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POLYTECHNIQUE MONTRÉAL
affiliée à l'Université de Montréal

Model Predictive Control For Demand Response Management Systems in Smart Buildings

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*
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Cette thèse intitulée :

Model Predictive Control for Demand Response Management Systems in Smart Buildings

présentée par **Saad ABOBAKR**
en vue de l'obtention du diplôme de *Philosophiæ Doctor*
a été dûment acceptée par le jury d'examen constitué de :

David SAUSSIÉ, président
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DEDICATION

To my parents and my wife, for their support and Doaa,

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This PhD thesis becomes a reality with the kind support and help of many individuals, I would like to extend my sincere thanks to all of them.

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RÉSUMÉ

Les bâtiments représentent une portion importante de la consommation énergétique globale. Par exemple, aux USA, le secteur des bâtiments est responsable de 40% de la consommation énergétique totale. Plus de 50% de la consommation d'électricité est liée directement aux systèmes de chauffage, de ventilation et de climatisation (CVC). Cette réalité a incité beaucoup de chercheurs à développer de nouvelles solutions pour la gestion de la consommation énergétique dans les bâtiments, qui impacte la demande de pointe et les coûts associés.

La conception de systèmes de commande dans les bâtiments représente un défi important car beaucoup d'éléments, tels que les prévisions météorologiques, les niveaux d'occupation, les coûts énergétiques, etc., doivent être considérés lors du développement de nouveaux algorithmes. Un bâtiment est un système complexe constitué d'un ensemble de sous-systèmes ayant différents comportements dynamiques. Par conséquent, il peut ne pas être possible de traiter ce type de systèmes avec un seul modèle dynamique. Récemment, différentes méthodes ont été développées et mises en application pour la commande de systèmes de bâtiments dans le contexte des réseaux intelligents, parmi lesquelles la commande prédictive (*Model Predictive Control* - MPC) est l'une des techniques les plus fréquemment adoptées. La popularité du MPC est principalement due à sa capacité à gérer des contraintes multiples, des processus qui varient dans le temps, des retards et des incertitudes, ainsi que des perturbations.

Ce projet de recherche doctorale vise à développer des solutions pour la gestion de consommation énergétique dans les bâtiments intelligents en utilisant le MPC. Les techniques développées pour la gestion énergétique des systèmes CVC permet de réduire la consommation énergétique tout en respectant le confort des occupants et les contraintes telles que la qualité de service et les contraintes opérationnelles. Dans le cadre des MPC, différentes contraintes de capacité énergétique peuvent être imposées pour répondre aux spécifications de conception pendant la durée de l'opération. Les systèmes CVC considérés reposent sur une architecture à structure en couches qui réduit la complexité du système, facilitant ainsi les modifications et l'adaptation. Cette structure en couches prend également en charge la coordination entre tous les composants. Étant donné que les appareils thermiques des bâtiments consomment la plus grande partie de la consommation électrique, soit plus du tiers sur la consommation totale d'énergie, la recherche met l'emphase sur la commande de ce type d'appareils. En outre, la propriété de dynamique lente, la flexibilité de fonctionnement et l'élasticité requise pour les performances des appareils thermiques en font de bons candidats pour la gestion réponse à la demande (*Demand Response* - DR) dans les bâtiments intelligents.

Nous étudions dans un premier temps la commande des bâtiments intelligents dans le cadre des systèmes à événements discrets (DES). Nous utilisons le fonctionnement d'ordonnancement fournie par cet outil pour coordonner l'opération des appareils thermiques de manière à ce que la demande d'énergie de pointe puisse être déplacée tout en respectant les contraintes de capacités d'énergie et de confort. La deuxième étape consiste à établir une nouvelle structure pour mettre en œuvre des commandes prédictives décentralisées (*Decentralized Model Predictive Control* - DMPC). La structure proposée consiste en un ensemble de sous-systèmes contrôlés par MPC localement et un contrôleur de supervision basée sur la théorie du jeu permettant de coordonner le fonctionnement des systèmes de chauffage tout en respectant le confort thermique et les contraintes de capacité. Dans ce système de commande hiérarchique, un ensemble de contrôleurs locaux travaille indépendamment pour maintenir le niveau de confort thermique dans différentes zones, tandis que le contrôleur de supervision central est utilisé pour coordonner les contraintes de capacité énergétique et de performance actuelle. Une optimalité globale est assurée en satisfaisant l'équilibre de Nash (NE) au niveau de la couche de coordination. La plate-forme Matlab/Simulink ainsi que la boîte à outils YALMIP de modélisation et d'optimisation ont été utilisées pour mener des études de simulation afin d'évaluer la stratégie développée.

La recherche a ensuite porté sur l'application de MPC non linéaire à la commande du débit de l'air de ventilation dans un bâtiment basé sur le modèle prédictif de dioxyde de carbone CO_2. La commande de linéarisation par rétroaction est utilisée en cascade avec la commande MPC pour garantir que la concentration de CO_2 à l'intérieur du bâtiment reste dans une plage limitée autour d'un point de fonctionnement, ce qui améliore à son tour la qualité de l'air intérieur (*Interior Air Quality* - IAQ) et le confort des occupants. Une approximation convexe locale est utilisée pour faire face à la non-linéarité des contraintes tout en assurant la faisabilité et la convergence des performances du système. Tout comme dans la première application, cette technique a été validée par des simulations réalisées sur la plate-forme Matlab/Simulink avec la boîte à outils YALMIP.

Enfin, pour ouvrir la voie à un cadre pour la conception et la validation de systèmes de commande de bâtiments à grande échelle et complexes dans un environnement de développement plus réaliste, nous avons introduit un ensemble d'outils de simulation logicielle pour la simulation et la commande de bâtiments, notamment EnergyPlus et Matlab/Simulink. Nous avons examiné la faisabilité et l'applicabilité de cet ensemble d'outils via des systèmes de commande CVC basés sur DMPC développés précédemment. Nous avons d'abord généré le modèle d'espace d'état linéaire du système thermique à partir des données EnergyPlus, puis nous avons utilisé le modèle d'ordre réduit dans la conception de DMPC. Ensuite, la performance du système a été validée en utilisant le modèle originale. Deux études de cas représentant deux bâtiments réels sont prises en compte dans la simulation.

ABSTRACT

Buildings represent the biggest consumer of global energy consumption. For instance, in the US, the building sector is responsible for 40% of the total power usage. More than 50% of the consumption is directly related to heating, ventilation and air-conditioning (HVAC) systems. This reality has prompted many researchers to develop new solutions for the management of HVAC power consumption in buildings, which impacts peak load demand and the associated costs.

Control design for buildings becomes increasingly challenging as many components, such as weather predictions, occupancy levels, energy costs, etc., have to be considered while developing new algorithms. A building is a complex system that consists of a set of subsystems with different dynamic behaviors. Therefore, it may not be feasible to deal with such a system with a single dynamic model. In recent years, a rich set of conventional and modern control schemes have been developed and implemented for the control of building systems in the context of the Smart Grid, among which model redictive control (MPC) is one of the most-frequently adopted techniques. The popularity of MPC is mainly due to its ability to handle multiple constraints, time varying processes, delays, uncertainties, as well as disturbances.

This PhD research project aims at developing solutions for demand response (DR) management in smart buildings using the MPC. The proposed MPC control techniques are implemented for energy management of HVAC systems to reduce the power consumption and meet the occupant's comfort while taking into account such restrictions as quality of service and operational constraints. In the framework of MPC, different power capacity constraints can be imposed to test the schemes' robustness to meet the design specifications over the operation time. The considered HVAC systems are built on an architecture with a layered structure that reduces the system complexity, thereby facilitating modifications and adaptation. This layered structure also supports the coordination between all the components. As thermal appliances in buildings consume the largest portion of the power at more than one-third of the total energy usage, the emphasis of the research is put in the first stage on the control of this type of devices. In addition, the slow dynamic property, the flexibility in operation, and the elasticity in performance requirement of thermal appliances make them good candidates for DR management in smart buildings.

First, we began to formulate smart building control problems in the framework of discrete event systems (DES). We used the schedulability property provided by this framework to coordinate the operation of thermal appliances so that peak power demand could be shifted

while respecting power capacities and comfort constraints. The developed structure ensures that a feasible solution can be discovered and prioritized in order to determine the best control actions. The second step is to establish a new structure to implement decentralized model predictive control (DMPC) in the aforementioned framework. The proposed structure consists of a set of local MPC controllers and a game-theoretic supervisory control to coordinate the operation of heating systems. In this hierarchical control scheme, a set of local controllers work independently to maintain the thermal comfort level in different zones, while a centralized supervisory control is used to coordinate the local controllers according to the power capacity constraints and the current performance. A global optimality is ensured by satisfying the Nash equilibrium (NE) at the coordination layer. The Matlab/Simulink platform along with the YALMIP toolbox for modeling and optimization were used to carry out simulation studies to assess the developed strategy.

The research considered then the application of nonlinear MPC in the control of ventilation flow rate in a building based on the carbon dioxide CO_2 predictive model. The feedback linearization control is used in cascade with the MPC control to ensure that the indoor CO_2 concentration remains within a limited range around a setpoint, which in turn improves the indoor air quality (IAQ) and the occupants' comfort. A local convex approximation is used to cope with the nonlinearity of the control constraints while ensuring the feasibility and the convergence of the system performance. As in the first application, this technique was validated by simulations carried out on the Matlab/Simulink platform with YALMIP toolbox.

Finally, to pave the path towards a framework for large-scale and complex building control systems design and validation in a more realistic development environment, we introduced a software simulation tool set for building simulation and control, including EneryPlus and Matlab/Simulation. We have addressed the feasibility and the applicability of this tool set through the previously developed DMPC-based HVAC control systems. We first generated the linear state space model of the thermal system from EnergyPlus, then we used a reduced order model for DMPC design. Two case studies that represent two different real buildings are considered in the simulation experiments.

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NOTATIONS AND LIST OF ABBREVIATIONS

NRCan	Natural Resources Canada
GHG	Greenhouse gas
DR	Demand response
DREAM	Demand Response Electrical Appliance Manager
PFP	Proportionally fair price
DSM	Demand-side management
AC	Admission controller
LB	Load balancer
DRM	Demand response management
HVAC	Heating, ventilation , and air conditioning
PID	Proportional-derivative-Integral
MPC	Model Predictive Control
MINLP	Mixed Integer Nonlinear Program
SREAM	Demand Response Electrical Appliance Manager
DMPC	Decentralized Model Predictive Control
DES	Discrete Event Systems
NMPC	Nonlinear Model Predictive Control
MIP	mixed integer programming
IAQ	Indoor air quality
FBL	Feedback linearization
VAV	Variable air volume
FSM	Finite-state machine
NE	Nash Equilibrium
IDF	EnergyPlus input data file
PRBS	Pseudo-Random Binary Signal

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CHAPTER 1 INTRODUCTION

1.1 Motivation and Background

The past few decades have shown the world's ever-increasing demand for energy, a trend that will only continue to grow. There is mounting evidence that energy consumption will increase annually by 28% between 2015 and 2040, as shown in Figure 1.1. Most of this demand for higher power is concentrated in countries experiencing strong economic growth; most of these are in Asia, predicted to account for 60% of the energy consumption increases in the period from 2015 through 2040 [2].

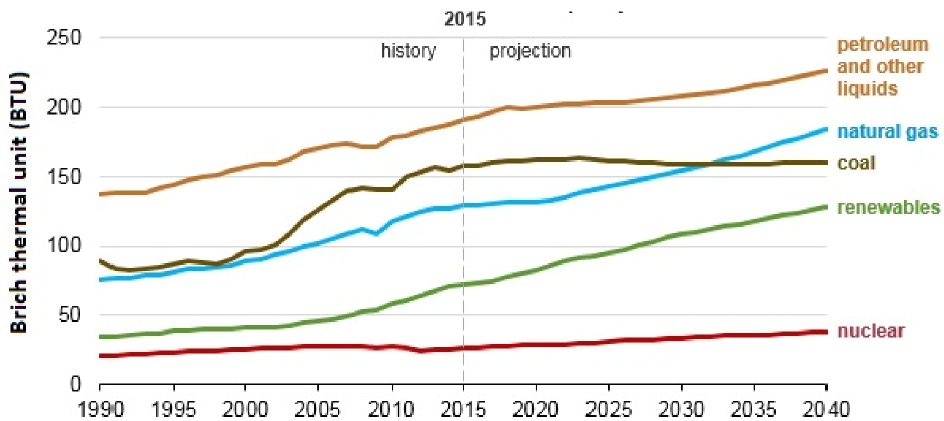

Figure 1.1 World energy consumption by energy source (1990-2040) [2].

Almost $20 - 40\%$ of the total energy consumption today comes from the building sectors, and this amount is increasing annually by $0.5 - 5\%$ in developed countries [8]. For instance, according to Natural Resources Canada (NRCan), and as shown in Figure 1.2, residential, commercial, and institutional sectors account for almost 37% of the total energy consumption in Canada [3].

In the context of greenhouse gas (GHG) emissions and their known adverse effects on the planet, the building sector is responsible for approximately 30% of the GHG emission released to the atmosphere each year [9]. For example, this sector accounts for nearly 11% of the total emissions in the US and in Canada [10, 11]. In addition, the increasing number and variety of appliances and other electronics generally require a high power capacity to guarantee the quality of services, which accordingly leads to increasing operational cost [12].

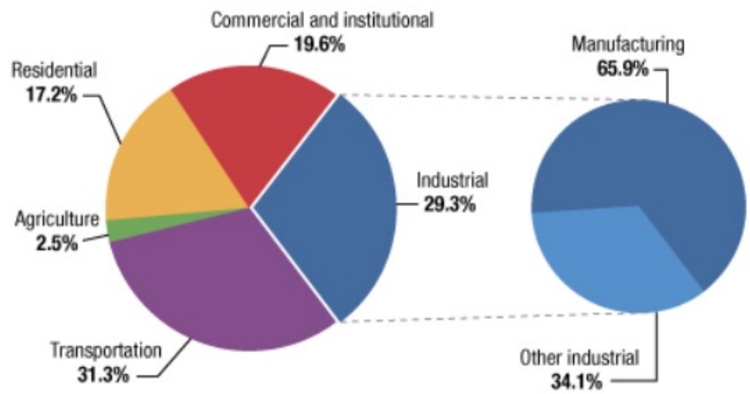

Figure 1.2 Canada's secondary energy consumption by sector, 2009 [3].

It is therefore economically and environmentally imperative to develop solutions to reduce buildings' power consumption. The emergence of the Smart Grid provides an opportunity to discover new solutions to optimize the total power consumption while reducing the operational costs in buildings in an efficient and cost-effective way that is beneficial for people, and the environment [13–15].

1.2 Smart Grid and Demand Response Management

In brief, a smart grid is a comprehensive use of the combination of sensors, electronic communication, and control strategies to support and improve the functionality of power systems [16]. It enables two-way energy flows and information exchanges between suppliers and consumers in an automated fashion [15, 17]. The benefits from using intelligent electricity infrastructures are manifold, for consumers, the environment, and the economy [14, 15, 18]. Furthermore, and most importantly, the smart grid paradigm allows improving power quality, efficiency, security, and reliability of energy infrastructures [19].

The ever-increasing power demand has placed a massive load on power networks worldwide [20]. Building new infrastructures to meet the high demand for electricity and to compensate for the capacity shortage during peak load times is a non-efficient classical solution increasingly being questioned for several reasons (e.g., larger upfront costs, contributing to the carbon emissions problem) [21–23]. Instead, we should leverage appropriate means to accommodate such problems and improve the grid's efficiency. With the emergence of the Smart Grid, demand response (DR) can have a significant impact on supporting power grid efficiency and reliability [24, 25].

The DR is an another contemporary solution that can increasingly be used to match consumers' power requests with the needs of electricity generation and distribution. DR incorporates the consumers as a part of the load management system, helping to minimize the peak power demand as well as the power costs [26, 27]. When consumers are engaged in the DR process, they have the access to different mechanisms that impact on their use of electricity, including [28, 29]:

- shifting the peak load demand to another time period;
- minimizing energy consumption using load control strategies; and
- using energy storage to support the power requests, thereby reducing their dependency on the main network.

DR programs are expected to accelerate the growth of the Smart Grid in order to improve end-users' energy consumption and to support the distribution automation. In 2015, North America accounted for the highest revenue share of the worldwide DR. For instance, in the US and Canada, buildings are expected to be gigantic potential resources for DR applications wherein the technology will play an important role in DR participation [4]. Figure 1.3 shows the anticipated Demand Response Management Systems' market by building type in the U.S between 2014 and 2025. DR has become a promising concept in the application of the Smart

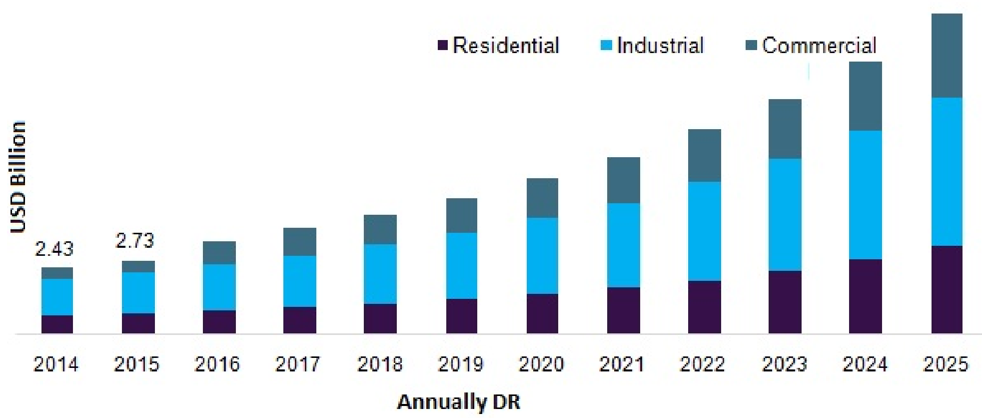

Figure 1.3 DR management systems market by applications in U.S (2014-2025) [4].

Grids and the electricity market [26, 27, 30]. It helps power utility companies and end-users to mitigate peak load demand and price volatility [23]; a number of studies have shown the influence of DR programs on managing buildings' energy consumption and demand reduction.

DR management has been a subject of interest since 1934 in the US. With increasing fuel prices and growing energy demand, finding algorithms for DR management became more common starting in 1970 [31]. [32] showed how the price of electricity was a factor to help heavy power consumers make their decisions regarding increasing or decreasing their energy consumption. Power companies would receive the requests from consumers in their bids and the energy price would be determined accordingly. Distributed DR was proposed in [33] and implemented on the power market, where the price is based on grid load. The concept depends on the proportionally fair price (PFP) demonstrated in an earlier work [34]. The work in [33] focused on the effects of considering the congestion pricing notion on the demand and on the stability of the network load. The total grid capacity was taken into account, such that the more consumers pay, the more sharing capacity they obtain. [35] presented a new DR scheme to maximize the benefits for DR consumers in terms of fair billing and cost minimization. In the implementation, they assume that the consumers share a single power source.

The purpose of the work [36] was to find an approach that could reduce peak demand during the peak period in a commercial building. The simulation results indicated that two strategies (pre-cooling and zonal temperature reset) could be used efficiently; shifting $80-100\%$ of the power load from on-peak to off-peak time. An algorithm is proposed in [37] for switching the appliances in single homes on or off, shifting and reducing the demand at specific times. They accounted for a type of prediction when implementing the algorithm. However, the main shortcoming of this implementation was that only the current status was considered when making the control decision.

As part of a study about demand-side management (DSM) in smart buildings [5], a particular layered structure as shown in Figure 1.4 was developed to manage power consumption of a set of appliances based on a scheduling strategy. In the proposed architecture, energy management systems can be divided into several components in three layers: an admission controller (AC), a load balancer (LB), and a demand response manager (DRM) layer. The AC is located at the bottom layer and interacts with the local agents based on the control command from the upper layers depending on the priority and power capacity. The DRM works as an interface to the grid and collect data from both the building and the grid to take decisions for demand regulation based on the price. The operation of DRM and AC are managed by LB in order to distributes the load over a time horizon by using along term scheduling. This architecture provides many features, including ensuring and supporting the coordination between different elements and components, allowing the integration of different energy sources, as well as being simple to repair and update.

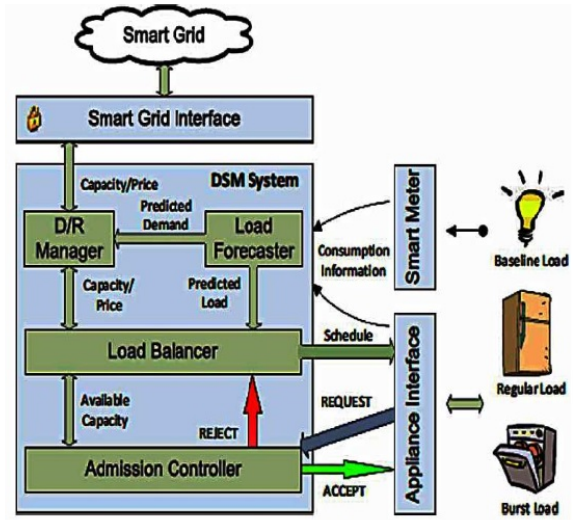

Figure 1.4 The layered structure model on demand side [5].

Game theory is another powerful mechanism in the context of smart buildings to handle the interaction between energy supply and request in energy demand management. It works based on modeling the cooperation and interaction of different decision makers (players) [38]. In [39], a game-theoretic scheme based on the Nash equilibrium (NE) is used to coordinate appliance operations in a residential building. The game was formulated based on a mixed integer programming (MIP) to allow the consumers to benefit from cooperating together. A game-theoretic scheme with model predictive control (MPC) was established in [40] for demand side energy management. This technique concentrated on utilizing anticipated information instead of one day-ahead for power distribution. The approach proposed in [41] is based on cooperative gaming to control two different linear coupled systems. In this scheme, the two controllers communicate twice at every sampling instant to make their decision cooperatively. A game interaction for energy consumption scheduling proposed in [42] functions while respecting the coupled constraints. Both the Nash equilibrium and the dual composition were implemented for demand response game. This approach can shift the peak power demand and reduce the peak-to-average ratio.

1.2.1 Buildings and HVAC Systems

Heating, ventilation and air-conditioning (HVAC) systems are commonly used in residential and commercial buildings where they make up 50% of the total energy utilization [6, 43]. According to [44, 45], the proportion of the residential energy consumption due to HVAC systems in Canada and in the U.K is 61%, and 43% in the U.S. Various research projects have therefore focused on developing and implementing different control algorithms to reduce the peak power demand and minimize the power consumption while controlling the operation of HVAC systems to maintain a certain comfort level [46]. In Section 1.2.1, we briefly introduce the concept of HVAC systems and the kind of services they provide in buildings, as well as some of the control techniques that have been proposed and implemented to regulate their operations from literature.

A building is a system that provides people with different services, such as ventilation, desired environment temperatures, heated water, etc. An HVAC system is the source that is responsible for supplying the indoor services that satisfy the occupants' expectation in an adequate living environment. Based on the type of services that HVAC systems supply, they have been classified into six levels as shown in Table 1.1. SL1 represents level one, which includes just the ventilation service, while class SL6 shows level six, which contains all of the HVAC services and is more likely to be used for museums and laboratories [1].

The block diagram included in Figure 1.5 illustrates the classification of control functions in HVAC systems, which are categorized into five groups [6]. Even though the first group, classical control, which includes the proportional-integral-derivative (PID) control and bang-bang control (ON/OFF), is the most popular and includes successful schemes to manage building power consumption and cost, these are not energy efficient and cost effective when considering overall system performance. Controllers face many drawbacks and problems in the mentioned categories regarding their implementations on HVAC systems. For example, an accurate mathematical analysis and estimation of stable equilibrium points are necessary for designing controllers in the hard control category. Soft controllers need a large amount of data to be implemented properly and manual adjustments are required for the classical group. Moreover, their performance becomes either too slow or too fast outside of the tuning band. For multi-zone buildings, it would be difficult to implement the controllers properly because the coupling must be taken into account while modelling the system.

Table 1.1 Classification of HVAC services [1].

Service Level/service	**Ventilation**	**Heating**	**Cooling**	**Humid**	**Dehumid**
SL1	*				
SL2	*	*			
SL3	*		*		
SL4	*	*	*		
SL5	*	*	*	*	
SL6	*	*	*	*	*

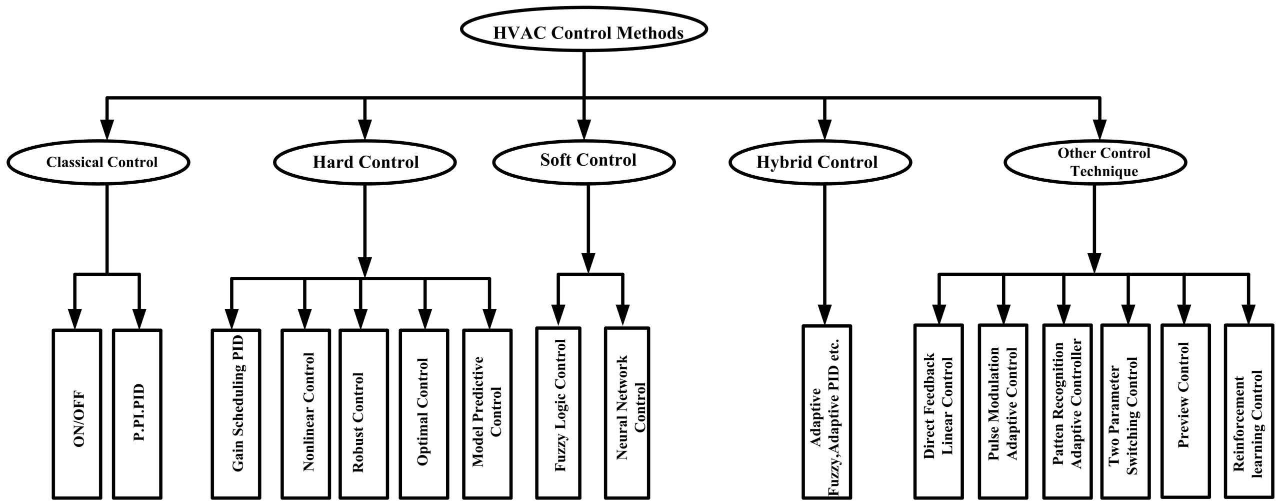

Figure 1.5 Classification of control functions in HVAC systems [6].

As the HVAC systems represent the largest contribution in energy consumption in buildings (approximately half of the energy consumption) [8, 47], controlling and managing their operation efficiently has a vital impact on reducing the total power consumption and thus the cost [6, 8, 17, 48]. This topic has attracted much attention for many years regarding various aspects, seeking to reduce energy consumption while maintaining occupants' comfort level in buildings.

Demand Response Electrical Appliance Manager (DREAM) was proposed by Chen et al. to ameliorate the peak demand of an HVAC system in a residential building by varying the price of electricity [49]. Their algorithm allows both the power costs and the occupant's comfort to be optimized. The simulation and experimental results proved that DREAM was able to correctly respond to the power cost by saving energy and minimizing the total consumption during the higher price period. Intelligent thermostats that can measure the occupied and unoccupied periods in a building were used to automatically control an HVAC system and save energy in [46]. The author's experiment, carried out on eight homes, showed that the technique reduced the HVAC energy consumption by 28%.

As the prediction plays an important role in the field of smart buildings to enhance energy efficiency and reduce the power consumption [50–54], the use of MPC for energy management in buildings has received noteworthy attention from the research community. The MPC control technique, which is classified as a hard controller as shown in Figure 1.5, is a very popular approach that is able to deal efficiently with the aforementioned shortcomings of classical control techniques, especially if the building model has been well-validated [6]. In this research, as a particular emphasis is put on the application of MPC for DR in smart buildings, a review of the existing MPC control techniques for HVAC system is presented in Section 1.3.

1.3 MPC-Based HVAC Load Control

MPC is becoming more and more applicable thanks to the growing computational power of building automation and the availability of a huge amount of building data. This opens up new avenues for improving energy management in the operation and regulation of HVAC systems because of its capability to handle constraints and neutralize disturbances, consider multiple conflicting objectives [6, 7, 30, 55–58]. MPC can be applied to several types of buildings (e.g., single/multi-zone and single/multi-story) for different design objectives [6].

There has been a considerable amount of research aimed at minimizing energy consumption in smart buildings, among which the technique of MPC plays an important role [12,30,59–64]. In addition, predictive control extensively contributes to the peak demand reduction, which has a very significant impact on real-life problems [30, 65]. The peak power load in buildings can cost as much as 200-400 times of the regular rate [66]. Peak power reduction has therefore a crucial importance for achieving the objectives of improving cost-effectiveness in building operations in the context of the Smart Grid (see, e.g., [5, 12, 67–69]). For example, a 50% price reduction during the peak time of the California electricity crisis in 2000/2001 was reached with just a 5% reduction of demand [70]. The following paragraphs review some of the MPC strategies that have already been implemented on HVAC systems.

In [71], an MPC-based controller was able to reach reductions of 17% to 24% in the energy consumption of the thermal system in a large university building while regulating the indoor temperature very accurately compared to the weather-compensated control method. Based on the work [5], an implementation of another MPC technique in a real eight-room office building was proposed in [12]. The control strategy used budget-schedulability analysis to ensure thermal comfort and reduce peak power consumption. Motivated by the work presented in [72], a MPC implemented in [61], was compared with a PID controller mechanism. The emulation results showed that the MPC's performance surpassed that of the PID controller, reducing the discomfort level by 97%, power consumption by 18%, and heat-pump periodic operation by 78%. An MPC controller with a stochastic occupancy model (Markov model) is proposed in [73] to control the HVAC system in a building. The occupancy prediction was considered as an approach to weight the cost function. The simulation was carried out relying on real-world occupancy data to maintain the heating comfort of the building at the desired comfort level with minimized power consumption. The work in [30] was focused on developing a method by using a cost-saving MPC that relies on automatically shifting the peak demand to reduce energy costs in a five-zone building. This strategy divided the daytime into five periods such that the temperature can change from one period to another, rather than revolve around a fixed temperature setpoint. An MPC controller has been applied to a water storage tank during the night, saving energy with which to meet the demand during the day [13]. A simplified model of a building and its HVAC system was used, with an optimization problem represented as a Mixed Integer Nonlinear Program (MINLP), solved using a tailored branch and bound strategy. The simulation results illustrated that close to 24.5% of the energy costs could be saved by using the MPC compared to the manual control sequence already in use. The MPC control method in [74] was able to save 15% to 28% of the required energy use, while considering the outdoor temperature and insulation level when controlling the building heating system of the Czech Technical University (CTU). The decentralized model predictive control (DMPC) developed in [59] was applied to single and multi-zone thermal buildings. The control mechanism designed based on buildings' future occupation profiles. By applying the proposed MPC technique, a significant energy consumption reduction was achieved, as indicated in the results, without affecting the occupants' comfort level.

1.3.1 MPC for Thermal Systems

Even though HVAC systems have various subsystems with different behavior, thermal systems are the most important and the most commonly-controlled systems for DR management in the context of smart buildings [6]. The dominance of thermal systems is attributable to two main causes: First, thermal appliances devices (e.g., heating, cooling, and hot water systems) consume the largest share of energy at more than one-third of buildings' energy usage [75]; for instance, they represent almost 82% of the entire power consumption in Canada [76], including space heating (63%), water heating (17%), and space cooling (2%). Second and most importantly, their elasticity features, such as their slow dynamic property, make them particularly well-placed for peak power load reduction applications [65]. The MPC control strategy is one of the most adopted techniques for thermal appliance control in the context of smart buildings. This is mainly due to its ability to work with constraints and handle time varying processes, delays, uncertainties as well as omit the impact of disturbances. In addition, it is also easy to integrate multiple-objective functions in MPC [6, 30]. There exists a set of control schemes aimed at minimizing energy consumption while satisfying an acceptable thermal comfort in smart buildings, among which the technique of MPC plays a significant role (see, e.g., [12, 59, 62–64, 73, 74].

