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Building Climate Control Using MPC

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Abstract

Building climate control problem is studied in this project where some basic concepts on building heat transfer are introduced and using one of the best and effective methods to solve the dynamic optimization problem based on Model predictive control. A simplified linear state space model that uses some geometry, architecture and civil engineering structure and environmental weather data is derived for designing the MPC controller. Simulations are conducted on a three-zone building to show the effectiveness of MPC control/ Several factors, in addition to the kind of our model, influence the performance of the MPC, including the disturbance from model uncertainty and approximated weather data.

ملخص

نق تمت دراسة مشكلة التحكم في المناخ بناء في هذا المشروع حيث يتم تقديم بعض المفاهيم الأساسية حول نقل الحرارة بناء واستخدام واحدة من أفضل الطرق وأكثرها فعالية لحل مشكلة التحسين الديناميكي على أساس التحكم التنبئي النموذجي. يتم اشتقاق نموذج فضاء الحالة الخطية المبسط الذي يستخدم بعض الهندسة المعمارية وهياكل الهندسة المدنية وبيانات الطقس البيئي لتصميم وحدة MPC تحكم. يتم إجراء عمليات المحاكاة على مبنى مكون من ثلاث مناطق لإظهار فعالية التحكم في / MPC تؤثر عدة عوامل ، بالإضافة إلى نوع نموذجنا ، على أداء MPC ، بما في ذلك الاضطراب الناتج عن عدم اليقين في النموذج وبيانات الطقس التقريبية.

Résumé

Le problème du contrôle climatique du bâtiment est étudié dans ce projet où certains concepts de base sur le transfert de chaleur du bâtiment sont introduits et en utilisant l'une des les meilleures méthodes pour résoudre le problème d'optimisation dynamique basé sur le contrôle prédictif du modèle. Un modèle d'espace d'état linéaire simplifié qui utilise la géométrie, l’architecture et la structure de génie civil et des données météorologiques environnementales est dérivé pour la conception du contrôleur MPC. Des simulations sont menées sur un bâtiment à trois zones pour montrer l'efficacité du contrôle du MPC. Plusieurs facteurs, en plus du type de notre modèle, influencent les performances du MPC, notamment la perturbation due à l'incertitude du modèle et aux données météorologiques approximatives.

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Nomenclatures

T temperature (℃)

Q heat flux (W)

P fraction of solar radiation entering floor

A surface area (m^{-2})

U thermal transmittance ($Wm^{-2}K^{-1}$)

U_v inner thermal transmittance ($Wm^{-2}K^{-1}$)

U_v outer thermal transmittance ($Wm^{-2}K^{-1}$)

U_v ventilation thermal transmittance (WK^{-1})

Subscripts:

w_1 external wall 1

w_2 external wall 2

f floor

c ceiling

ip internal partition

ai air – internal

ao air – external

s solar

g glazing

e casual sources (internal heat gains)

p plant

General Introduction

In the last few years, new concepts and technologies have been designed to face the critical issue of increasing energy sustainability in buildings. From a life cycle perspective, this can be accomplished through improving the energy efficiency of the building envelope and systems, as well as optimizing the use of on-site Renewable Energy Sources (RES), all while maintaining occupant thermal comfort. In fact, in the EU and the US, residential and commercial buildings account for over 40% of total primary energy [1,2], and the influence of heating, ventilation, and air conditioning (HVAC) systems is significant.

Model predictive control techniques have been used in the process industry for nearly 30 years and are considered to be methods that provide good performance and can run for long periods of time with little or no intervention. However, the main reason that model predictive control is such a popular control technique in modern industry is that it is the only technique that allows system restrictions to be taken into consideration.

Although nonlinear dynamics are present in the majority of industrial processes, most MPC applications are based on linear models. The original process must be operating in the vicinity of a stationary point for these linear models to work. However, some processes cannot be represented by a linear model and must be represented using nonlinear models. collaborating with nonlinear models present a number of challenges, including a nonconvex optimization problem, various approaches to ensuring stability, and a slow process in general.

Model Predictive Control (MPC) is a well-known method for limited control that has recently gotten a lot of interest from researchers working on constructing and active component control. MPC combines feedback control and numerical optimization concepts. It allows for the use of energy storage capabilities as well as the optimization of RES on-site generation. MPC can forecast the energy needs of the building and optimize its thermal behavior based on set control goals by combining predictions of future disruptions (e.g., internal gains, weather, etc.) with given requirements (e.g., comfort ranges). Constraints are incorporated directly into the optimization problem at each sample phase. Because of its high computing demand in enormous optimization problems, the MPC framework had a long road to practical application until the last decade. MPC is becoming more widely used in various sorts of buildings and energy systems as new processors, graphics processing units, and Cloud computing (and hence the exponential rise in available computational power) are developed. An assessment of modern building control systems in 2009 classified predictive optimal controllers, such as MPC, as marginal methods [3].

In this project the objective is to make a linear MPC algorithm for the building climate model. We will have checked out of the 3 cases of control heating in different zones. The algorithm is implemented in MatLab . We will be looking at building climate control and then study the MPC leading to improved energy efficiency and thermal comfort in building. And see The potential benefits of the application of MPC.

Chapter I: Building Climate Modeling and Control

I.1 Introduction

In an ever-more energy-conscious environment, improving the efficiency of energy-consuming systems is a critical issue. Buildings consume a significant amount of energy, accounting for more than 70% of total energy consumption in the US [4]. The Heating, Ventilation, and Air Conditioning (HVAC) system accounts for 40% of the building's total energy usage. This significant portion of energy use has been the subject of intensive study into ways to improve energy efficiency and minimize emissions by utilizing advanced technologies and control approaches.

I.2 The main objectives of building control

The objectives of building control and the most important aspects of room automation are discussed here. Building control aims to fulfill the following objectives, by order of importance:

• Maintain occupant comfort in the building, for example keeping the temperature in occupied spaces at an appropriate level.

• Maintain the equipment in a safe operating mode, for example avoiding excessive cycling of compressors in heat pumps.

• Optimize the cost of operation of the building, for example by minimizing the energy consumption, using storage systems efficiently, and operating the equipment at its optimal coefficient of performance.

The key control challenges for the building's temperature management are not regulation and stability.

I.3 Comfort in buildings

Americans spend 87% of their time indoors [5], and since comfort conditions directly influence the productivity and well-being of building occupants [6], comfort is a crucial objective in the design and operation of building spaces and equipment.

Indoor comfort is influenced by a number of elements, including temperature, humidity, air quality, and illumination. It's vital to remember that interior comfort is determined by the indoor space's design, such as the materials used in construction, as well as the appropriate operation and active control of the HVAC system and other features like blinds. Thermal comfort has been extensively researched, and several models have been developed to quantify it. such as the predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD) [7], [8], As a result, academic research has increasingly concentrated on building energy efficiency, particularly building control systems [9], [10].

I.4 Energy Cost

Buildings are responsible for 37% of the total energy consumed in the European Union [11], with commercial buildings accounting for one-third and residential buildings accounting for the remainder. The HVAC system is thought to absorb nearly half of the energy consumed in buildings. This is a significant portion of total global energy consumption and a great target for potential savings [12]. Recently, policies have centered on establishing new building energy efficiency criteria, such as the recently enacted European Building Energy Performance Directive [13], reflecting a worldwide desire to improve building energy efficiency.

I.5 Modeling of Building climate

I.5.1 State-space modeling

In order to formulate the reduced model of the building, usual simplifying assumptions as time invariant parameters, uniformly distributed properties, etc. are considered. Models derived from physical relations are naturally represented in state-space by a set of first order differential equations. Moreover, the used MPC algorithm also requires the model of the system in state-space representation.

I.5.2 Modeling assumptions

The following assumptions are made when creating the thermal model of a building:

-1-All points in a room space have the same indoor air temperature.

-2-Air density is constant throughout all rooms.

-3-The ventilation system removes the same amount of air from the building (and each room).

-4-The geometry of the building and thermal properties of the materials used to construct the building are known.

I.5.3 Modeling approach for a single room

Consider a single room of a building that is enclosed by walls, floor, and ceiling. The room has usually several windows and is accessible via doors. The temperature of the air inside the room with the volume V_i is assumed to be uniform and is denoted as T_i . Denote by Q_i^{in} the thermal power transferred to the room (applied thermal power) and by Q_i^{out} the thermal power transferred out of the room (dissipated thermal power). The relationship in the time domain between the heat that is transferred to or from the room and the temperature of the air inside the room can be expressed by the following equation:

$$\frac{\mathrm{d}T_i}{\mathrm{d}t} = \frac{1}{c\rho V_i}\left(Q_i^{\mathrm{in}} - Q_i^{\mathrm{out}}\right), T_i(0) = T_i^0 \qquad \text{(I.1)}$$

where c is the specific heat capacity of air, ρ is the density of air, T_i^0 denotes the initial temperature.

I.5.4 Dissipated thermal power

The overall thermal power loss from a room can be expressed as follows

$$Q_i^{\mathrm{out}} = Q_i^{\mathrm{tc}} + Q_i^{\mathrm{ve}} \qquad \text{(I.2)}$$

Where Q_i^{tc} relates to heat loss by thermal conduction through walls, windows, doors, ceiling, etc., and Q_i^{ve} relates to heat loss by ventilation .

I.5.5 Heat loss by thermal conduction

The heat loss by thermal conduction can be calculated as (e.g. [14])

$$Q_i^{\mathrm{tc}} = \sum_{j=-1}^{N} A_{i,j} U_{i,j}\left(T_i - T_j\right) \qquad \text{(I.3)}$$

Where $A_{i,j}$ is the area of the exposed surface between i-the and j-the room, $U_{i,j}$ is the resultant overall heat transfer coefficient that corresponds to $A_{i,j}$, N is the total number of rooms in the building, the room indexed as j = −1 stands for the earth, and j = 0 stands for the outer space.

The resultant heat transfer coefficient can be calculated as a weighted average of the elements that the surface $A_{i,j}$ is composed of [15], that is

$$U_{i,j} = \frac{\sum_k A_{i,j,k} U_{i,j,k}}{\sum_k A_{i,j,k}} \qquad \text{(I.4)}$$

Where $\sum_k A_{i,j,k} = A_{i,j}$

I.5.6 Heat loss by ventilation

The heat loss due to ventilation without heat recovery can be expressed as (e.g., [16])

$$Q_i^{\mathrm{ve}} = c\rho q_i(T_i - T_0) \qquad \text{(I.5)}$$

where q_i denotes air volume flow.

The heat loss due to ventilation with heat recovery can be expressed as

$$Q_i^{\mathrm{ve}} = (1-\beta)c\rho q_i(T_i - T_0) \qquad \text{(I.6)}$$

where β stands for heat recovery efficiency.

I.5.7 Applied thermal power

The heat gains of the room include the heat from central heating system (radiator heat gain), the heat from solar radiation (solar heat gain), and the heat from occupants, lights, equipment and machinery (internal heat gains):

$$Q_i^{\mathrm{in}} = Q_i^{\mathrm{u}} + Q_i^{\mathrm{sol}} + Q_i^{\mathrm{int}} \qquad \text{(I.7)}$$

I.5.8 Radiator heat gain

Most central heating systems are based on heated water that is delivered from a central boiler to each room of the house where it transmits the heat to the air through a radiator or some other radiant heating devices. The amount of heat emitted from a radiator can be considered as a regulated parameter in a thermal control system [17].

$$Q_i^{\mathrm{u}} = Q_i^{\mathrm{un}} \left(\frac{T_i^{\mathrm{uin}} - T_i^{\mathrm{uout}}}{T_{\mathrm{c}} \ln \frac{T_i^{\mathrm{uin}} - T_i}{T_i^{\mathrm{uoul}} - T_i}} \right)^n \qquad \text{(I.8)}$$

Where Q_i^u is the emitted heat, Q_i^{un} is the nominal heat emission specified by the manufacturer, , T_i^{uin} is the actual water inlet temperature of the radiator, T_i^{uout} is the actual outlet water temperature from the radiator, Tc = 49:833K is the constant temperature difference, n is a constant describing the type of radiator.

