.Temperature behavior (a) and control signals (b) obtained by MPC distributed and MPC decentralized with dynamic temperature set-points for each zone.

The distributed MPC strategy with dynamic weighting coefficients of the objective function was found to be the best one in terms of energy consumptions and comfort levels. However the dynamic temperature set-points strategy was easier to apply. Future works will focus on the transition of this MPC application to an EMPC strategy, considering the energy price in the objective function and a greater (e.g. 6, 12 or 24 hours) prediction horizon.

5. Conclusions

In this paper the advantages connected to the application of MPC strategies applied to the ADR buildings context was presented. The benefits of such approach were showed in terms of optimal control of consumptions, indoor comfort level and costs. DSM and ADR strategies allow to increase grid capacity, efficiency, reliability, power quality, sustainability and most of them are based on load shifting strategies. In order to optimize the demand profile, these techniques use scheduling algorithms based on an intensive communication about the day-ahead between utility and users. The more recent DSM techniques lie on the utility side and sometimes are difficult to be understood by the users, so more initiatives for encouraging their participation are needed. Another critical aspect is the system-model mismatch: in order to ensure that DSM algorithms work efficiently, a very accurate representation of system model is needed. Devices whose functions are not time-critical (as HVAC systems) should be assumed to be really deferrable. In this regard, the first research experiences gained by the authors in the ADR building context with particular attention to MPC applications were presented. Two research activities were carried on concerning the optimal control of HVAC consumption and users comfort requirements, highlighting the energy savings obtained. Future works will consider also the energy price as a further optimal control variable in the EMPC context.

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