The MPC-based technique can be formulated into centralized, decentralized, distributed, cascade, and hierarchical structure [6, 59, 60]. Some centralized MPC-based thermal appliance control strategies for thermal comfort regulation and power consumption reduction were proposed and implemented in [12,61,62,75]. The most used architectures for thermal appliances control in buildings are decentralized or distributed [59, 60]. In [63], a robust decentralized model predictive control based on H_∞-performance measurement was proposed for HVAC control in a multi-zone building while considering disturbances and respecting restrictions. In [77], centralized, decentralized, and distributed MPC controllers, as well as PID control, were applied to a three-zone building to track the indoor temperature variation to be kept within a desired range while reducing the power consumption. The results revealed that the DMPC achieved 5.5% less power consumption compared to the proportional-integral (PI) controller.

A hierarchical MPC was used for the power management of a smart grid in [78]. The charging of electrical vehicles was incorporated into the design to balance the load and production. An application of DMPC to minimize the computational load integrated a term to enable flexible regulation into the cost function in order to tune the level of guaranteed quality of service is reported in [64]. For the decentralized control mechanism, some contributions have been proposed in recent years for a range of objectives in [79–85]. In this thesis, the DMPC proposed in [79] is implemented on thermal appliances in a building to maintain a desired thermal comfort with reduced power consumption, as presented in Chapter 3 and Chapter 5.

1.3.2 MPC Control for Ventilation Systems

Ventilation systems are also investigated in this work as part of MPC control applications in smart buildings. The major function of the ventilation system in buildings is to circulate the air from outside to inside in order to supply a better indoor environment [86]. Diminishing the ventilation system volume flow while achieving the desired level of indoor air quality (IAQ) in buildings has an impact on energy efficiency [87]. As people spent most of their life time inside buildings [88], IAQ is an important comfort factor for building occupants. Improving IAQ has understandably become an essential concern for responsible building owners in terms of occupant's health and productivity [87, 89], as well as in terms of the total power consumption. For example, in office buildings in the U.S., ventilation represents almost 61% of the entire energy consumption in office HVAC systems [90].

Research has made many advances in adjusting the ventilation flow rate based on the MPC technique in smart buildings. For instance, the MPC control was proposed as a means to control the Variable Air Volume (VAV) system in a building with multiple zones in [91]. A multi-input multi-output controller is used to regulate the ventilation rate and temperature while considering four different climate conditions. The results proved that the proposed strategy was able to effectively meet the design requirements of both systems within the zones. An MPC algorithm was implemented in [92] to eliminate the instability problem while using the classical control methods of axial fans. The results proved the effectiveness and soundness of the developed approach compared to a PID-control approach in terms of ventilation rate stability.

In [93], an MPC algorithm on an underground ventilation system based on a Bayesian environmental prediction model. About 30% of the energy consumption was saved by using the proposed technique while maintaining the preferred comfort level. The MPC control strategy developed in [94] was capable to regulate the indoor thermal comfort and IAQ for a livestock stable at the desired levels while minimizing the energy consumption required to operate the valves and fans.

Controlling the ventilation flow rate based on the carbon dioxide (CO_2) concentration has drawn much attention in recent yearS, as the CO_2 concentration represents a major factor of people comfort in term of IAQ [87, 89, 95–98]. However, and to the best of our knowledge, there have been no applications of nonlinear MPC control technique to ventilation systems based on CO_2 concentration model in buildings. Consequently, a hybrid control strategy of MPC control with feedback linearization (FBL) control is presented and implemented in this thesis to provide an optimum ventilation flow rate to stabilize the indoor CO_2 concentration in a building based on a CO_2 predictive model.

In summay, MPC is one of the most popular options for HVAC system power management applications because of its many advantages that empower it to outperform the other controllers if the system model and future input values are well known [30]. In the smart buildings field, an MPC controller can be incorporated into the scheme of AC. Thus, we can impose performance requirements upon peak load constraints to improve the quality of service while respecting capacity constraints and simultaneously reducing costs. This work focuses on DR management in smart buildings based on the application of MPC control strategies.

1.4 Research Problem and Methodologies

Energy efficiency in buildings has justifiably been a popular research area for many years. Power consumption and cost are the factors that generally come first to researcher's minds when they think about smart buildings. Setting meters in a building to monitor the energy consumption by time (time of use) is one of the simplest and easiest strategies that can be used to begin to save energy. However, this is a simple approach that merely shows how easy it could be to reduce energy costs. In the context of smart buildings, power consumption management must be accomplished automatically by using control algorithms and sensors. The real concern is how to exploit the current technologies to construct effective systems and solutions that lead to the optimal use of energy.

In general, a building is a complex system that consists of a set of subsystems with different dynamic behaviors. Numerous methods have been proposed to advance the development and use of innovative solutions to reduce the power consumption in buildings by implementing DR algorithms. However, it may not be feasible to deal with a single dynamic model for multiple subsystems, that may lead to a unique solution in the context of DR management in smart buildings. In addition, most of the current solutions are dedicated to particular purposes and thus may not be applicable to real-life buildings as they lack adequate adaptability and extensibility. The layered structure model on demand side [5], as shown in Figure 1.4, has established a practical and reasonable architecture to avoid the complexities and provide better coordination between all the subsystems and components. Some limited attention has been given to the application of power consumption control schemes in a layered structure model (e.g., see [5,12,65,99]). As the MPC is one of the most frequently-adopted techniques in this field, this PhD research aims to contribute to filling this research gap by applying the MPC control strategies to HVAC systems in smart buildings in the aforementioned structure. The proposed strategies facilitate the management of the power consumption of appliances at the lower layer based on a limited power capacity provided by the grid at a higher layer to meet the occupant's comfort with lower power consumption.

The regulation of both heating and ventilation systems are considered as case studies in this thesis. In the former, and inspired by the advantages of using some discrete event system (DES) properties such as schedulability and observability, we first introduce the AC application to schedule the operation of thermal appliances in smart buildings in the DES framework. The DES allows the feasibility of the appliance's schedulability to be verified in order to design complex control schemes to be carried out in a systematic manner. Then, as an extension of this work, based on the existing literature and in view of the advantages of using control techniques such as game theory concept and MPC control in the context DR management in smart buildings, two-layer structure for decentralized control (DMPC and game-theoretic scheme) was developed and implemented on thermal system in DES framework. The objective is to regulate the thermal appliances to achieve a significant reduction of the peak power consumption while providing an adequate temperature regulation performance. For ventilation systems, a nonlinear model predictive control (NMPC) is applied to control the ventilation flow rate depending on a CO_2 predictive model. The goal is to keep the indoor concentration of CO_2 at a certain setpoint as an indication of IAQ with minimized power consumption while guaranteeing the closed loop stability.

Finally, to pave the path towards a framework for large-scale and complex building control systems design and validation in a more realistic development environment, the EnergyPlus software for energy consumption analysis was used to build model of differently-zoned buildings. The Openbuild Matlab toolbox was utilized to extract data form EnergyPlus to generate state space models of thermal systems in the chosen buildings that are suitable for MPC control problems. We have addressed the feasibility and the applicability of these tools set through the previously developed DMPC-based HVAC control systems.

Matlab/Simlink is the platform on which we carried out the simulation experiments for all of the proposed control techniques throughout this PhD work. The YALMIP toolbox was used to solve the optimization problems of the proposed MPC control schemes for the selected HVAC systems.

1.5 Research Objectives and Contributions

This PhD research aims at highlighting the current problems and challenges of DR in smart buildings, in particular developing and applying new MPC control techniques to HVAC systems to maintain a comfortable and safe indoor environment with lower power consumption. This work shows and emphasizes the benefit of managing the operation of building systems in a layered architecture as developed in [5] to decrease the complexity and to facilitate control scheme applications to ensure better performance with minimized power consumption. Furthermore, through this work, we have affirmed and highlighted the significance of peak load shaving on real-life problems in the context of smart buildings to enhance building operation efficiency and to support the stability of the grid. Different control schemes are proposed and implemented on HVAC systems in this work over a time horizon to satisfy the desired performance while assuring that load demands will respect the available power capacities at all times. As a summary, within this framework, our work addresses the following issues :

- peak load shaving and its impact on real-life problem in the context of smart buildings;
- application of DES as a new framework for power management in the context of smart buildings;
- application of DMPC to the thermal systems in smart buildings in the framework of DSE;
- application of MPC to the ventilation systems based on CO_2 predictive model;

- simulation of smart buildings MPC control system design-based on EnergyPlus model.

The main contributions of this thesis includes:

- Applies admission control of thermal appliances in smart buildings in the framework of DES. This work :
    1. introduces a formal formulation of power admission control in the framework of DES;
    2. establishes criteria for schedulability assessment based on DES theory;
    3. proposes algorithms to schedule appliances' power consumption in smart buildings, which allows for peak power consumption reduction.

- Inspired by the literature and in view of the advantages of using DES to schedule the operation of thermal appliances in smart buildings as reported in [65], we developed a DMPC-based scheme for thermal appliance control in the framework of DES to guarantee the occupant thermal comfort level with lower power consumption while respecting certain power capacity constraints. The proposed work offers twofold contributions:
    1. We propose a new scheme for DMPC-based game-theoretic power distribution in the framework of DES for reducing the peak power consumption of a set of thermal appliances while meeting the prescribed temperature in a building, simultaneously ensuring that the load demands respect the available power capacity constraints over the simulation time. The developed method is capable of verifying *a priori* the feasibility of a schedule and allows for the design of complex control schemes to be carried out in a systematic manner.
    2. We establish an approach to ensure the system performance by considering some of the observability properties of DES, namely co-observability and $\mathcal{P}$-observability. This approach provides a means for deciding whether a local controller requires more power to satisfy the desired specifications by enabling events through a sequence based on observation.

- Considering the importance of ventilation systems as a part HVAC systems in improving both energy efficiency and occupant's comfort, an NMPC, which is an integration of FBL control with MPC control strategy, was applied to a system to:

1. Regulate the ventilation flow rate based on a CO_2 concentration model to maintain the indoor CO_2 concentration at a comfort setpoint in term of IAQ with minimized power consumption.
2. Guarantee the closed loop stability of the system performance with the proposed technique using a local convex approximation approach.

- Building thermal system models based on the EnergyPlus is more reliable and realistic to be used for MPC application in smart buildings. By extracting a building thermal model using OpenBuild toolbox based on EnergyPlus data, we:
  1. Validate the simulation-based MPC control with a more reliable and realistic development environment, which allows paving the path toward a framework for the design and validation of large and complex building control systems in the context of smart buildings.
  2. Illustrate the applicability and the feasibility of DMPC-based HVAC control system with more complex building systems in the proposed co-simulation framework.

The results obtained in the research are presented in the following papers:

1. S. A. Abobakr, W. H. Sadid, et G. Zhu, "Game-theoretic decentralized model predictive control of thermal appliances in discrete-event systems framework", *IEEE Transactions on Industrial Electronics*, vol. 65, no. 8, pp. 6446–6456, 2018.
2. Saad Abobakr and Guchuan Zhu ,"A Nonlinear Model Predictive Control for Ventilation Systems in Smart Buildings", Submitted to the *Energy and Buildings*, March 2019.
3. Saad Abobakr and Guchuan Zhu, "A Co-simulation-Based Approach for Building Control Systems Design and Validation", Submitted to the *Control Engineering Practice*, March, 2019.

1.6 Outlines of the Thesis

The remainder of this thesis is organized into six chapters:

Chapter 2 outlines the required background of some theories and tools used through our research to control the power consumption of selected HVAC systems. We first introduce the basic concept of the MPC controller and its structure. Next, we explain the formulation and the implementation mechanism of the MPC controller including a brief description of centralized and decentralized MPC controllers. After that, a background and some basic notations of DES are given. Finally, game theory concept is also addressed. In particular, we show the concept and definition of the NE strategy.

Chapter 3 shows our first application of the developed MPC control in a decentralized formulation to thermal appliances in a smart building. The dynamic model of the thermal system is addressed first, and the formulation of both centralized and decentralized MPC systems are explained. Next, we present a heuristic algorithm for searching the NE. The notion of $\mathcal{P}$-Observability and the design of the supervisory control based on decentralized DES are given later in this chapter. Finally, two case studies of simulation experiments are utilized to validate the efficiency of the proposed control algorithm at meeting design requirements.

Chapter 4 introduces the implementation of a nonlinear MPC control strategy on a ventilation system in a smart building based on a CO_2 predictive model. The technique makes use of a hybrid control that combines MPC control with FBL control to regulate the indoor CO_2 concentration with reduced power consumption. First, we present the dynamic model of the CO_2 concentration and its equilibrium point. Then, we introduce a brief description of the FBL control technique. Next, the MPC control problem setup is addressed with an approach of stability and convergence guarantee. This chapter ends with the some simulation results of the proposed strategy comparing to a classical ON/OFF controller.

Chapter 5 presents a simulation-based smart buildings control system design. It is a realistic implementation of the proposed DMPC in Chapter 3 on EnergyPlus thermal model of a building. First, the state space models of the thermal systems are created based on input and outputs data of the EnergyPlus, then the lower order model is validated and compared with the original extracted higher order model to be used for the MPC application. Finally, two case studies of two different real buildings are simulated with the DMPC to regulate the thermal comfort inside the zones with lower power consumption.

Chapter 6 provides a general discussion about the research work and the obtained results detailed in Chapter 3, Chapter 4, and Chapter 5.

Lastly, the conclusions of this PhD research and some future recommendations are presented in Chapter 7.

CHAPTER 2 TOOLS AND APPROACHES FOR MODELING, ANALYSIS AND OPTIMIZATION OF THE POWER CONSUMPTION IN HVAC SYSTEMS

In this chapter, we introduce and describe some tools and concepts that we have utilized to construct and design our proposed control techniques to manage the power consumption of HVAC systems in smart buildings.

2.1 Model Predictive Control

MPC is a control technique that was first used in an industrial setting in the early nineties and has developed considerably since. MPC has the ability to predict a plant's future behavior and decide on suitable control action. Currently, MPC is not only used in the process control, but also in other applications such as robotics, clinical anesthesia [7] and energy consumption minimization in buildings [6, 56, 57]. In all of these applications, the controller shows a high capability to deal with such time varying processes, imposed constraints, while achieving the desired performance.

In the context of smart buildings, MPC is a popular control strategy, helping regulate the energy consumption and achieve peak load reduction in commercial and residential buildings [58]. This strategy has the ability to minimize a building's energy consumption by solving an optimization problem, while accounting for the future system's evolution prediction [72]. The MPC implementation on HVAC systems has been its widest use in smart buildings. Its popularity in HVAC systems is due to its ability to handle time varying processes and slow processes with time delay, constraints and uncertainties, as well as disturbances. In addition, it is able to use objective functions for multiple purposes for local or supervisory control [6, 7, 30, 57].

Despite the features that make MPC one of the most appropriate and popular choices, it does have some drawbacks, such as:

- The controller's implementation is easy, but its design is more complex than that of some conventional controllers such as PID controllers; and
- An appropriate system model is needed for the control law calculation. Otherwise, the performance will not be as good as expected.

2.1.1 Basic Concept and Structure of MPC

The control strategy of MPC, as shown in Figure 2.1, is based on both prediction and optimization. The predictive feedback control law is computed by minimizing the predicted performance cost, which is a function of the control input (u) and the state (x). The open loop optimal control problem is solved at each step, and only the first element of the input sequences is implemented on the plant. This procedure will be repeated at a certain period, while considering new measurements [56].

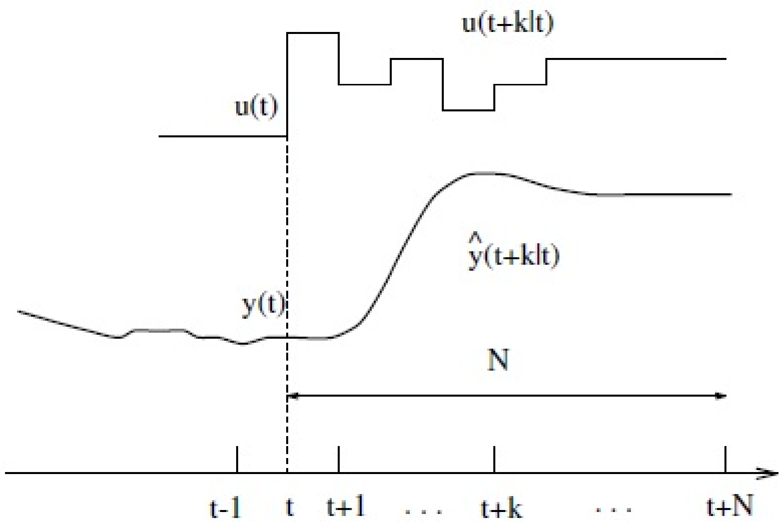

Figure 2.1 Basic strategy of MPC [7].

The basic structure of applying the MPC strategy is shown in Figure 2.2. The controller depends on the plant model, which is most often supposed to be linear and obtained by system identification approaches.

The predicted output is produced by the model based on the past and current values of the system output and on the optimal future control input from solving the optimization problem, while accounting for the constraints. An accurate model must be selected to guarantee an accurate capture of the dynamic process [7].

2.1.2 MPC Components

1. **Cost Function** Since the control action is produced by solving an optimization problem, the cost function is required to decide the final performance target. The cost function formulation relies on the problem objectives. The goal is to force the future output on the considered horizon to follow a determined reference signal [7]. For MPC-based HVAC control, some cost functions such as quadratic cost function, terminal

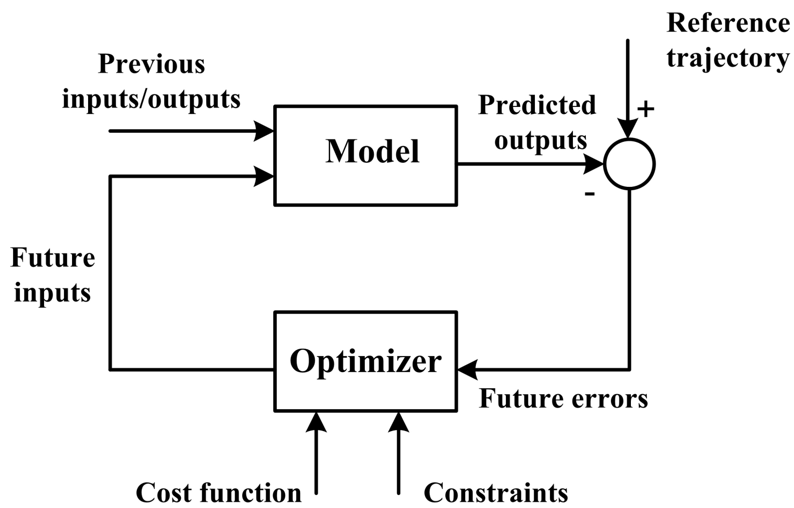

Figure 2.2 Basic structure of MPC [7].

cost, combination of demand volume and energy prices, tracking error or operating cost could be used [6].

2. **Constraints**

   One of the main features of the MPC is the ability to work with the equality and/or inequality constraints on state, input, output or actuation effort. It gives the solution and produces the control action without violating the constraints [6].

3. **Optimization Problem** After formulating the system model, the disturbance model, the cost function and the constraints, MPC solves constrained optimization problem to find the optimal control vector. A classification of linear and nonlinear optimization methods for HVAC control. Optimization schemes commonly used by HVAC researchers contain linear programming, quadratic programming, dynamic programming and mix integer programming [6].

4. **Prediction horizon, control horizon and control sampling time** The prediction horizon is the time required to calculate the system output by MPC, while the control horizon is the period of time for which the control signal will be found. Control sampling time is the period of time during which the value of the control signal does not change [6].

2.1.3 MPC Formulation and Implementation

A general framework of MPC formulation for buildings is given by the following finite-horizon optimization problem:

$$\min_{u_0,\ldots,u_{N-1}} \sum_{k=0}^{N-1} L_k(x_k, u_k) \tag{2.1a}$$

$$\text{s.t.} \quad x_{k+1} = f(x_k, u_k), \tag{2.1b}$$

$$x_0 = x(t), \tag{2.1c}$$

$$(x_k, u_k) \in X_k \times U_k \tag{2.1d}$$

where $L_k(x_k, u_k)$ is the cost function, $x_{k+1} = f(x_k, u_k)$ is the dynamics, $x_k \in \mathbb{R}^n$ is the system state with set of constraints X_k, $u_k \in \mathbb{R}^m$ is the control input with set of constraints U_k, and N is prediction horizon.

The implementation diagram for an MPC controller on a building is shown in Figure 2.3. As illustrated, the building's dynamic model, the cost function, and the constraints are the

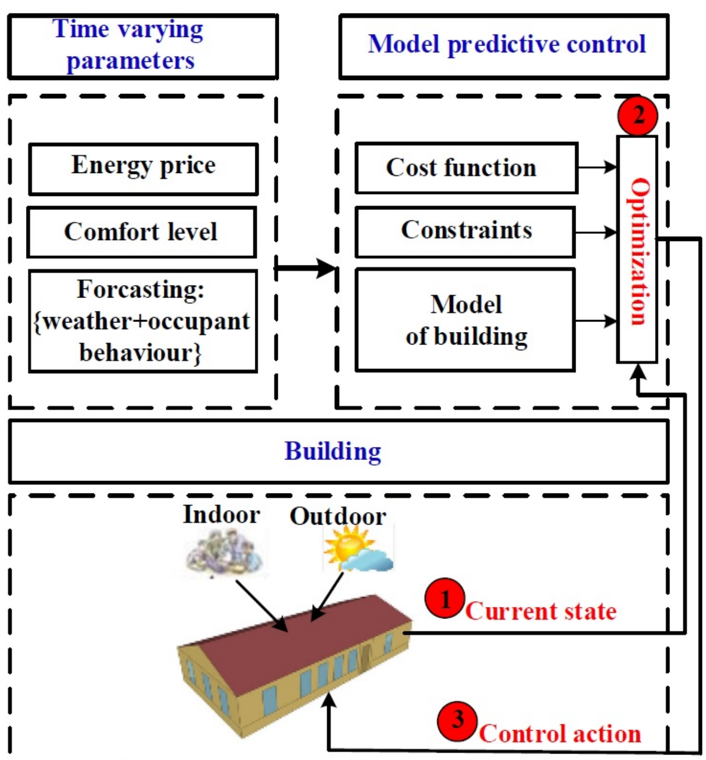

Figure 2.3 Implementation diagram of MPC controller on a building.

three main elements of the MPC problem that work together to determine the optimal control solution, depending on the selected MPC framework. The implementation mechanism of the MPC control strategy on a building contains three steps as indicated below:

1. At the first sampling time, information about systems' states along with indoor and outdoor activity conditions are sent to the MPC controller.
2. The dynamic model of the building together with disturbance forecasting is used to solve the optimization problem and produce the control action over the selected horizon.
3. The produced control signal is implemented, and at the next sampling time all the steps will be repeated.

As mentioned in Chapter 1, MPC can be formulated as centralized, decentralized, distributed, cascade, or hierarchical control [6]. In a centralized MPC, as shown in Figure 2.4, the entire states and constraints must be considered to find a global solution of the problem. In real-life large buildings, centralized control is not desirable because the complexity grows exponentially with the system size and would require a high computational effort to meet the required specifications [6, 59]. Furthermore, a failure in a centralized controller could cause a severe problem for the whole building's power management and thus its HVAC system [6, 55].

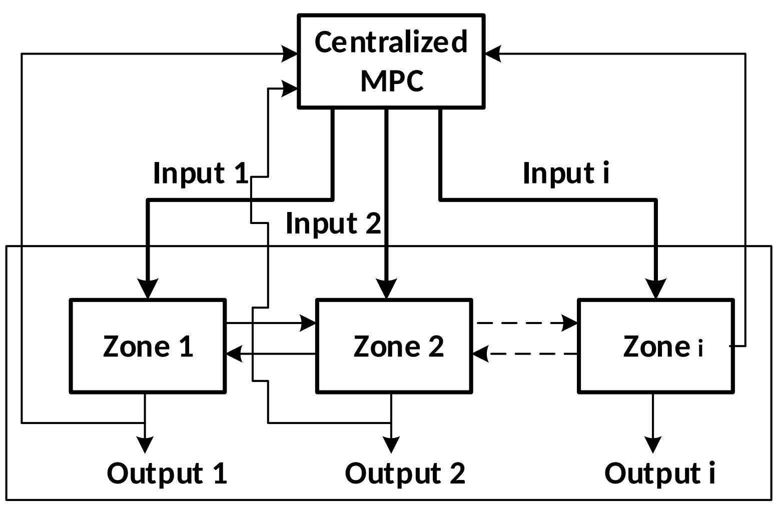

Figure 2.4 Centralized model predictive control.

In the DMPC, as shown in Figure 2.5, the whole system is partitioned into a set of subsystems, each with its own local controller that works based on a local model by solving an optimization problem. As all the controllers are engaged in regulating the entire system [59], a coordination control at the high layer is needed for DMPC to assure the overall optimality performance.

Such a centralized decision layer allows levels of coordination and performance optimization to be achieved, that would be very difficult to meet using a decentralized or distributed control manner [100].

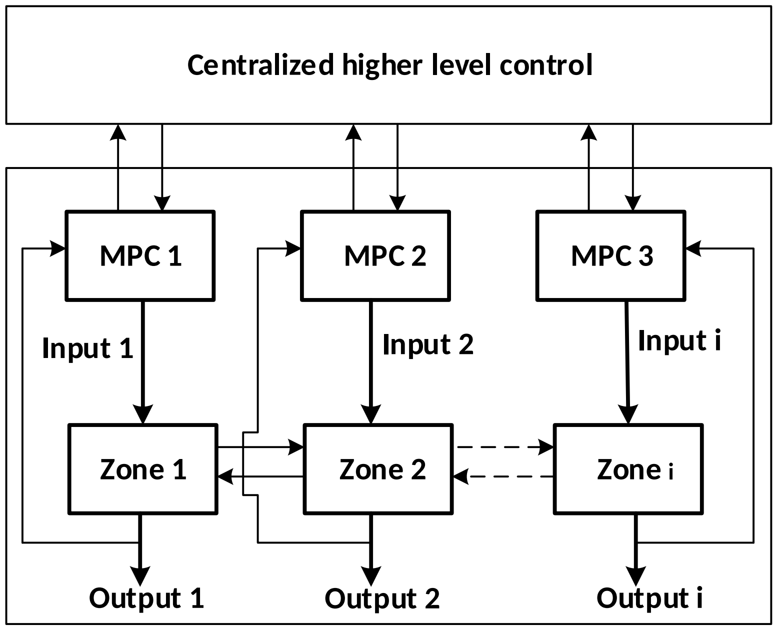

Figure 2.5 Decentralized model predictive control.

In the day-to-day life of our computer-dependent world, two things can be observed. First, most of the data quantities that we cope with are discrete. For instance, integer numbers (number of calls, number of airplanes that are on runway). Second, many of the processes we use in our daily life are instantaneous events, such as turning appliances on/off, clicking a keyboard key on computers and phones. In fact, the currently developed technology is event-driven: computer program executing, communication network are typical examples [101]. Therefore, smart buildings' power consumption management problems and approaches can be formulated in a DES framework. This framework has the ability to establish a system so that the appliances can be scheduled to provide lower power consumption and better performance.

2.2 Discrete Event Systems Applications in Smart Buildings Field

The DES is a framework to model systems that can be represented by transitions among a set of finite states. The main objective is to find a controller capable of forcing a system to react based on a set of design specifications within certain imposed constraints. Supervisory control is one of the most common control structurers for the DES [102–104]. The system states can only be changed at discrete points of time responding to events. Therefore, the state space of DES is a *discrete* set, and the transition mechanism is *event-driven.* In DES, a system can be represented by a finite-state machine (FSM) as a regular language over a finite set of events [102].

The application of the framework of DES allows for the design of complex control systems to be carried out in a systematic manner. The main behaviors of a control scheme, such as the schedulability with respect to the given constraints, can be deduced from the basic system properties, in particular the controllability and the observability. In this way, we can benefit from the theory and the tools developed since decades for DES design and analysis to solve diverse problems with ever growing complexities arising from the emerging field of the Smart Grid. Moreover, it is worth noting that the operation of many power systems, such as economic signaling, demand-response, load management, and decision making, exhibits a discrete event nature. This type of problems can eventually be handled by utilizing continuous-time models. For example, the Demand Response Resource Type II (DRR Type II) at Midcontinent ISO market is modeled similar to a generator with continuous-time dynamics (see, e.g., [105]). Nevertheless, the framework of DES remains a viable alternative for many modeling and design problems related to the operation of the Smart Grid.

The problem of scheduling the operation of number of appliances in a smart building can be expressed by a set of states and events and finally formulated in DES system framework to manage the power consumption of a smart building. For example, the work proposed in [65] represents the first application of DES in the field of smart grid. The work focuses on the AC of thermal appliances in the context of the layered architecture [5]. It is motivated by the fact that the AC interacts with the energy management system and the physical building, which is essential for the implementation of the concept and the solutions of smart buildings.

2.2.1 Background and Notations on DES

We begin by simply explaining the definition of DES, and then we present some essential notations associated with system theory that have been developed over the years.

The behavior of a DES requiring control and the specifications are usually characterized by regular languages. These can be denoted by $\mathcal{L}$ and $\mathcal{K}$ respectively. A language $\mathcal{L}$ can be recognized by a finite-state machine (FSM), which is a 5-tuple:

$$\mathcal{M}_{\mathcal{L}} = (Q, \Sigma, \delta, q_0, Q_{\mathsf{m}}), \tag{2.2}$$

where Q is a finite set of states, Σ is a finite set of events, $\delta : Q \times \Sigma \to Q$ is the transition relation, $q_0 \in Q$ is the initial state, and Q_{m} is the set of marked states (e.g., they may signify the completion of a task).

The specification is a subset of the system behavior to be controlled, i.e., $\mathcal{K} \subseteq \mathcal{L}$. The controllers issue control decisions to prevent the system from performing behavior in $\mathcal{L} \setminus \mathcal{K}$, where $\mathcal{L} \setminus \mathcal{K}$ stands for the set of behaviors of $\mathcal{L}$ that are not in $\mathcal{K}$. Let s be a sequence of events and denote by $\overline{\mathcal{L}} := \{s \in \Sigma^* \mid (\exists s' \in \Sigma^*)$ such that $ss' \in \mathcal{L}\}$ the *prefix closure* of a language $\mathcal{L}$.

The closed behavior of a system, denoted by $\mathcal{L}$, contains all the possible event sequences the system may generate. The marked behavior of the system is $\mathcal{L}_{\mathsf{m}}$, which is a subset of the closed behavior, representing completed tasks (behaviors), and is defined as $\mathcal{L}_{\mathsf{m}} := \{s \in \mathcal{L} \mid \delta(q_0, s) =\in Q_{\mathsf{m}}\}$. A language $\mathcal{K}$ is said to be $\mathcal{L}_{\mathsf{m}}$-closed if $\mathcal{K} = \overline{\mathcal{K}} \cap \mathcal{L}_{\mathsf{m}}$. An example of $\mathcal{M}_{\mathcal{L}}$ is shown in Figure 2.6, the language that generated from $\mathcal{M}_{\mathcal{L}}$ is $\mathcal{L} = \{\varepsilon, \mathsf{a}, \mathsf{b}, \mathsf{ab}, \mathsf{ba}, \mathsf{abc}, \mathsf{bac}\}$ includes all the sequences ,where ε is the empty one . In case the system specification includes only the solid line transition, then $\mathcal{K} = \{\varepsilon, \mathsf{a}, \mathsf{b}, \mathsf{ab}, \mathsf{ba}, \mathsf{abc}\}$.