Thermal conductivity values of typical building materials shown below

Material	W/Mk
Blockwork (light)	0.38
Blockwork (medium)	0.51
Blockwork (dense)	1.63
Brick (exposed)	0.84
Brick (protected)	0.62
Chipboard	0.15
Concrete (aerated)	0.16
Concrete (dense)	1.4
Fiberglass quilt	0.033
Glass	1.05
Glass foam aggregate (dry)	0.08
Hemp slabs	0.40
Hempcrete	0.25

Table I.1 Thermal conductivity values of typical building materials

I.5.9 Simplified building thermal models

Lorenz and Masy (1982) describe a simple lumped capacity model which has since been frequently used. This is a two-time constant model, one time constant associated with the air mass and the other associated with the internal and external structural mass. The two time constants describe the traditionally accepted form of building cooling profile, a relatively rapid fall in room temperature associated with the air capacity followed by a slower fall in room temperature associated with the structural mass.

Levermore (1992) develops a heating system optimizer model that considers the building as a first order description. In this model all the building fabric initial temperature are assumed to be variant. The various construction elements are assumed to warm up and cool down to their relative steady-state temperatures. The internal structure is considered to be at the same temperature as the internal air and any internal resistance to heat flow is ignored.

Levermore (1988) states that a typical two-time constant model has a short time constant associated with the air, windows and doors and a dominant time constant associated with the fabric. The dominant time constant was considered to be the controlling factor. This assumption effectively ignores the short time constant and is considered adequate for temperature prediction for optimizer controls but is clearly limited when investigating high frequency problems in which the heating system dynamics are required to play a part.

McLaughlin et al (1981) in discussing cooling response curves state that buildings exhibit two or three time constants. In contrast to Levermore and Lorenz and Masy the shorter time constant is claimed to be due to the cooling of the air and the heat emitter and not the air capacity alone.

Tindale (1993) refined the basic Lorenz and Masy model to address some of the reported inadequacies. One of these inadequacies was the poor modelling of buildings with very high thermal capacity. As many modern buildings have these characteristics, or are "thermally heavyweight" as defined by the CIBSE response factor method (CIBSE, 1986), it was considered important that the building model proposed in the present work adequately modelled thermally heavyweight spaces.

I.5.10 Lumped capacitance model

The Lorenz and Masy model achieves its simple two-time constant form by including a proportion of the internal structure (floors, ceilings and partitions) in the single lumped external structural capacity [18]. This simplification had benefits at the time of development, but the advent of cheap computing power has diluted the case for very simplified models. Hence the model used in this work is based on the description first proposed by Lorenz & Masy, subsequently applied by Crabb et al (1987) and, later, by Tindale (1993). A similar approach has also been taken by Bérnard et al (1985). The difference here is that simplifications regarding the treatment of internal construction elements which were adopted by the previous workers were not assumed in the present work. Our approach is similar to that used by Achterbosch et al (1992) though their work was based on housing whereas the present work is relating to commercial-scale buildings with high thermal capacity.

The procedure described in the following considers a room model consisting of external wall elements and internal floor, ceiling and partition walls. This is the same as the room from which experimental data (described later) have been obtained. However, the method is sufficiently transparent for alternative room formats to be easily considered. An analogue circuit form of interpretation is shown in Figure I.1.

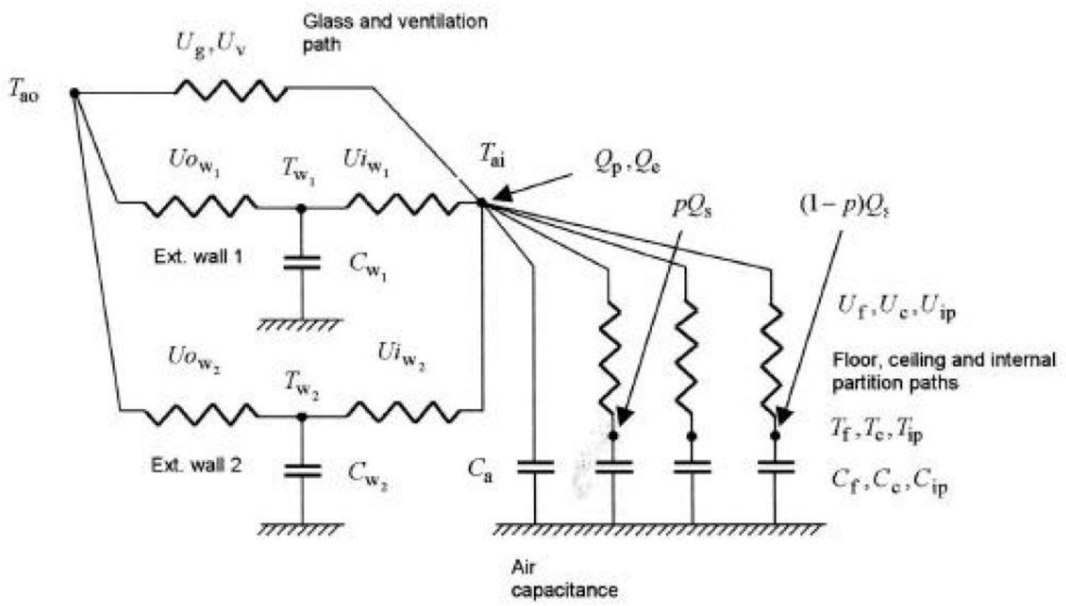

Figure I.1 Lumped Capacitance Model

Whilst the thermal resistances (hence thermal transmittances) and thermal capacitances can be calculated trivially, the Lorenz and Mays (1982) prescriptions for the single capacity equivalent of a multi-layer construction have been used to calculate the split between inner and outer region thermal resistances for the external walls – the "accessibility factor".

Based upon Figure I.1, energy balances about each internal temperature node give rise the to following.

External Wall 1

$$\frac{\mathrm{d}T_{\mathrm{w}_1}}{\mathrm{dt}} = \frac{A_{w_1}}{C_{\mathrm{w}_1}}\left[Ui_{\mathrm{w}_1}\left(T_{\mathrm{ai}} - T_{\mathrm{w_l}}\right) + Uo_{\mathrm{w}_1}\left(T_{\mathrm{ao}} - T_{\mathrm{w}_1}\right)\right] \quad \textbf{(I.9)}$$

External Wall 2

$$\frac{\mathrm{d}T_{\mathrm{w}_2}}{\mathrm{d}} = \frac{A_{\mathrm{w}_2}}{C_{\mathrm{w}_2}}\left[Ui_{w2}\left(T_{\mathrm{ai}} - T_{\mathrm{w}_2}\right) + Uo_{\mathrm{w}_2}\left(T_{\mathrm{ao}} - T_{\mathrm{w}_2}\right)\right] \quad \textbf{(I.10)}$$

Floor

$$\frac{dT_f}{dt} = \frac{A_f}{C_f}\left[\frac{pQ_s}{A_f} + U_f(T_{ai} - T_f)\right] \quad \textbf{(I.11)}$$

Ceiling

$$\frac{dT_c}{dt} = \frac{A_c}{C_c}\left[U_c(T_{ai} - T_c)\right] \quad \textbf{(I.12)}$$

Partition

$$\frac{dT_{ip}}{dt} = \frac{A_{ip}}{C_{ip}}\left[\frac{(1-p)Q_s}{A_{ip}} + U_{ip}\left(T_{ai} - T_{ip}\right)\right] \quad \textbf{(I.13)}$$

Air

$$\frac{dT_{ai}}{dt} = \frac{1}{C_a}\begin{bmatrix} Q_p + Q_c + \\ \left(A_g U_g + U_v\right)(T_{ao} - T_{ai}) + \\ A_{w_1} Ui_{w_1}\left(T_{w_1} - T_{ai}\right) + \\ A_{w_2} Ui_{w_2}\left(T_{w_2} - T_{ai}\right) + \\ A_f U_f(T_f - T_{ai}) + \\ A_c U_c(T_c - T_{ai}) + \\ A_{ip} U_{ip}\left(T_{ip} - T_{ai}\right) \end{bmatrix} \quad \textbf{(I.14)}$$

Equations (I.9) - (I.14) can be readily stacked using the state-space notation:

$$\dot{T} = \mathrm{AT} + \mathrm{Bi}$$

in which $\dot{T}$ is a vector of derivatives; A,B are matrices of coefficients; T is a vector of states and i a vector of inputs (Equation (I.15).

$$\begin{bmatrix} \dot{T}_{w1} \\ \dot{T}_{w2} \\ \dot{T}_f \\ \dot{T}_c \\ \dot{T}_{ip} \\ \dot{T}_{ai} \end{bmatrix} = \begin{bmatrix} \frac{A_{w_1}}{C_{w_1}}[Ui_{w_1} + Uo_{w_1}] & 0 & 0 & 0 & 0 & \frac{A_{w_1}Ui_{w_1}}{C_{w_1}} \\ 0 & \frac{-A_{w_2}}{C_{w_2}}[Ui_{w2} + Uo_{w_2}] & 0 & 0 & 0 & \frac{A_{w_2}Ui_{w2}}{C_{w_2}} \\ 0 & 0 & \frac{-A_f}{C_f}U_f & 0 & 0 & \frac{A_f}{C_f}U_f \\ 0 & 0 & 0 & \frac{-A_c}{C_c}U_c & 0 & \frac{A_c}{C_c}U_c \\ 0 & 0 & 0 & 0 & \frac{-A_{ip}}{C_{ip}}U_{ip} & \frac{A_{ip}}{C_{ip}}U_{ip} \\ \frac{A_{w_1}Ui_{w_1}}{C_a} & \frac{A_{w_2}Ui_{w2}}{C_a} & \frac{A_fU_f}{C_a} & \frac{A_cU_c}{C_a} & \frac{A_{ip}U_{ip}}{C_a} & \frac{-1}{C_a}\begin{bmatrix} A_gU_g + U_v + \\ A_{w_1}Ui_{w2} + A_{w_2}Ui_{w2} + \\ A_fU_f + A_cU_c + A_{ip}U_{ip} \end{bmatrix} \end{bmatrix} \times \begin{bmatrix} T_{w1} \\ T_{w2} \\ T_f \\ T_c \\ T_{ip} \\ T_{ai} \end{bmatrix} + \dots$$

$$\dots \begin{bmatrix} 0 & 0 & 0 & \frac{A_{w_1}Ui_{w_1}}{C_{w_1}} \\ 0 & 0 & 0 & \frac{A_{w_2}UO_{w2}}{C_{w_2}} \\ 0 & 0 & \frac{p}{C_f} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{(1-p)}{C_{ip}} & 0 \\ \frac{1}{C_a} & \frac{1}{C_a} & 0 & \frac{(A_gU_g+U_v)}{C_a} \end{bmatrix} \times \begin{bmatrix} Q_P \\ Q_e \\ Q_s \\ T_{ao} \end{bmatrix} \qquad \textbf{(I.15)}$$

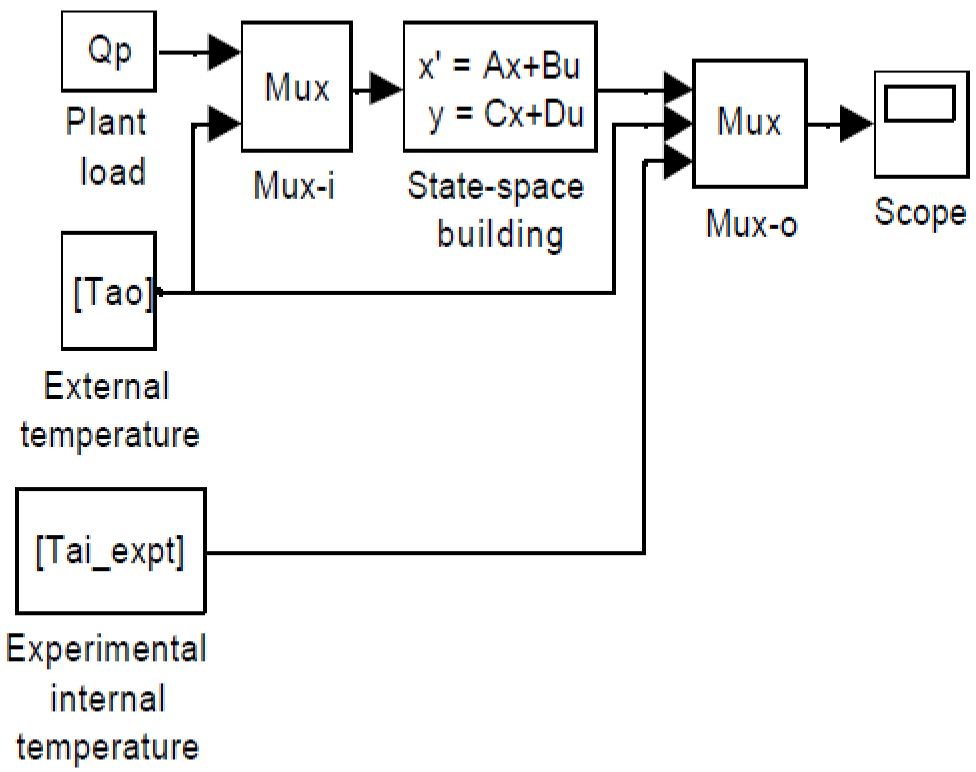

Figure I.2 Simulink Model Structure

I.6 Buildings dynamic energy simulation tools

Various tools have been developed for building modeling, simulation and control design. Their strengths and weaknesses vary depending on the application. The most mature ones include SIMBAD, TRNSYS and Energy Plus.