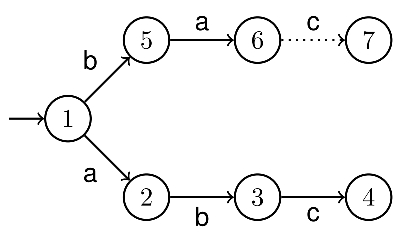

Figure 2.6 An finite state machine ($\mathcal{M}_{\mathcal{L}}$).

The synchronous product of two FSMs $M_i = (Q_i, \Sigma_i, \delta_i, q_{0i}, Q_{\mathsf{m}i})$, for $i = \{1, 2\}$, is denoted by $M_1 \| M_2$. It is defined as $M_1 \| M_2 = (Q_1 \times Q_2, \Sigma_1 \cup \Sigma_2, \delta_1 \| \delta_2, (q_{01}, q_{02}), Q_{\mathsf{m}1} \times Q_{\mathsf{m}2})$, where

$$\delta_1 \| \delta_2((q_1, q_2), \sigma) = \begin{cases} (\delta_1(q_1, \sigma), \delta_2(q_2, \sigma)), & \text{if } \delta_1(q_1, \sigma)! \wedge \\ & \delta_2(q_2, \sigma)! \wedge \\ & \sigma \in \Sigma_1 \cap \Sigma_2; \\ (\delta_1(q_1, \sigma), q_2), & \text{if } \delta_1(q_1, \sigma)! \wedge \\ & \sigma \in \Sigma_1 \setminus \Sigma_2; \\ (q_1, \delta_2(q_2, \sigma)), & \text{if } \delta_2(q_2, \sigma)! \wedge \\ & \sigma \in \Sigma_2 \setminus \Sigma_1; \\ \textit{undefined}, & \text{otherwise.} \end{cases} \tag{2.3}$$

By assumption, the set of events Σ is partitioned into disjoint sets of controllable and uncontrollable events, denoted by Σ_c and Σ_{uc}, respectively. Only controllable events can be prevented from occurring (i.e., may be disabled), as uncontrollable events are supposed to be permanently enabled. If in a supervisory control problem, only a subset of events can be observed by the controller, then the events set Σ can be partitioned also into the disjoint sets of observable and unobservable events, denoted by Σ_o and Σ_{uo}, respectively.

The controllable events of the system can be dynamically enabled or disabled by a controller according to the specification, so that a particular subset of the controllable events is enabled to form a control pattern. The set of all control patterns can be defined as:

$$\Gamma = \{\gamma \in P(\Sigma) | \gamma \supseteq \Sigma_{uc}\}, \tag{2.4}$$

where γ is a control pattern consisting only of a subset of controllable events that are enabled by the controller. $P(\Sigma)$ represents the power set of Σ. Note that the uncontrollable events are also a part of the control pattern since they cannot be disabled by any controller.

A supervisory control for a system can be defined as a mapping from the language of the system to the set of control patterns as $S : \mathcal{L} \to \Gamma$. A language $\mathcal{K}$ is controllable if and only if [102]

$$\overline{\mathcal{K}}\Sigma_{uc} \cap \mathcal{L} \subseteq \overline{\mathcal{K}}. \tag{2.5}$$

The controllability criterion means that an uncontrollable event $\sigma \in \Sigma_{uc}$ cannot be prevented from occurring in $\mathcal{L}$. Hence, if such an event σ occurs after a sequence $s \in \overline{\mathcal{K}}$, then σ must remain through the sequence $s\sigma \in \overline{\mathcal{K}}$. For example, in Figure 2.6, $\mathcal{K}$ is controllable if the event c is controllable; otherwise, $\mathcal{K}$ is uncontrollable. For event based control, a controller's view of the system behavior can be modeled by the natural projection, $\pi : \Sigma^* \to \Sigma_o^*$, defined as

$$\pi(\sigma) = \begin{cases} \varepsilon, & \text{if } \sigma \in \Sigma \setminus \Sigma_o; \\ \sigma, & \text{if } \sigma \in \Sigma_o, \end{cases} \tag{2.6}$$

This operator removes the events σ from a sequence in Σ^* that are not found in Σ_o. The above definition can be extended to sequences as follows: $\pi(\varepsilon) = \varepsilon$, and $\forall s \in \Sigma^*, \sigma \in \Sigma.\ \pi(s\sigma) = \pi(s)\pi(\sigma)$. The inverse projection of π for $s' \in \Sigma_o^*$ is the mapping from Σ_o^* to $P(\Sigma^*)$:

$$(\forall s, s' \in \mathcal{L})\pi(s) = \pi(s') \Rightarrow \Gamma(\pi(s)) = \Gamma(\pi(s')). \tag{2.7}$$

A language $\mathcal{K}$ is said to be observable with respect to $\mathcal{L}, \pi$, and Σ_c if for all $s \in \overline{\mathcal{K}}$ and all $\sigma \in \Sigma_c$ it holds [106].

$$(s\sigma \notin \overline{\mathcal{K}}) \wedge (s\sigma \in \mathcal{L}) \Rightarrow \pi^{-1}[\pi(s)]\sigma \cap \overline{\mathcal{K}} = \emptyset. \tag{2.8}$$

In other words, the projection π provides the necessary information to the controller to decide whether an event to be enabled or disabled to attain the system specification. If the controller receives the same information through different sequences $s, s' \in \mathcal{L}$, it will take the same action based on its partial observation. Hence, the decision is made in observationally equivalent manner as below:

$$(\forall s, s' \in \mathcal{L})\pi(s) = \pi(s') \Rightarrow \Gamma(\pi(s)) = \Gamma(\pi(s')). \tag{2.9}$$

When the specification $\mathcal{K} \subseteq \mathcal{L}$ is both controllable and observable, a controller can be synthesized. This means that the controller can take correct control decision based only on its observation of a sequence.

2.2.2 Appliances operation Modeling in DES Framework

As mentioned earlier each load or appliance can be represented by FSM. In other words, the operation can be characterized by a set of states and events where the appliance's state changes when it executes an event. Therefore, it can be easily formulated in DES, which describes the behavior of the load requiring control and the specification as regular languages (over a set of discrete events). We denote these behaviors by $\mathcal{L}$ and $\mathcal{K}$ respectively, where $\mathcal{K} \subseteq \mathcal{L}$. The controller issues a control decision (e.g., enabling or disabling an event) to find a sub-language of $\mathcal{L}$, and the control objective is reached when the pattern of control decisions to keep the system in $\mathcal{K}$ has been issued.

Each appliance's status is represented based on the states of the FSM, as shown in Figure. 2.7 below:

State 1 (Off): it is not enabled.

State 2 (Ready): it is ready to start.

State 3 (Run): it runs and consumes power.

State 4 (Idle): it stops and consumes no power.

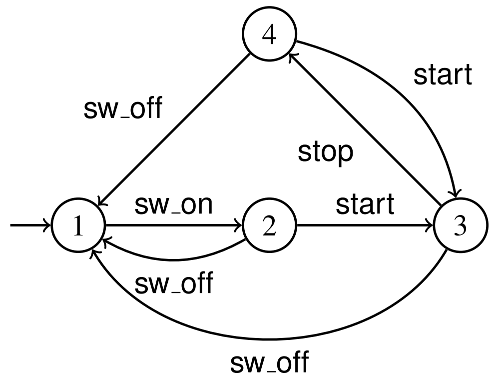

Figure 2.7 A finite-state automaton of an appliance.

In the following, controllability and observability represent the two main properties in DES that we consider when we schedule the appliances operation. A controller will take the decision to enable the events through a sequence relying on its observation which tell the supervisor control to accept or reject a request. Consequently, in control synthesis, a view $\mathcal{C}_i$ is first designed for each appliance i from controller perspective. Once the individual views are generated for each appliance, a centralized controller's view $\mathcal{C}$ can be formulated by taking the synchronous product of the individual views in (2.3). The schedulability of such a scheme will be assessed based on the properties of the considered system and the controller. Figure 2.8 illustrates the process for accepting or rejecting the request of an appliance.

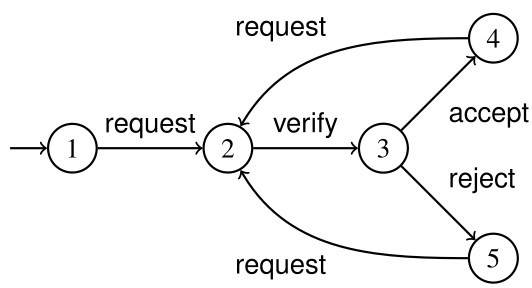

Figure 2.8 Accepting or rejecting the request of an appliance.

Let $\mathcal{L}_\mathcal{C}$ be the language generated from $\mathcal{C}$ and $\mathcal{K}_\mathcal{C}$ be the specification. Then the control law is a map

$$\Gamma : \pi(\mathcal{L}_\mathcal{C}) \rightarrow 2^\Sigma,$$

such that $\forall s \in \Sigma^*$, $\Sigma_{\mathcal{L}_\mathcal{C}}(s) \cap \Sigma_{uc} \subseteq \overline{\mathcal{K}}_\mathcal{C}$, where $\Sigma_\mathcal{L}(s)$ defines the set of events that occurring after the sequence $s : \Sigma_\mathcal{L}(s) = \{\sigma \in \Sigma | s\sigma \in \overline{\mathcal{L}}\}$, $\forall \mathcal{L} \subseteq \Sigma^*$. The control decisions will be made in observationally equivalent manner as specified in (2.9).

Definition 2.1 *Denote by $\Gamma/\mathcal{L}_{\mathcal{C}}$ the controlled system under the supervision of Γ. The closed behaviour of $\Gamma/\mathcal{L}_{\mathcal{C}}$ is defined as a language $\mathcal{L}(\Gamma/\mathcal{L}_{\mathcal{C}}) \subseteq \mathcal{L}_{\mathcal{C}}$, such that*

(i) $\varepsilon \in \mathcal{L}(\Gamma/\mathcal{L}_{\mathcal{C}})$, *and*

(ii) $\forall s \in \mathcal{L}(\Gamma/\mathcal{L}_{\mathcal{C}})$ *and* $\forall \sigma \in \Gamma(s)$, $s\sigma \in \mathcal{L}_{\mathcal{C}} \Rightarrow s\sigma \in \mathcal{L}(\Gamma/\mathcal{L}_{\mathcal{C}})$.

The marked behaviour of $\Gamma/\mathcal{L}_{\mathcal{C}}$ is $\mathcal{L}_m(\Gamma/\mathcal{L}_{\mathcal{C}}) = \mathcal{L}(\Gamma/\mathcal{L}_{\mathcal{C}}) \cap \mathcal{L}_m$.

Denote by $\Gamma/M_{L_{\mathcal{C}}}$ the system $M_{L_{\mathcal{C}}}$ under the supervision of Γ and let $\mathcal{L}(\Gamma/M_{L_{\mathcal{C}}})$ be the language generated by $\Gamma/M_{L_{\mathcal{C}}}$. Then, the necessary and sufficient conditions for the existence of a controller satisfying $K_{\mathcal{C}}$ are given by the following theorem [102].

Theorem 2.1 *There exists a controller Γ for the system $M_{\mathcal{L}_{\mathcal{C}}}$ such that $\Gamma/M_{\mathcal{L}_{\mathcal{C}}}$ is nonblocking and the closed behaviour of $\Gamma/M_{\mathcal{L}_{\mathcal{C}}}$ is restricted to $\mathcal{K}$ (i.e., $\mathcal{L}(\Gamma/M_{\mathcal{L}_{\mathcal{C}}}) \subseteq \mathcal{K}_{\mathcal{C}}$) if and only if*

(i) $K_{\mathcal{C}}$ *is controllable w.r.t.* $L_{\mathcal{C}}$ *and* Σ_{uc},

(ii) $K_{\mathcal{C}}$ *is observable w.r.t.* $L_{\mathcal{C}}$, π *and* Σ_c, *and*

(iii) $K_{\mathcal{C}}$ *is* L_m*-closed.*

The work presented in [65] is considered as the first application of DES in the smart buildings field. It focuses on thermal appliances power management in smart buildings in DES framework-based power admission control. In fact, this application opens a new avenue for smart grids by integrating the DES concept into the smart buildings field to manage power consumption and reduce peak power demand. A Scheduling Algorithm validates the schedulability for the control of thermal appliances was developed to reach an acceptable thermal comfort of four zones inside a building with a significant peak demand reduction while respecting the power capacity constraints. A set of variables: preemption, status, heuristic value and requested power are used to characterize each appliance. For each appliance, its priority and the interruption should be taken into account during the scheduling process. Accordingly, preemption and heuristic values are used for these tasks.. In section 2.2.3, we introduce an example as proposed in [65] to manage the operation of thermal appliances in a smart building in the framework of DES.

2.2.3 Case Studies

To verify the ability of the scheduling algorithm in a DES framework to maintain the room temperature within a certain range with lower power consumption, simulation study was carried out in a Matlab/Simulink platform for four zone building. The toolbox [107] was used to generate the centralized controller's view ($\mathcal{C}$) for each of the appliances, creating a system with 4096 states and 18432 transitions. Two different types of thermal appliances, a heater and a refrigerator, are considered in the simulation.

The dynamical model of the heating system and the refrigerators are taken from [12, 108], respectively. Specifically, the dynamics of the heating system are given by:

$$\frac{\mathrm{d}T_i}{\mathrm{d}t} = \frac{1}{C_i R_i^a}(T_a - T_i) + \frac{1}{C_i}\sum_{j=1, j\neq i}^{N} \frac{1}{R_{ji}}(T_j - T_i) + \frac{1}{C_i}\Phi_i, \tag{2.10}$$

where N is the number of rooms, T_i is the interior temperature of room i, $i \in \{1, \ldots, N\}$, T_a is the ambient temperature, R_i^a is the thermal resistance between room i and the ambient, R_{ji} is the thermal resistance between Room i and Room j, C_i is the heat capacity and Φ_i is the power input to the heater of room i. The parameters of thermal system model that we used in the simulation are listed in Table 2.1 and Table 2.2.

Table 2.1 Configuration of thermal parameters for heaters.

Room	1	2	3	4
R_j^a	69.079	88.652	128.205	105.412
C_j	0.94	0.94	0.78	0.78

Table 2.2 Parameters of thermal resistances for heaters.

R_{12}^r, R_{21}^r	R_{13}^r, R_{31}^r	R_{14}^r, R_{41}^r	R_{23}^r, R_{32}^r	R_{24}^r, R_{42}^r
709.2	1063.8	1063.8	1063.8	1063.8

The dynamical model of the refrigerator takes a similar, but simpler form:

$$\frac{\mathrm{d}T_r}{\mathrm{d}t} = \frac{1}{C_r R_r^a}(T_a - T_r) - \frac{A_c}{C_r}\Phi_c, \tag{2.11}$$

where T_r is the refrigerator chamber temperature, T_a is the ambient temperature, C_r is a thermal mass representing the refrigeration chamber, the insulation is modeled as a thermal resistance, R_r^a, A_c is the overall coefficient performance, and Φ_c is the refrigerator power input. Both refrigerator model parameters are given in Table 2.3

Table 2.3 Model parameters of refrigerators.

Fridge	R_r^a	C_r	$T_r(0)$	A_c	Φ_c
1	1.4749	893.74	5	0.34017	500
2	1.4749	804.37	5	0.2846	500

In the experimental setup, two of the rooms contain only one heater (Rooms 1 and 2) and the other two have both a heater and a refrigerator (Rooms 3 and 4). The time span of the simulation is normalized to 200 time steps and the ambient temperature is set to 10 °C. A PI controller is used to control the heating system, with maximal temperature set to 24 °C, and a bang-bang (ON/OFF) approach is utilized to control the refrigerators that are turned on when the chamber temperature reaches 3 °C and turned off when temperature is 2 °C.

Example 2.1 *In this example, we apply the Scheduling algorithm in [65] to the thermal system with initial power 1600 W for each heater in Rooms 1 and 2 , and 1200 W for heater in Rooms 3 and 4. In addition, 500 W as a requested power for each refrigerator.*

While the acceptance status of the heaters $(H1, \ldots, H4)$ and the refrigerators $(FR1, FR2)$ is shown in Figure 2.9, the room temperature $(R1, \ldots, R4)$ and refrigerator temperatures $(FR1, FR2)$, are illustrated in Figure 2.10.

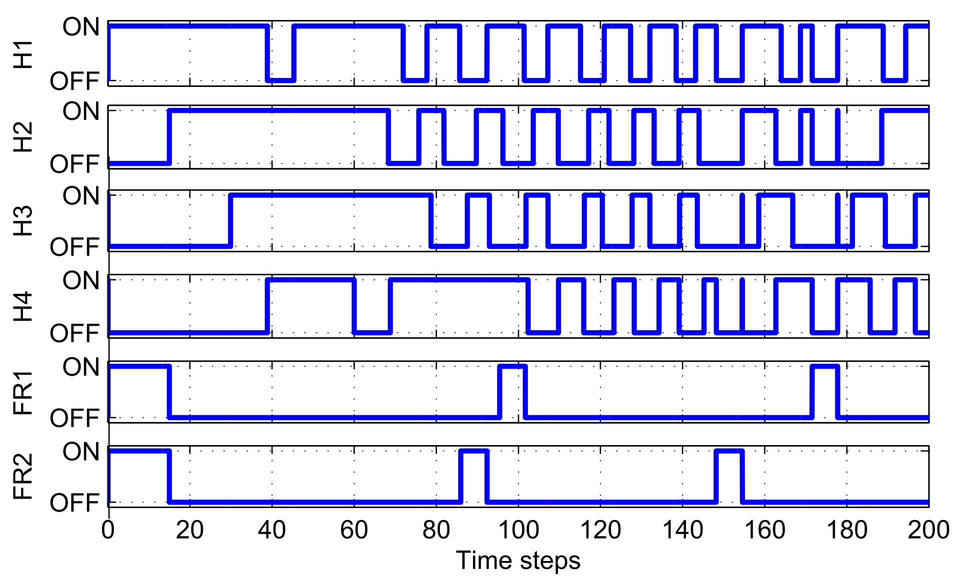

Figure 2.9 Acceptance of appliances using scheduling algorithm (algorithm for admission controller).

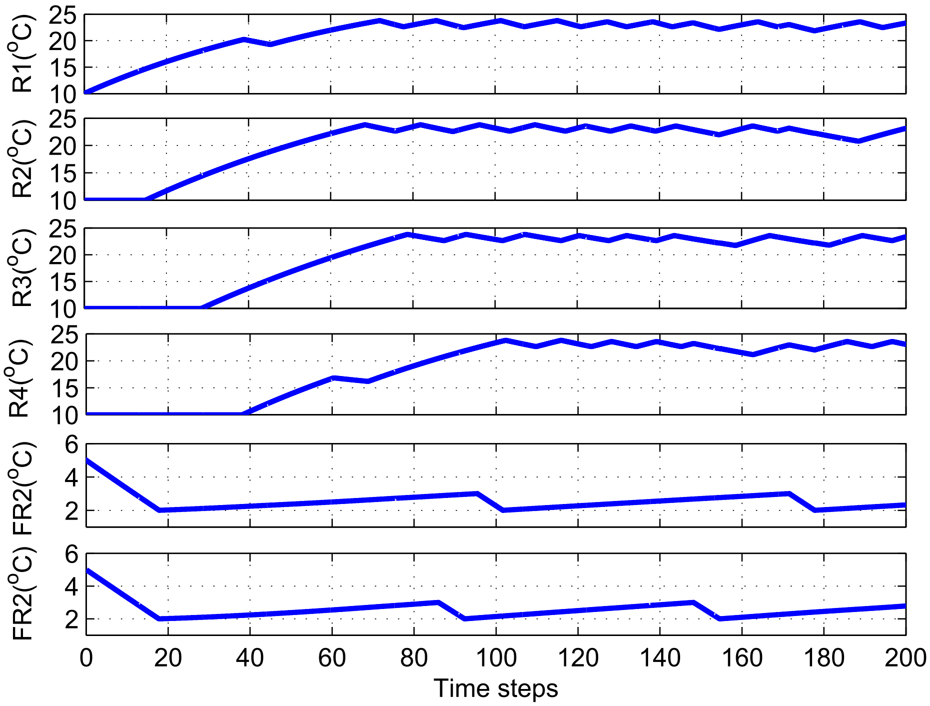

Figure 2.10 Room and refrigerator temperatures using scheduling algorithm((algorithm for admission controller)).

The individual power consumption of the heaters ($H1, \ldots, H4$) and the refrigerators ($FR1, FR2$) are shown in Figure 2.11 , and the total power consumption with respect to the power capacity constraints are depicted in Figure 2.12.

From the results, it can been seen that the overall power consumption never goes beyond the available power capacity which reduces over three periods of time (see Figure 2.12). We start with 3000 W for the first period (until 60 time steps), then we reduce the capacity to 1000 W during the second period (until 120 time steps), then the capacity is set to be 500 W (7.5% of the worst case peak power demand) over the last period. Despite the lower value of the imposed capacity comparing to the required power (it is less than half the required power (3000) W), the temperature in all rooms as shown in Figure 2.10 is maintained at an acceptable value between 22.6°C and 24°C. However, after 120 time steps and with the lowest implemented power capacity (500 W), there is a slight performance degradation at some points with a temperature as low as 20.8° when a refrigerator is ON.

Note that the dynamic behavior of the heating system is very slow. Therefore, in the simulation experiment in Example 1 that carried out in Matlab/Simulink platform, the time span was normalized to 200 time units where each time unit represents 3 min in the corresponding

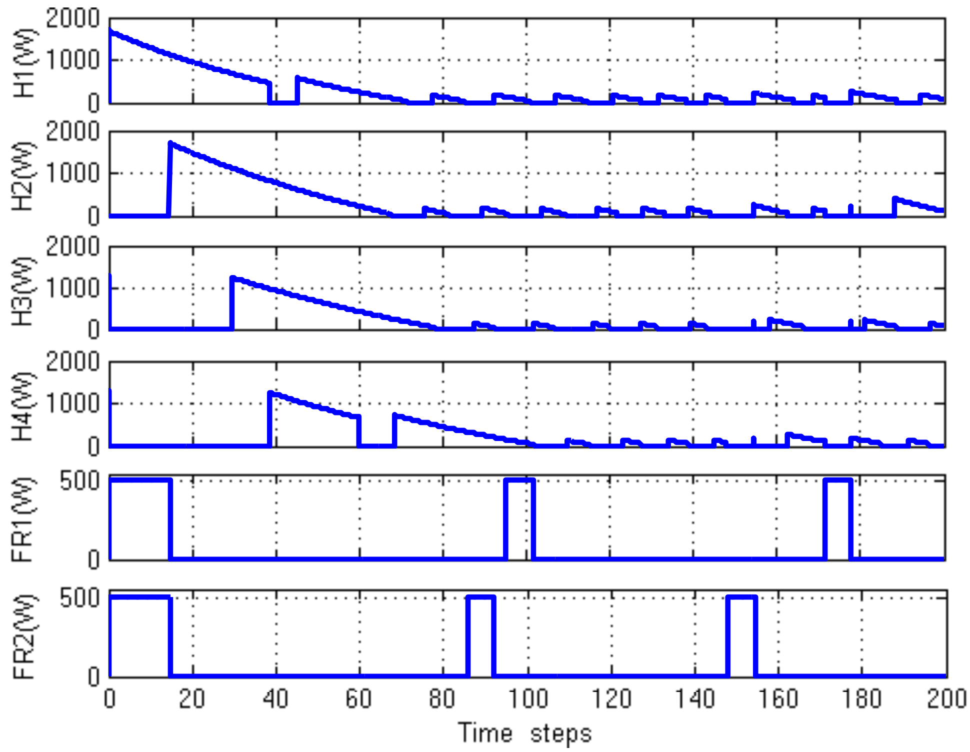

Figure 2.11 Individual power consumption using scheduling algorithm ((algorithm for admission controller)).

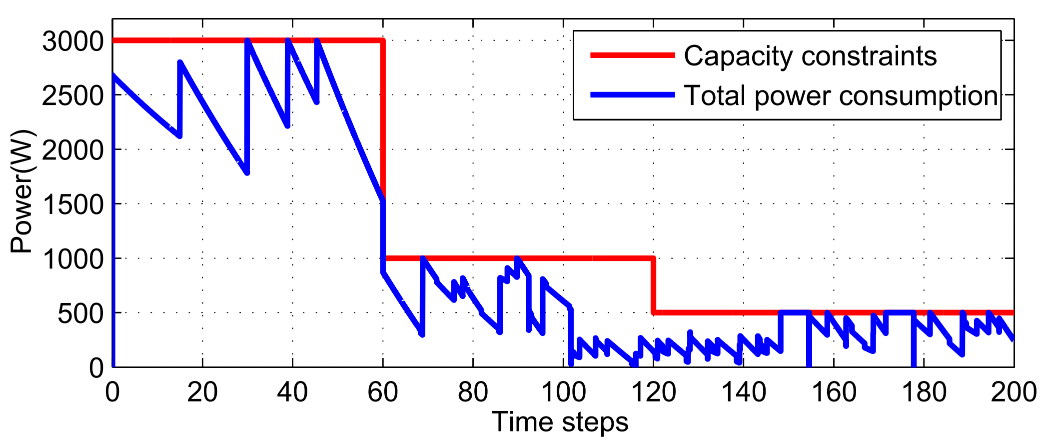

Figure 2.12 Total power consumption of appliances using scheduling algorithm((algorithm for admission controller)).

real time-scale. The same mechanism has been used for the applications of MPC through the thesis where the sampling time can be chosen as five to ten times less than the time constant of the controlled system

2.3 Game Theory Mechanism

2.3.1 Overview

Game theory was formalized in 1944 by Von Neumann and Morgenstern [109]. It is a powerful technique for modeling the interaction of different decision makers (players). Game theory studies situations where a group of interacting agents make simultaneous decisions in order to minimize their costs or maximize their utility functions. The utility function of an agent is reliant upon its decision variable as well as on that of the other agents. The main solution concept is the Nash equilibrium(NE), formally defined by John Nash in 1951 [110]. In the context of power consumption management, the game theoretic mechanism is a powerful technique with which to analysis the interaction of consumers and utility operators.

2.3.2 Nash Equilbruim

Equilibrium is the main idea in finding multi-agent system's optimal strategies. To optimize the outcome of an agent, all the decisions of other agents are considered by the agent while assuming that they act so as to optimizes their own outcome. An NE is an important concept in the field of game theory to help determine the equilibria among a set of agents. The NE is a group of strategies, one for each agent, such that if all other agents adhere to their strategies, an agent's recommended strategy is better than any other strategy it could execute. Without the loss of generality, the NE is each agent's best response with respect to the strategies of the other agents [111].

Definition 2.2 *For the system with N agents, let $A = A_1 \times \cdots \times A_N$, where A_i is a set of strategies of a gent i. Let $u_i : A \rightarrow \mathbb{R}$ denote a real-valued cost function for agent i. Let suppose the problem of optimizing the cost functions u_i. A set of strategies $a^* = (a_1^*, \ldots, a_n^*) \in A$ is a Nash equilibrium, if*

$$(\forall i \in N)(\forall a_i \in A_i) u_i(a_i^*, a_{-i}^*) \leq u_i(a_i, a_{-i}^*),$$

where a_{-i} indicates the set of strategies $\{a_k | k \in N \text{ and } k \neq i\}$

In the context of power management in smart buildings, there will be always a competition among the controlled subsystems to get more power in order to meet the required performance. Therefore, the game theory (e.g., NE concept) is a suitable approach to distribute the available power and ensure the global optimality of the whole system while respecting the power constraints.

In summary, game-theoretic mechanism can be used together with the MPC in the DES and to control HVAC systems operation in smart buildings with an efficient way that guarantee a desired performance with lower power consumption. In particular, in this thesis, we will use the mentioned techniques for either thermal comfort or IAQ regulation.

CHAPTER 3 ARTICLE 1: A GAME-THEORETIC DECENTRALIZED MODEL PREDICTIVE CONTROL OF THERMAL APPLIANCES IN DISCRETE-EVENT SYSTEMS FRAMEWORK

The chapter is a reproduction of the paper published in IEEE Transactions on Industrial Electronics [112]. I am the first author of this paper and made major contributions to this work.

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Abstract–This paper presents a decentralized model predictive control (MPC) scheme for thermal appliances coordination control in smart buildings. The general system structure consists of a set of local MPC controllers and a game-theoretic supervisory control constructed in the framework of discrete-event systems (DES). In this hierarchical control scheme, a set of local controllers work independently to maintain the thermal comfort level in different zones, and a centralized supervisory control is used to coordinate the local controllers according to the power capacity and the current performance. Global optimality is ensured by satisfying the Nash equilibrium at the coordination layer. The validity of the proposed method is assessed by a simulation experiment including two case studies. The results show that the developed control scheme can achieve a significant reduction of the peak power consumption while providing an adequate temperature regulation performance if the system is $\mathcal{P}$-observable.

Index Terms–Discrete-event systems (DES), game theory, Model predictive control (MPC), smart buildings, thermal appliance control.

3.1 Introduction

The peak power load in buildings can cost as much as 200 to 400 times the regular rate [66]. Peak power reduction has therefore a crucial importance for achieving the objectives of improving cost-effectiveness in building operations. Controlling thermal appliances in heating, ventilation, and air conditioning (HVAC) systems is considered to be one of the most promising and effective ways to achieve this objective. As the highest consumers of electricity with more than one-third of the energy usage in a building [75], and due to their slow dynamic property, thermal appliances have been prioritized as the equipment to be regulated for peak power load reduction [65].

There exists a rich set of conventional and modern control schemes that have been developed and implemented for the control of building systems in the context of the Smart Grid, among which Model Predictive Control (MPC) is one of the most frequently adopted techniques. This is mainly due to its ability to handle constraints, time varying processes, delays, and uncertainties, as well as disturbances. In addition, it is also easy to incorporate multiple-objective functions in MPC [6, 30]. There has been a considerable amount of research aimed at minimizing energy consumption in smart buildings, among which the technique of MPC plays an important role [6, 12, 30, 59–64].

MPC can be formulated into centralized, decentralized, distributed, cascade, or hierarchical structures [6, 59, 60]. In a centralized MPC, the entire states and constraints have to be considered to find a global solution of the problem. While in the decentralized model predictive control (DMPC), the whole system is partitioned into a set of subsystems, each with its own local controller. As all the controllers are engaged in regulating the entire system [59], a coordination control is required for DMPC to ensure the overall optimality.

Some centralized MPC-based thermal appliance control schemes for temperature regulation and power consumption reduction were implemented in [12, 61, 62, 75]. In [63], a robust DMPC based on H_∞-performance measurement was proposed for HVAC control in a multi-zone building in the presence of disturbance and restrictions. In [77], centralized, decentralized, and distributed controllers based on MPC structure, as well as proportional-integral-derivative (PID) control, were applied to a three-zone building to track the temperature and to reduce the power consumption. A hierarchical MPC was used for power management of an intelligent grid in [78]. Charging electrical vehicles was integrated in the design to balance the load and production. An application of DMPC to minimize the computational load is reported in [64]. A term enabling the regulation flexibility was integrated into the cost function to tune the level of guaranteed quality of service.

Game theory is another notable tool, which has been extensively used in the context of smart buildings to assist the decision making process and to handle the interaction between energy supply and request in energy demand management. Game theory provides a powerful means for modeling the cooperation and interaction of different decision makers (players) [38]. In [39], a game-theoretic scheme based on Nash equilibrium (NE) is used to coordinate appliance operations in a residential building. A game-theoretic MPC was established in [40] for demand side energy management. The proposed approach in [41] was based on cooperative gaming to control two different linear coupled systems. A game interaction for energy consumption scheduling is proposed in [42] by taking into consideration the coupled constraints. This approach can shift the peak demand and reduce the peak to average ratio.

Inspired by the existing literature and in view of the advantages of using discrete-event systems (DES) to schedule the operation of thermal appliances in smart buildings as reported in [65], our goal is to develop a DMPC-based scheme for thermal appliance control in the framework of DES. Initially, the operation of each appliance is expressed by a set of *states* and *events*, which represent the status and the actions of the corresponding appliance. A system can then be represented by a finite-state machine (FSM) as a regular language over a finite set of events in DES [102]. Indeed, appliance control can be constructed using the MPC method if the operation of a set of appliances is schedulable. Compared to *trial and error* strategies, the application of the theory and tools of DES allow for the design of complex control systems arising in the field of the Smart Grid to be carried out in a systematic manner.

Based on the architecture developed in [5], we propose a two-layer structure for decentralized control as shown in Fig. 3.1. A supervisory controller at the upper layer is used to coordinate a set of MPC controllers at the lower layer. The local control actions are taken independently relying only on the local performance. The control decision at each zone will be sent to the upper layer and a game theoretic scheme will take place to distribute the power over all the appliances while considering power capacity constraints. Note that HVAC is a heterogenous system consisting of a group of subsystems that have different dynamics and natures [6]. Therefore, it might not be easy to find a single dynamic model for control design and power consumption management of the entire system. Indeed, with a layered structure, an HVAC system can be split into a set of subsystems to be controlled separately. A coordination control, as proposed in the present work, can be added to manage the operation of the whole system. The main contributions of this work are twofold:

1. We propose a new scheme for DMPC-based game-theoretic power distribution in the framework of DES for reducing the peak power consumption of a set of thermal appliances while meeting the prescribed temperature in a building. The developed method is capable of verifying *a priori* the feasibility of a schedule and allows for the design of complex control schemes to be carried out in a systematic manner.

2. We establish an approach to ensure the system performance by considering some observability properties of DES, namely co-observability and $\mathcal{P}$-observability. This approach provides a means for deciding whether a local controller requires more power to satisfy the desired specifications by enabling events through a sequence based on the observation.

In the remainder of the paper, Section 3.2 presents the model of building thermal dynamics. The settings of centralized and decentralized MPC are addressed in Section 3.3. Section 3.4 introduces the basic notions of DES and presents a heuristic algorithm for searching the NE

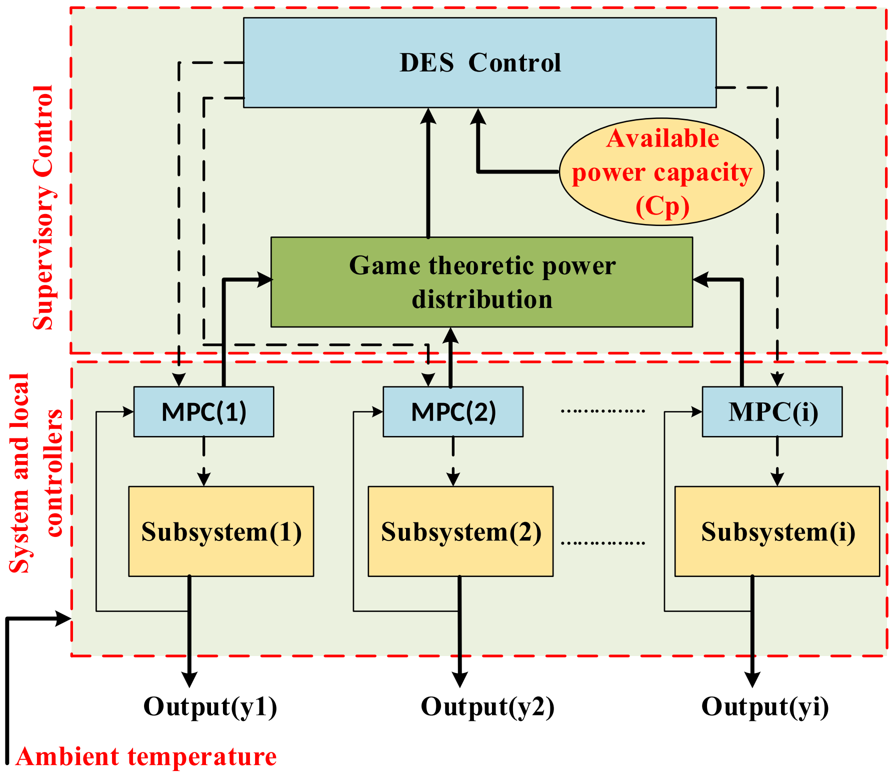

Figure 3.1 Architecture of a decentralized MPC-based thermal appliance control system.

employed in this work. The concept of $\mathcal{P}$-Observability and the design of the supervisory control based on decentralized DES are presented in Section 3.5. Simulation studies are carried out in Section 3.6, followed by some concluding remarks provided in Section 3.7.

3.2 Modeling of building thermal dynamics

In this section, the continuous time differential equation is used to present the thermal system model as proposed in [12]. The model will be discretized later for the predictive control design. The dynamic model of the thermal system is given by:

$$\frac{\mathrm{d}T_i}{\mathrm{d}t} = \frac{1}{C_i R_i^a}(T_a - T_i) + \frac{1}{C_i}\sum_{j=1, j\neq i}^{M} \frac{1}{R_{ji}^d}(T_j - T_i) + \frac{1}{C_i}\Phi_i, \tag{3.1}$$

where M is the number of zones, T_i, $i \in \{1, \ldots, M\}$, is the interior temperature of Zone i (the indoor temperature), T_j is the interior temperature of a neighboring Zone j, $j \in \{1, \ldots, M\}\backslash i$, T_a is the ambient temperature (the outdoor temperature), R_i^a is the thermal resistance between Zone i and the ambient temperature, R_{ji}^d is the thermal resistance between Zone i and Zone j, C_i is the heat capacity of Zone i, and Φ_i is the power input to the thermal appliance located in Zone i. Note that the first term on the right hand side of (3.1) represents the indoor temperature variation rate of a zone due to the impact of the outdoor temperature, and the second term captures the interior temperature of a zone due to the effect of thermal coupling of all of the neighboring zones. Therefore, it is a generic model, widely used in the literature.

The system (3.1) can be expressed by a continuous time state-space model as:

$$\begin{aligned} \dot{x} &= Ax + Bu + Ed \\ y &= Cx, \end{aligned} \tag{3.2}$$

where $x = [T_1, T_2, \ldots, T_M]^T$ is the state vector and $u = [u_1, u_2, \ldots, u_M]^T$ is the control input vector. The output vector is $y = [y_1, y_2, \ldots, y_M]^T$ where the controlled variable in each zone is the indoor temperature, and $d = [T_a^1, T_a^2, \ldots, T_a^M]^T$ represents the disturbance in Zone i. The system matrices $A \in \mathbb{R}^{M\times M}$, $B \in \mathbb{R}^{M\times M}$, and $E \in \mathbb{R}^{M\times M}$ in (3.2) are given by:

$$\begin{aligned} A &= \begin{bmatrix} A_1 & \frac{1}{R_{21}^d C_1} & \cdots & \frac{1}{R_{M1}^d C_1} \\ \frac{1}{R_{12}^d C_2} & A_2 & \cdots & \frac{1}{R_{M2}^d C_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{R_{1M}^d C_N} & \frac{1}{R_{2M}^d C_N} & \cdots & A_M \end{bmatrix}, \\ B &= \text{diag}\begin{bmatrix} B_1 & \cdots & B_M \end{bmatrix}, E = \text{diag}\begin{bmatrix} E_1 & \cdots & E_M \end{bmatrix}, \end{aligned}$$

with

$$A_i = -\frac{1}{R_i^a C_i} - \frac{1}{C_i}\sum_{j=1, j\neq i}^{M} \frac{1}{R_{ji}^d}, B_i = \frac{1}{C_i},\ E_i = \frac{1}{R_i^a C_i}.$$

In (3.2), C is an identity matrix of dimension M. Again, the system matrix A captures the dynamics of the indoor temperature and the effect of thermal coupling between the neighboring zones.

3.3 Problem Formulation

The control objective is to reduce the peak power while respecting comfort level constraints, which can be formalized as an MPC problem with a quadratic cost function which will penalize the tracking error and the control effort. We begin with the centralized formulation and then we find the decentralized setting by using the technique developed in [113].

3.3.1 Centralized MPC Setup

For the centralized setting, a linear discrete time model of the thermal system can be derived from discretizing the continuous time model (3.2) by using the standard zero-order hold with a sampling period T_s, which can be expressed as:

$$\begin{aligned} x(k+1) &= A_d x(k) + B_d u(k) + E_d d(k), \\ y(k) &= C_d x(k), \end{aligned} \tag{3.3}$$

where $x(k) \in \mathbb{R}^M$ is the state vector, $u(k) \in \mathbb{R}^M$ is the control vector, and $y(k) \in \mathbb{R}^M$ is the output vector. The matrices in the discrete-time model can be computed from the continous-time model in (3.2) and are given by $A_d = e^{AT_s}$, B_d=$\int_0^{T_s} e^{As} B\mathrm{d}s$, and E_d=$\int_0^{T_s} e^{As} D\mathrm{d}s$; $C_d = C$ is an identity matrix of dimension M.

Let $x_d(k) \in \mathbb{R}^M$ be the desired state and $e(k) = x(k) - x_d(k)$ be the vector of regulation error. The control to be fed into the plant is resulted by solving the following optimization problem at each time instance t:

$$f = \min_{u_i(0)} e(N)^T P e(N) + \sum_{k=0}^{N-1} e(k)^T Q e(k) + u^T(k) R u(k) \tag{3.4a}$$

$$\text{s.t.}\ \ x(k+1) = A_d x(k) + B_d u(k) + E_d d(k), \tag{3.4b}$$

$$x_0 = x(t), \tag{3.4c}$$

$$x_{\min} \leq x(k) \leq x_{\max}, \tag{3.4d}$$

$$0 \leq u(k) \leq u_{\max}, \tag{3.4e}$$

for $k = 0, \ldots, N$, where N is the prediction horizon. In the cost function in (3.4), $Q = Q^T \geq 0$ is a square weighting matrix to penalize the tracking error, $R = R^T > 0$ is square weighting matrix to penalize the control input, and $P = P^T \geq 0$ is a square matrix that satisfies the Lyapunov equation

$$A_d^T P A_d - P = -Q \tag{3.5}$$

for which the existence of matrix P is ensured if A in (3.2) is a strictly Hurwitz matrix. Note that in the specification of state and control constraints, the symbol "$\leq$" denotes componentwise inequalities, i.e., $x_{i\,\min} \leq x_i(k) \leq x_{i\,\max}$, $0 \leq u_i(k) \leq u_{i\,\max}$, for $i = 1, \ldots, M$.

The solution of the problem (3.4) provides a sequence of controls $U^*(x(t)) = \{u_0^*, \ldots, u_N^*\}$, among which only the first element $u(t) = u_0^*$ will be applied to the plant.

3.3.2 Decentralized MPC Setup

For the DMPC setting, the thermal model of the building will be divided into a set of subsystem. In the case where the thermal system is stable in open loop, i.e., the matrix A in (3.2) is strictly Hurwitz, we can use the approach developed in [113] for decentralized MPC design. Specifically, for the considered problem, let $x^j \in \mathbb{R}^{n_j}$, $u^j \in \mathbb{R}^{n_j}$, and $d^j \in \mathbb{R}^{n_j}$ be the state, control, and disturbance vectors of the j^{th} subsystem with $n_1 + n_2 + \cdots + n_m = M$. Then for $j = 1, \cdots, m$, x^j, u^j, and d^j of the subsystem can be represented as:

$$x^j = W_j^T x = \begin{bmatrix} x_1^j & \cdots & x_{n_j}^j \end{bmatrix}^T \in \mathbb{R}^{n_j}, \tag{3.6a}$$

$$u^j = Z_j^T u = \begin{bmatrix} u_1^j & \cdots & u_{m_j}^j \end{bmatrix}^T \in \mathbb{R}^{n_j}, \tag{3.6b}$$

$$d^j = H_j^T d = \begin{bmatrix} d_1^j & \cdots & d_{l_j}^j \end{bmatrix}^T \in \mathbb{R}^{n_j}. \tag{3.6c}$$

where $W_j \in \mathbb{R}^{M \times n_j}$ collects the n_j columns of identity matrix of order n, $Z_j \in \mathbb{R}^{M \times n_j}$ collects the m_j columns of identity matrix of order m, and $H_j \in \mathbb{R}^{M \times n_j}$ collects the l_j columns of identity matrix of order l. Note that the generic setting of the decomposition can be found in [113]. The dynamic model of the j^{th} subsystem is given by:

$$\begin{aligned} x^j(k+1) &= A_d^j x^j(k) + B_d^j u^j(k) + E_d^j d^j(k), \\ y^j(k) &= x^j(k), \end{aligned} \tag{3.7}$$

where $A_d^j = W_j^T A_d W_j$, $B_d^j = W_j^T B_d Z_j$, and $E_d^j = W_j^T E_d H_j$ are sub-matrices of A_d, B_d and E_d, respectively, which are in general dependent on the chosen decoupling matrices W_j, Z_j and H_j. As in the centralized setting, the open-loop stability of the DMPC are guaranteed if A_d^j in (3.7) is strictly Hurwitz for all $j = 1, \ldots, m$.

Let $e^j = W_j^T e$. The j^{th} sub-problem of the DMPC is then given by:

$$\begin{aligned} f^j &= \min_{u^j(0)} \sum_{k=0}^{\infty} e^{jT}(k) Q_j e^j(k) + u^{jT}(k) R_j u^j(k) \\ &= \min_{u^j(0)} e^{jT}(k) P_j e^j(k) + e^{jT}(k) Q_j + u^{jT}(k) R_j u^j(k) \end{aligned} \tag{3.8a}$$

$$\text{s.t.} \quad x^j(t+1) = A_d^j x^j(t) + B_d^j u^j(0) + E_d^j d^j, \tag{3.8b}$$

$$x^j(0) = W_j^T x(t) = x^j(t), \tag{3.8c}$$

$$x_{\min}^j \le x^j(k) \le x_{\max}^j, \tag{3.8d}$$

$$0 \le u^j(0) \le u_{\max}^j, \tag{3.8e}$$

where the weighting matrices are $Q_j = W_j^T Q W_j$, $R_j = Z_j^T R Z_j$, and the square matrix P_j is the solution of the following Lyapunov equation

$$A_d^{jT} P_j A_d^j - P_j = -Q_j. \tag{3.9}$$

At each sampling time, every local MPC provides a local control sequence by solving the problem (3.8). Finally, the closed-loop stability of the system with this DMPC scheme can be assessed by using the procedure proposed in [113].

3.4 Game Theoretical Power Distribution

A *normal-form* game is developed as a part of the supervisory control to distribute the available power based on the total capacity and the current temperature of the zones. The supervisory control is developed in the framework of DES [102, 103] to coordinate the operation of the local MPCs.

3.4.1 Fundamentals of DES

DES is a dynamic system which can be represented by transitions among a set of finite states. The behavior of a DES requiring control and the specifications are usually characterized by regular languages. These can be denoted by $\mathcal{L}$ and $\mathcal{K}$ respectively. A language $\mathcal{L}$ can be recognized by a finite-state machine (FSM), which is a 5-tuple:

$$\mathcal{M}_{\mathcal{L}} = (Q, \Sigma, \delta, q_0, Q_{\mathsf{m}}),$$

where Q is a finite set of states, Σ is a finite set of events, $\delta : Q \times \Sigma \to Q$ is the transition relation, $q_0 \in Q$ is the initial state, and Q_{m} is the set of marked states. Note that the event set Σ includes the control components u^j of the MPC setup. The specification is a subset of the system behavior to be controlled, i.e., $\mathcal{K} \subseteq \mathcal{L}$. The controllers issue control decisions to prevent the system from performing behavior in $\mathcal{L} \setminus \mathcal{K}$, where $\mathcal{L} \setminus \mathcal{K}$ stands for the set of behaviors of $\mathcal{L}$ that are not in $\mathcal{K}$. Let s be a sequence of events and denote by $\overline{\mathcal{L}} := \{s \in \Sigma^* \mid (\exists s' \in \Sigma^*) \text{ such that } ss' \in \mathcal{L}\}$ the *prefix closure* of a language $\mathcal{L}$.

The closed behavior of a system, denoted by $\mathcal{L}$, contains all the possible event sequences the system may generate. The marked behavior of the system is $\mathcal{L}_{\mathsf{m}}$, which is a subset of the closed behavior, representing completed tasks (behaviors), and is defined as $\mathcal{L}_{\mathsf{m}} := \{s \in \mathcal{L} \mid \delta(q_0, s) = q' \wedge q' \in Q_{\mathsf{m}}\}$. A language $\mathcal{K}$ is said to be $\mathcal{L}_{\mathsf{m}}$-closed if $\mathcal{K} = \overline{\mathcal{K}} \cap \mathcal{L}_{\mathsf{m}}$.

3.4.2 Decentralized DES

The decentralized supervisory control problem considers the synthesis of $m \geq 2$ controllers that cooperatively intend to keep the system in $\overline{\mathcal{K}}$ by issuing control decisions to prevent the system from performing behavior in $\mathcal{L} \backslash \overline{\mathcal{K}}$ [103,114]. Here we use $\mathcal{I} = \{1, \ldots, m\}$ as an index set for the decentralized controllers. The ability to achieve a correct control policy relies on the existence of at least one controller that can make the correct control decision to keep the system within $\overline{\mathcal{K}}$.

In the context of the decentralized supervisory control problem, Σ is partitioned into two sets for each controller $j \in \mathcal{I}$: controllable events $\Sigma_{c,j}$ and uncontrollable events $\Sigma_{uc,j} := \Sigma \backslash \Sigma_{c,j}$. The overall set of controllable events is $\Sigma_c := \bigcup_{j=\mathcal{I}} \Sigma_{c,j}$. Let $\mathcal{I}_c(\sigma) = \{j \in \mathcal{I} | \sigma \in \Sigma_{c,j}\}$ be the set of controllers that control event σ.

Each controller $j \in \mathcal{I}$ also has a set of observable events, denoted by $\Sigma_{o,j}$, and unobservable events $\Sigma_{uo,j} = \Sigma \backslash \Sigma_{o,j}$. To formally capture the notion of partial observation in decentralized supervisory control problems, the natural projection is defined for each controller $j \in \mathcal{I}$ as $\pi_j : \Sigma^* \rightarrow \Sigma_{o,j}^*$. Thus for $s = \sigma_1 \sigma_2 \ldots \sigma_m \in \Sigma^*$, the partial observation $\pi_j(s)$ will contain only those events $\sigma \in \Sigma_{o,j}$:

$$\pi_j(\sigma) = \begin{cases} \sigma, & \text{if } \sigma \in \Sigma_{o,j}; \\ \varepsilon, & \text{otherwise}, \end{cases}$$

which is extended to sequences as follows: $\pi_j(\varepsilon) = \varepsilon$, and $\forall s \in \Sigma^*$, $\forall \sigma \in \Sigma$, $\pi_j(s\sigma) = \pi_j(s)\pi_j(\sigma)$. The operator π_j eliminates those events from a sequence that are not observable to controller j. The inverse projection of π_j is a mapping $\pi_j^{-1} : \Sigma_{o,j}^* \rightarrow Pow(\Sigma^*)$ such that for $s' \in \Sigma_{o,j}^*$, $\pi_j^{-1}(s') = \{u \in \Sigma^* \mid \pi_j(u) = s'\}$, where $Pow(\Sigma)$ represents the power set of Σ.

3.4.3 Co-Observability and Control Law

When a global control decision is made, at least one controller can make a correct decision by disabling a controllable event through which the sequence leaves the specification $\mathcal{K}$. In that case, $\mathcal{K}$ is called *co-observable*. Specifically, a language $\mathcal{K}$ is *co-observable* w.r.t. $\mathcal{L}$, $\Sigma_{o,j}$, and $\Sigma_{c,j}$ $(j \in \mathcal{I})$ if [103]

$$\begin{aligned} &(\forall s \in \overline{\mathcal{K}})(\forall \sigma \in \Sigma_c)\ s\sigma \in \mathcal{L} \backslash \overline{\mathcal{K}} \Rightarrow \\ &\quad (\exists j \in \mathcal{I})\ \pi_j^{-1}[\pi_j(s)]\sigma \cap \overline{\mathcal{K}} = \emptyset. \end{aligned}$$

In other words, there exists at least one controller $j \in \mathcal{I}$ that can make the correct control decision (i.e., determine that $s\sigma \in \mathcal{L}\backslash\overline{\mathcal{K}}$) based only on its partial observation of a sequence. Note that an MPC has no feasible solution when the system is not co-observable. However, the system can still work without assuring the performance.

A decentralized control law for Controller j, $j \in \mathcal{I}$, is a mapping $U^j : \pi_j(\mathcal{L}) \rightarrow Pow(\Sigma)$ that defines the set of events that Controller j should *enable* based on its partial observation of the system behavior. While Controller j can choose to enable or disable events in $\Sigma_{c,j}$, all events in $\Sigma_{uc,j}$ must be enabled, i.e.,

$$(\forall j \in \mathcal{I})(\forall s \in \mathcal{L})\ U^j(\pi_j(s)) = \{u \in Pow(\Sigma) \mid u \supseteq \Sigma_{uc,j}\}.$$

Such a controller exists if the specification $\mathcal{K}$ is co-observable, controllable, and $\mathcal{L}_{\mathsf{m}}$-closed [103].

3.4.4 Normal-Form Game and Nash Equilibrium

At the lower layer each subsystem requires a certain amount of power to run the appliances according to the desired performance. Hence, there is a competition among the controllers if there is any shortage of power when the system is not co-observable. Consequently, a normal-form game is implemented in this work to distribute the power among the MPC controllers. The decentralized power distribution problem can be formulated as a normal form game as below:

A (finite, n-player) *normal-form* game is a tuple $(\mathcal{N}, \mathcal{A}, \eta)$ [115], where:

- $\mathcal{N}$ is a finite set of n players, indexed by j;
- $\mathcal{A} = \mathcal{A}^1 \times \ldots \times \mathcal{A}^n$, where $\mathcal{A}^j$ is a finite set of actions available to Player j. Each vector $a = \langle a^1, ..., a^n \rangle \in \mathcal{A}$ is called an action profile;
- $\eta = (\eta^1, ..., \eta^n)$ where $\eta^j : \mathcal{A} \rightarrow \mathbb{R}$ is a real-valued utility function for Player j.

At this point, we consider a decentralized power distribution problem with

- a finite index set $\mathcal{M}$ representing m subsystems;
- a set of cost functions F^j for subsystem $j \in \mathcal{M}$ for corresponding control action $U^j = \{u^j | u^j = \langle u^j_1, ..., u^j_{m_j} \rangle\}$, where $F = F^1 \times \ldots \times F^m$ is a finite set of cost functions for m subsystems and each subsystem $j \in \mathcal{M}$ consists of m_j appliances;

- and a utility function $\eta_k^j : F \rightarrow\ x_k^j$ for Appliance k of each subsystem $j \in \mathcal{M}$ consisting m_j appliances. Hence, $\eta^j = \langle \eta_1^j, ..., \eta_{m_j}^j \rangle$, with $\eta = (\eta^1, ..., \eta^m)$.

The utility function defines the comfort level of the k^{th} appliance of the subsystem corresponding to Controller j, which is a real value $\eta_k^{j,\mathsf{min}} \leq \eta_k^j \leq \eta_k^{j,\mathsf{max}}, \forall j \in \mathcal{I}$, where $\eta_k^{j,\mathsf{min}}$ and $\eta_k^{j,\mathsf{max}}$ are the corresponding lower and upper bounds of the comfort level.

There are two ways in which a controller can choose its action: (i) select a single action and execute it; (ii) randomize over a set of available actions based on some probability distribution. The former case is called a *pure* strategy, and the latter is called a *mixed* strategy. A mixed strategy for a controller specifies the probability distribution used to select a particular control action $u^j \in U^j$. The probability distribution for Controller j is denoted by $p^j : u^j \rightarrow [0, 1]$, such that $\sum_{u^j \in U^j} p^j(u^j) = 1$. The subset of control actions corresponding to the mixed strategy u^j is called the *support* of U^j.

Theorem 3.1 *([116, Proposition 116.1]) Every game with a finite number of players and action profiles has at least one mixed strategy Nash equilibrium.*

It should be noticed that the control objective in the considered problem is to retain the temperature in each zone inside a range around a set-point rather than to keep tracking the set-point. This objective can be achieved by using a sequence of discretized power levels taken from a finite set of distinct values. Hence, we have a finite number of strategies depending on the requested power. In this context, an NE represents the control actions for each local controller based on the received power that defines the corresponding comfort level. In the problem of decentralized power distribution, the NE can now be defined as follows. Given a capacity C for m subsystems, distribute C among the subsystems $(pw^1, \ldots, pw^m)$ $\wedge \left(\sum_{j=1}^m pw^j \leq C\right)$ in such a way that the control action $U^* = \langle u^1, \ldots, u^m \rangle$ is an NE if and only if

(i) $\eta^j(f^j, f_{_j}) \geq \eta^j(\tilde{f}^j, f_{_j})$for all $\tilde{f}^j \in F^j$;

(ii) f^* and $\langle \tilde{f}^j, f_{\_j} \rangle$ satisfy (3.8),

where f^j is the solution of the cost function corresponds to the control action u^j for j^{th} subsystem, and $f_{\_j}$ denote the set $\{f^k \mid k \in \mathcal{M} \wedge k \neq j\}$, and $f^* = (f^j, f_{\_j})$.

The above formulation seeks a set of control decisions for m subsystems that provides the best comfort level to the subsystems based on the available capacity.

Theorem 3.2 *The decentralized power distribution problem with a finite number of subsystems and action profiles has at least one NE point.*

Proof 3.1 *In the decentralized power distribution problem, there are a finite number of subsystems $\mathcal{M}$. In addition, each subsystem $m \in \mathcal{M}$ conforms a finite set of control actions $U^j = \{u^1, \ldots, u^j, \ldots\}$ depending on the sequence of discretized power levels, with the probability distribution $\sum_{u^j \in U^j} p^j(u^j) = 1$. That means that the DMPC problem has a finite set of strategies for each subsystem including both pure and mixed strategies. Hence, the claim of this theorem follows from Theorem 3.1.*

3.4.5 Algorithms for Searching the NE

An approach for finding a sample NE for normal-form games is proposed in [115], as presented by Algorithm 3.1. This algorithm is referred to as the SEM (Support-Enumeration Method), which is a heuristic-based procedure based on the space of supports of DMPC controllers and a notion of *dominated* actions that are diminished from the search space. The following algorithms show how the DMPC-based game theoretic power distribution problem is formulated to find the NE. Note that the complexity to find an exact NE point is exponential. Hence, it is preferable to consider heuristics-based approaches that can provide a solution very close to the exact equilibrium point with a much lower number of iterations.

Algorithm 3.1 NE in DES

for all $x = (x^1, \ldots, x^n)$ sorted in increasing order of first $\sum\limits_{j \in \mathcal{M}} x^j$ followed by $max_{j,k \in \mathcal{M}}(|x^j - x^k|)$ **do**
  $\forall j \; \tilde{U}^j \leftarrow \emptyset$ // *uninstantiated supports*
  $\forall j \; D^{x_j} \leftarrow \{u^j \in U^j \mid \sum\limits_{k \in \mathcal{M}} |u^{j,k}| = x^j\}$ // *domain of supports*
  if RecursiveBacktracking($\tilde{U}, D^x, 1$) returns NE U^* **then**
    return U^*
  end if
end for

It is assumed that a DMPC controller assigned for a subsystem $j \in \mathcal{M}$ acts as an agent in the normal-form game. Finally, all the individual DMPC controllers are supervised by a centralized controller in the upper layer. In Algorithm 3.1, x^j defines the support size of the control action available to subsystem $j \in \mathcal{M}$. It is ensured in the SEM that balanced supports are examined first, so that the lexicographic ordering is performed on the basis of the increasing order of the difference between the support sizes. In the case of a tie, this is followed by the balance of the support sizes.

An important feature of the SEM is the elimination of solutions that will never be NE points. Since we look for the best performance in each subsystem based on the solution of the corresponding MPC problem, we want to eliminate the solutions that result always in a lower performance than the other ones. An exchange of a control action $u^j \in U^j$ (corresponding to the solution of the cost function $f^j \in F^j$) is *conditionally dominated* given the sets of available control actions $U_{\_j}$ for the remaining controllers, if $\exists \tilde{u}^j \in U^j$ such that $\forall u_{\_j} \in U_{\_j}$, $\eta^j(f^j, f_{\_j}) < \eta^j(\tilde{f}^j, f_{\_j})$.

Procedure 1 Recursive Backtracking

Input: $\tilde{U} = \tilde{U}^1 \times \ldots \times \tilde{U}^m$; $D^x = (D^{x_1}, \ldots, D^{x_m})$; j
Output: NE U^* or failure
1: **if** $j = m + 1$ **then**
2: $\quad \tilde{U} \leftarrow \{(\gamma^1, \ldots, \gamma^m) \mid (\gamma^1, \ldots \gamma^m) \leftarrow \textit{feasible}(u^1, \ldots, u^m), \forall u^j \in \prod_{j \in \mathcal{M}} \tilde{U}^j\}$
3: $\quad \tilde{U} \leftarrow \tilde{U} \setminus \{(\gamma^1, \ldots, \gamma^m) \mid (\gamma^1, \ldots \gamma^m)$ does not solve the control problem$\}$
4: $\quad$ **if** Program 1 is feasible for $\tilde{U}$ **then**
5: $\quad\quad$ **return** found NE U^*
6: $\quad$ **else**
7: $\quad\quad$ **return** failure
8: $\quad$ **end if**
9: **else**
10: $\quad \tilde{U}^j \leftarrow D^{x_j}$
11: $\quad D^{x_j} \leftarrow \emptyset$
12: $\quad$ **if** IRDCA($\tilde{U}^1, \ldots, \tilde{U}^j, D^{x_{j+1}}, \ldots, D^{x_m}$) succeeds **then**
13: $\quad\quad$ **if** RecursiveBacktracking($\tilde{U}, D^x, j + 1$) returns NE U^* **then**
14: $\quad\quad\quad$ **return** found NE U^*
15: $\quad\quad$ **end if**
16: $\quad$ **end if**
17: **end if**
18: **return** failure

In addition, the algorithm for searching NE points relies on recursive backtracking (Procedure 1) to instantiate the search space for each player. We assume that in determining conditional domination, all the control actions are feasible, or are made feasible for the purposes of testing conditional domination. In adapting SEM for the decentralized MPC problem in DES, Procedure 1 includes two additional steps: (i) if u^j is not feasible, then we must make the prospective control action feasible (where feasible versions of u^j are denoted by γ^j) (Line 2); and (ii) if the control action solves the decentralized MPC problem (Line 3).

The input to Procedure 2 (Line 12 in Procedure 1) is the set of domains for the support of each MPC. When the support for an MPC controller is instantiated, the domain contains only the instantiated supports. The domain of other individual MPC controllers contains

Procedure 2 Iterated Removal of Dominated Control Actions (IRDCA)

Input: $D^x = (D^{x_1}, \ldots, D^{x_m})$
Output: Updated domains or failure

repeat
  dominated$\leftarrow$ *false*
  for all $j \in \mathcal{M}$ **do**
    for all $u^j \in D^{x_j}$ **do**
      for all $\tilde{u}^j \in \{U^j\}$ **do**
        if u^j is conditionally dominated by $\tilde{u}^j$ given $D\_^{x_j}$ **then**
          $D^{x_j} \leftarrow D^{x_j} \setminus \{u^j\}$
          dominated$\leftarrow$ *true*
          if $D^{x_j} = \emptyset$ **then**
            return failure
          end if
        end if
      end for
    end for
  end for
until *dominated* $=$ *false*
return D^x

the supports of x^j that were not removed previously by earlier calls to this procedure.