SIMBAD

SIMBAD (SIMulator of Building and Devices) is a Matlab/Simulink toolbox created by CSTB2 for thermal dynamic simulation of buildings.

A mono-zone model based on the Resistance-Capacitance analogy [19] was the first type of building simulator provided by SIMBAD. Three resistances and two capacitors completely describe the model. The user must specify the type of accommodation (individual housing, flat), the size category, and the construction period when creating a simulator. After that, the toolbox assigns the model with common parameters. These typical parameters were pre-processed based on a typological study of 120 residential lodgings that were representative of the population. These typical parameters were pre-processed using a typological study of 120 residential lodgings that are representative of the French building stock.

The subsequent version of SIMBAD permitted multi-zone building thermal modeling with thorough descriptions of the envelope and HVAC systems [20]. The simulator is divided into Simulink blocks, with the physical modeling of thermal phenomena coded in Matlab and hidden from the end-user. After that, the blocks are linked together. Homogeneous air zone, multilayer wall, window, infrared heat exchange, and solar irradiation models are the fundamental building blocks. SIMBDI was used in that version (Simbad Building Description Interface) as a user interface is introduced. It allows users to sketch buildings in two dimensions, floor by floor, with envelope features. The interface then creates a thermal zone for each floor automatically. [21] The latest version of SIMBAD has been rewritten in C++

for faster simulations and less memory usage. Some models, such as the air quality model, have also been added.

SIMBAD is especially useful for applications that use the Simulink graphical interface to design control techniques for HVAC, shading, or lighting systems. The Functional Mock-up Interface (FMI) standard is supported by newer versions of Matlab/Simulink3. FMI allows models to be exported as Functional Mock-up Units (FMUs), which can interchange inputs and outputs with other software modules in a co-simulation framework during the simulation run. SIMBAD was used as the simulation environment to evaluate MPC techniques implemented in [Morosan, 2011] and [22] PhD theses.

TRNSYS

TRNSYS (TRaNsient SYStem simulation tool) is a commercial simulation program created by TESS4 and the University of Wisconsin – Solar Energy Laboratory (United States), CSTB (France), and TRANSSOLAR Energietechnik in partnership (Germany).

TRNSYS is built on a modular architecture, which means that complicated models are implemented using a component-based method. There is now a large library of components available. The majority of these elements (sometimes referred to as Types) are written in Fortran. Users can enhance current models or create new ones. An executable file can be launched to run the simulation engine once models have been constructed in the Simulation Studio visual interface (or Kernel). The simulation engine reads and processes input files before solving a system of algebraic and differential equations iteratively and producing output files. An online plotter allows visualization of variable evolution after the executable call. The user determines the fixed integration time step; it may be less than a minute, but it must be 1/n of an hour, where n is an integer.

TRNSYS features a multi-zone building thermal simulator that is very accurate (called Type 56). TRNSYS3D is a Sketch Up plugin that allows users to draw architectural geometry in 3D. Internal surface view factors, overhangs, and side fins are all depicted in the drawings, and their shading effects are accounted for in the radiation distribution and exchange model. All non-geometry data, such as construction material properties, HVAC system control settings, and internal heat gain profiles, are then loaded into the TRNSYS Building environment – TRNBuild.

Here are some significant characteristics of TRNSYS's building modeling. The solar irradiation balance is meticulously modeled, with view factors for long wave radiant exchange across inside surfaces determined exactly using detailed geometric data. The insertion of several air nodes accounts for stratification. The model is used to simulate convective heat transfer across zones. Thermal bridges are taken into account in the design of an external wall. Each zone in the simulator can be connected to a radiator model with a thermostatic valve. For heating and cooling floors and ceilings, an integrated model for thermo-active walls can be employed. The ground-coupled heat transmission is studied in detail using a slab model with a 3D finite difference soil field. Moisture balance is calculated for each zone and may be used in humidity control devices in HVAC systems. Clothing factor, metabolic rate, external work, and relative air velocity are all factors in a thermal comfort model. Humidity, direct and diffuse sun irradiation are not taken into account. The heat capacity of furnishing items should be taken into account by the user to correct the heat capacity of the zone air volume [23] TRNSYS models can be exported as FMUs using the TRNSYS FMU Export Utility for interoperability. As a result, it may co-simulate with models created with other tools. TRNSYS and Matlab/Simulink are also interchangeable: a TRNSYS component may be exported into a Simulink project, and a Simulink subsystem can be converted to a TRNSYS component.

TRNSYS is utilized in [24]'s work to model a building's HVAC system. Inverse modeling is then utilized with this simulator to infer a reduced model of the system, which is then used in operational optimization to manage the building set-point temperature using thermal inertia to save money. In [25], TRNSYS thorough building thermal simulation was combined with Matlab powerful HVAC control mechanisms for load shifting MPC applications.

Energy Plus

The US Department of Energy created Energy Plus as a modular simulation engine to combine two hourly building energy modeling programs: BLAST and DOE-2.

Energy Plus is a Fortran program. It's just a simulation engine; numerous graphical user interfaces (GUIs) have been created to wrap around it, the most popular of which being Design Builder and Open Studio. Users draw out the 3D building geometry of multi-zone buildings (similar to TRNSYS) and add HVAC systems using these GUIs. To calculate building thermal load, the simulation engine uses a zone heat balance approach that comprises surface heat balance and air heat balancing. Energy Plus has a customizable time step feature that ranges from 1 minute to 1 hour.

One of the unique characteristics of Energy Plus thermal modeling is the ability to select from a variety of solution algorithms; for example, for heat conduction, a transfer function and a finite difference approach are both available and can be user-specified. Internal mass can be represented as multi-layer internal walls with thermal capacitance separate from the zone air volume. On one hand, they interact with the zone heat balance, while on the other, they are adiabatic. They do not receive direct solar irradiation, but they do exchange long waves with all other interior surfaces. An anisotropic sky model is included in Energy Plus.so sky radiance is calculated as a function of the sun position for accurate diffuse of solar irradiation on tilted surfaces. Simulators may have controllable blinds glazing systems. For accurate diffusion of solar irradiation on slanted surfaces, sky radiance is computed as a function of sun position. Controllable blinds glazing systems may be available in simulators. Interior daylight illuminance from windows is computed using a model, which allows dimming control operations. [26] Energy Plus also contains a thermal comfort model based on the inside dry bulb temperature, occupant activity, air humidity, and radiation. These characteristics, in addition to its user-friendly interface, made Energy Plus very popular among engineers for thermal load estimates in buildings.

It is feasible to co-simulate with Energy Plus. The Energy Plus To FMU Python package can be used to export simulators as FMUs. Alternatively, the Building Controls Virtual Test Bed (BCVTB) [27] can be used to link Energy Plus and exchange data while it is being integrated with software that does not support the FMI standard.

[28] employed Energy Plus in an MPC application to explore latent heat storage in buildings using heat exchangers including phase-change material. In [29], it was also utilized to apply MPC, depending on a linear reduced-order model discovered from data collected by radiant floor heated simulators. [30] used Energy Plus in a study of the effect of interior mass on building peak loads.

Chapter II: Model Predictive Control

II.1 Introduction

The Model predictive control (MPC) strategy has been discovered and re-invented several times. Receding horizon approaches were used in the 1960s and 70s to define computational methods for optimal control problems that have no closed-form solution. Predictive control reappeared in the entirely different context of industrial process control in the 1980s as a means of exploiting continual improvements in computational resources to improve performance. More recently the approach has been used as a general technique for deriving stabilizing controllers for constrained systems. At the same time, the availability of faster computers and improvements.

MPC is an approach to control design. It does not imply a specific control law or algorithm; it rather describes a strategy primary based on anticipation and calculation of consequences. On another note, optimal control involves mathematical formulation of a problem and its resolution for the best solution. One possible framework to implement optimal control is within the MPC approach. In this chapter, we intend to clarify the concepts of MPC Linear Model.

II.2 Model Predictive Control – Background

The key feature that distinguishes MPC from most other control strategies is the receding horizon principle. An MPC controller solves, at each sampling instant, a finite horizon optimal control problem. Only the first value of the resulting optimal control variable solution is then applied to the plant, and the rest of the solution is discarded. The same procedure is then repeated at each sampling instant, and the prediction horizon is shifted forward one step. Thereby the name receding horizon control. This strategy includes solving on-line an optimal control problem, which enables the controller to deal explicitly with MIMO (multi input multi output) plants and constraints. On the downside are the computational requirements. Solving the optimization problem may introduce computational delay, which, if not considered, may degrade control performance. Also, MPC is a model based control strategy, and a model of the process to be controlled is a necessary requirement for MPC. [31].

II.3 Principle Basic of predictive control

It consists in predicting the behavior of the process on a prediction horizon Np, which depends on the dynamics of the process using a state model and in calculating a command sequence on n control horizon Nc. The calculated command consists in minimizing a criterion on the output of the system and the command itself.

The idea is simple and practiced quite systematically in everyday life: for example, the driver of a vehicle knows the desired reference trajectory in advance (the road) over a finite control horizon (his visual field)., and by taking into account the characteristics of the car (mental model of the behavior of the vehicle), he decides which actions (accelerate, brake or turn the steering wheel) must be carried out in order to follow the desired trajectory. Only the first driving action is performed at any time and the procedure is repeated again for the next actions, on each control horizon faint visual field. The philosophy of the predictive control law is presented in figure II.1

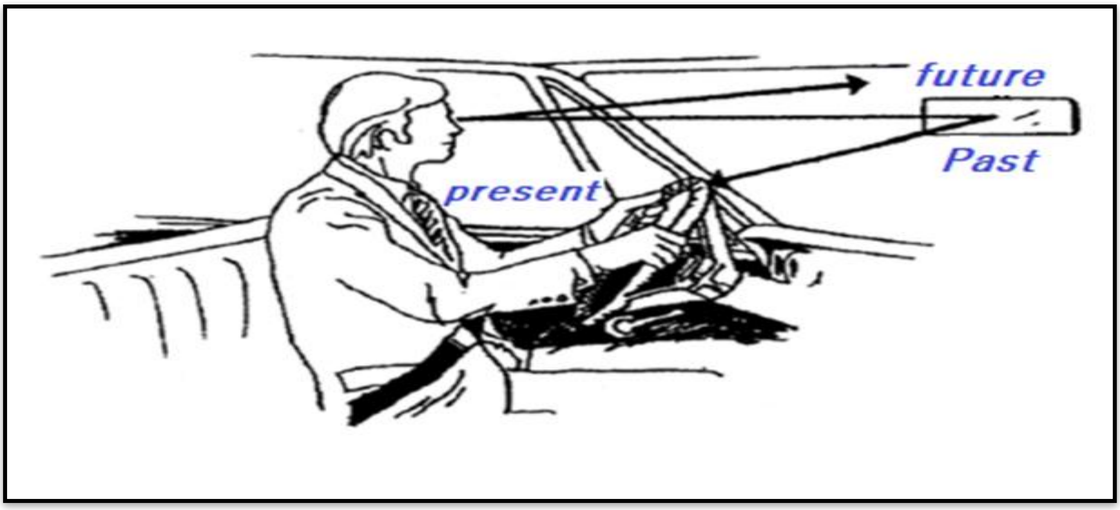

Figure II.1 The philosophy of the predictive control

Ⅱ.4 Linear Model Predictive Control

In this section, an MPC formulation based on linear discrete-time state space models will be described. The presentation is based on [32].