Remark 3.1 *In general, the NE point may not be unique and the first one found by the algorithm may not necessarily be the global optimum. However, in the considered problem, every NE represents a feasible solution that guarantees that the temperature in all the zones can be kept within the predefined range, as far as there is enough power, while meeting the global capacity constraint. Thus, it is not necessary to compare different power distribution schemes as long as the local and global requirements are assured. Moreover, and most importantly, using the first NE will drastically reduce the computational complexity.*

We also adopted a feasibility program from [115], as shown in Program 1, to determine whether or not a potential solution is an NE. The input is a set of feasible control actions corresponding to the solution to the problem (3.8), and the output is a control action that satisfies NE. The first two constraints ensure that the MPC has no preference for one control action over another within the input set and it must not prefer an action that does not belong to the input set. The third and the fourth constraints check that the control actions in the input set are chosen with a non-zero probability. The last constraint simply assesses that there is a valid probability distribution over the control actions.

Program 1 Feasibility Program TGS (Test Given Supports)

Input: $U = U^1 \times \ldots \times U^m$

Output: u is an NE if there exist both $u = (u^1, \ldots, u^m)$ and $v = (v^1, \ldots, v^m)$ such that:

1: $\forall j \in \mathcal{M}, u^j \in U^j : \sum_{u\_j \in U\_j} p^{-j}(u\_j)\eta^j(u^j, u\_j) = v^j$

2: $\forall j \in \mathcal{M}, u^j \notin U^j : \sum_{u\_j \in U\_j} p^{-j}(u\_j)\eta^j(u^j, u\_j) \leq v^j$

3: $\forall j \in \mathcal{M}, u^j \in U^j : p^j(u^j) \geq 0$

4: $\forall j \in \mathcal{M}, u^j \notin U^j : p^j(u^j) = 0$

5: $\forall j \in \mathcal{M} : \sum_{u^j \in U^j} p^j(u^j) = 1$

Remark 3.2 *It is pointed out in [115] that Program 1 will prevent any player from deviating to a pure strategy aimed at improving the expected utility, which is indeed the condition for assuring the existence of NE in the considered problem.*

3.5 Supervisory Control

3.5.1 Decentralized DES in the Upper Layer

In the framework of decentralized DES, a set of m controllers will cooperatively decide the control actions. In order for the supervisory control to accept or reject a request issued by an appliance, a controller decides which events are enabled through a sequence based on its own observations. The schedulability of appliances operation depends on two basic properties of DES: controllability and co-observability. We will examine a schedulability problem in decentralized DES, where the given specification $\mathcal{K}$ is controllable but not co-observable.

When $\mathcal{K}$ is not co-observable, it is possible to synthesize the extra power, so that all the MPC controllers guarantee their performance. To that end, we resort to the property of $\mathcal{P}$-*observability* and denote the content of additional power for each subsystem by $\Sigma_j^p = \{\mathsf{extp}^j\}$. A language $\mathcal{K}$ is called $\mathcal{P}$-observable w.r.t. $\mathcal{L}$, $\Sigma_{o,j} \cup \left(\cup_{j \in \mathcal{I}} \Sigma_j^p \right)$, and $\Sigma_{c,j}$ $(j \in \mathcal{I})$ if

$$(\forall s \in \overline{\mathcal{K}})(\forall \sigma \in \Sigma_c)\ s\sigma \in \mathcal{L} \backslash \overline{\mathcal{K}} \Rightarrow$$
$$(\exists j \in \mathcal{I})\ \pi_j^{-1}[\pi_j(s)]\sigma \cap \overline{\mathcal{K}} = \emptyset.$$

3.5.2 Control Design

DES is used as a part of the supervisory control in the upper layer to decide whether any subsystem needs more power to accept a request. In the control design, a controller's view $\mathcal{C}_j$

is first developed for each subsystem $j \in \mathcal{M}$. Figure 3.2 illustrates the process for accepting or rejecting a request issued by an appliance of subsystem $j \in \mathcal{M}$.

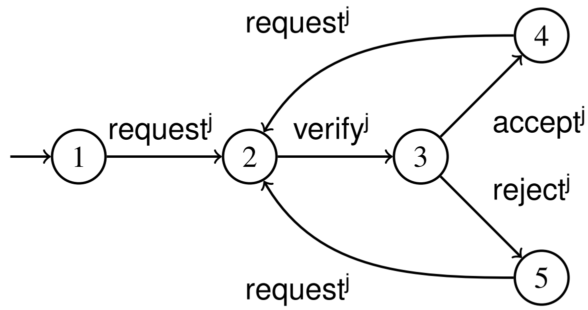

Figure 3.2 Accepting or rejecting a request of an appliance.

If the distributed power is not sufficient for a subsystem $j \in \mathcal{M}$, this subsystem will request for extra power (extp^j) from the supervisory controller, as shown in Figure. 3.3. The controller of the corresponding subsystem will accept the request of its appliances after getting the required power.

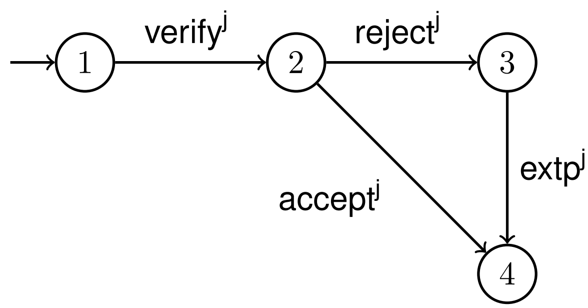

Figure 3.3 Extra power provided to subsystem $j \in \mathcal{M}$.

Finally, the system behavior $\mathcal{C}$ is formulated by taking the synchronous product [102] of $\mathcal{C}_j, \forall j \in \mathcal{M}$, and $\mathsf{extp}^j, \forall j \in \mathcal{M}$. Let $\mathcal{L}_\mathcal{C}$ be the language generated from $\mathcal{C}$ and $\mathcal{K}_\mathcal{C}$ be the specification. A portion of $\mathcal{L}_\mathcal{C}$ is shown in Figure 3.4. The states to avoid are denoted by double circle. Note that, the supervisory controller ensures this by providing additional power.

Denote by $U/\mathcal{L}_\mathcal{C}$ the controlled system under the supervision of $U = \wedge_{j=1}^{\mathcal{M}} U^j$. The closed behavior of $U/\mathcal{L}_\mathcal{C}$ is defined as a language $\mathcal{L}(U/\mathcal{L}_\mathcal{C}) \subseteq \mathcal{L}_\mathcal{C}$, such that

(i) $\varepsilon \in \mathcal{L}(U/\mathcal{L}_\mathcal{C})$, and

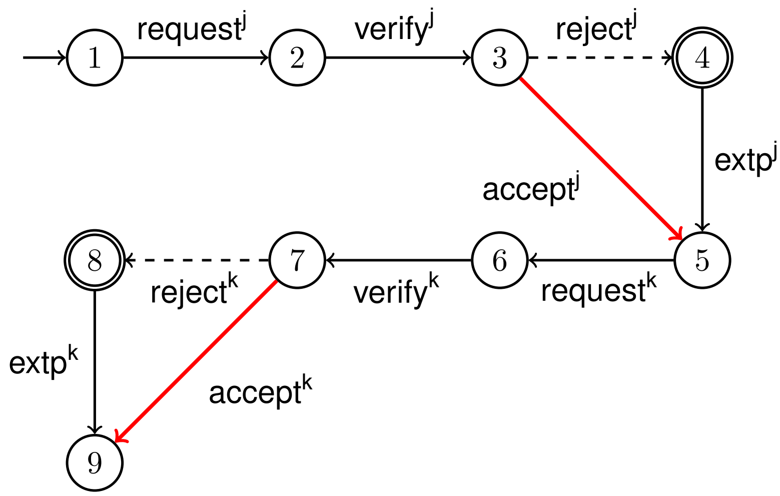

Figure 3.4 A portion of $\mathcal{L}_\mathcal{C}$.

(ii) $\forall s \in \mathcal{L}(U/\mathcal{L}_\mathcal{C})$ and $\forall \sigma \in U(s)$, $s\sigma \in \mathcal{L}_\mathcal{C} \Rightarrow s\sigma \in \mathcal{L}(U/\mathcal{L}_\mathcal{C})$.

The marked behavior of $U/\mathcal{L}_\mathcal{C}$ is $\mathcal{L}_\mathsf{m}(U/\mathcal{L}_\mathcal{C}) = \mathcal{L}(U/\mathcal{L}_\mathcal{C}) \cap \mathcal{L}_\mathsf{m}$.

When the system is not co-observable, the comfort level cannot be achieved. Consequently, we have to make the system $\mathcal{P}$-observable to meet the requirements. The states followed by reject^j for a subsystem $j \in \mathcal{M}$ must be avoided. It is assumed that when a request for subsystem j is rejected (reject^j), additional power (extp^j) will be provided in the consecutive transition. As a result, the system becomes controllable and $\mathcal{P}$-observable and the controller can make the correct decision.

Algorithm 3.2 shows the implemented DES mechanism for accepting or rejecting a request based on the game-theoretic power distribution scheme. When a request is generated for subsystem $j \in \mathcal{M}$, its acceptance is verified through the event verify^j. If there is an enough power to accept the $\mathsf{request}^j$, the event accept^j is enabled and reject^j is disabled. When there is a lack of power, a subsystem $j \in \mathcal{M}$ requests for extra power expt^j to enable the event accept^j and disable reject^j.

A unified modeling language (UML) activity diagram is depicted in Figure 3.5 to show the execution flow of the whole control scheme. Based on the analysis from [117], the following theorem can be established.

Theorem 3.3 *There exists a set of control actions $\{U^1, \dots, U^m\}$ such that the closed behavior of $\wedge_{j=1}^m U^j/\mathcal{L}_\mathcal{C}$ is restricted to $\mathcal{K}_\mathcal{C}$ (i.e., $\mathcal{L}(\wedge_{j=1}^m U^j/\mathcal{L}_\mathcal{C}) \subseteq \mathcal{K}_\mathcal{C}$) if and only if*

(i) $\mathcal{K}_\mathcal{C}$ is controllable w.r.t. $\mathcal{L}_\mathcal{C}$ and Σ_{uc},

(ii) $\mathcal{K}_{\mathcal{C}}$ *is* $\mathcal{P}$*-observable w.r.t.* $\mathcal{L}_{\mathcal{C}}$*,* π_j *and* $\Sigma_{c,j}$*, and*

(iii) $\mathcal{K}_{\mathcal{C}}$ *is* $\mathcal{L}_m$*-closed.*

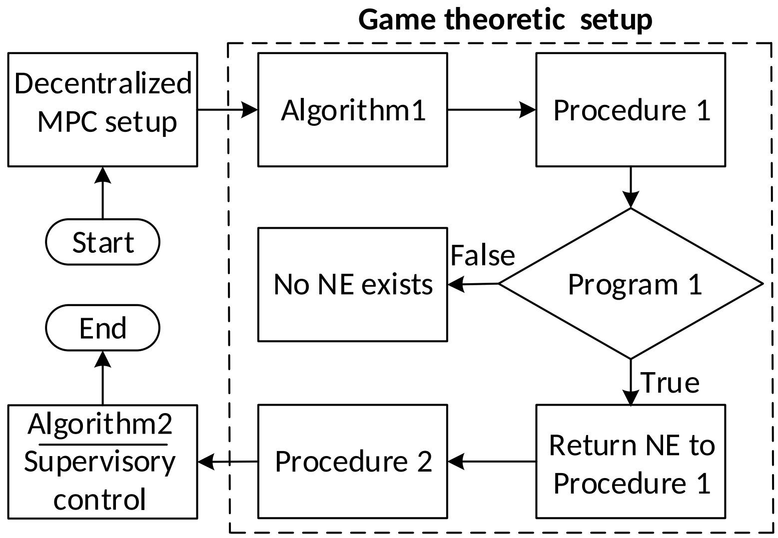

Figure 3.5 UML activity diagram of the proposed control scheme.

3.6 Simulation Studies

3.6.1 Simulation Setup

The proposed DMPC has been implemented on a Matlab-Simulink platform. In the experiment, the YALMIP toolbox [118] is used to implement the MPC in each subsystem, and the DES centralized controllers view $\mathcal{C}$ is generated using the Matlab Toolbox DECK [107]. As each subsystem represents a scalar problem, there is no concern regarding the computational effort. A four-zone building, equipped with one heater in each zone, is considered in the simulation. The building layout is represented in Figure 3.6. Note that the thermal coupling occurs through the doors between the neighboring zones and the isolation of the walls is supposed to be very high ($R^d_{\text{wall}} = \infty$). Note also that experimental implementations or the use of more accurate simulation software, e.g., EnergyPlus [119], may provide a more reliable assessment of the proposed work.

In this simulation experiment, the thermal comfort zone is chosen as $(22 \pm 0.5)°C$ for all the zones. The prediction horizon is chosen to be $N = 10$ and $T_s = 1.5$ time steps which is about 3 min in the coressponding real time-scale. The system is decoupled into four subsystems, corresponding to a setting with $m = M$. Furthermore, it has been verified that the system

Algorithm 3.2 DES-based Admission Control

Input:

- $\mathcal{M}$: set of subsystems
- m: number of subsystems
- j: subsystem $\in \mathcal{M}$
- pw^j: power for subsystem $j \in \mathcal{M}$ from the NE
- $cons$: total power consumption of the accepted requests
- C: available capacity

$cons = 0$
if $\sum_{j \in \mathcal{M}} pw^j <= C$ **then**
    $j = 1$
    repeat
        if there is a request from $j \in \mathcal{M}$ **then**
            enable accept^j and disable reject^j
            $cons = cons + pw^j$
        end if
        $j \leftarrow j + 1$
    until $j <= m$
else
    $j = 1$
    repeat
        if there is a request from $j \in \mathcal{M}$ **then**
            request for extp^j
            enable accept^j and disable reject^j
            $cons = cons + pw^j$
        end if
        $j \leftarrow j + 1$
    until $j <= m$
end if

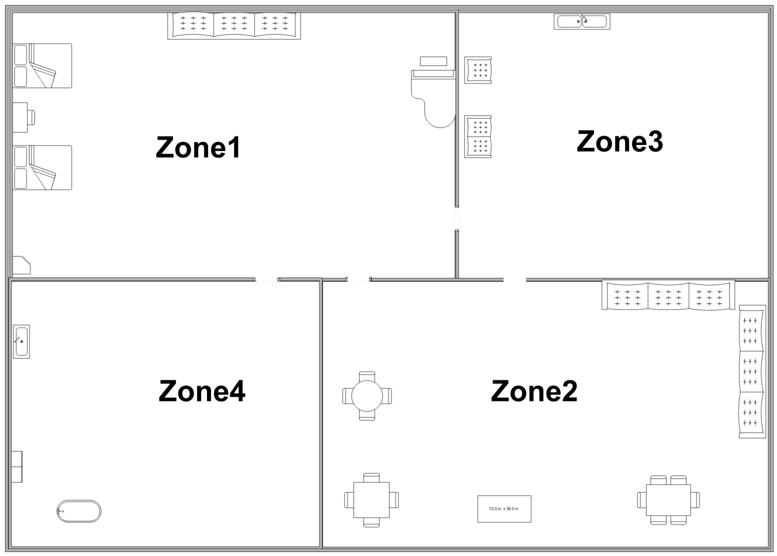

Figure 3.6 Building layout.

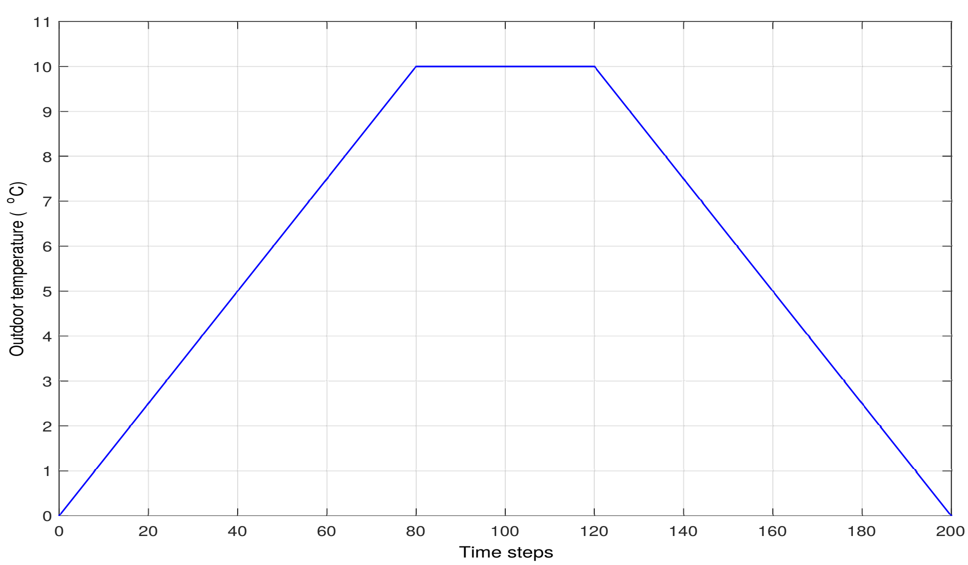

Figure 3.7 Ambient temperature.

and the decomposed subsystems are all stable in open loop. The variation of the outdoor temperature is presented in Figure 3.7.

The co-observability and $\mathcal{P}$-observability properties are tested with high and low constant power capacity constraints, respectively. It is supposed that the heaters in Zone 1 and 2 need 800 W each as the initial power while the heaters in Zone 3 and 4 require 600 W each. The requested power is discretized with a step of 10 W. The initial indoor temperatures are set to 15 °C inside all the zones.

The parameters of the thermal model are listed in Table 3.1 and Table 3.2, and the system decomposition is based on the approach presented in [113]. The submatrices A_i, B_i, and E_i can be computed as presented in Section 3.3.2 with the decoupling matrices given by $W_i = Z_i = H_i = e_i$, where e_i is the i^{th} standard basic vector of $\mathbb{R}^4$.

Table 3.1 Configuration of thermal parameters for heaters.

Room	1	2	3	4
R_j^a	69.079	88.652	128.205	105.412
C_j	0.94	0.94	0.78	0.78

Table 3.2 Parameters of thermal resistances for heaters.

R_{12}^r, R_{21}^r	R_{13}^r, R_{31}^r	R_{14}^r, R_{41}^r	R_{23}^r, R_{32}^r	R_{24}^r, R_{42}^r
709.2	1063.8	1063.8	1063.8	1063.8

3.6.2 Case 1: Co-observability Validation

In this case, we validate the proposed scheme to test the co-observability property for various power capacity constraints. We split the whole simulation time into two intervals, $[0, 60)$ and $[60, 200]$, with 2800 W and 1000 W as power constraints, respectively. At the start-up, a power capacity of 2800 W is required as the initial power for all the heaters.

The zone's indoor temperatures are depicted in Figure 3.8. It can be seen that the DMPC has the capability to force the indoor temperatures in all zones to stay within the desired range if there is enough power. Specifically, the temperature is kept in the comfort zone until 140 time steps. After that, the temperature in all the zones attempts to go down due to the effect of the ambient temperature and the power shortage. In other words, the system is no longer co-observable and hence, the thermal comfort level cannot be guaranteed.

The individual and the total power consumption of the heaters over the specified time intervals are shown in Figure 3.9 and Figure 3.10, respectively. It can be seen that in the

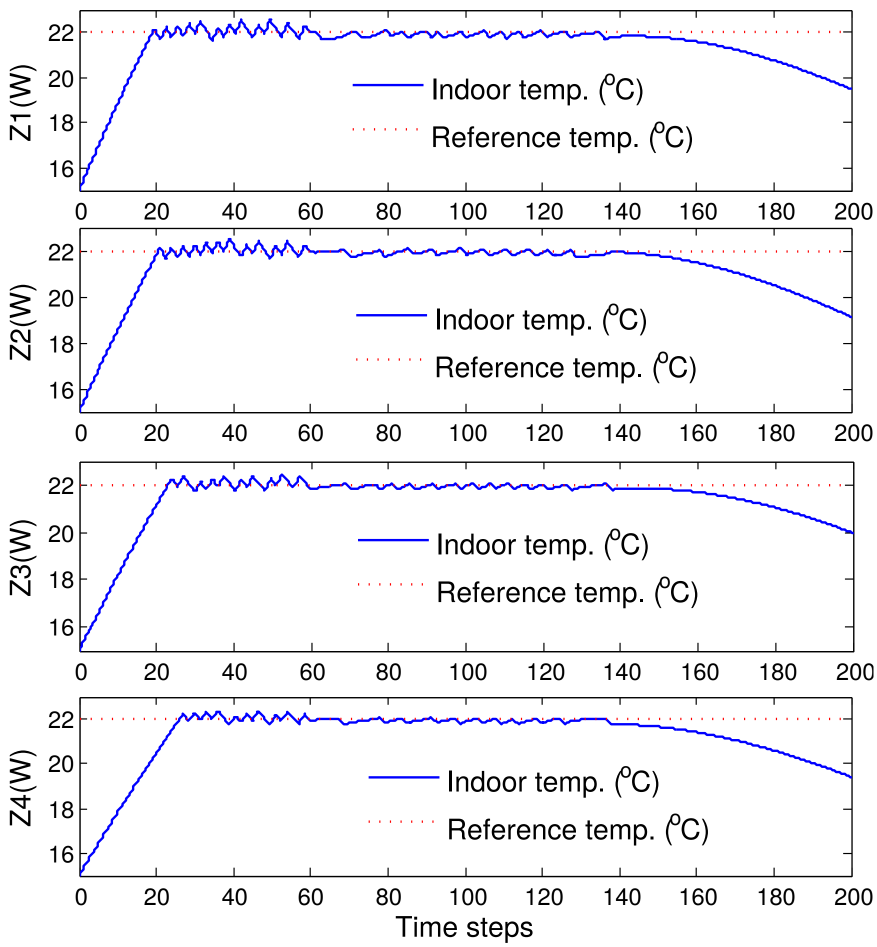

Figure 3.8 Temperature in each zone by using DMPC strategy in Case 1: co-observability validation.

second interval, all the available power is distributed to the controllers, and the total power consumption is about 36% of the maximum peak power.

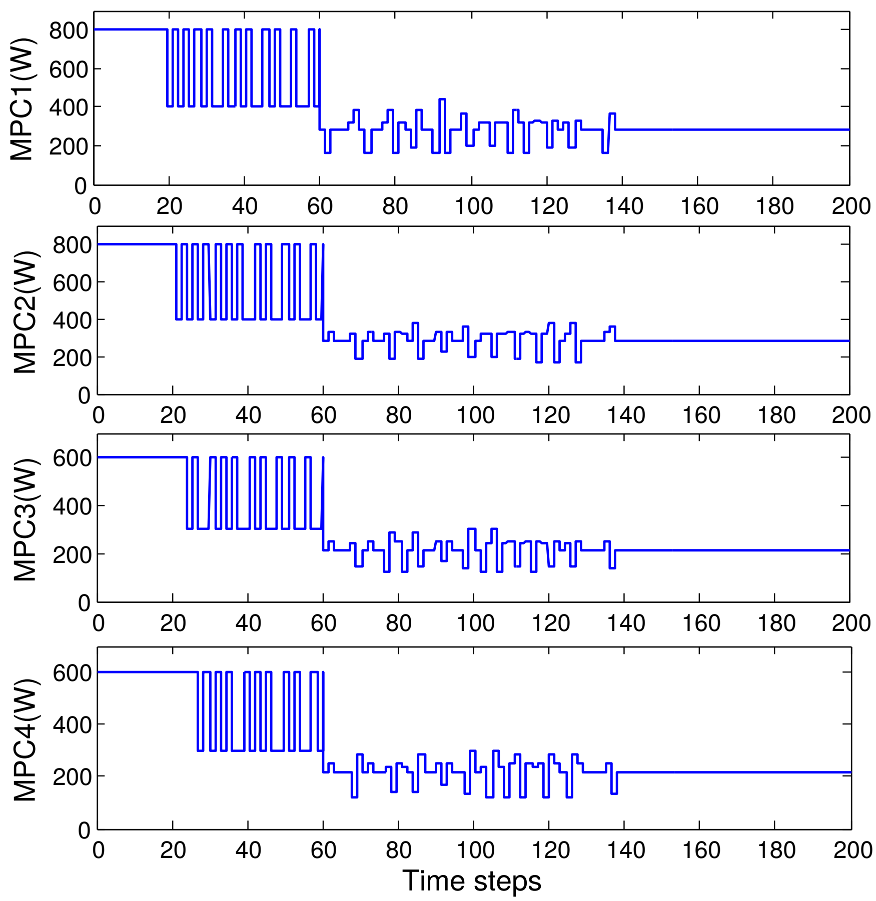

Figure 3.9 The individual power consumption for each heater by using DMPC strategy in Case 1: co-observability validation.

3.6.3 Case 2: $\mathcal{P}$-Observability Validation

In the second test, we consider three time intervals $[0, 60)$, $[60, 140)$, and $[140, 200]$. In addition, we raise the level of power capacity to 1600 W in the third time interval. The indoor temperature of all zones is shown in Figure 3.11. It can be seen that the temperature is maintained within the desired range over all the simulation time steps, despite the diminishing of the outdoor temperature. Therefore, the performance is achieved and the system becomes $\mathcal{P}$-observable. The individual and the total power consumption of the heaters are illustrated in Figure 3.12 and Figure 3.13, respectively. Note that the power capacity applied over the third interval (1600 W) is about 57% of the maximum power, which is a significant reduction of power consumption. It is worth noting that when the system fails to ensure

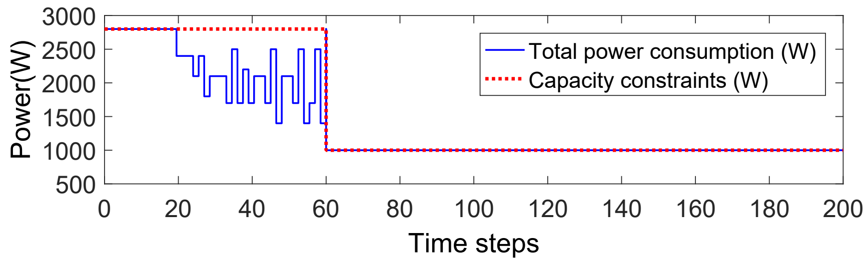

Figure 3.10 Total power consumption by using DMPC strategy in Case 1: co-observability validation.

the performance due to the lack of the supplied power, the upper layer of the proposed control scheme can compute the amount of extra power that is required to ensure the system performance. The corresponding DES will become $\mathcal{P}$-observable if extra power is provided.

Finally, it is worth noting that the simulation results confirm that in both Case 1 and Case 2, power distributions generated by the game-theoretic scheme are always fair. Moreover, as the attempt of any agent to improve its performance does not degrade the performance of the others, it eventually allows avoiding the selfish behavior of the agents.

3.7 Concluding Remarks

This work presented a hierarchical decentralized scheme consisting of a decentralized DES supervisory controller based on a game-theoretic power distribution mechanism and a set of local MPC controllers for thermal appliance control in smart buildings. The impact of observability properties on the behavior of the controllers and the system performance have been thoroughly analyzed, and algorithms for running the system in a numerically efficient way have been provided. Two case studies were conducted to show the effect of co-observability and $\mathcal{P}$-observability properties related to the proposed strategy. The simulation results confirmed that the developed technique can efficiently reduce the peak power while maintaining the thermal comfort within an adequate range when the system was $\mathcal{P}$-observable. In addition, the developed system architecture has a modular structure and can be extended to appliance control in a more generic context of HVAC systems. Finally, it might be interesting to address the applicability of other control techniques, such as those presented in [120, 121], to smart building control problems.

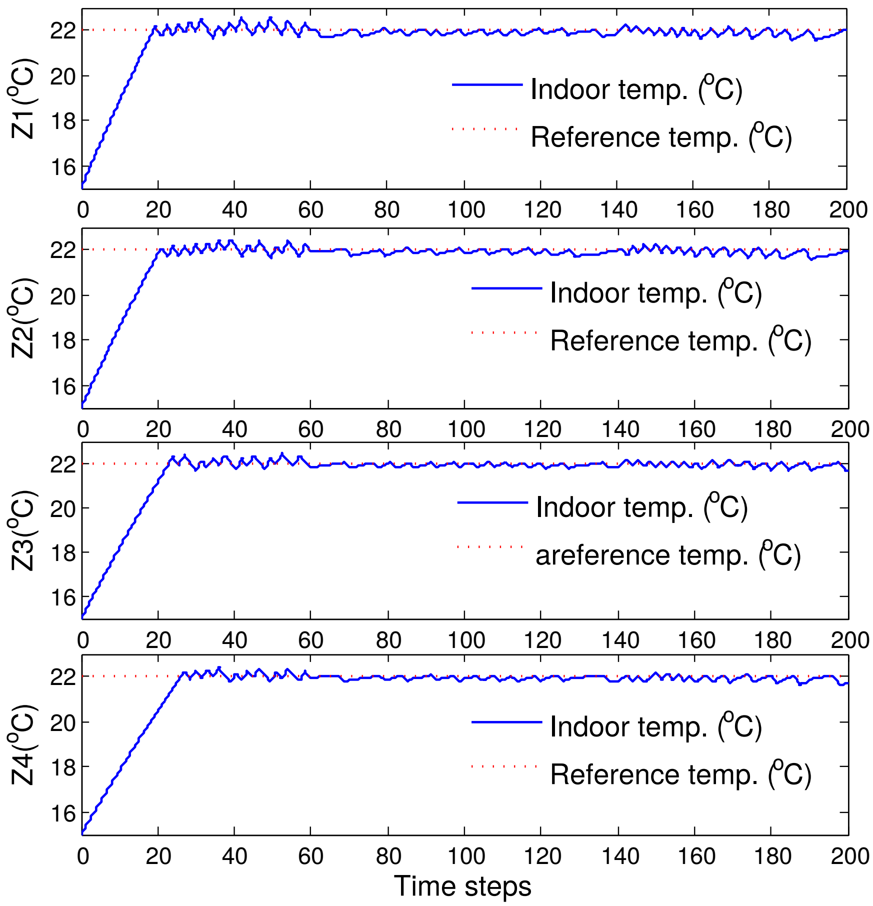

Figure 3.11 Temperature in each zone in using DMPC strategy in Case 2: $\mathcal{P}$-Observability validation.

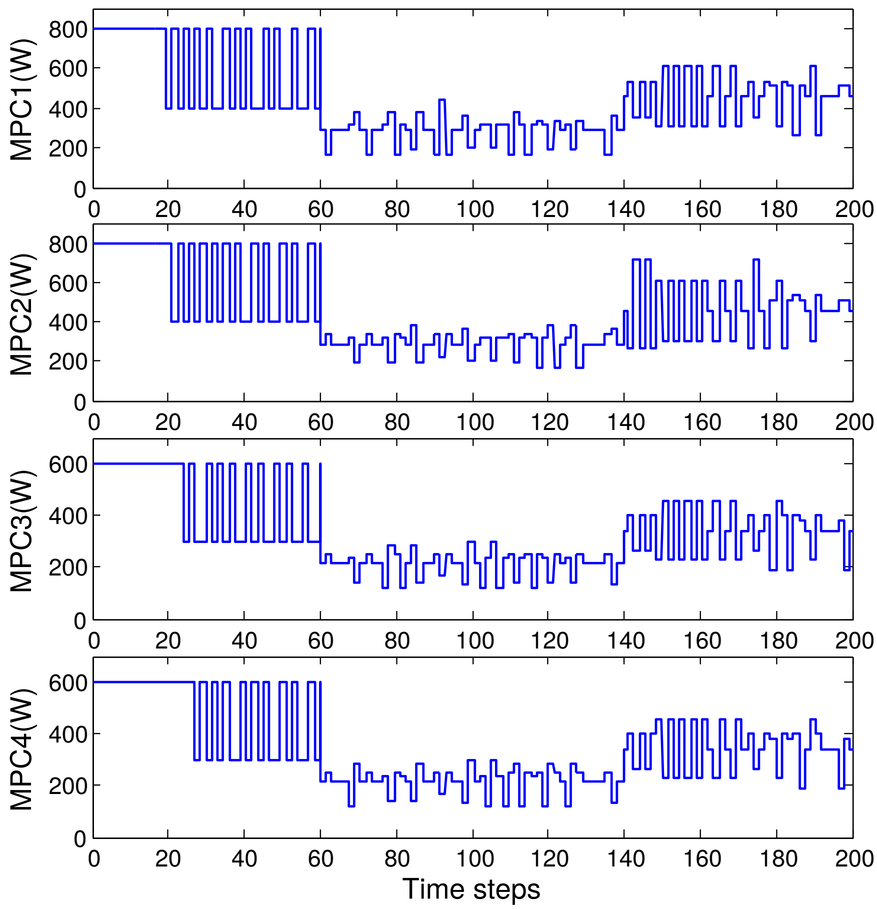

Figure 3.12 The individual power consumption for each heater by using DMPC strategy in Case 2: $\mathcal{P}$-Observability validation.

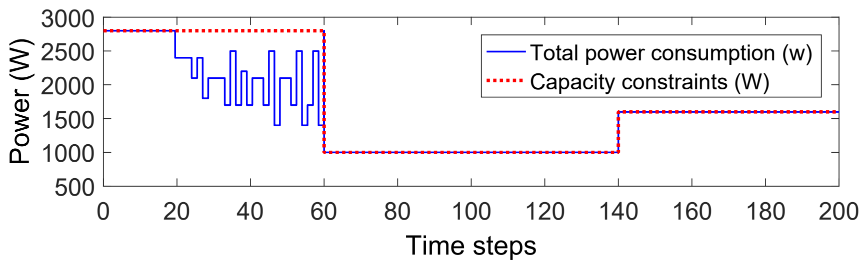

Figure 3.13 Total power consumption by using DMPC strategy in Case 2: $\mathcal{P}$-Observability validation.

CHAPTER 4 ARTICLE 2: A NONLINEAR MODEL PREDICTIVE CONTROL FOR VENTILATION SYSTEMS IN SMART BUILDING

The chapter is a paper submitted to Energy and Building. I am the first author of this paper and made major contributions to this work.

Authors–Saad A. Abobakr and Guchuan Zhu

Abstract–This paper describes an application of nonlinear model predictive control (NMPC) using feedback linearization (FBL) to the ventilation system of smart buildings. A hybrid cascade control strategy is used to regulate the ventilation flow rate to retain the indoor CO_2 concentration close to an adequate comfort level with minimal power consumption. The control structure has an internal loop controlled by the FBL to cancel the nonlinearity of the CO_2 model and a model predictive control (MPC) as a master controller in the external loop based on a linearized model under both input and output constraints. The outdoor CO_2 levels as well as the occupants' movement patterns are considered in order to validate performance and robustness of the closed-loop system. A local convex approximation is used to cope with the nonlinearity of the control constraints while ensuring the feasibility and the convergence of the system performance over the operation time. The simulation, carried out in a Matlab/Simulink platform, confirmed that the developed scheme efficiently achieves the desired performance with a reduced power consumption compared to a traditional ON/OFF controller.

Index Terms–Nonlinear model predictive control (NMPC), feedback linearization control (FBL), indoor air quality (IAQ), ventilation system, energy consumption.

4.1 Introduction

Almost half of the total energy consumption in buildings comes from their heating, ventilation, and air-conditioning (HVAC) systems [122]. Indoor air quality (IAQ) is an important factor of the comfort level inside buildings. In many places of the world, people may spend 60% to 90% of their lifetime inside buildings [88] and hence, improving IAQ has become an essential concern for responsible building owners in terms of occupant's health and productivity [89]. Controlling volume flow in ventilation systems to achieve the desired level of IAQ in buildings has a significant impact on energy efficiency [87, 95]. For example, in office buildings in the US, ventilation represents almost 61% of the entire energy consumption in office HVAC systems [90].

Carbon dioxide (CO_2) concentration represents a major factor of human comfort in term of IAQ [89, 95]. Therefore, it is essential to ensure that the CO_2 concentration inside building's occupied zones is accurately adjusted and regulated by using appropriate techniques that can efficiently control the ventilation flow with minimal power requirements [95, 123]. Various control schemes have been developed and implemented on ventilation systems to control and distribute the ventilation flow to improve the IAQ and minimize the associated energy use. However, the majority of the implemented control techniques are based on feedback mechanism designed to maintain the comfort level rather to promote efficient control actions. Therefore, optimal control techniques are still needed to manage the operation of such systems to provide an optimum flow rate with minimized power consumption [124]. To the best of our knowledge, there have been no applications of nonlinear model predictive control (NMPC) techniques to ventilation systems based on a CO_2 concentration model in buildings. The nonlinear behavior of the CO_2 model and the problem of convergence are the two main problems that must be addressed in order to apply MPC to CO_2 nonlinear model. In the following, we introduce some existing approaches to control ventilation systems in buildings including MPC-based techniques.

A robust CO_2-based demand-controlled ventilation (DCV) system is proposed in [96] to control CO_2 concentration and enhance the energy efficiency in a two-story office building. In this scheme, a PID controller was used with the CO_2 sensors in the air duct to provide the required ventilation rate. An intelligent control scheme [95] was proposed to control the indoor concentration of CO_2 to maintain an acceptable IAQ in a building with minimum energy consumption. By considering three different case studies, the results showed that their approach leads to a better performance when there is sufficient and insufficient energy supplied, compared to the traditional ON/OFF control and a fixed ventilation control. Moreover, in term of economic benefits, the intelligent control saves 15% of the power consumption compared to a bang-bang controller. In [87] an approach was developed to control the flow rate based on the pressure drop in the ducts of a ventilation system and the CO_2 levels. This method derives the required air volume flow efficiently while satisfying the comfort constraints with lower power consumption. Dynamic controlled ventilation [97] has been proposed to control the CO_2 concentration inside a sports training area. The simulation and experimental results of this control method saved 34% on the power consumption while maintaining the indoor CO_2 concentration close to the set-point during the experiments. This scheme provided a better performance than both proportional and exponential controls. Another control mechanism that works based on direct feedback linearization to compensate the nonlinearity of the CO_2 model was implemented for the same purpose [98].

Much research has been invested in adjusting the ventilation flow rate based on the MPC technique in smart buildings [91–94, 125]. A number of algorithms can be used to solve nonlinear MPC problems to control ventilation systems in buildings, such as Sequential Quadratic Programming, Cost and Constraints Approximation, and the Hamilton-Jacobi-Bellman algorithm [126]. However, these algorithms are much more difficult to solve than linear ones in term of their computational cost, as they are based on non-convex cost functions [127]. Therefore, a combination of MPC mechanism with feedback linearization (FBL) control is presented and implemented in this work to provide an optimum ventilation flow rate to stabilize the indoor CO_2 concentration in a building based on the CO_2 predictive model [128]. A local convex approximation is integrated in the control design to overcome the nonlinear constraints of the control signal while assuring the feasibility and convergence of the system performance.

While it is true that some simple classical control approaches, such as a PID controller, could be used together with the technique of FBL control to regulate the flow rate in ventilation systems, such controllers lack the capability to impose constraints on the system states and the inputs as well as to reject the disturbances. The advantage of MPC-based schemes over such control methods is their ability to anticipate the output by solving a constrained optimization problem at each sampling instant to provide the appropriate control action. This problem-solving prevents sudden variation in the output and control input behavior [129]. In fact, the MPC mechanism can provide a trade-off between the output performance and the control effort and thereby achieve more energy-efficient operations with reduced power consumption while respecting the imposed constraints [93, 124]. Moreover, the feasibility and the convergence of system performance can be assured by integrating some approaches in the MPC control formulation that would not be possible in the PID control scheme. The main contribution of this paper lies in the application of MPC-FBL to control the ventilation flow rate in a building based on a CO_2 predictive model. The cascade control approach forces the indoor CO_2 concentration level in a building to stay within a limited comfort range around a setpoint with lower power consumption. The feasibility and the convergence of the system performance are also addressed.

The rest of the paper is organized as follows. Section 4.2 presents the CO_2 predictive model with its equilibrium point. Brief descriptions of FBL control, the nonlinear constraints treatment approach, as well as the MPC problem setup are provided in Section 4.3. Section 4.4 presents the simulation results to verify the system performance with the suggested control scheme. Finally, Section 4.5 provides some concluding remarks.

4.2 System Model Description

The main function of a ventilation system is to circulate the air from outside to inside to provide appropriate IAQ in a building. Both supply and exhaust fans are used to exchange the air; the former provides the outdoor air and the latter removes the indoor air [86]. In this work, a CO_2 concentration model is used as an indicator of the IAQ that is affected by the airflow generated by the ventilation system.

A CO_2 predictive model is used to anticipate the indoor CO_2 concentration, which is affected by the number of people inside the building as well as by the outside CO_2 concentration [95,128,130]. For simplicity, the indoor CO_2 concentration is assumed to be well-mixed at all times. The outdoor air is pulled inside the building by a fan that produces the air circulation flow based on the signal received from the controller. A mixing box is used to mix up the returned air with the outside air, as shown in Figure 4.1. The model for producing the indoor CO_2 can be described by the following equation, in which the inlet and outlet ventilation flow rates are assumed to be equal with no air leakage [128]:

$$M\dot{O}(t) = u(O_{\text{out}}(t) - O(t)) + RN(t), \tag{4.1}$$

where O_{out} is the outdoor (inlet air) CO_2 concentration in ppm at time t, $O(t)$ is the indoor CO_2 concentration within the room in ppm at time t, R is the CO_2 generation rate per person L/s, $N(t)$ is the number of people inside the building at time t, u is the overall ventilation rate into (and out of) m^3/s, and M is the volume of the building in m^3.

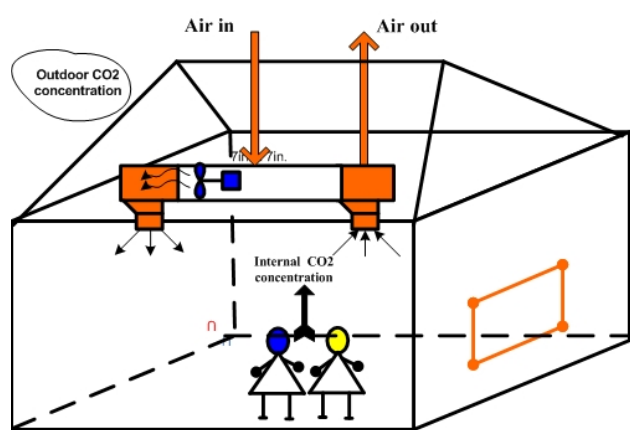

Figure 4.1 Building ventilation system

In (4.1), the nonlinearity in the system model is due to the multiplication of the ventilation rate u with the indoor concentration $O(t)$.

The equilibrium point of the CO_2 model (4.1) is given by:

$$O_{\mathrm{eq}} = \frac{G}{u_{\mathrm{eq}}} + O_{\mathrm{out}} \tag{4.2}$$

where O_{eq} is the equilibrium CO_2 concentration and $G = RN(t)$ is the design generation rate. The resulted u from the above equation ($u_{\mathrm{eq}} = G/(O_{\mathrm{eq}} - O_{\mathrm{out}})$) is the required space ventilation rate which will be regulated by the designed controller.

There are two main remarks regarding the system model in (4.1): First, (4.2) shows that there is no single equilibrium point that can represent the whole system and be used for model linearization. To eliminate this problem, in this work the technique of feedback linearization is integrated into the control design. Second, the system equilibrium point in (4.2) shows that the system has a singularity, which must be avoided in control design. Therefore, the MPC technique is used in cascade with the FBL control to impose the required constraints to avoid the system singularity, which would not be possible using a PID controller.

4.3 Control Strategy

4.3.1 Controller Structure

As stated earlier, a combination of the MPC technique and FBL control is used to control the indoor CO_2 concentration with lower power consumption while guaranteeing the feasibility and the convergence of the system performance. The schematic of the cascade controller is shown in Figure 4.2. The control structure has internal (Slave controller) and external loops (Master controller). While the internal loop is controlled by the FBL to cancel the nonlinearity of the system, the outer (master) controller is the MPC that produces an appropriate control signal v based on the linearized model of the nonlinear system. The implemented control scheme works in ON/OFF mode and its efficiency is compared with the performance of a classical ON/OFF control system.

An algorithm proposed in [127] is used to overcome the problem of nonlinear constraints arising from feedback linearization. Moreover, to guarantee the feasibility and the convergence, local constraints are used instead of considering the global nonlinear constraints that arise from feedback linearization. We use a lower bound that is convex, and an upper bound that is concave. Finally, the constraints are integrated into a cost function to solve the MPC problem. To approximate a solution with a finite-horizon optimal control problem for the discrete system, we use the following cost function to implement the MPC [127]:

$$
\begin{aligned}
&\min_{u} \quad \Psi(x_{k+N}) + \sum_{i=0}^{N-1} l(x_{k+i}, u_{k+i}) && \text{(4.3a)}\\
\text{s.t.} \quad & x_{k+i+1} = f(x_{k+i}, u_{k+i}), && \text{(4.3b)}\\
& x_{k+i} \in \chi, && \text{(4.3c)}\\
& u_{k+i} \in \Upsilon, && \text{(4.3d)}\\
& x_{k+N} \in \tau, && \text{(4.3e)}
\end{aligned}
$$

for $i = 0, \ldots, N$, where N is the prediction, x is the sate vector and u is the control input vector. The first sample, u_k, from the resulting control sequence is applied to the system, and then all the steps will be repeated again at next sampling instance to produce u_{k+1} control action and so on until the last control action is produced and implemented.

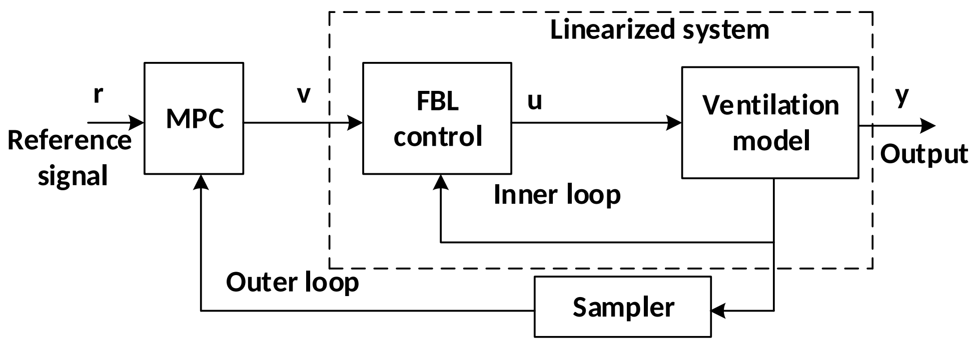

Figure 4.2 Schematic of MPC-FBL cascade controller of a ventilation system.

4.3.2 Feedback Linearization Control

The FBL is one of the most practical nonlinear control methods that is used to transform the nonlinear systems into linear ones by getting rid of the nonlinearity in the system model. Consider the SISO affine state space model as follows:

$$
\begin{aligned}
\dot{x} &= f(x) + g(x)u \\
y &= h(x)
\end{aligned}
\tag{4.4}
$$

where x is the state variable, u is the control input, y is the output variable, and f, g, and h are smooth functions in a domain $D \subset R^n$.

If there exists a mapping Φ that transfers the system (4.4) to the following form:

$$\begin{aligned} y &= h(x) = \xi_1, \\ \dot{\xi}_1 &= \xi_2 \\ \dot{\xi}_2 &= \xi_3 \\ &\vdots \\ \dot{\xi}_n &= b(x) + a(x)u, \end{aligned} \tag{4.5}$$

then in the new coordinates, the linearizing feedback law is:

$$u = \frac{1}{a(x)}(-b(x) + v), \tag{4.6}$$

where v is the transformed input variable. Denoting $\xi = (\xi_1 \ \cdots \ \xi_n)^T$, the linearized system is then given by:

$$\begin{aligned} \dot{\xi} &= A\xi + Bv, \\ y &= C\xi, \end{aligned} \tag{4.7}$$

where

$$A = \begin{pmatrix} 0 & 1 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & 1 & 0 & \cdots & \vdots \\ \vdots & \vdots & 0 & \ddots & \ddots & 0 \\ \vdots & \vdots & \vdots & \ddots & \ddots & 1 \\ 0 & \cdots & \cdots & \cdots & \ddots & 0 \end{pmatrix}, \quad B = \begin{pmatrix} 0 \\ \vdots \\ \vdots \\ 0 \\ 1 \end{pmatrix},$$
$$C = \begin{pmatrix} 1 & 0 & \cdots & \cdots & 0 \end{pmatrix}.$$

If we discretize (4.7) with sampling time T_s and by using zero order hold, it results in:

$$\xi_{k+1} = A_d\xi_k + B_d v_k, \tag{4.8a}$$

$$y_k = C_d\xi_k, \tag{4.8b}$$

where A_d, B_d, and C_d are constant matrices that can be computed from continuous system matrices: A, B, and C in (4.7), respectively.

In this control strategy, we assume that the system described in (4.4) is input-output feedback linearizable by the control signal in (4.6) and the linearized system has a discrete state-sapce model as described in (4.8). In addition, $\psi(\cdot)$ and $l(\cdot)$ in (4.3) satisfy the stability conditions [131] and the sets Υ and χ are convex polytope.

If we apply the FBL and MPC to the nonlinear system in (4.4), we get the following MPC control problem:

$$\min_{u} \quad \Psi(\xi_{k+N}) + \sum_{i=0}^{N-1} l(\xi_{k+i}, v_{k+i}) \tag{4.9a}$$

$$\text{s.t.} \quad \xi_{k+i+1} = A\xi_{k+i} + Bv_{k+i}, \tag{4.9b}$$

$$\xi_{k+i} \in \chi, \tag{4.9c}$$

$$\xi_{k+N} \in \tau, \tag{4.9d}$$

$$v_{k+i} \in \Pi, \tag{4.9e}$$

where $\Pi = \{v_{k+i} \mid \pi(\xi_{k+i}, \underline{u}) \leqslant v_{k+i} \leqslant \pi(\xi_{k+i}, \overline{u})\}$, and the functions $\pi(\cdot)$ are the nonlinear constraints.

4.3.3 Approximation of the Nonlinear Constraints

The main problem is that the FBL will impose nonlinear constraints on the control signal v and hence, (4.9) will no longer be convex. Therefore, we use the scheme proposed in [127] to deal with the problem of nonlinearity constraints on the ventilation rate v, as well as to guarantee the recursive feasibility and the convergence. This approach depends on using the exact constraints for the current time step and a set of inner polytope approximations for the future steps.

First, to overcome the nonlinear constraint (4.9e), we replace the constraints with a global inner convex polytopic approximation:

$$\Omega = \{(\xi, v) \mid \xi \in \chi, g_l(\chi) \leqslant v \leqslant g_u(\chi)\}, \tag{4.10}$$

where $g_u(\chi) \leqslant \pi(\chi, \overline{u})$ and $g_l(\chi) \geqslant \pi(\chi, \underline{u})$ are concave piecewise affine function and convex piecewise function, respectively.

If the current state is known, the exact nonlinear constraint on v is:

$$\pi(\xi_k, \underline{u}) \leqslant v_k \leqslant \pi(\xi_k, \overline{u}). \tag{4.11}$$

Note that this approach is based on the fact that for a limited subset of state space, there may be a local inner convex approximation that is better than the global one in (4.10). Thus, a convex polytype L over the set χ_{k+1} is constructed with constraint (ξ_{k+1}, v_{k+1}) to this local approximation. To ensure the recursive stability of the algorithm, both the inner approximations of the control inputs for actual decisions and the outer approximations of control inputs for the states are considered.

The outer approximation of the i^{th} step reachable set χ_{k+1} is defined at time k as:

$$\chi_{k+1} = A_d \chi_{k+i-1} + B_d \Phi_{k+i-1} \tag{4.12}$$

where $\chi_k = \{x_k\}$. The set Φ_{k+i} is an outer polytopic approximation of the nonlinear constraints defined as:

$$\Phi_{k+i} = \left\{ v_{k+i} \mid \omega_l^{k+i}(\chi_{k+i}) \leqslant v_{k+i} \leqslant \omega_u^{k+i}(\chi_{k+i}) \right\}, \tag{4.13}$$

where $\omega_u^{k+i}(\cdot)$ is a concave piecewise affine function that satisfies $\omega_u^{k+i}(\chi_{k+1}) \geqslant \pi(\chi_{k+1}, \overline{u})$, and $\omega_l^{k+i}(\cdot)$ is a convex piecewise affine function such as $\pi(\chi_{k+1}, \underline{u}) \geqslant \omega_l^{k+i}(\chi_{k+1})$.

Assumption 4.1 *For all reachable sets χ_{k+i}, $i = 1, \ldots, N-1$, $\chi_{k+i} \cap \chi \neq 0$ and the local convex approximation, I_i^k, has to be an inner approximation to the nonlinear constraints, as well as on the subset χ_{k+1} such as $\Omega \subseteq I_i^k$.*

The following constraints should be satisfied for the polytope:

$$h_l^{k+i}(\chi_{k+i} \cap \chi) \leqslant v_{k+i} \leqslant h_u^{k+i}(\chi_{k+i} \cap \chi), \tag{4.14}$$

where $h_u^{k+i}(\cdot)$ is concave piecewise affine function that satisfies: $g_u(\chi_{k+1}) \leqslant h_u^{k+i}(\chi_{k+1}) \leqslant \pi(\chi_{k+1}, \overline{u})$, and $h_l^{k+i}(\cdot)$ is convex piecewise affine function that satisfies: $\pi(\chi_{k+1}, \underline{u}) \leqslant h_l^{k+i}(\chi_{k+1}) \leqslant g_l(\chi_{k+1})$.

4.3.4 MPC Problem Formulation

Based on the procedure outlined in the previous sections, the resulting finite horizon MPC optimization problem is:

$$\min_{u} \quad \Psi(\xi_{k+N}) + \sum_{i=0}^{N-1} l(\xi_{k+i}, v_{k+i}), \tag{4.15a}$$

$$\text{s.t.} \quad \xi_{k+i+1} = A_d \xi_{k+i} + B_d v_{k+i}, \tag{4.15b}$$

$$\pi(\xi_k, \underline{u}) \leqslant v_k \leqslant \pi(\xi_k, \overline{u}), \tag{4.15c}$$

$$(\xi_{k+i}, v_{k+i}) \in I_i^k, \ \forall i = 1, \ldots, N_l \tag{4.15d}$$

$$(\xi_{k+i}, v_{k+i}) \in \Omega, \ \forall i = N_l + 1, \ldots, N-1, \tag{4.15e}$$

$$\xi_{k+N} \in \tau, \tag{4.15f}$$

where the state and control are constrained to the global polytopes for horizon $N_l < i < N$ and to the local polytopes until horizon $N_l \leq N-1$. The updating of the local approximation I_i^{k+1} can be computed as below:

$$I_i^{k+1} = I_{i+1}^k \ \ \forall i = 1, \ldots, N_l - 1. \tag{4.16}$$

The invariant set τ in (4.15f) is calculated from the global convex approximation Ω as:

$$\tau = \{\xi \mid (A_d \xi + B_d k(x) \in \tau \ \forall \xi \in \tau), (\xi, k(\xi)) \in \Omega\}. \tag{4.17}$$

Finally, using the above cost function and considering all the imposed constraints, the stability and the feasibility of the system (4.8) using MPC-FBL controller will be guaranteed [127].

4.4 Simulation Results

To validate the MPC-FBL control scheme for indoor CO_2 concentration regulation in a building, we conducted a simulation experiment to show the advantages of using nonlinear MPC over the classical ON/OFF controller in terms of set-point tracking and power consumption reduction.

4.4.1 Simulation Setup

The simulation experiment was implemented on a Matlab/Simulink platform in which the YALMIP toolbox [118] was utilized to solve the optimization problem and provide the appropriate control signal. The time span in the simulation was normalized to 150 time steps such that the provided power was assumed to be adequate over the whole simulation time. The prediction horizon for the MPC problem was set as $N = 15$ and the sampling time as $T_s = 0.03$.

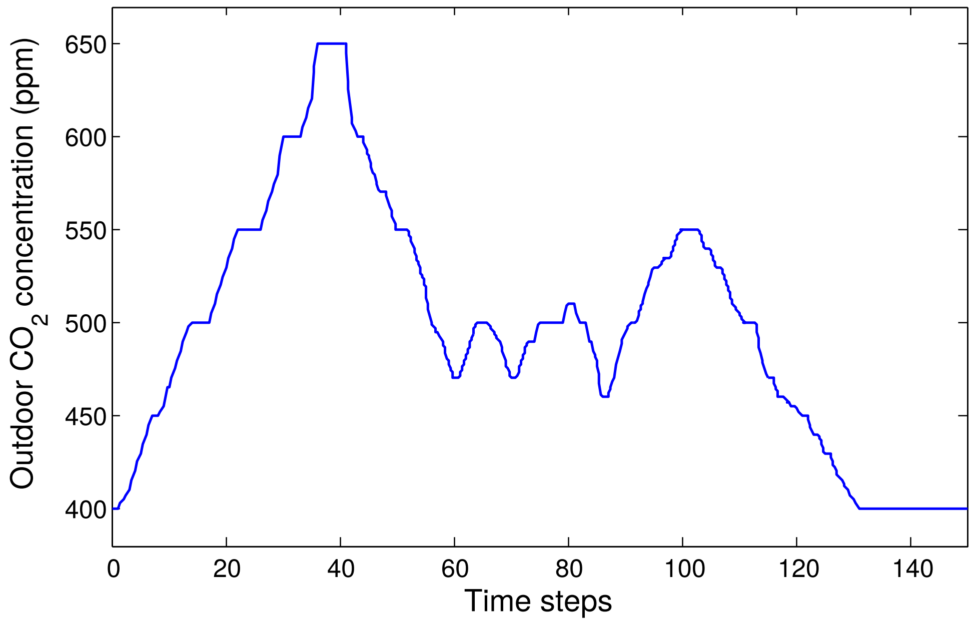

Figure 4.3 Outdoor CO_2 concentration.

Both the occupancy pattern inside the building and the outdoor CO_2 concentration outside of the building were considered in the simulation experiment. In general, the occupancy pattern is either predictable or can be found by installing some specific sensors inside the building. We assume that the outdoor CO_2 concentration and the number of occupants inside the building change with time, as shown in Figure 4.3 and in Figure 4.4, respectively. Note that while the maximum number of occupants in the building is set to be 40, the two maximum peaks of the CO_2 concentration are 650 ppm between $(30 - 40)$ time steps, and 550 ppm between $(100 - 110)$ time steps.

To implement the proposed control strategy on the CO_2 concentration model (4.1), we first used the FBL control in (4.6) to cancel the nonlinearity of the CO_2 model in (4.1) as:

$$M\dot{O}(t) = u(O_{\text{out}}(t) - O(t)) + RN(t) = -O(t) + v. \tag{4.18}$$

Thus, the input-output feedback linearization control law is given by:

$$u = \frac{(v - O(t)) - RN(t)}{O_{\text{out}} - O(t)}, \tag{4.19}$$

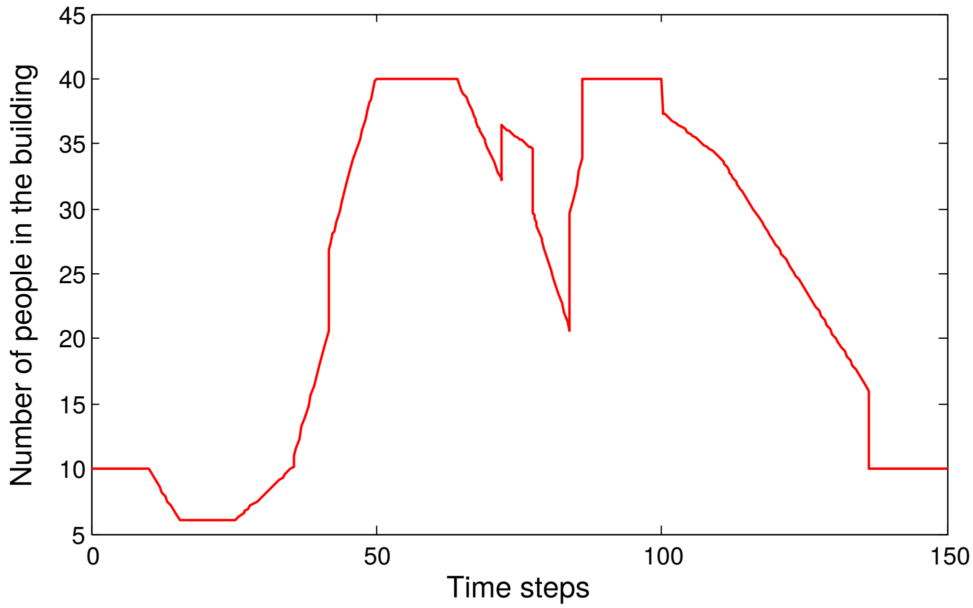

Figure 4.4 The occupancy pattern in the building.

with constraints $O_{\min} \leq O \leq O_{\max}$ and $u_{\min} \leq u \leq u_{\max}$, the nonlinear feedback imposes the following nonlinear constraints on the control action v:

$$O + u_{\min}(O - O_{\text{out}}) + RN) \leq v \leq O + u_{\max}(O - O_{\text{out}}) + RN. \tag{4.20}$$

The linearized model of the system after implementing the FBL is:

$$\begin{aligned} M\dot{O}(t) &= -O(t) + v, \\ y &= O(t). \end{aligned} \tag{4.21}$$

For simplicity, we denote $O(t) = \xi(t)$ and hence, the continuous state space model is:

$$\begin{aligned} M\dot{\xi} &= -\xi + v, \\ y &= \xi. \end{aligned} \tag{4.22}$$

From the linearized continuous state space model (4.22), the state space parameters determined as $A = -1/M$, $B = 1/M$, and $C = 1$. The MPC in the external loop works according to a discretized model of (4.22) and based on the cost function of (4.3) to maintain the internal CO_2 around the set-point of 800 ppm. Satisfying all the constraints guarantees the feasibility and the convergence of the system performance.

The minimum value of the $O_{\text{out}} = 400$ ppm is shown in Figure 4.3. Thus, the minimum value of indoor CO_2 should be at least $O_{\min}(t) \geq 400$. Otherwise, there is no feasible control solution. Table 4.1 contains the values of the required model parameters. Note that the CO_2 generated per person (R) is determined to be 0.017 L/s, which represents a heavy work activity inside the building.

Table 4.1 Parameters description

Variable name	Defunition	Value	Unit
M	Building volume	300	m^3
N_{max}	Max. No. of occupants	40	-
O_{t_0}	Initial indoor CO_2 conentration	500	ppm
O_{set}	Setpoint of desired CO_2 concentration	800	ppm
R	CO_2 generation rate per person	0.017	L/s

4.4.2 Results and Discussion

Figure 4.5 depicts the indoor CO_2 concentration and the power consumption with MPC-FBL control while considering the outdoor CO_2 concentration and the occupancy pattern inside the building.