Ⅱ.4.1 Receding horizon control

The MPC scheme makes use of the receding horizon principle, illustrated in Figure II.2. At each sample, a finite horizon optimal control problem is solved over a fixed interval of time, the prediction horizon. We assume that we would like the controlled variables, $z(k)$, to follow some set point trajectory, $r(k)$. The optimal control problem is formulated using a cost function penalizing deviations of the controlled variables as well as variations in the control signal. A common choice is to use a quadratic cost function, which in combination with a linear system model yields a finite horizon LQ problem. Figure II.2 shows the predicted optimal trajectories $\hat{z}(k + |k)$ and $\hat{u}(k + |k)$ starting at time k.

The predictions necessary to solve the optimization problem is obtained using a model of the controlled system. The prediction of the controlled variable z is performed over an interval with length H_p samples. The control signal is assumed to be fixed after H_u samples. H_p and H_u are referred to as the prediction horizon and the control horizon respectively. The distinction between the prediction and control horizons is useful since the number of decision variables in the optimization problem increases with H_u, but is independent of H_p. Normally, $H_u < H_p$ in order to reduce the complexity of the optimization problem.

When the solution of the optimal control problem has been obtained, the value of the first control variable in the optimal trajectory, $u(k|k)$, is applied to the process. The rest of the predicted control variable trajectory is discarded, and at the next sampling interval the entire procedure is repeated.

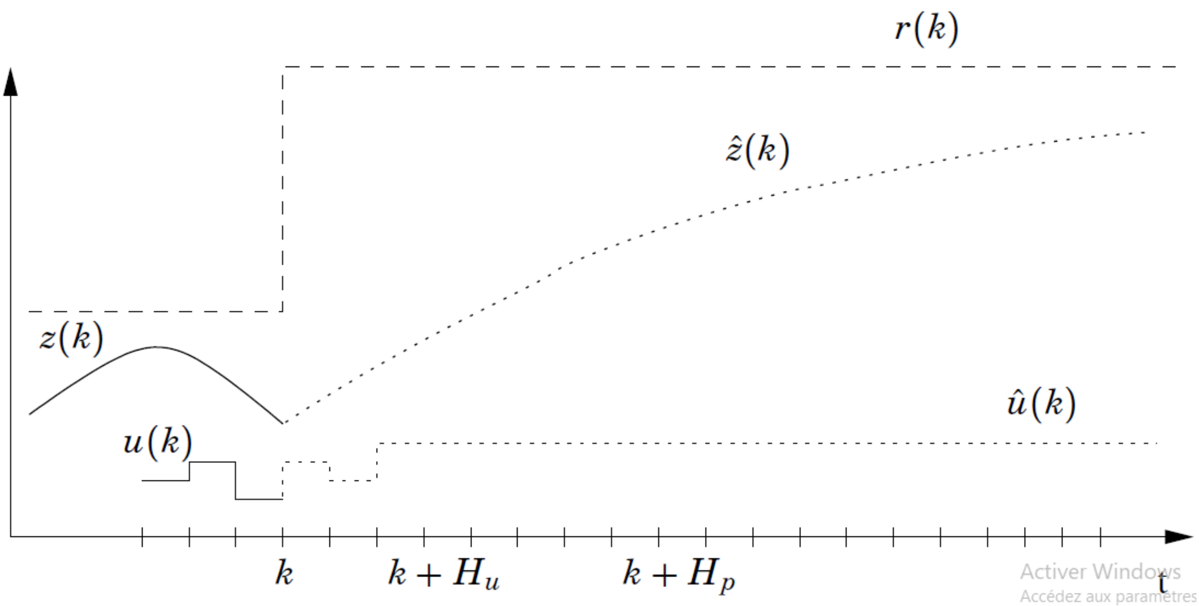

Figure II.2 The idea of MPC. Here $r(k)$is the set point trajectory, $z(k)$ represents the controlled output and $u(k)$ the control signal.

Ⅱ.4.2 Model assumptions

We assume that a model on the form

$$x(k+1) = Ax(k) + Bu(k)$$

$$y(k) = C_Y x(k) \qquad \text{(II,1)}$$

$$z(k) = C_z x(k) + D_z u(k)$$

$$z_c(k) = C_c x(k) + D_c u(k)$$

is available. Here $y(k) \in R^{p_y}$ is the measured output, z(k) $\in R^{p_z}$ the controlled output and $u(k) \in R^m$ the input vector. The state vector is $x(k) \in R^n$. The MPC controller should also respect constraints on control variables as well as the constrained outputs, $z_c(k) \in R^{p_c}$

$$D_{min} \leq Du(k) \leq D_{max}$$

$$u_{min} \leq u(k) \leq u_{max}$$

$$z_{min} \leq ZC(k) \leq z_{max} \qquad \text{(II,2)}$$

where $\Delta u(k)= u(k) - u(k-1)$ are the control increments.

The distinction between controlled and constrained variables is natural, since only the controlled variables have specified reference values. This distinction is not made in [32], but is quite useful. For example, there may be plant variables that must respect constraints, without having corresponding reference values. In some cases, the constrained variables may not be included in the set of measured variables. In this case, an observer can be used to obtain estimates of such variables. The constraints are then enforced for the estimated outputs, which may not be equal to the true constrained outputs. The same argument applies to the controlled outputs, which will be discussed further in the section dealing with error free tracking.

Ⅱ.4.3 An optimal control problem

We will now formulate the optimal control problem that is the core element of the MPC algorithm. Consider the following quadratic cost function:

$$j(k) = \sum_{i=H_w}^{H_p+H_w-1} \|\tilde{z}(k+i|k) - r(k+i|k)\|_Q^2 + \sum_{i=0}^{H_u-1} \|\Delta\tilde{u}(k+i|k)\|_R^2 \qquad \text{(II,3)}$$

where $\tilde{z}(k+i|k)$ are the predicted controlled outputs at time k and $\Delta\tilde{u}(k+i|k)\|$ are the predicted control increments. The matrices $Q \geq 0$ and $R > 0$ are weighting matrices, which are assumed to be constant over the prediction horizon. The length of the prediction horizon is H_p, and the first sample to be included in the horizon is H_w. H_w may be used to shift the control horizon, but in the following presentation we will assume that $H_w = 0$. The control horizon is given by H_u. In the cost function (II..3) $\Delta u(k)$is penalized rather than $u(k)$, which is common in LQ control. The reason for this is that for a non-zero set point, r (k), the corresponding steady state control signal u (k) is usually also non-zero. By avoid penalizing u(k), this conflict is avoided. A different method that has been used is to introduce a set point also for the control variable, u_r (k), and to penalize deviations of $u(k)$, from u_r. This approach may be implemented in the above formulation by choosing C_z= 0 and D_z= I, and thereby let $u(k)$, be part of the controlled variables.

The cost function (II.3) may be rewritten as

$$j(k) = \|Z(k) - \Gamma(k)\|_Q^2 + \|\Delta u\|_R^2$$

Where

$$Z(k) = \begin{bmatrix} \tilde{z}(k|k) \\ \vdots \\ \tilde{z}(k + H_p - 1\ |\text{k}) \end{bmatrix} \qquad \Gamma(k) = \begin{bmatrix} r(k|k) \\ \vdots \\ r(k + H_p - 1\ |\text{k}) \end{bmatrix}$$

$$\Delta u(k) = \begin{bmatrix} \Delta u(k|k) \\ \vdots \\ \Delta u(k + H_u - 1\ |\text{k}) \end{bmatrix} \qquad Q = \begin{bmatrix} Q & 0 & \dots & 0 \\ 0 & Q & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & Q \end{bmatrix}$$

$$R = \begin{bmatrix} R & 0 & \dots & 0 \\ 0 & R & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & R \end{bmatrix}$$

By deriving the prediction expressions, we can write

$$Z(k) = \Psi \mathrm{x(k)} + \Gamma u(k-1) + \Theta \Delta u(k) \qquad (II,4)$$

where

$$\Psi = \begin{bmatrix} C_z \\ C_z A \\ C_z A^2 \\ \vdots \\ C_z A^{H_p-1} \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} D_z \\ C_z B + D_z \\ C_z A B + C_z B + D_z \\ \vdots \\ C_z \sum_{i=0}^{H_p-2} A^i B + D_z \end{bmatrix}$$

$$\Theta = \begin{bmatrix} D_z & 0 & \cdots & 0 \\ C_z B + D_z & D_z & & \\ C_z A B + C_z B + D_z & \ddots & \vdots & \\ \vdots & \ddots & 0 & \\ C_z \sum_{i=0}^{H_w-2} A^i B + D_z & \cdots & D_z & \\ \vdots & & \cdots & \vdots \\ C_z \sum_{i=0}^{H_p-2} A^i B + D_z & & \cdots & C_z \sum_{i=0}^{H_p-Hu-1} A^i B + D_z \end{bmatrix}$$

Also, let

$$\mathcal{E}(k) = \mathcal{T}(k) - \Psi x(k) - \Gamma u(k-1) \quad (II,5)$$

This quantity could be interpreted as the free response of the system, if all the decision variables at $t = k$, $\Delta u(k)$, were set to zero. Inserting the prediction expressions into the cost function (II.3) we obtain

$$J(k) = \Delta \mathcal{U}^T \mathcal{H} \Delta \mathcal{U} - \Delta \mathcal{U}^T G + \mathcal{E}^T Q \mathcal{E}$$

Where:

$$\begin{aligned} \mathcal{G} &= 2\Theta^T Q \mathcal{E}(k) \\ \mathcal{H} &= \Theta^T Q \Theta + \mathcal{R} \end{aligned}$$

The problem of minimizing the cost function (II.5) is a quadratic programming (QP) problem. If $\mathcal{H}$ is positive definite, the problem is convex, and the solution may be written on closed form. Positive definiteness of $\mathcal{H}$ follows from the assumption that $Q \geq 0$ and $\mathcal{R} > 0$. The solution is given by

$$\Delta\mathcal{U} = \frac{1}{2}\mathcal{H}^{-1}\mathcal{G}$$

Notice that the matrix $\mathcal{H}^{-1}$ does not depend on k, and may be pre-calculated. In fact, the controller is linear, and may be calculated off-line. This will be discussed in detail in Section □. 4.8 .

III.4.4 Constraints

Let us now introduce constraints on the constrained and control variables, z_c and u. In general, linear constraints may be expressed as:

$$W\Delta\mathcal{U}(k) \leq w \qquad \text{(II,6)}$$

$$F\mathcal{U}(k) \leq f \qquad \text{(II,7)}$$

$$GZ_c(k) \leq g \qquad \text{(II,8)}$$

This formulation allows for very general constraints, but in the following, only the constraints specified by (II.2) will be considered. Using (II.2), we obtain

$$W = F = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ -1 & & & \\ 0 & 1 & & \vdots \\ \vdots & & \ddots & 0 \\ & & & 1 \\ 0 & \cdots & 0 & -1 \end{bmatrix} G = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ -1 & & & \\ 0 & 1 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & -1 \end{bmatrix}$$

$$w = \begin{bmatrix} \Delta u_{\max} \\ -\Delta u_{\min} \\ \vdots \\ \Delta u_{\max} \\ -\Delta u_{\min} \end{bmatrix} f = \begin{bmatrix} u_{\max} \\ -u_{\min} \\ \vdots \\ u_{\max} \\ -u_{\min} \end{bmatrix} g = \begin{bmatrix} z_{\max} \\ -z_{\min} \\ \vdots \\ z_{\max} \\ -z_{\min} \end{bmatrix}$$

Notice that W and F may not be of the same size as G, though the structure is the same. Since $\mathcal{U}(k)$ and $Z_c(k)$ are not explicitly included in the optimization problem, we rewrite the above constraints in terms of $\Delta\mathcal{U}(k)$. This gives

$$\begin{bmatrix} \mathcal{F} \\ G\Theta_c \\ W \end{bmatrix} \Delta\ell l \leq \begin{bmatrix} -\mathcal{F}_1 u(k-1) + f \\ -G(\Psi_c x(k) + \Gamma_c u(k-1)) + g \\ w \end{bmatrix} \quad \text{(II.9)}$$

Where:

$$\mathcal{F} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ -1 & & & \\ 1 & 1 & & \vdots \\ -1 & -1 & & \\ \vdots & & \ddots & 0 \\ 1 & & & 1 \\ -1 & \cdots & & -1 \end{bmatrix} \mathcal{F}_1 = \begin{bmatrix} 1 \\ -1 \\ 1 \\ -1 \\ \vdots \\ 1 \\ -1 \end{bmatrix}$$

The definitions of Ψ_c, Θ_c and Γ_c are equivalent to those of Ψ, Θ and Γ. As we can see, the left side of the inequality is not dependent on k, and could be calculated off-line. The right side depends on the last control signal and the present estimation of the state vector, and should thus be evaluated at each sample.