Figure 4.6 illustrates the classical ON/OFF controller that is applied under the same environmental conditions as above, indicating the indoor CO_2 concentration and the power consumption.

Figure 4.5 and Figure 4.6 show that both control techniques are capable of maintaining the indoor CO_2 concentration within the acceptable range around the desired set-point throughout the total simulation time, despite the impact of the outdoor CO_2 concentration increasing to 650 over $(37-42)$ time steps and reaching up to 550 ppm during $(100-103)$ time steps, and the effects of a changing number of occupants that reached a maximum value of 40 during two different time steps as shown in Figure 4.4. The results confirm that the MPC-FBL control is more efficient than the classical ON/OFF control at meeting the desired performance level, as its output has much less variation around the set-point compared to the output behavior of the system with the regular ON/OFF control.

For the power consumption need of the two control schemes, Figure 4.5 and Figure 4.6 illustrate that the MPC-based controller outperforms the traditional ON/OFF controller in term of power reduction most of the time over the simulation. The MPC-based controller tends to minimize the power consumption as long as the input and output constraints are met, while the regular ON/OFF controller tries to force the indoor concentration of CO_2 to

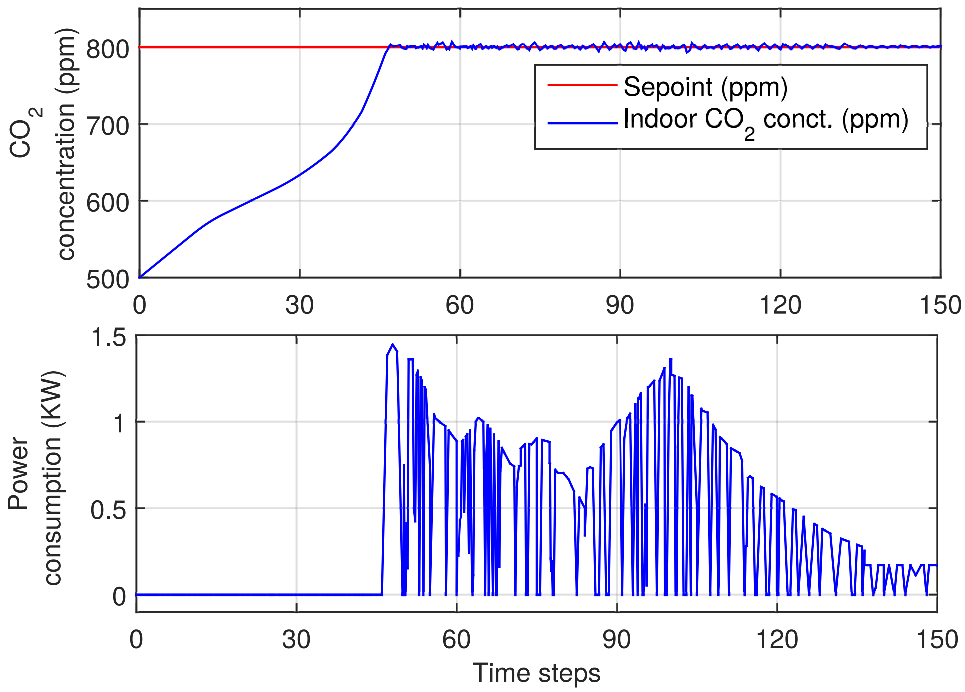

Figure 4.5 The indoor CO_2 concentration and the consumed power in the buidling using MPC-FBL control.

track the setpoint despite the control effort required. While the former controller's maximum power requirement is almost 1.5 KW, the latter controller's maximum power need is about 1.8 KW. Notably, the MPC-based controller has the ability to maintain the indoor CO_2 concentration slightly below or exactly at the desired value while it respects the imposed constraints, but the regular ON/OFF mechanism keeps the indoor CO_2 much lower than the setpoint, which requires more power.

Finally, it is worth emphasizing that the MPC-FBL is more efficient and effective than the classical ON/OFF controller in terms of IAQ and energy savings. It can save almost 14% of the consumers power usage compared to the ON/OFF control method. In addition, the output convergence of the system using the MPC-FBL control can always be ensured, as we can use the local convex approximation approach which is not the case with the traditional ON/OFF control.

4.5 Conclusion

A combination of MPC and FBL control was implemented to control a ventilation system in a building based on a CO_2 predictive model. The main objective was to maintain the indoor

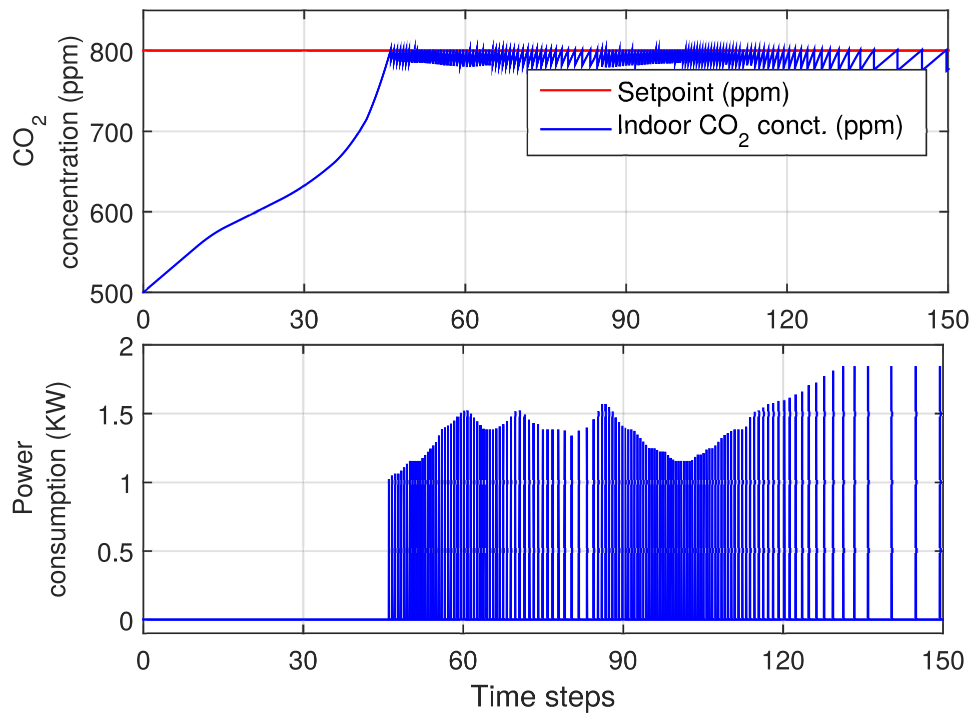

Figure 4.6 The indoor CO_2 concentration and the consumed power in the buidling using conventional ON/OFF control.

CO_2 concentration at a certain set-point, leading to a better comfort level of the IAQ with a reduced power consumption. According to the simulation results, the implemented MPC scheme successfully meets the design specifications with convergence guarantees. In addition, the scheme provided a significant power saving compared to the system performance managed by using the traditional ON/OFF controller, and did so under the impacts of varying both the number of occupants and the outdoor CO2 concentration.

CHAPTER 5 ARTICLE 3: A CO-SIMULATION-BASED APPROACH FOR BUILDING CONTROL SYSTEMS DESIGN AND VALIDATION

The chapter is a paper submitted to Control Engineering Practice. I am the first author of the this paper and made major contributions to this work.

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Abstract–In the Smart Grid environment, building systems and control systems are two different domains that need to be well linked together to provide occupants with better services at a minimum cost. Co-simulation solutions provide a means able to bridge the gap between the two domains and to deal with large-scale and complex energy systems. In this paper, the toolbox of OpenBuild is used along with the popular simulation software EnergyPlus and Matlab/Simulink to provide a realistic and reliable environment in smart building control system development. This toolbox extracts the input/output data from EnergyPlus and automatically generates a high dimension linear state-space thermal model that can be used for control design. Two simulation experiments for the applications of decentralized model predictive control (DMPC) to two different multi-zone buildings are carried out to maintain the occupant's thermal comfort within an acceptable level with a reduced power consumption. The results confirm the necessity of such co-simulation tools for demand response management in smart buildings and validate the efficiency of the DMPC in meeting the desired performance with a notable peak power reduction.

Index Terms– Model predictive control (MPC), smart buildings, thermal appliance control, EnergyPlus, OpenBuild toolbox.

5.1 Introduction

Occupant's comfort level, indoor air quality (IAQ), and the energy efficiency represent three main elements to be managed in smart buildings control [132]. Model predictive control (MPC) has been successfully used over the last decades for the operation of heating, ventilation, and air-conditioning (HVAC) systems in buildings [133]. Numerous MPC control schemes in centralized, decentralized and distributed formulations have been explored for thermal systems control to regulate the thermal comfort with reduced power consumption [12, 30, 61, 62, 64, 73, 74, 77, 79, 83, 112]. The main limitation to the deployment of MPC in buildings is the availability of prediction models [7, 132]. Therefore, simulation software tools for buildings modeling and control design are required to provide adequate models that lead to feasible control solutions of MPC control problems. Also, it will allow the control designers to work within a more reliable and realistic development environment.

Modeling of building systems can be classed as black box (data-driven), white-box (physics-based) or grey-box (combination of physics-based and data-driven) modeling approaches [134]. On one hand, thermal models can be derived from the data and parameters in industrial experiments (forward model or physic-based model) [135, 136]. In this modeling branch, the Resistance-Capacitance (RC) network of nodes is a commonly used approach as an equivalent circuit to the thermal model that represents a first-order dynamic system (see, e.g., [65,74,112, 137]). The main drawback of this approach is that it suffers from generalization capabilities and it is not easy to be applied to multi-zone buildings [138, 139]. On the other hand, several types of modeling schemes use the technique of system identification (data-driven model) including auto-regressive exogenous (ARX) model [140], auto-regressive (AR) model, and auto-regressive moving average (ARMA) model [141]. The main advantage of this modeling scheme is that they do not rely directly on the knowledge of the physical construction of the buildings. Nevertheless, a large set of data is required in order to generate an accurate model [134].

To provide feasible solutions for building modeling and control design, diverse software tools have been developed and used for building modeling, power consumption analysis, and control design, amount which we can find EnergyPlus [119], Transient System Simulation Tool (TRNSYS) [142], ESP-r [143], and Quick Energy Simulation Tool (eQuest) [144]. EnergyPlus is a building energy simulation tool developed by the U.S. Department of Energy (DOE) for building, HVAC systems, occupancy, and lighting. It represents one of the most significant energy analysis and buildings modeling simulation tools that consider different types of HVAC system configurations with environmental conditions [119, 132].

The software tool of EnergyPlus provides a high-order detailed building geometry and modeling capability [145]. Compared to the RC or data-driven models, those obtained from EnergyPlus are more accessible to be updated corresponding to building structure change [146]. EnergyPlus models have been experimentally tested and validated in the literature [56, 138, 147, 148]. For heat balance modeling in buildings, EnergyPlus uses a similar way as other energy simulation tools to simulate the building surface constructions depending on conduction transfer function (CTF) transformation. However, EnergyPlus models outperform the models created by other methods because the use of conduction finite difference (CondFD) solution algorithm as well which allows simulating more elaborated constructions [146].

However, the capabilities of EnergyPlus and other building system simulation software tools for advanced control design and optimization are insufficient because of the gap between building modeling domain and control systems domain [149]. Furthermore, the complexity of these building models make them inappropriate in optimization-based control design for prediction control techniques [134]. Therefore, co-simulation tools such as MLEP [149], Building Controls Virtual Test Bed (BCVTB) [150], and OpenBuild Matlab toolbox [132] have been proposed for end-to-end design of energy-efficient building control to provide a systematic modeling procedure. In fact, these tools will not only provide an interface between EnergyPlus and Matlab/Simulink platforms, but also create a reliable and realistic building simulation environment.

OpenBuild is a Matlab toolbox that has been developed for building thermal systems modeling and control design with an emphasize putting on MPC control applications on HVAC systems. This toolbox aims at facilitating the design and validation of predictive controllers for building systems. This toolbox has the ability to extract the input/output data from EnergyPlus and create high-order state-space models of building thermodynamics, making it convenient for control design that requires an accurate prediction model [132].

Due to the fact that thermal appliances are the most commonly-controlled systems for DR management in the context of smart buildings [12, 65, 112], and by taking advantages of the recently developed energy software tool OpenBuild for thermal systems modeling, in this work, we will investigate the application of DMPC [112] to maintain the thermal comfort inside buildings constructed by EnergyPlus within an acceptable level while respecting certain power capacity constraints.

The main contributions of this paper are:

1. Validate the simulation-based MPC control with a more reliable and realistic development environment, which allows paving the path toward a framework for the design and validation of large and complex building control systems in the context of smart buildings.

2. Illustrate the applicability and the feasibility of DMPC-based HVAC control system with more complex building systems in the proposed co-simulation framework.

5.2 Modeling Using EnergyPlus

5.2.1 Building's Geometry and Materials

Two differently-zoned buildings from EnergyPlus 8.5 example's folder are considered in this work for MPC control application. Google Sketchup 3D design software is used to generate the virtual architecture of the EnergyPlus sample buildings, as shown in Figure 5.1, and Figure 5.2.

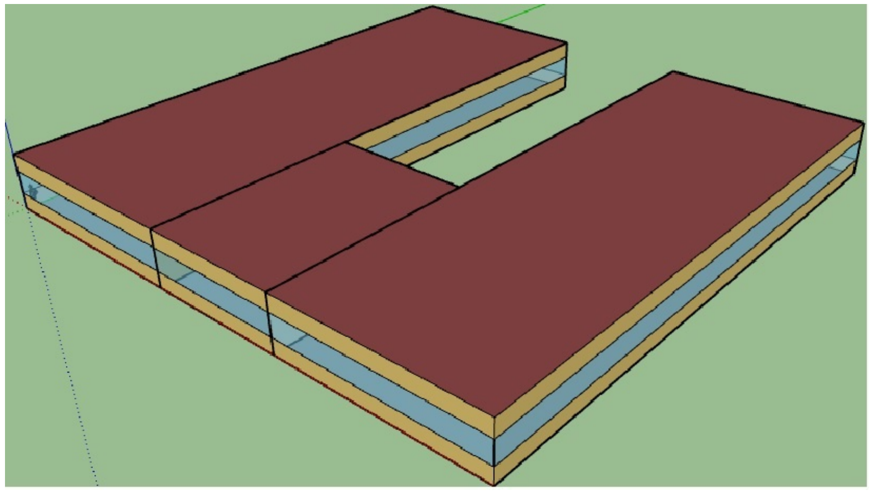

Figure 5.1 The layout of three zones building (Boulder-US) in Google Sketchup.

Figure 5.1 shows the layout of a three-zone building (U-shaped) located in Boulder, Colorado, in the northwestern U.S. While Zone 1 (Z_1) and Zone 3 (Z_3) on each side are identical in size, at 30.4 m^2, Zone 2 (Z_2) in the middle is different, at 10.4 m^2. The building characteristics are given in Table 5.1.

Table 5.1 Characteristic of the three-zone building (Boulder-US)

Definition	Value
Building size	71.4 m^2
No. of zones	3
No. of floors	1
Roof type	metal
Windows thickness	0.003 m

The building diagram in Figure 5.2 is for a small office building in Chicago, IL (U.S.). The building consists of five zones. A core zone (Z_C) in the middle, which has the biggest size, 40 m^2, surrounded by four other zones . While the first (Z_1) and the third zone (Z_3) are identical in size, at 9.23 m^2 each, the second zone (Z_2) and the fourth zone (Z_4) are identical in size as well, at 21.4 m^2 each. The building structure specifications are presented in Table 5.2.

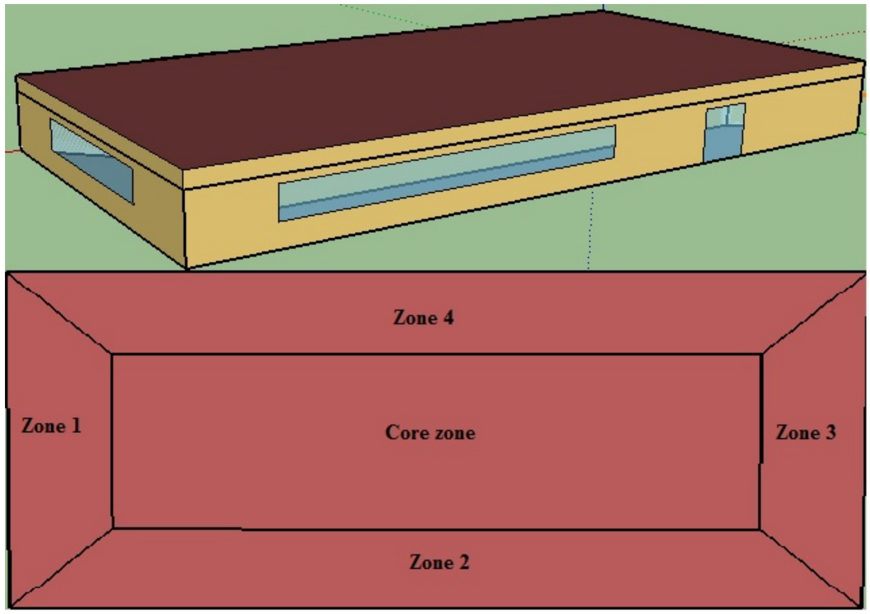

Figure 5.2 The layout of small office five-zone building (Chicago-US) in Google Sketchup.

Table 5.2 Characteristic of the small office five-zones building (Chicago-US)

Definition	Value
Building size	101.26 m^2
No. of zones	5
No. of floors	1
Roof type	metal
Windows thickness	0.003 m

5.3 Simulation framework

In this work, the OpenBuild toolbox is at the core of the framework, as it plays a significant role in system modeling. This toolbox collects data from EnergyPlus and creates a linear state-space model of a building's thermal system. The whole process of the modeling and control application can be summarized in the following steps:

1. Create an EnergyPlus model that represents the building with its HVAC system.
2. Run EnergyPlus to get the output of the chosen building and prepare the data for the next step.
3. Run the OpenBuild toolbox to generate a state-space model of the building's thermal system based on the input data file (IDF) from EnergyPlus.

4. Reduce the order of the generated high-order model to be compatible for MPC control design.

5. Finally, implement the DMPC control scheme and validate the behavior of the system with the original high-order system.

Note that the state-space model identified by the OpenBuild Matlab toolbox is a high-order model, as the system states represent the temperature at different nodes in the considered building. This toolbox generates a model that is simple enough for MPC control design to capture the dynamics of the controlled thermal systems. The windows are modeled by a set of algebraic equations and are assumed to have no thermal capacity. The extracted state-space model of a thermal system can be expressed by a continuous time state-space model of the form:

$$\begin{aligned} \dot{x} &= Ax + Bu + Ed, \\ y &= Cx, \end{aligned} \tag{5.1}$$

where x is the state vector and u is the control input vector. The output vector is y where the controlled variable in each zone is the indoor temperature, and d indicates the disturbance. The matrices A, B, C, and E are the state matrix, the input matrix, the output matrix, and the disturbance matrix, respectively.

5.4 Problem Formulation

A quadratic cost function is used for the MPC optimization problem to reduce the peak power while respecting a certain thermal comfort level. Both the centralized the decentralized problem formulation are presented in this section, based on the scheme proposed in [112,113].

First, we discretize the continuous time model (5.1) by using the standard zero-order hold with a sampling period T_s, which can be written as:

$$\begin{aligned} x(k+1) &= A_d x(k) + B_d u(k) + E_d d(k), \\ y(k) &= C_d x(k), \end{aligned} \tag{5.2}$$

where $x(k) \in \mathbb{R}^M$ is the state vector, $u(k) \in \mathbb{R}^M$ is the control vector, and $y(k) \in \mathbb{R}^M$ is the output vector. A_d, B_d, and E_d can be computed from A, B, and E in (5.1); $C_d = C$ is an identity matrix of dimension M. The matrices in the discrete-time model can be computed from the continous-time model in (3.2) and are given by $A_d = e^{AT_s}$, $B_d{=}\int_0^{T_s} e^{As} B \mathrm{d}s$, and $E_d{=}\int_0^{T_s} e^{As} D \mathrm{d}s$; $C_d = C$ is an identity matrix of dimension M.

Let $x_d(k) \in \mathbb{R}^M$ be the desired state and $e(k) = x(k) - x_d(k)$ be the vector of regulation error. The control to be fed into the plant is given by solving the following optimization problem:

$$
\begin{aligned}
f = \min_{u_i(0)} \; & e(N)^T G e(N) + \sum_{k=0}^{N-1} e(k)^T Q e(k) + u^T(k) R u(k) && \text{(5.3a)}\\
\text{s.t.} \;\; & x(k+1) = A_d x(k) + B_d u(k) + E_d d(k), && \text{(5.3b)}\\
& x_0 = x(t), && \text{(5.3c)}\\
& x_{\min} \leq x(k) \leq x_{\max}, && \text{(5.3d)}\\
& 0 \leq u(k) \leq u_{\max}, && \text{(5.3e)}
\end{aligned}
$$

for $k = 0, \ldots, N$, where N is the prediction horizon. The variables $Q = Q^T \geq 0$ and $R = R^T > 0$ are square weighting matrices used to penalize the tracking error and the control input, respectively. The $G = G^T \geq 0$ is a square matrix that satisfies the Lyapunov equation:

$$A_d^T G A_d - G = -Q, \tag{5.4}$$

where the stability condition of the matrix A in (5.1) will assure the existence of the matrix G. Solving the above MPC problem provides a sequence of controls $U^*(x(t)) = \{u_0^*, \ldots, u_N^*\}$, among which only the first element $u(t) = u_0^*$ is applied to the controlled system.

For the DMPC problem formulation setting, let $x^j \in \mathbb{R}^{n_j}$, $u^j \in \mathbb{R}^{n_j}$, and $d^j \in \mathbb{R}^{n_j}$ be the state, control, and disturbance vectors of the j^{th} subsystem with $n_1 + n_2 + \cdots + n_m = M$. Then for $j = 1, \cdots, m$, x^j, u^j, and d^j of the subsystem can be represented as:

$$
\begin{aligned}
x^j &= W_j^T x = \begin{bmatrix} x_1^j & \cdots & x_{n_j}^j \end{bmatrix}^T \in \mathbb{R}^{n_j}, && \text{(5.5a)}\\
u^j &= Z_j^T u = \begin{bmatrix} u_1^j & \cdots & u_{m_j}^j \end{bmatrix}^T \in \mathbb{R}^{n_j}, && \text{(5.5b)}\\
d^j &= H_j^T d = \begin{bmatrix} d_1^j & \cdots & d_{l_j}^j \end{bmatrix}^T \in \mathbb{R}^{n_j}. && \text{(5.5c)}
\end{aligned}
$$

where $W_j \in \mathbb{R}^{M \times n_j}$ collects the n_j columns of identity matrix of order n, $Z_j \in \mathbb{R}^{M \times n_j}$ collects the m_j columns of identity matrix of order m, and $H_j \in \mathbb{R}^{M \times n_j}$ collects the l_j columns of identity matrix of order l. The dynamic model of the j^{th} subsystems is given by:

$$
\begin{aligned}
x^j(k+1) &= A_d^j x^j(k) + B_d^j u^j(k) + E_d^j d^j(k),\\
y^j(k) &= x^j(k),
\end{aligned} \tag{5.6}
$$

where $A_d^j = W_j^T A_d W_j$, $B_d^j = W_j^T B_d Z_j$, and $E_d^j = W_j^T E_d H_j$ are sub-matrices of A_d, B_d and

E_d, respectively, which are in general dependent on the chosen decoupling matrices W_j, Z_j and H_j. As in the centralized setting, the open-loop stability of the DMPC is guaranteed if A_d^j in (5.6) is strictly Hurwitz for all $j = 1, \ldots, m$.

Let $e^j = W_j^T e$. The j^{th} sub-problem of the DMPC is then given by:

$$\begin{aligned} f^j &= \min_{u^j(0)} \sum_{k=0}^{\infty} e^{jT}(k) Q_j e^j(k) + u^{jT}(k) R_j u^j(k) \\ &= \min_{u^j(0)} e^{jT}(k) G_j e^j(k) + e^{jT}(k) Q_j + u^{jT}(k) R_j u^j(k) \end{aligned} \tag{5.7a}$$

$$\text{s.t.} \quad x^j(t+1) = A_d^j x^j(t) + B_d^j u^j(0) + E_d^j d^j, \tag{5.7b}$$

$$x^j(0) = W_j^T x(t) = x^j(t), \tag{5.7c}$$

$$x_{\min}^j \leq x^j(k) \leq x_{\max}^j, \tag{5.7d}$$

$$0 \leq u^j(0) \leq u_{\max}^j, \tag{5.7e}$$

where the weighting matrices are $Q_j = W_j^T Q W_j$, $R_j = Z_j^T R Z_j$, and the square matrix G_j is the solution of the following Lyapunov equation

$$A_d^{jT} G_j A_d^j - G_j = -Q_j. \tag{5.8}$$

5.5 Results and Discussion

This paper considered two simulation experiments with the objective of reducing the peak power demand while ensuring the desired thermal comfort. The process considers model validation and MPC control application to the EnergyPlus thermal system models.

5.5.1 Model Validation

In this section, we reduce the order of the original high-order model extracted from the EnergyPlus IDF file by the toolbox of OpenBuild. We begin by selecting the reduced model that corresponds to the number of states in the controlled building (e.g., for the three-zone building, we chose a reduced model in (3×3) state-space from the original model). Next, both the original and the reduced models are excited by using the Pseudo-Random Binary Signal (PRBS) as an input signal in open loop in the presence of the ambient temperature to compare their outputs and validate their fitness. Note that Matlab System Identification Toolbox [151] can eventually be used to find the low-order model from the extracted thermal system models.

First, for the model validation of the three-zone building in Boulder, CO, U.S. we utilize outdoor temperature trend in Boulder for the first week of January according to the EnergyPlus weather file, shown in Figure 5.3.

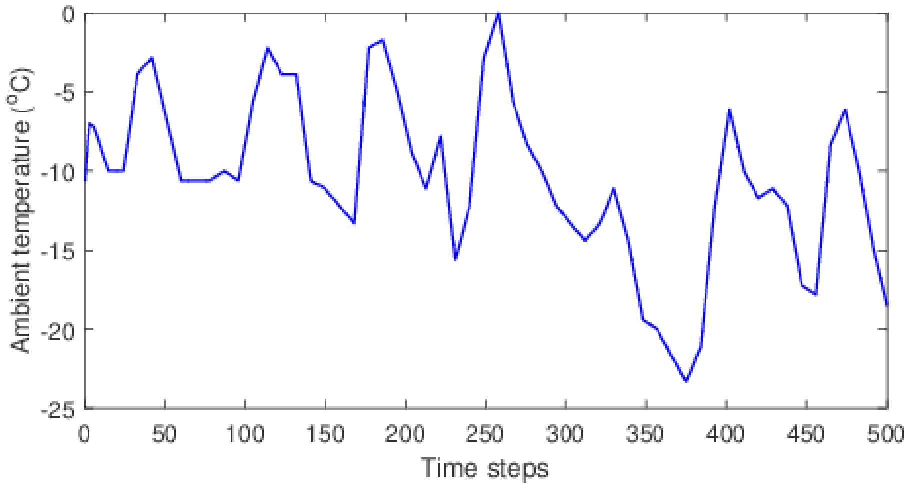

Figure 5.3 The outdoor temperature variation in Boulder-US for the first week of January based on EnergyPlus weather file.

The original thermal model of this building extracted from EnergyPlus is a 71^{th}-order model based on one week of January data. The dimensions of the extracted state-space model matrices are: $A(71 \times 71)$, $B(71 \times 3)$, $E(71 \times 3)$, and $C(3 \times 71)$. The reduced-order thermal model is a (3×3) dimension model with matrices $A(3 \times 3)$, $B(3 \times 3)$, $E(3 \times 3)$, and $C(3 \times 3)$. The comparison of the output response (indoor temperature) of both models in each of the zones is shown in Figure 5.4.

Second, for model validation of the five-zone building in Chicago, IL, U.S., we use the ambient temperature variation for the first week of January based on the EnergyPlus weather file shown in Figure 5.5.

The building's high-order model extracted from the IDF file by the OpenBuild toolbox is a 139^{th}-order model, based on the EnergyPlus weather file for the first week of January. The dimensions of the extracted state-space matrices of the generated high-order model are: $A(139 \times 139)$, $B(139 \times 5)$, $E(193 \times 5)$, and $C(5 \times 139)$. The reduced-order thermal model is a fifth-order model with matrices $A(5 \times 5)$, $B(5 \times 5)$, $E(5 \times 5)$, and $C(5 \times 5)$. The indoor temperature (the output response) in all of the zones for both the original and the reduced models is shown in Figure 5.6.

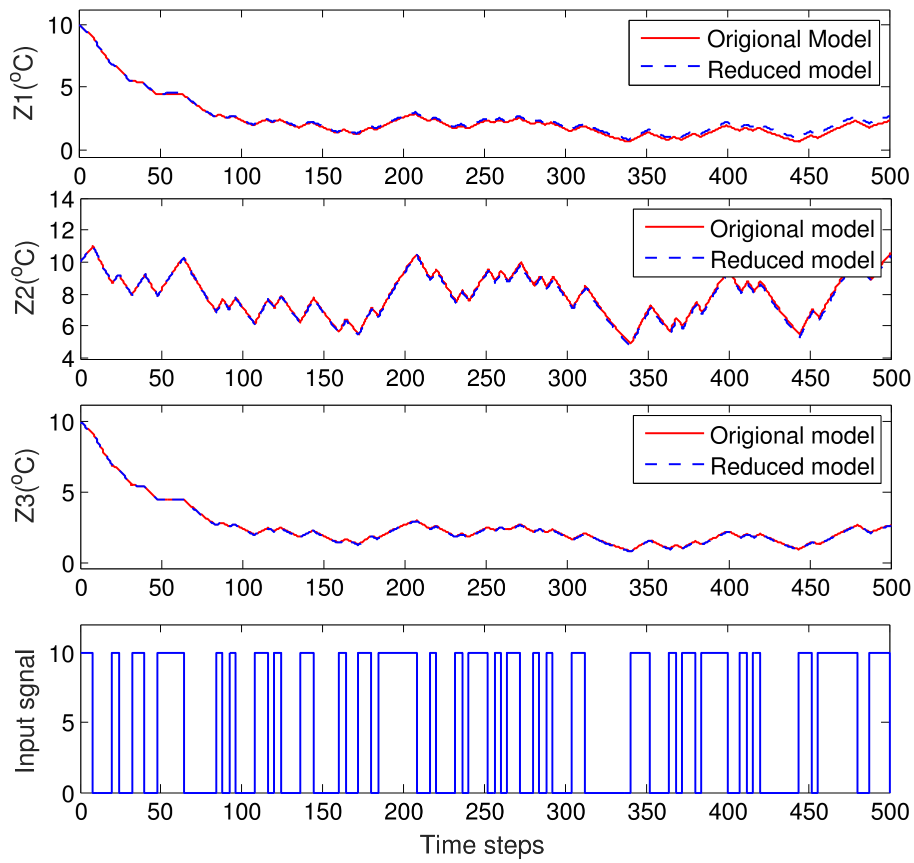

Figure 5.4 Comparison between the output of reduced model and the output of the original model for the three-zone building.