The optimization problem can now be rewritten using (II.3) and (II.9)

$$\begin{aligned} &\text{m } J(k) = \Delta\mathcal{U}^T \mathcal{H} \Delta\ell - \Delta\mathcal{Z}l^T G + \mathcal{E}^T Q \mathcal{E} \\ &\text{subject to } \Omega\Delta U \leq \omega \end{aligned}$$

The problem is still recognized as a quadratic programming problem, but now with linear inequality constraints. The problem is convex, but due to the constraints, it is not possible to write the solution on closed form. Rather iterative algorithms have to be employed. This issue will be discussed further in Section Ⅱ.5

Ⅱ.4.5 State estimation

The algorithm for obtaining the optimal control signal at each sample assumes that the present state vector is available. Since this is often not the case, state estimation is required. The celebrated separation principle, stating that the optimal control and optimal estimation problems solved independently, yields a globally optimal controller for linear systems, suggests an attractive approach. We let the solution of the optimization problem be based on an estimate of the state vector, $\hat{x}(k)$ instead of the true state vector $x(k)$. For this purpose, a Kalman filter.

$$\hat{x}(k+1) = A\hat{x}(k) + Bu(k) + K\big(y(k) - C_y\hat{x}(k)\big)$$

can be used. If the covariance matrices of the states, W, and the measurement noise, V, are assumed to be known, the gain matrix K may be obtained by solving an algebraic Riccati equation, see for example[33].

Apart from estimating the state of the system, an estimator could be used to estimate disturbances, assuming that a disturbance model is available. For example, error-free tracking may be achieved by including a particular disturbance model in the observer.

Ⅱ.4.6 Error-free tracking

In practical applications, there are always modeling errors and disturbances present. The MPC formulation described above contains no explicit mechanism to deal with these complications. In order for the controller to be useful in practice, these problems have to be considered. Commonly, the controller is designed so that it contains integral action, which ensures zero steady-state error. There are several methods for achieving integral action in a controller. For SISO (single input single output) systems, introduction of integral action is quite straight forward. A common approach is to introduce an integrator state in the state space model:

$$\begin{bmatrix} x(k+1) \\ x_1(k+1) \end{bmatrix} = \begin{bmatrix} A & 0 \\ -C_z & I \end{bmatrix} x(k) + \begin{bmatrix} B \\ 0 \end{bmatrix} u(k) + \begin{bmatrix} 0 \\ I \end{bmatrix} r(k)$$
$$y(k) = [C_y \quad 0]$$
$$z(k) = [C_z \quad 0]$$

A stabilizing feedback control law may then be calculated based on the extended model. The integrator state is implemented in the controller, and used for feedback together with the true or estimated states. From the definition of the extended system model, it is clear that in steady state, $z = r$. This approach does not work so well for MPC controllers. In particular, it is not clear how the integral state should be introduced in the cost function in order for the integral action to work properly.

A different approach to achieve integral action is to use a disturbance observer. In summary, the extended system model

$$\begin{bmatrix} x(k+1) \\ v_a(k+1) \\ d(k+1) \end{bmatrix} = \begin{bmatrix} A & 0 & B \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} x(k) \\ v_a(k) \\ d(k) \end{bmatrix} + \begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix} u(t)$$

$$z(k) = y_z(k) = [C_z \quad 0 \quad 0]$$

$$y_a(k) = [C_a \quad I \quad 0][x(k)^T \; v_a(k)^T \; d(k)^T]^T$$

is used. It is assumed that the number of controlled outputs, z, equals the number of inputs, u. Additional outputs, if any, are denoted y_a. Also, the controlled variables are assumed to be included in the set of measured variables. A detailed treatment of this method is given in [34].

Ⅱ.4.7 Blocking factors

In some situations it may be advantageous to let the control signal be fixed over several consecutive predicted samples. In this way, the control horizon may be increased without increasing the complexity of the optimization problem. Also, ringing behavior of the control signal may be avoided. For example, suppose that the control horizon has to be increased in order to increase closed loop performance. If the control horizon is increased, the time to solve the optimization problem will also increase. If this is not acceptable, one approach might be to include only every other decision variable in the optimization problem, assuming that the control signal is fixed over two consecutive sampling intervals. We denote the set of predicted sample indexes for which the control signal is allowed to vary by I_u.

In the MPC formulation given above this means that some $\Delta\hat{u}(k+i \mid k)$: s are set to zero for certain i:s. This means that the corresponding columns in the matrices Θ, W and F may be neglected.

In a similar way it is possible to generalize the prediction horizon. Instead of including all predicted values in the interval $[k \dots k+H_p-1]$, we introduce the set I_p consisting of all sample indexes for which the corresponding predicted output values are included in the cost function and for which the constraints are enforced. The last point is critical. It may be tempting to introduce a sparse set of predicted sampling instants in order to obtain a longer prediction horizon. However, since the inter-sample behavior is neglected, this may lead to the constraint in effect being violated at some points.

This generalization is easily introduced by neglecting the rows of the matrices Ψ, Γ, Θ and G corresponding to sample indexes not present in I_{p*} Using the notation introduced above, the cost function may be rewritten as

$$J(k) = \sum_{i \in I_p} \| \hat{z}(k+i \mid k) - r(k+i \mid k) \|_Q^2 + \sum_{i \in I_\Sigma} \| \Delta\hat{u}(k+i \mid k) \|_R^2 \qquad \text{(II.10)}$$

II.4.8 Linear properties of the MPC controller

The behavior of the MPC controller is intrinsically nonlinear, since constraints on state and control variables are taken into account. However, if no constraints are present in the problem formulation, the controller is linear. Also, the controller behaves linearly during operation when no constraints are active. In the first case, the control law, could (and should) be calculated off-line, whereas in the second case, the optimization procedure must be done each sample. There are however, methods for avoiding on-line solution of the optimization problem. Using the observation that the MPC control law is piecewise linear in the states, it is possible to calculate, off-line, all possible control laws. The on-line optimization problem is then transformed into a search problem, where the objective is to find the appropriate partition in the state space, identifying the corresponding control law. This approach is described in [35].

We will now analyze the linear properties of the MPC controller. The analysis is valid for the case when no constraints are present or the controller operates so that no constraints are active. In this case, the minimizing solution of the quadratic programming problem is

$$\begin{aligned}
\Delta\mathcal{Z}\ell(k) &= (\Theta^T Q\Theta + \mathbb{R})^{-1}\Theta^T Q E(k) \\
&= (\Theta^T Q\Theta + \mathbb{R})^{-1}\Theta^T Q \begin{bmatrix} \begin{bmatrix} I \\ \vdots \\ I \end{bmatrix} - \Gamma \ - \Psi \end{bmatrix} \begin{bmatrix} r(k) \\ u(k-1) \\ \hat{x}(k) \end{bmatrix} \\
&= \bar{K}_s \begin{bmatrix} r(k) \\ u(k-1) \\ \hat{x}(k) \end{bmatrix}
\end{aligned}$$

Now, since only the first of the predicted control signals are applied we can write the control law as

$$\begin{aligned}
\Delta u(k \mid k) = \Delta u(k) &= K_s[r^T(k)\; u^T(k-1)\; \hat{x}^T(k)]^T \\
&= [K_{ar} \quad K_{su} \quad K_{sx}][r^T(k) \quad u^T(k-1) \quad \hat{x}^T(k)]^T
\end{aligned}$$

where K_s is given by the first m rows of $\bar{K}_3$. This control law is linear, and the constant gain matrix K_s may be calculated off-line. The block diagram of the controller may now be drawn as in Figure II.3. In this figure, the transfer function (matrix) of the plant is given by $P(z)$, and $H_u(z)$ and $H_y(z)$ represents the observer. This block diagram is readily converted into a feedback system on standard form shown in Figure II.4, with

$$P(z) = C_y(zI - A)^{-1}B$$
$$F(z) = K_{sr}$$
$$H(z) = -K_{ar}H_y(z)$$
$$K(z) = \frac{z}{z-1}\left[I - \frac{1}{z-1}K_{su} - \frac{z}{z-1}K_{ax}H_u(z)\right]^{-1}$$
$$H_y(z) = \left(zI - A + KC_y\right)^{-1}K$$
$$H_u(z) = \left(zI - A + KC_y\right)^{-1}B$$

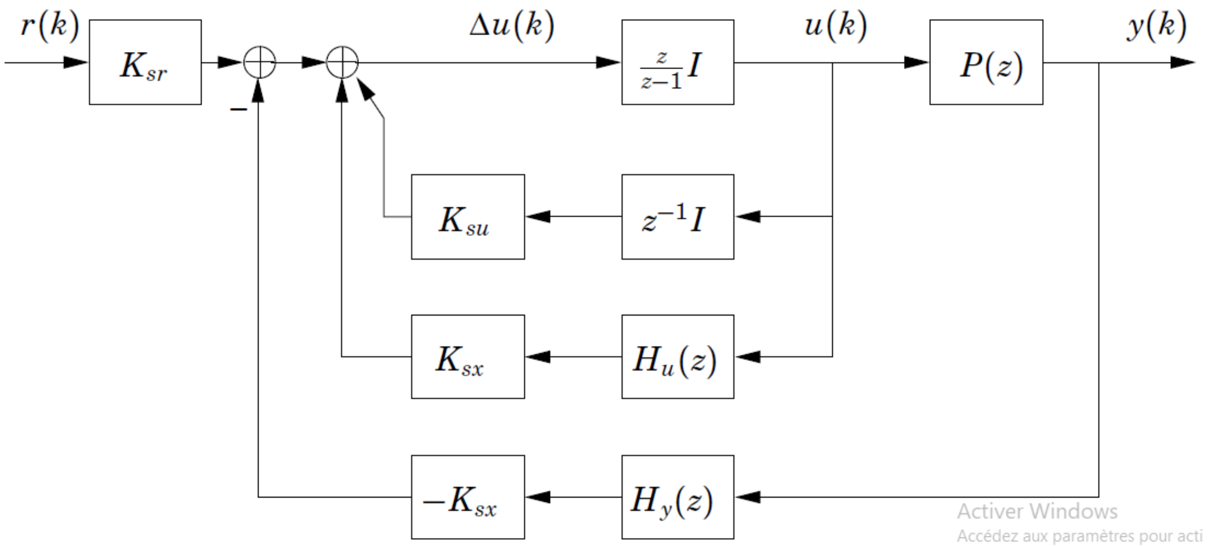

Figure II.3 The block diagram for the MPC controller

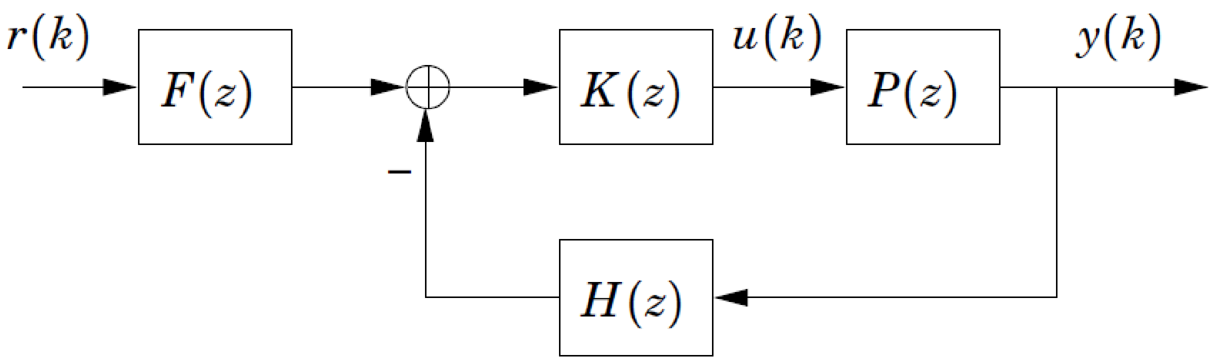

Figure II.4 A standard feedback structure.