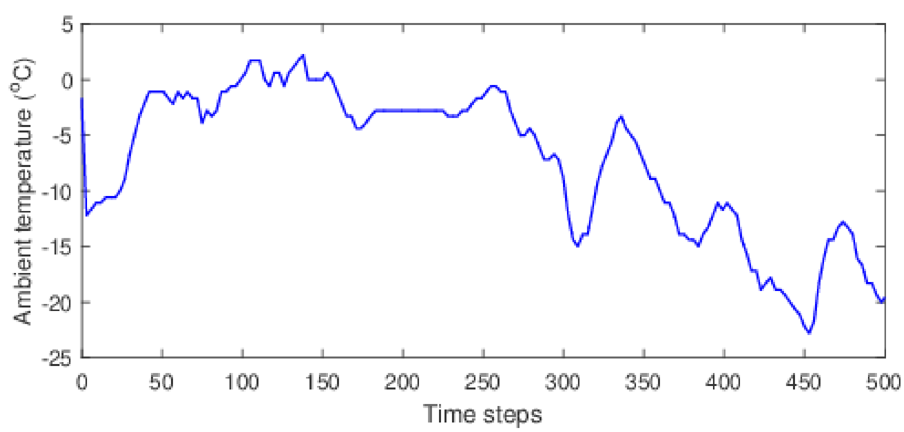

Figure 5.5 The outdoor temperature variation in Chicago-U.S for the first week of January based on EnergyPlus weather file.

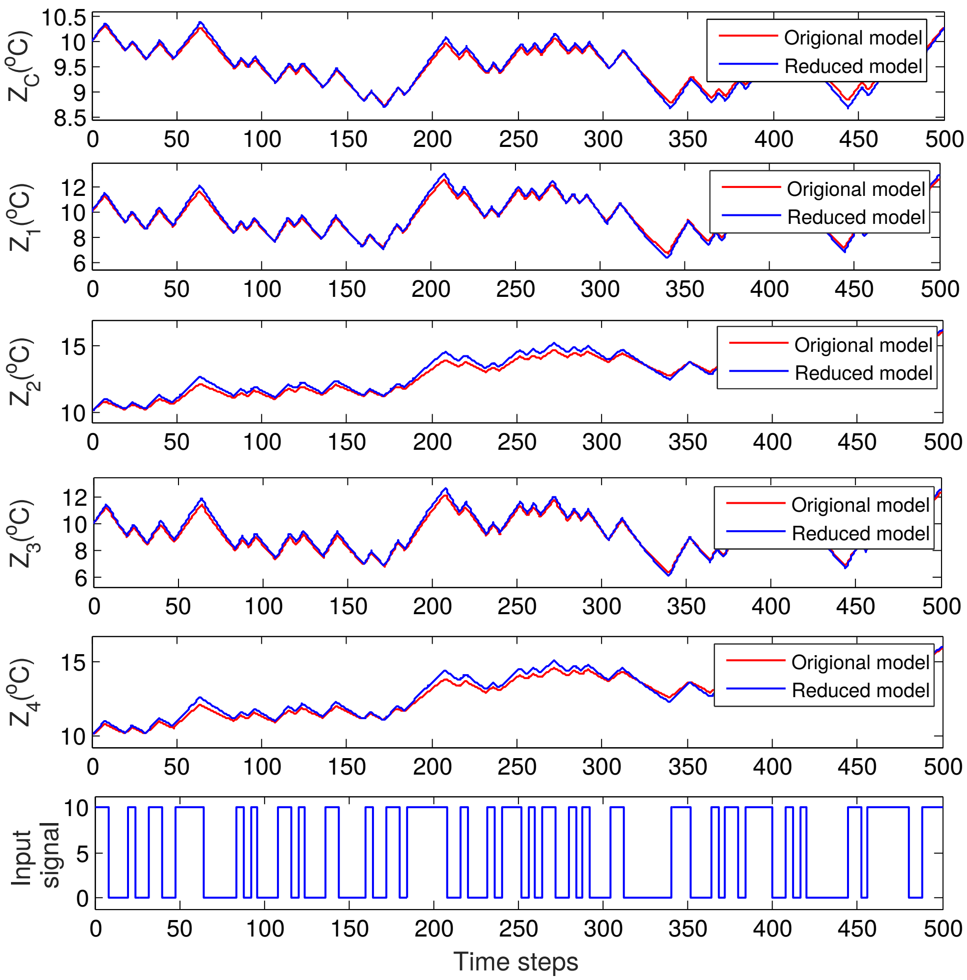

Figure 5.6 Comparison between the output of reduced model and the output of the original model for the five-zone building.

5.5.2 DMPC Implementation Results

In this section, we apply DMPC to thermal systems to maintain the indoor air temperature in a building's zones at around 22 ^{o}C with reduced power consumption. Matlab/Simulink is used as an implementation platform along with the YALMIP toolbox [118] to solve the MPC optimization problem based on the validated reduced model. In both experiments, the prediction horizon is set to be N=10 and the sampling time is T_s=0.1. The time span is normalized to 500-time units.

Example 5.1 *In this example, we control the operation of thermal appliances in the three-zone building. While the initial requested power is* 1500 *W for each heater in* Z_1 *and* Z_3*, it is set to be* 500 *W for the heater in* Z_2*. Hence, the total required power is* 3500 *W. The implemented MPC controller works throughout the simulation time to respect the power capacity constraints of 3500 W over (0,100) time steps, 2500 W for (100,350) time steps, and 2800 W over (350,500) time steps.*

The indoor temperature of the three zones and the appliances' individual power consumption compared to their requested power are depicted in Figure 5.7 and Figure 5.8, respectively.

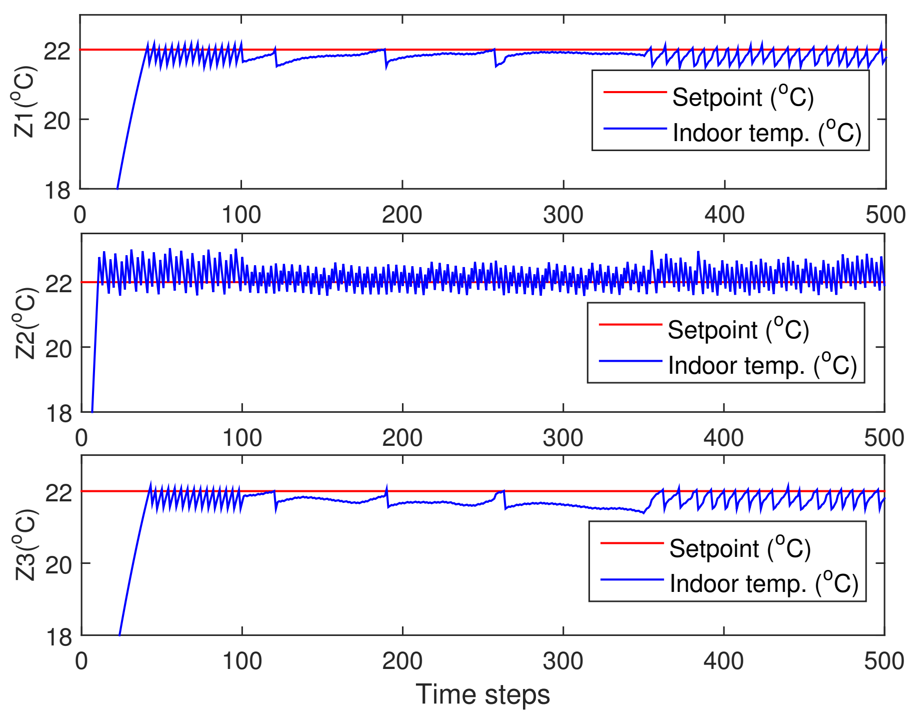

Figure 5.7 The indoor temperature in each zone for the three-zone building.

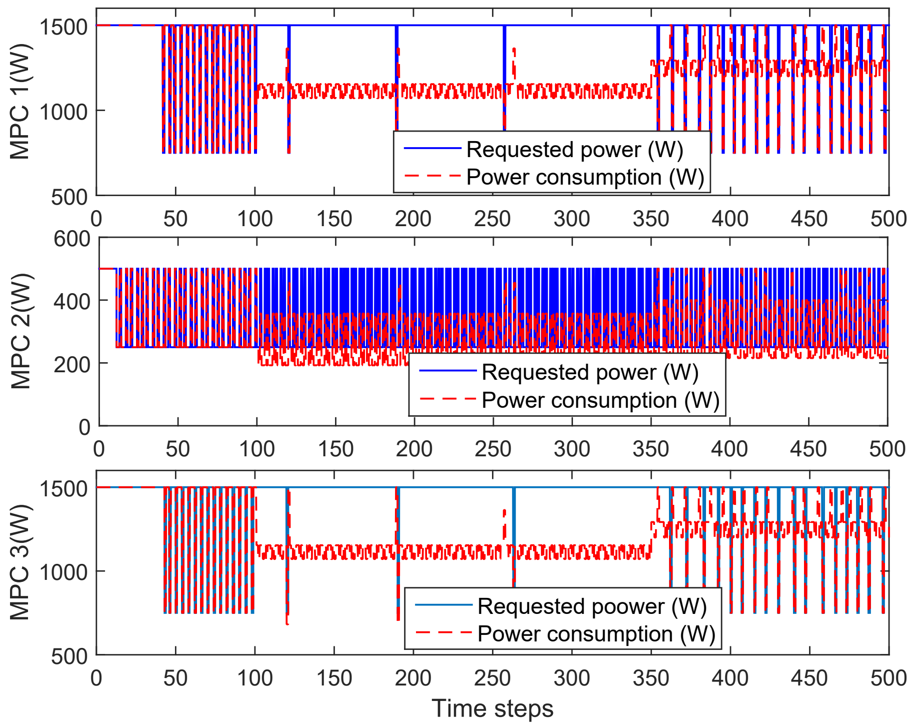

Figure 5.8 The individual power consumption and the individual requested power in the three-zone building.

The total consumed power and the total requested power of the whole thermal system in the three-zone building with reference to the imposed capacity constraints are shown in Figure 5.9.

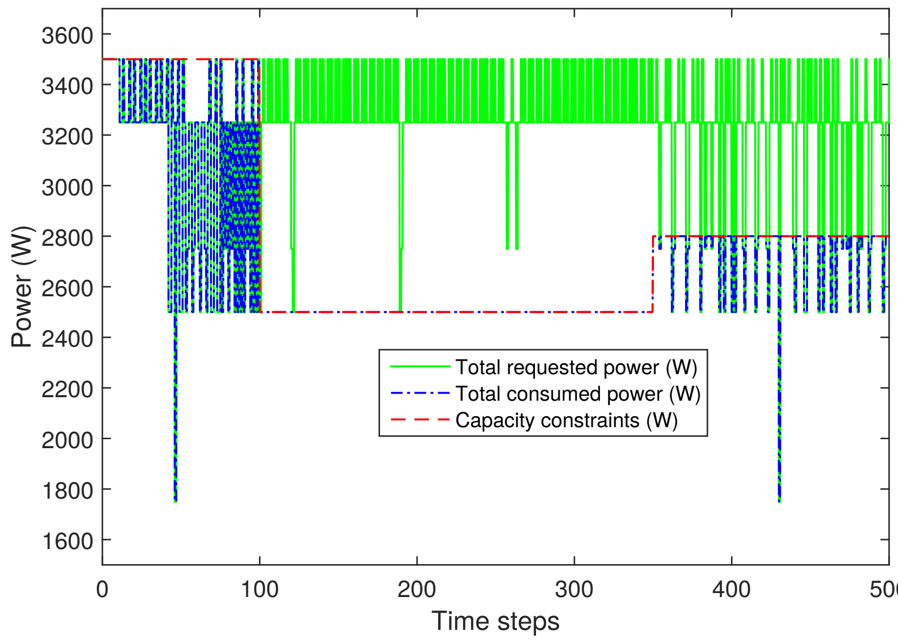

Figure 5.9 The total power consumption and the requested power in three-zone building.

Example 5.2 *This experiment has the same setup as in Example 5.1, except that we begin with* 5000 *W of power capacity for* 50 *time steps, then the imposed power capacity is reduced to* 2200 *W until the end.*

The indoor temperature of the five zones and the comparison between the appliances' individual power consumption and their requested power levels are illustrated in Figure 5.10, Figure 5.11, respectively.

The total power consumption and the total requested power of the five appliances in the five-zone building with respect to the imposed power capacity constraints are shown in Figure 5.12.

In both experiments, the model validations and the MPC implementation results show and confirm the ability of the OpenBuild toolbox to extract appropriate and compact thermal models that enhance the efficiency of the MPC controller to better manage the operation of thermal appliances to maintain the desired comfort level with a notable peak power reduction. Figure 5.4 and Figure 5.6 show that in both buildings' thermal systems, the reduced models

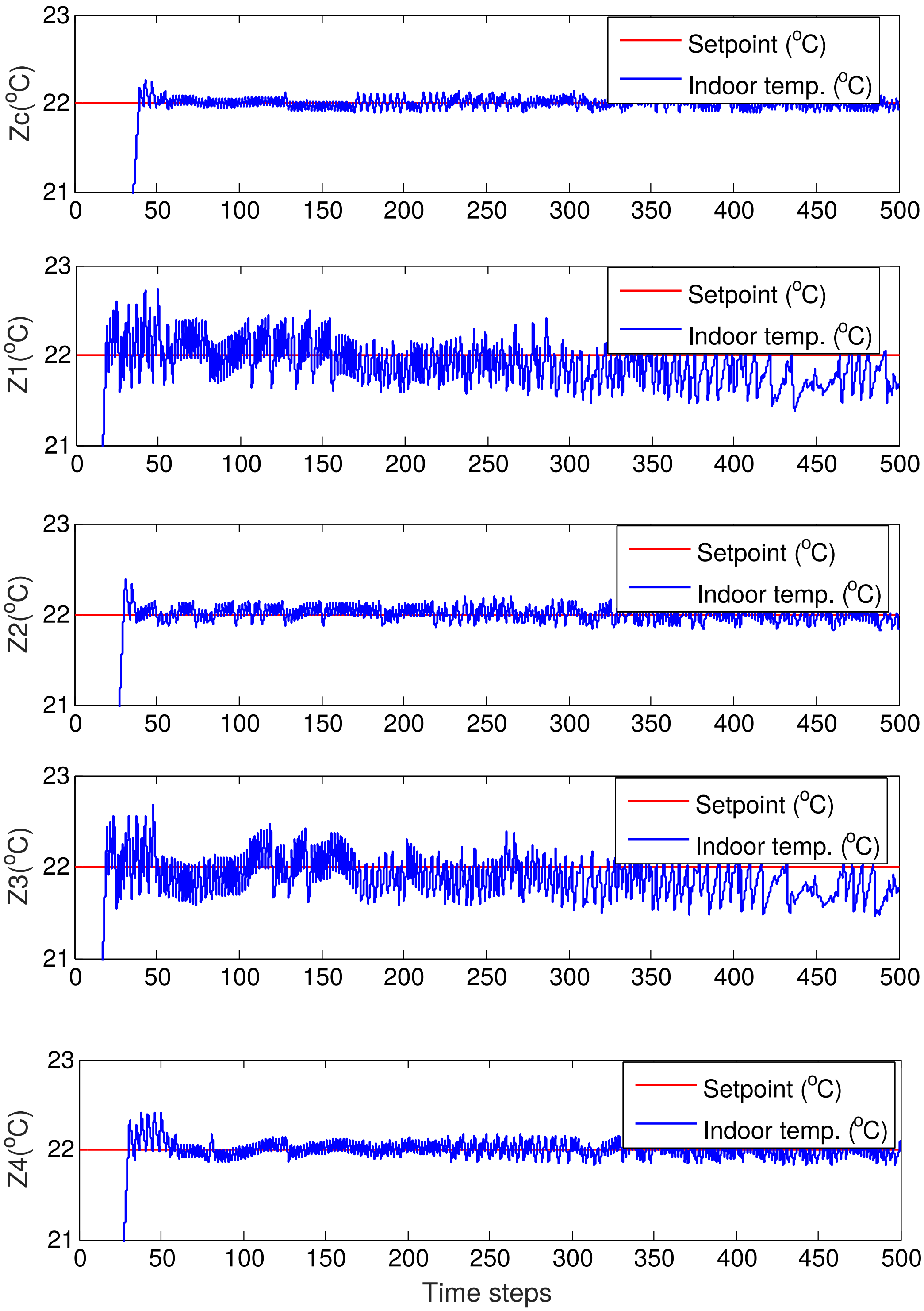

Figure 5.10 The indoor temperature in each zone in the five-zone building.

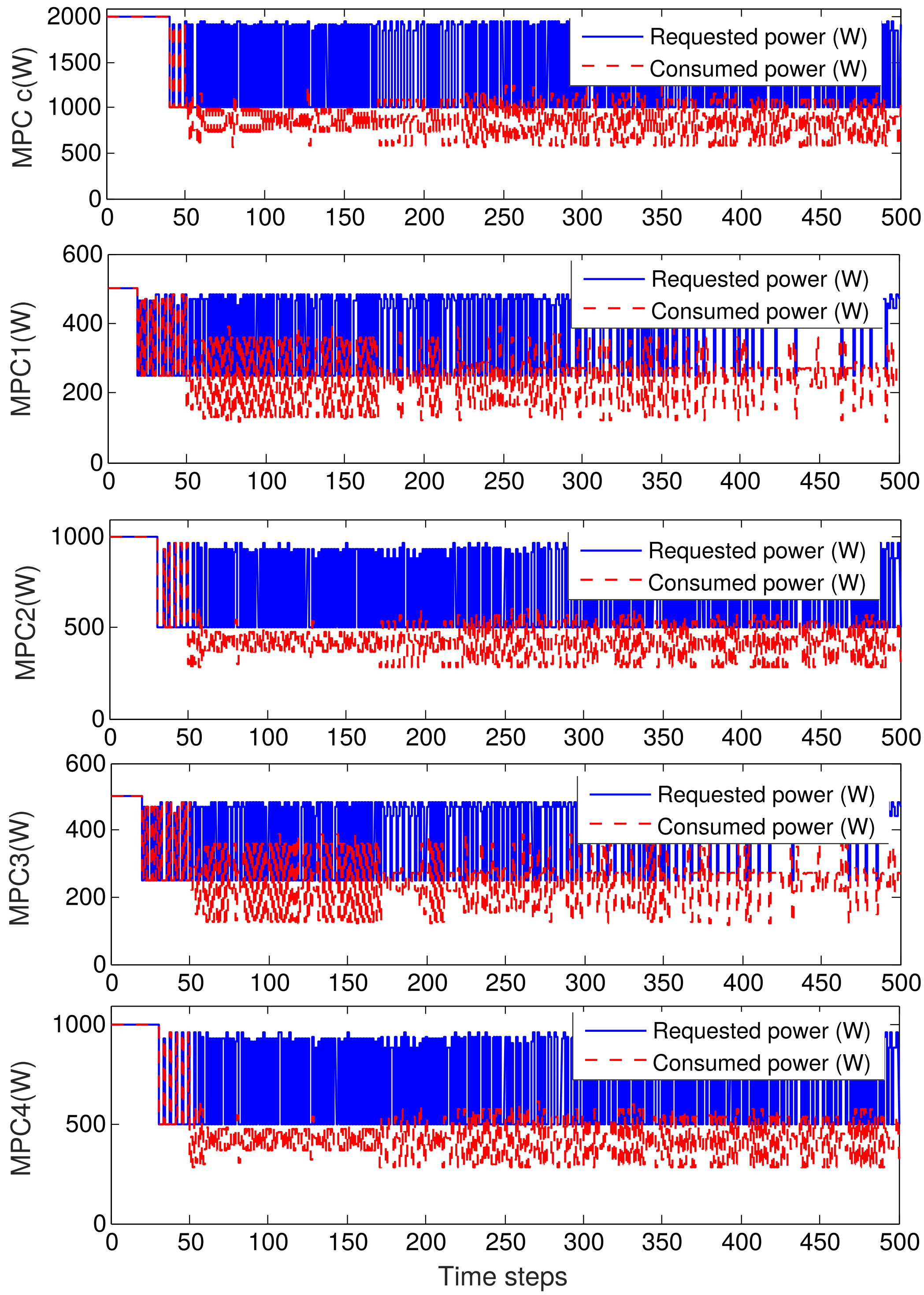

Figure 5.11 The individual power consumption and the individual requested power in the five-zone building.

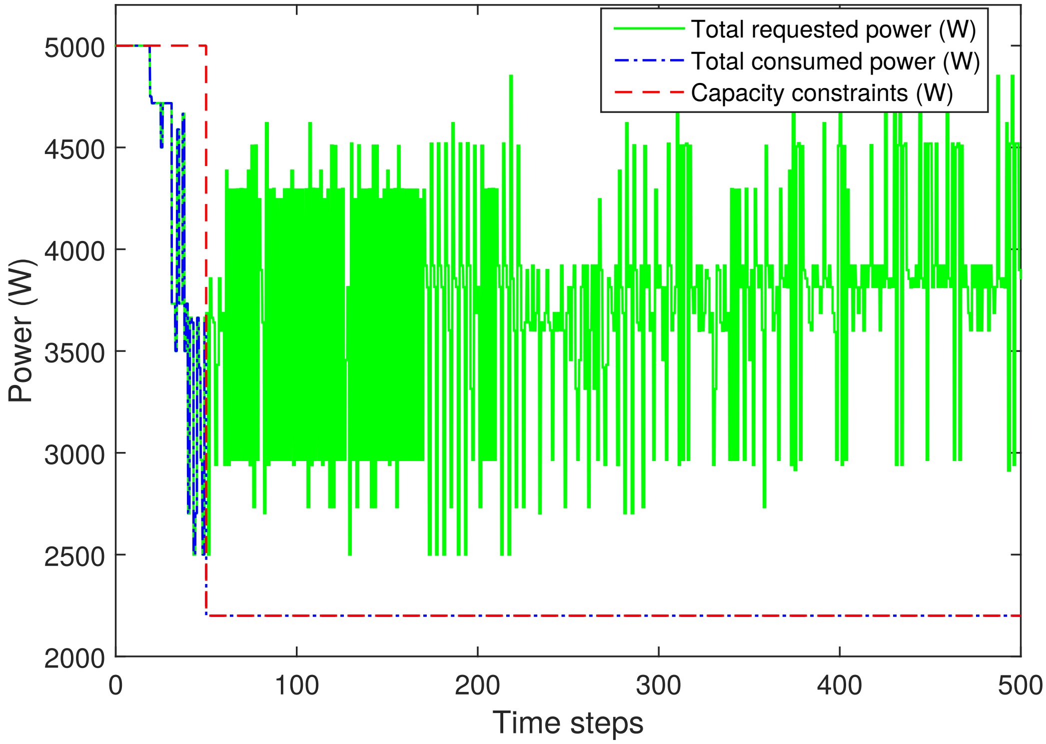

Figure 5.12 The total power consumption and the requested power in the five-zone building.

have the same behavior as the high-order models, with only a small discrepancy in some appliances' behavior in the five-zone building model.

The requested power consumption of all the thermal appliances in both the three- and five-zone buildings often reach the maximum required power level, and half of the maximum power level over the simulation time as illustrated in Figure 5.9 and Figure 5.12. However, the power consumption respects the power capacity constraints imposed by the MPC controller while maintaining the indoor temperature in all zones within a limited range around 22 ± 0.6 ^{o}C as shown in Figure 5.7 and Figure 5.10. While in the 3-zone building, the power capacity was reduced twice by 14% and 12.5%, it was reduced by almost 23% in the 5-zone building.

5.6 Conclusion

This work confirms the effectiveness of co-simulating between the building modeling domain (EnergyPlus) and the control systems design domain (Matlab/Simulink) that offers rapid prototyping and validation of models and controllers. The OpenBuild Matlab toolbox successfully extracted the state-space models of two differently-zoned buildings based on an EnergyPlus model that is appropriate for MPC design. The simulation results validated the applicability and the feasibility of DMPC-based HVAC control systems with more complex buildings constructed using EnergyPlus software. The extracted thermal models used for the DMPC design to meet the desired comfort level with a notable peak power reduction in the studied buildings.

CHAPTER 6 GENERAL DISCUSSION

The past few decades have shown the world's ever-increasing demand for energy, a trend that will only continue to grow. More than 50% of the consumption is directly related to heating, ventilation and air-conditioning (HVAC) systems. Therefore, energy efficiency in buildings has justifiably been a common research area for many years. The emergence of the Smart Grid provides an opportunity to discover new solutions to optimize the power consumption while reducing the operational costs in buildings in an efficient and cost-effective way.

Numerous types of control schemes have been proposed and implemented for HVAC systems power consumption minimization, among which the MPC is one of the most popular options. Nevertheless, most of the proposed approaches treat buildings as a single dynamic system with one solution, which may very well not be feasible in real systems. Therefore, in this PhD research, we focus on DR management in smart buildings based on MPC control techniques while considering an architecture with a layered structure for HVAC system problems. Accordingly, a complete controlled system can be split into sub-systems, reducing the system complexity and thereby facilitating modifications and adaptations. We first introduced the concepts and background of discrete event systems (DES) as an appropriate framework for smart building control applications. The DES framework thus allows for the design of complex control systems to be conducted in a systematic manner. The proposed work focused on thermal appliance power management in smart buildings in DES framework-based power admission control, while managing building appliances in the context of the above-mentioned layered architecture to provide lower power consumption and better thermal comfort.

In the next step, a DMPC technique is incorporated into power management systems in the DES framework for the purpose of peak demand reduction while providing an adequate temperature regulation performance. The proposed hierarchical structure consists of a set of local MPC controllers in different zones and a game-theoretic supervisory control at the upper layer. The control decision at each zone will be sent to the upper layer and a game theoretic scheme will distribute the power over all the appliances while considering power capacity constraints. A global optimality is ensured by satisfying the Nash equilibrium (NE) at the coordination layer. The Matlab/Simulink platform along with the YALMIP toolbox were used to carry out simulation studies to assess the developed strategy.

Building ventilation systems have a direct impact on occupant's health, productivity and a building's power consumption. This research therefore considered the application of nonlinear MPC in the control of a building's ventilation flow rate, based on the CO_2 predictive model. The applied control technique is a hybrid control mechanism that combines MPC control in cascade with FBL control to ensure that the indoor CO_2 concentration remains within a limited range around a setpoint, thereby improving the IAQ and thus the occupants' comfort. To handle the nonlinearity problem of the control constraints while assuring the convergence of the controlled system, a local convex approximation mechanism is utilized with the proposed technique. The results of the simulation, conducted in Matlab/Simulink platform with the YALMIP toolbox, confirmed that this scheme efficiently achieves the desired performance with less power consumption than that of a conventional classical ON/OFF controller.

Finally, we developed a framework for large-scale and complex building control systems design and validation in a more reliable and realistic simulation environment in smart building control system development. The emphasis on the effectiveness of co-simulating between building simulation software tools and control systems design tools that allows the validation of both controllers and models. The OpenBuild Matlab toolbox and the popular simulation software EnergyPlus were used to extract thermal system models for two differently-zoned EnergyPlus buildings that can be suitable for MPC design problems. We first generated the linear state space model of the thermal system from an EnergyPlus IDF file, and then we used the reduced order model for the DMPC design. This work showed the feasibility and the applicability of this tool set through the previously developed DMPC-based HVAC control systems.

CHAPTER 7 CONCLUSION AND RECOMMENDATIONS

7.1 Summary

In this thesis, we studied DR management in smart buildings based on MPC applications. The work aims at developing MPC control techniques to manage the operation of either thermal systems or ventilation systems in buildings to maintain a comfortable and safe indoor environment with minimized power consumption.

Chapter 1 explains the context of the research project. The motivation and background of power consumption management of HVAC systems in smart buildings was followed by a review of the existing control techniques for DR management, including the MPC control strategy. We closed Chapter 1 with the research objectives, methodologies, and contributions of this work.

Chapter 2 provides the details of and explanations about some design methods and tools we used over the research. This began with simply introducing the concept, the formulation and the implementation of the MPC control technique. The background and some notations of DES were introduced next, then we presented modeling of appliance operation in DES framework using the finite-state automation. After that an example that shows the implementation of a scheduling algorithm to manage the operation of thermal appliances in DES framework was given. At the end, we presented game theory concept as an effective mechanism in the Smart Grid field.

Chaper 3 is an extension of the work presented in [65]. It introduced an application of DMPC to thermal appliances in a DES framework. The developed strategy is a two-layered structure that consists of an MPC controller for each agent at the lower layer and a supervisory control at the higher layer, which works based on a game-theoretic mechanism for power distribution through the DES framework. This chapter started with the building's thermal dynamic model, and then presented the problem formulation for the centralized and decentralized MPC. Next, a normal form game for the power distribution was addressed with a heuristic algorithm for NE. Some of the results from two simulation experiments for a four-zone building were presented. The results confirmed the ability of the proposed scheme to meet the desired thermal comfort inside the zones with lower power consumption. Both the Co-Observability and the $\mathcal{P}$-Observability concepts were validated through the experiments.

Chapter 4 shows the application of the MPC-based technique to a ventilation system in a smart building. The main objective was to control the level of the indoor CO_2 concentration based on the CO_2 predictive model. A hybrid control scheme that combined the MPC control and the FBL control was utilized to maintain indoor CO_2 concentration in a building within a certain range around a setpoint. A nonlinear model of the CO_2 concentration in a building and its equilibrium point were addressed first, and then the FBL control concept was introduced. Next, the MPC cost function was presented together with a local convex approximation to ensure the feasibility and the convergence of the system. Finally, we ended up with some simulation results of the control technique compared to a traditional ON/OFF controller.

Chapter 5 presents a realistic simulation environment for large-scale and complex building control systems design and validation. The OpenBuild Matlab toolbox is introduced first to extract high-order building thermal systems from an EnergyPlus IDF file, and then used the validated lower order model for DMPC control design. Next, the MPC setup in centralized and decentralized formulations is introduced. Two examples of differently-zoned buildings are studied to evaluate the effectiveness of such a framework, as well as to validate the applicability and the feasibility of DMPC-based HVAC control systems.

7.2 Future Directions

The first possible future direction would be to combine the work presented in Chaper 3 and Chapter 4 to appliances control in a more generic context of HVAC systems. The system architecture could be represented by the same layered structure that we have used through the thesis.

In the proposed DMPC presented in Chaper 3, we can extend the MPC controller application to be a robust one which can handle the impact of the solar radiation that has an effect on the indoor temperature in a building. In addition, online implementation could be an interesting extension of the work by using a co-simulation interface that connects the MPC controller with the EnergyPlus file for building energy.

Working with renewable energy in the Smart Grid field has a great interest. Implementing the developed control strategies introduced in the thesis on an entire HVAC while integrating some renewable energy resources (e.g., solar energy generation) in the framework of DES is another future promising work in this field to reduce the peak power demand.

Throughout the thesis, we focus on power consumption and peak demand reduction while respecting certain capacity constraints. Another possible direction is to use the proposed MPC controllers as an economic ones, by reducing energy cost and demand cost for building HVAC systems in the framework of DES.

Finally, a main challenge direction that could be considered in the future as an extension of the proposed work is to implement our developed control strategies on a real building to manage the operation of HVAC system.

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APPENDIX A PUBLICATIONS

1. Saad A. Abobakr and Guchuan Zhu , “A Nonlinear Model Predictive Control for Ventilation Systems in Smart Buildings”, Submitted to the *Energy and Buildings*, March 2019.

2. Saad A. Abobakr and Guchuan Zhu, “A Co-simulation-Based Approach for Building Control Systems Design and Validation”, Submitted to the *Control Engineering Practice*, March 2019.

3. Saad A. Abobakr, W. H. Sadid, et G. Zhu, “Game-theoretic decentralized model predictive control of thermal appliances in discrete-event systems framework”, *IEEE Transactions on Industrial Electronics*, vol. 65, no. 8, pp. 6446–6456, 2018.

4. W. H. Sadid, Saad A. Abobakr, et G. Zhu, “Discrete-event systems-based power admission control of thermal appliances in smart buildings”, *IEEE Transactions on Smart Grid*, vol. 8, no. 6, pp. 2665–2674, 2017.