It is now straight forward to apply standard linear analysis methods. For example, the poles and zeros of the closed loop system may be calculated, as well as the sensitivity of the system.

Ⅱ.5. Quadratic Programming Algorithms

An important element of the MPC algorithm described above is the algorithm for solving the Linear Inequality Constrained Quadratic Programming LICQP problem. The problem at hand

$$minj(k) = \Delta u^t H \Delta u - \Delta u^T G + E^T Q E$$

$$subject\ to \Omega \Delta U \leq \omega$$

This problem has several nice features. For example, the objective function is convex, since it is quadratic with positive definite Hessian. Also, the constraints are also convex. Given these conditions, it is a well-known result that a local minimum, if it exists, is also a global minimum. See for example [36]. When designing numerical algorithms, this property is of course very valuable, since we know in advance that if we find a minimum, it is indeed a global minimum.

There exist several algorithms for constrained optimization, see for example [37]. For quadratic programming problem the two most common approaches are primal-dual internal point methods and active set methods [32].

The active set algorithm assumes an initial point in the decision variable space that fulfills the constraints. The active set is defined as the set of all active constraints at this point. A constraint is said to be active if a particular point in the search space is at the boundary of the feasible region defined by the constraint. In the case of linear constraints, these boundary surfaces are given by hyper-planes. In each iteration step, a quadratic programming problem with linear equality constraints (namely those in the active set) is solved. The solution of this problem may be written on closed form. Possibly this solution leads to the introduction of a new constraint into the active set. By calculating the Lagrange multipliers for the problem at each iteration, it is possible to conclude if a constraint may be relaxed, that is, removed from the active set. The algorithm terminates when the gradient of the associated Lagrange function is identically zero, and all Lagrange multipliers are positive.

One problem remains to deal with; the feasible initial point. In order to start the active set algorithm, we need a feasible solution, that is, we would like to find a solution that fulfills the constraints $\Omega\Delta U \leq \omega$. Of course, such a solution is not likely to be unique. Several methods exist for obtaining the desired solution. For example, the problem may be cast as an LP problem, and solved by the simplex algorithm. Another and possibly more attractive alternative is given in [37]. This strategy employs an active set technique similar to the one for solving the main quadratic programming problem. However, in this case, the objective function is defined at each iteration as the sum of the violated constraint functions. Primal-dual interior point methods on the other hand, explores the Karush- Kuhn-Tucker conditions explicitly. The name of this family of QP algorithms stems from the fact that the primal and the dual problems are solved simultaneously. It is important to note however, that the term interior point refers to the fact that the algorithm maintains a solution in the interior of the dual space. In fact, the primal solution may not be feasible during the optimization run, except at the optimal point. This constitutes an important difference between active set methods and primal-dual interior point methods. Specifically, in the former case it is possible to terminate the optimization algorithm prematurely and still obtain a feasible, but sub-optimal, solution whereas in the latter case, the algorithm may terminate only when the optimal solution is found.

Concerning performance, both methods have advantages and disadvantages when applied to MPC. Rather, the key to achieve good performance lies in exploring the special structure of the MPC QP problem. See [38] for a comparison between interior point and active set methods.

Chapter III: MPC for building control

III.1 Introduction

The purpose of the following chapter is to compactly define and summarize the general MPC framework for building applications, and applies a three Scenarios the Model Predictive Control (MPC) method based by consider a linear model of three zones building, see[vv], in this section we want to design an optimal controller policy by Reduce energy cost and maximizing the thermal comfort according to the desired requirements

Ⅲ.2 Model predictive building control

In building control, one would aim at optimizing the energy delivered (or cost of the energy) subject to comfort constraints During each sampling interval, a finite horizon optimal control problem is formulated and solved over a finite future window. The result is a trajectory of inputs and states into the future, respecting the dynamics and constraints of the building while optimizing some given criteria. In terms of building control, this means that at the current control step, a heating/cooling etc. plan is obtained for the next several hours or days, based on a weather forecast. Predictions of any other disturbances (e.g. internal gains), time-dependencies of the control costs (e.g. dynamic electricity prices), or of the constraints (e.g. thermal comfort range) can be readily included in the optimization.

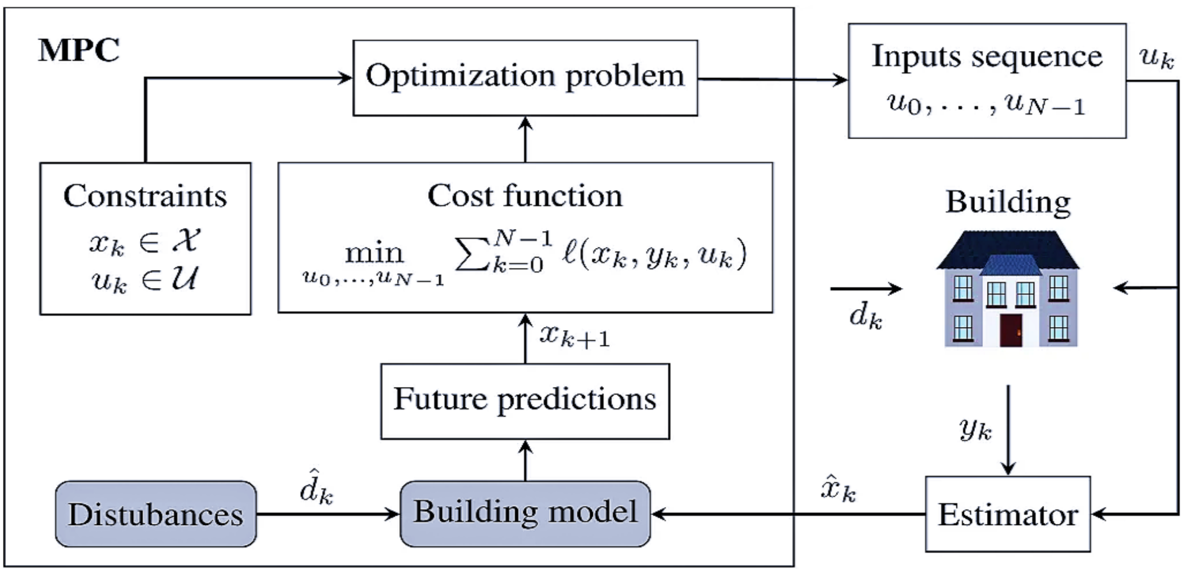

Figure III.1 Schematic representation of the standard closed-loop system for building control with MPC and state estimator.

III.2.1 Standard MPC scheme

Fig. 2 illustrates a typical abstract closed-loop MPC scheme which can describe most of the building control applications. The control loop consists of the building affected by disturbances d (e.g., weather conditions), predicted by weather forecast $\hat{d}$, the state estimator providing the state estimates$\hat{x}$ and the MPC controller which optimally manipulates the control actions u (e.g., heat flows, valves opening, pump powers), e.g., such that it minimizes used energy and keeps the output vector y (e.g., room temperatures) within the given comfort bounds[39].

Figure III.2 Model Predictive Control ingredients in buildings

III.2.2 General MPC formulation for buildings

The Figure II.2 summarizes the major components required for MPC implementation in buildings. They have gathered:

- the building model, which is made up of a dynamical description of the component of the building that has to be controlled

- the prediction on the most important external elements that influence the building's behavior (weather, energy rate, occupancy).
- . the objective function describing the criterion to be optimized (energy or invoice minimization while meeting comfort requirements).
- the mathematical solver that allows the underlying optimization problems to be solved.

And The general MPC formulation for buildings can be represented as the following optimal control problem (OCP) in discrete time:

$$\min_{u0,.\,.\,.uN-1} \sum_{k=0}^{N-1} l_k(x_k, u_k) \quad \text{Cost function} \qquad \text{(III.1)}$$

subject to

$$x\,0 = x \qquad \text{Current state}$$

$$x_{k+1} = f(x_k, u_k, w_k) \qquad \text{Dynamics – state update} \qquad \text{(III.3)}$$

$$y_k = g(x_k, u_k, w_k) \qquad \text{Dynamics – system output} \qquad \text{(III.4)}$$

$$(x_k, u_k) \in X_k, U_k \qquad \text{Contraints} \qquad \text{(III.5)}$$

Ⅲ.2.3 Standard MPC notation

Table III.1 summarizes the standard notation and meaning of the variables used in the control community together with most common

Notation	Controller	building	Units
x	states	building structure temperatures	[°C]
y	outputs	room operative temperatures	[°C]
u	inputs	heat flows to the zones	[W]
a	actuators	valve and pump modulations	[%]
m	measurements	HVAC states	[°C, W, %]
d	disturbances	ambient temperatures, solar radiation,	[°C, W]
		and internal heat gains	[W]
r	references	comfort zones, set points	[°C]
s	slack variables	discomfort measures	[°C]
ξ	parameters	aggregate of the building states,	[°C]
		references, and disturbances	[°C,W]
Q	weighting factors	importance of particular objective	[-]
N	prediction horizon	predicted future time window	[-]
Nc	control horizon	optimized future time window	[-]

Table III.1 Standard notation and most common physical representation of the variables used in MPC for buildings

Ⅲ.3 Simulations of MPC in Building Climate Control

we want to implement a three different cases of MPC controller on a three zones building's heating system that will regulate the thermal comfort and energy of the system.

Ⅲ.3.1 System model identification

Ⅲ.3.1.1 Building model

We were provided with a discrete-time state space model of a building which has the following form:

$$x_{k+1} = Ax_{k+1} + Bu_k + Ed_k \quad \text{(III.6)}$$

$$y_k = Cx_k \quad \text{(III.7)}$$

Where

$u_k \in R^3$ is the input of the model constitutes the electrical power input (kW) to the heating system of the three zones input, $d_k \in R^3$ is the disturbance wish constitutes the outside temperature (°C), solar gains (kW), and internal gains (kW), The output of the model $y_k \in R^3$ is the temperature in the three building zones. the system matrices have the following structure;

$$A = \begin{bmatrix} 0.9902 & -0.0341 & -0.0350 & 0.0004 & 0.0179 & 0.0001 & 0.0099 & 0.0011 & 0.0000 & 0.0016 \\ -0.0295 & 0.7157 & -0.2578 & 0.0023 & -0.0720 & -0.0003 & 0.0880 & -0.0410 & 0.0002 & 0.0115 \\ -0.0322 & -0.2623 & 0.7249 & 0.0025 & 0.0203 & 0.0014 & 0.1298 & -0.0282 & 0.0005 & 0.0222 \\ 0.0004 & 0.0023 & 0.0025 & 0.9759 & -0.0020 & 0.0950 & -0.0019 & -0.0001 & 0.0167 & -0.0004 \\ 0.0189 & -0.0629 & 0.0232 & -0.0021 & 0.5609 & -0.0008 & -0.0952 & -0.1662 & 0.0006 & -0.0454 \\ 0.0001 & -0.0002 & 0.0014 & 0.0950 & -0.0011 & 0.5137 & 0.0002 & -0.0013 & -0.1399 & -0.0004 \\ 0.0071 & 0.0821 & 0.1172 & -0.0017 & -0.0810 & 0.0003 & 0.7507 & -0.0128 & -0.0001 & -0.1199 \\ -0.0462 & -0.0462 & -0.0423 & 0.0002 & -0.1300 & -0.0010 & -0.0209 & 0.7322 & 0.0005 & -0.1097 \\ -0.0000 & 0.0002 & 0.0004 & 0.0167 & 0.0008 & -0.1399 & -0.0001 & 0.0004 & 0.7510 & -0.0007 \\ 0.0002 & 0.0022 & 0.0047 & -0.0001 & -0.0105 & -0.0003 & -0.0245 & -0.0016 & -0.0006 & 0.6690 \end{bmatrix}_{10\times10}$$

$$\boldsymbol{B} = \begin{bmatrix} -1.2863 & -5.1272 & -1.2770 \\ 1.0377 & -23.6399 & 1.0663 \\ -1.8578 & -16.3977 & -1.9549 \\ 4.0922 & 0.1203 & -3.9829 \\ 8.4912 & -3.8495 & 8.3930 \\ -10.2013 & -0.0081 & 10.2844 \\ 2.4016 & 2.3285 & 2.3727 \\ 1.9483 & -0.9055 & 1.9478 \\ -0.9551 & 0.0058 & 0.9584 \\ 0.5215 & 0.1422 & 0.5228 \end{bmatrix}_{10\times3} ; \ \boldsymbol{E} = \begin{bmatrix} -1.6520 & -0.3622 & -6.0955 \\ -0.0796 & 0.0328 & -2.1627 \\ -1.0544 & -0.0709 & -6.0163 \\ 0.0192 & -0.0157 & 0.1062 \\ 2.0559 & 0.1062 & 11.7490 \\ 0.0102 & 0.0008 & 0.0587 \\ -0.7847 & -0.3193 & 0.1290 \\ -0.9027 & -0.2630 & -0.1840 \\ -0.0041 & -0.0131 & -0.0076 \\ 1.9182 & 0.1396 & -0.8360 \end{bmatrix}_{10\times3}$$

$$\boldsymbol{C} = \begin{bmatrix} -0.0033 & 0.0011 & -0.0036 & 0.0042 & 0.0141 & -0.0122 & 0.0029 & 0.0031 & -0.0022 & 0.0015 \\ -0.0064 & -0.0284 & -0.0226 & 0.0002 & -0.0037 & -0.0000 & 0.0058 & -0.0025 & 0.0000 & 0.0011 \\ -0.0033 & 0.0012 & -0.0037 & -0.0040 & 0.0140 & 0.0124 & 0.0029 & 0.0031 & 0.0022 & 0.0015 \end{bmatrix}_{3\times10}$$

Where

A is the system matrix, B the input matrix, E the disturbance matrix and, C is the output matrix

Ⅲ.3.1.2 The disturbance inputs

Figure III.3 shows the values of the three disturbance inputs for a period of eight days. the outside temperature values (°C), solar gains(kW), and internal gains(kW), with 20 minutes sampling rate (T_s=20$_{min}$)

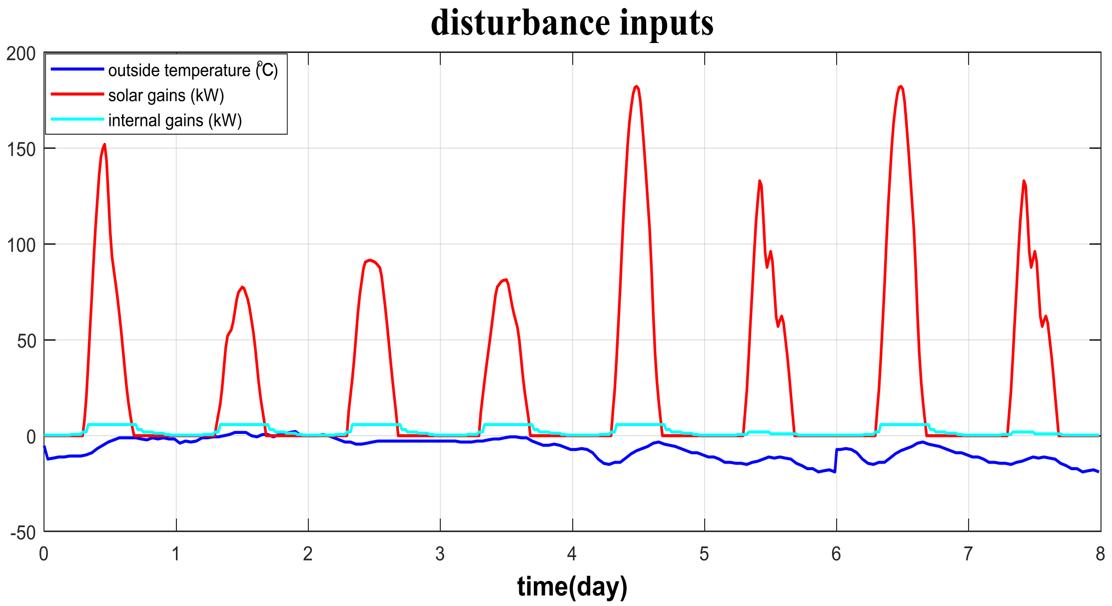

Figure Ⅲ.3 the three disturbance inputs of the model

Ⅲ.3.1.3 Constraint specification

The inputs and the outputs of the model are subject to constraints:

- $u_{min} \leq u_k \leq u_{max}$ (III.8)
- $y_{min} \leq y_k \leq y_{max}$ (III.9)

The input constraints capture the heating capacity of the HVAC system.

$(u_{min} = 0kw | u_{max} = 15kw)$.

while the output constraints ensure comfort in the building.

$(y_{min} = 22°C | y_{max} = 26°C)$

Ⅲ.3.1.4 Form of the cost function

$$J = \sum_{k=1}^{N} \left(Cx_k - y_{ref}\right)^T Q\left(Cx_k - y_{ref}\right) + u_k^T R\, u_k \qquad \text{(III.1a)}$$

We take prediction horizon $N = 10$ of this quadratic optimization problem, and we have the set point y_{ref} which is the reference output (y_{ref} =24°C) for all the three zones in every case and (Q, R) stands for weighting parameters

$$y_{ref} = [24 \quad 24 \quad 24]^T$$

Ⅲ.3.2 Simulation results and discussion

Cas1: Comfort Zone Tracking

In this first case we are interested in providing thermal comfort in all three zones regardless of electrical cost by taking weighting parameters:

$$Q_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_1 = 0$$

Figure Ⅲ.4 shows the variation values of the temperature in the three building zones in eight days, we see the efficiency of our MPC command and how it kept the temperature in all of three zones on the set point (y_{ref}), with keeping the consumption of the energy Power under the value that specified in the constraints in Figure Ⅲ.5

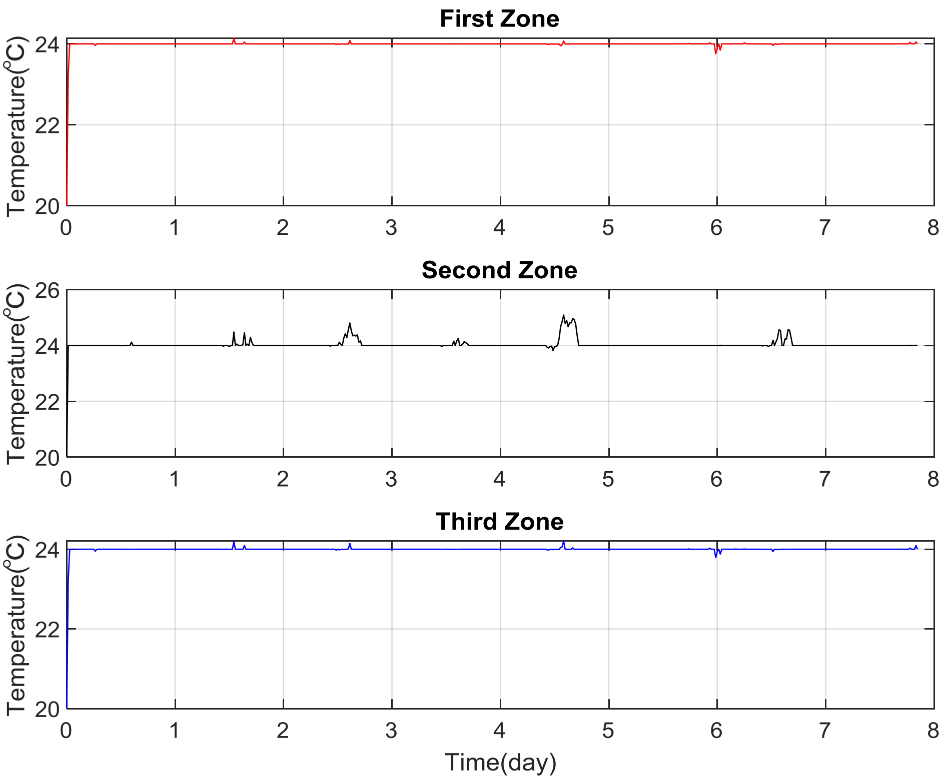

Figure Ⅲ-4 the temperature in the three building zones for the first case

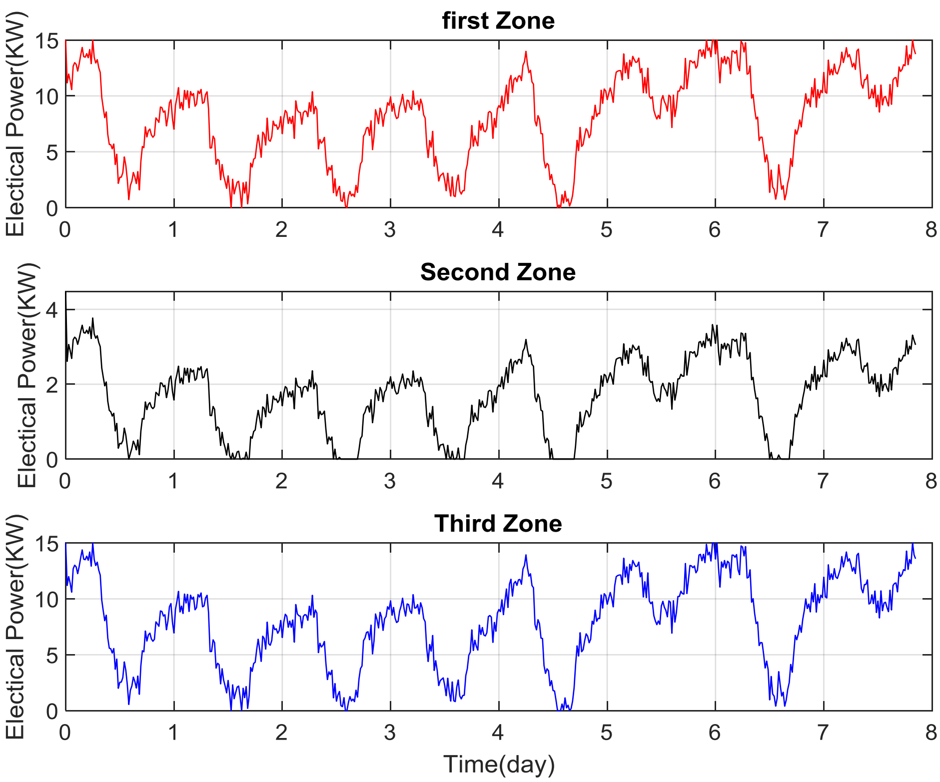

Figure Ⅲ-5 Electrical Power of the three zone for the first case

Case 2: Reference Tracking with Energy Minimization

In the second case We'd want to formulate an Economic MPC in such a way that the inside temperature is kept as close as possible to the set point (y_{ref}), with minimize the energy cost By consider the weighting parameters:

$$Q_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

in Figure Ⅲ.6 we see the variation values of the temperature in the three building zones in this case we note that the temperature is not stable at the set point(y_{ref}), While not exceeding the minimum temperature that specified in the constraints, but on the other hand, we see that the energy consumption in Figure Ⅲ.7 has been reduced comparing with the first case while maintaining thermal comfort, perhaps not ideal but appropriate

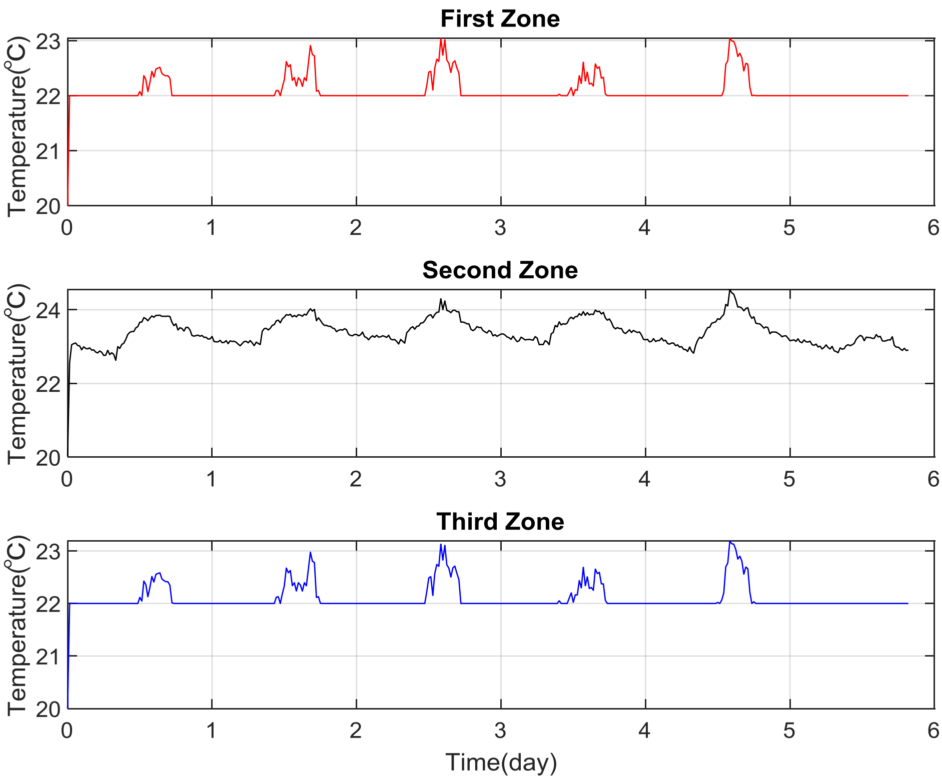

Figure Ⅲ.6 the temperature in the three building zones for the second case

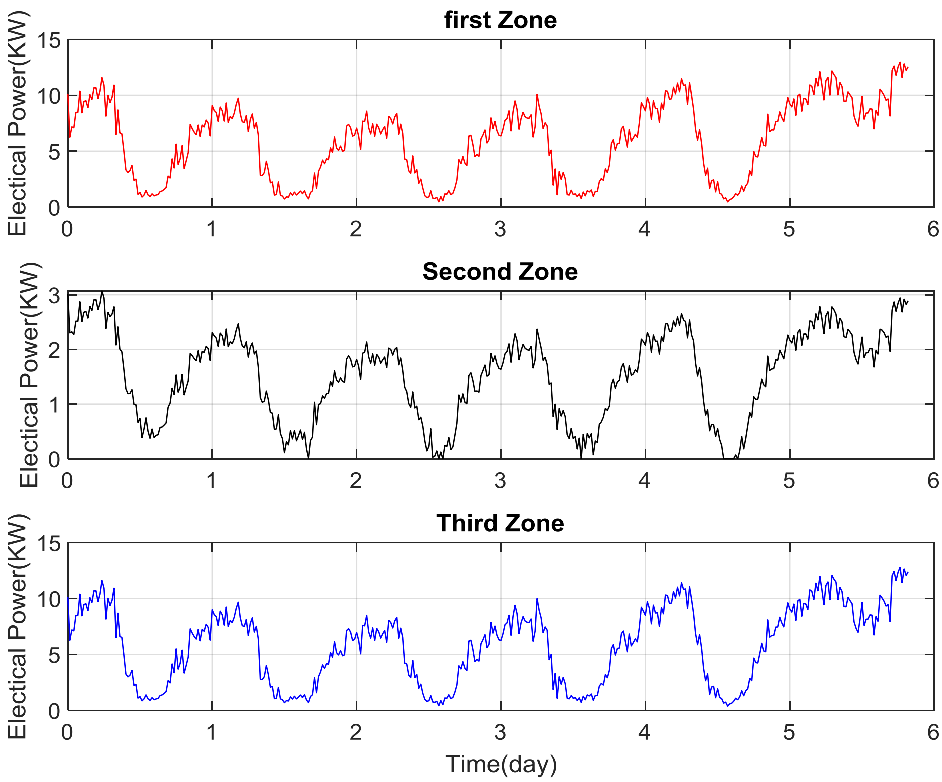

Figure Ⅲ.7 Electrical Power of the three zone for the second case

Case 3 Reference Tracking in one zone with Energy Minimization in the others

In this last case we are interested in providing thermal comfort in the third zone on the set point (y_{ref}) but we want to save energy cost in the other two zones and keep the inside temperature as close as possible to the setpoint (y_{ref})

we take the weighting parameters:

$$Q_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 150 \end{bmatrix}$$

$$R_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

in Figure Ⅲ.8 we see the variation values of the temperature in the three building zones in this case we note that the temperature is not stable at the set point (y_{ref}), in the first and second zones but appropriate unlike the third zone that kept the thermal comfort ideal on the set pointing Figure Ⅲ.9 we see that the power consumption is low in first and second zones unlike the third zone which consumed more than the other zones

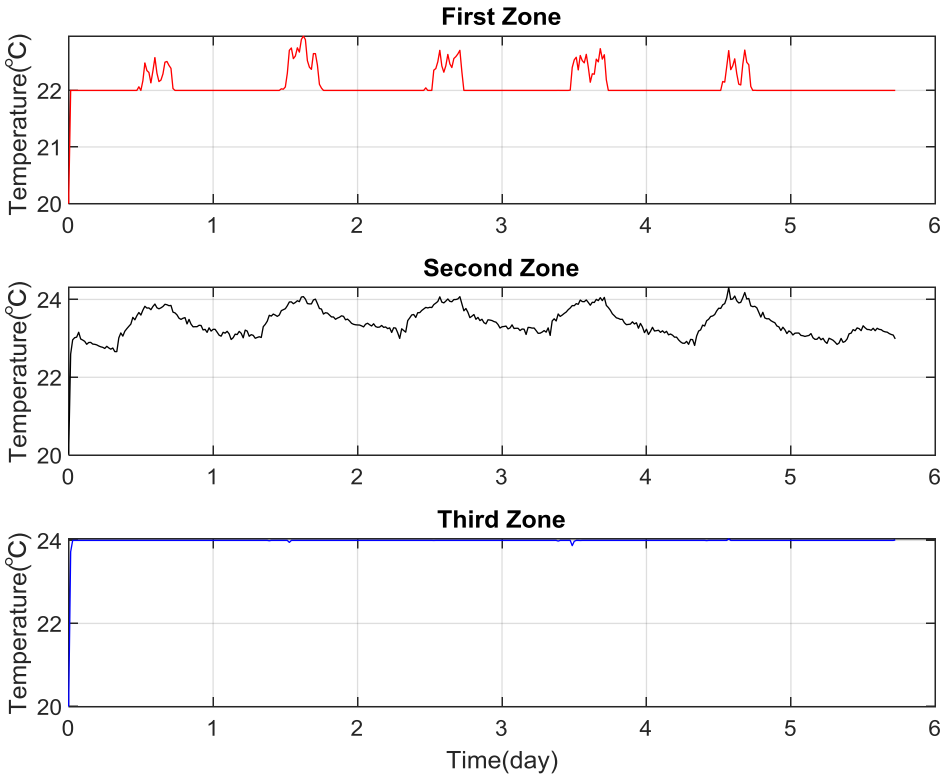

Figure Ⅲ.8 the temperature in the three building zones for the third case

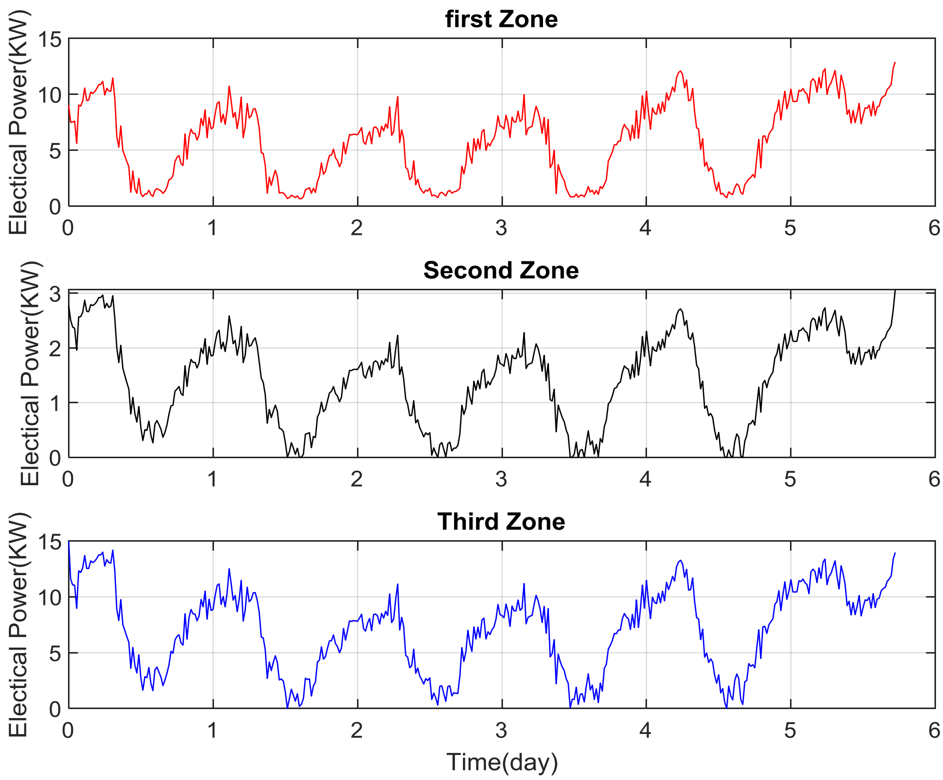

Figure Ⅲ.9 Electrical Power of the three zone for the third case

Ⅲ-4-Conclusion

We have presented in this chapter the concept of the model predictive control in buildings models and we applied a multi scenarios of the MPC command on a three zones buildings models and saw how this command can be Adjusting the energy cost while maintaining thermal comfort While respecting the constraints

General Conclusion

Thesis is made of two parts:

Theoretical part and simulation part. The theoretical part is intended to identify the theoretical basis of this project, studies on generalities on building climate control and MPC.

We specialized the first chapter to talk about an overview of building climate control and their mainly objectives of it, in addition to explain how the comfort in building is too important in our daily lives and how can be done it. For sure We can't forget to tell people how much Energy cost's building is and how we can reach to an optimal Energy efficiency. We also present a building climate model and applies the modeling on it.

In the second chapter, we decided to discuss all about MPC. And how it works and explain their process strategies, we were also exposed to show the demonstration of the MPC equations of linear model and we ended the chapter with linear properties of MPC and quadratic programming algorithms.

Finally, in the third and most important chapter, we got to talk about the simulation part and show all the results that we ended up with, we used MATLAB 2018a to simulate our results by using YALMIP tool box.

Our building model had 3 zones and we choose 3 studies cases to be done, first case we were interested to keep thermal comfort in our wished set point, second case we wanted to minimize the Energy cost in the 3 building zones, last case we wanted minimized Energy cost in 2 zones and an ideal thermal comfort in the rest zone, and the simulation time is 8 days.

In the end we found that the result that we received is perhaps suitable for our command, we see that the calculation of MPC doesn't finish and simulation time just has stopped in day 6 in second and third case.

So, in conclusion, based on this dissertation’s results, MPC is so useful in process control and can leading to Improve the thermal comfort and minimizing Energy cost.

And finally, for those who want to research and publish in this project, I suggest that they find a model of a real building by using simulation programs with MPC for better and more accurate results.

Annexes

Annexes A: YALMIP Toolbox

YALMIP is a free MATLAB toolbox for rapid prototyping of optimization problems. The package initially aimed at the control community and focused on semidefinite programming, but the latest release extends this scope significantly. can be used for linear programming, quadratic programming, second order cone programming semidefinite programming non-convex semidefinite programming, mixed integer programming, multi-parametric programming, geometric programming The main features of YALMIP are: Easy to install since it is entirely based on MATLAB code. Easy to learn new commands are all the user needs to get started. Easy to use: you define your constraints and objective functions using intuitive and standard MATLAB code. Automatic categorization of problems, and automatic solver selection Supports numerous external solvers, both free and commercial.

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