OPTIMIZATION OF BUILDING ENERGY CONSUMPTION USING SIMPLIFIED MODELS AND NEW CONTROL METHODS

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To Damascus..

To my family..

To Wassim..

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Dedication

I would like to dedicate this thesis to my loving parents. You have always believed in me and that is the reason I am this person now. The hardest thing in this thesis was being far away from you. Thank you for being the best parents ever. My sister Touna and brother Loude, I love you so much..

To my Grandmother...

My lovely Papi, I cannot find the words to thank you and tell you how much you mean to me. You are my source of inspiration, encouragement, and most importantly smile and hope in my life. Thank you for being there. Thank you for believing in me.

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Jim, Here comes the dream true, OUR dream. I love you so much.

My Godfather Jim...

Fadi, you are my source of energy, wisdom and adventures. Thank you for being always there when I need you. I love you and miss you.
My best friend Rasha, your presence has been a constant source of support and laughter during the challenges of life. With you, I spend the best and worst memories of these three years but together we could make it through. I am truly thankful for having you in my life.
To family Barrow, Mieke, I can't think of a better gift Khaldoun could have left for me. Our friendship and your family love. I am proud to know you and to be a small part of your lives.
Tom.. Thank you for being the shoulder I cry on!
Valentin: "Je voudrais une baguette s'il vous plait", My best French teacher and « mon petit » forever.
Ammosh.. Do you think we would have made it without having the same exact up and downs together???????

Abstract

With the highly developing concerns about the future of energy resources, the optimization of energy consumption becomes a must in all sectors. A lot of research was dedicated to buildings regarding that they constitute the highest energy consuming sector mainly because of their heating needs. Many proposals of new strategies to minimize building consumption were done. These proposals vary between recommending better insulation, advising change in occupants' behavior and changing the heating control management.

This thesis proposes a new control method that helps minimizing the heating consumption and expenses. This method generates an energy plan over a defined prediction horizon respecting the occupants' thermal comfort. It is based on the application of Monte Carlo method, i.e., a random generator for the heating system scenarios. The aim is to determine the optimal heating plan for the prediction horizon that fulfills the constraints regarding the following three factors:

- The thermal comfort of occupants;
- The minimization of the energy consumption/expenses;
- Load shifting.

However, to test this method, an identification of the building thermal behavior was needed. Thus, a building thermal model to simulate the building behavior was developed. This model was meant to be simplified in order to better integrate it in the control process. Furthermore, a new parameter estimation approach as well as a real time temperature control method are presented to ensure the implementation of the optimal predicted plan.

Résumé

L'inquiétude croissante concernant le futur des ressources énergétique a fait de l'optimisation énergétique une priorité dans tous les secteurs. De nombreux sujets de recherche se sont focalisés sur celui du bâtiment étant le principal consommateur d'énergie, en particulier à cause de ses besoins en chauffage. Beaucoup de propositions pour réduire la consommations ont été faites. Ceux-ci vont de l'amélioration de l'isolation au changement du système de gestion du thermostat en passant par la formation des occupants à une meilleure gestion de leur bâtiment.

Cette thèse propose une nouvelle méthode de contrôle qui permet de minimiser la consommation énergétique et dépenses budgétaires. La méthode génère un planning énergétique sur une période de temps pré-définie, ceci en prenant compte du confort thermique des occupants. Elle est basée sur l'application de la méthode de Monte Carlo, un générateur aléatoire appliqué au système de chauffage. L'objectif est de déterminer le planning de chauffage optimal, qui respecte les trois contraintes suivantes :

- Le confort thermique des résidents;
- La minimisation de l'énergie consommée / du budget;
- Le déplacement de la charge.

De plus, pour tester cette méthode, l'identification du comportement thermique du bâtiment a été requise. De ce fait, un modèle thermique du bâtiment a été développé. Ce modèle a été volontairement simplifié afin de l'intégrer plus simplement dans le processus de contrôle. De plus, une nouvelle approche d'identification thermique du bâtiment aussi bien qu'une nouvelle méthode de controle en temps réel ont été présentées.

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Chapter 1

State of the Art

Introduction

The energy consumption over the world is still increasing with almost 2% per year [PLOP08]. The diminution of the fossil fuels resources together with the need to reduce the green house gas effect, make it crucial to reconsider the energy consumption as well as the gas emissions. In cold climates, heating is responsible for approximately 50% of the total final energy consumption [RR12]. The energy consumed for heating is affected by several factors such as the insulation, the environment and the heating regulation....etc. In order to be able to reduce the consumption, a better understanding of the building performance as well as regulation methods is needed.

In this research, a study of the building thermal performance identification and modeling is proposed in order to represent the building thermal behavior and to integrate it in the control of the heating system. This integration of the building behavior in the control process allows having a considerable economy in the energy consumption by editing heating profiles and improving the heat planning process. This chapter is a presentation of the problem considered in this thesis work, a short explanation about the motivation of this work and the challenges met.

1.1 Context

The consumption of energy differs between sectors. Figure 1.1 shows the distribution of energy consumption between different sectors in France 2012 [Car06].

Buildings account for the highest energy consuming assets with 44% of the total energy consumption, 19% of the green house gas emissions and 76.5% of the final electricity consumption (Figure 1.2) according to ADEME, INSEE and EDF France [Car06] [Rou12].

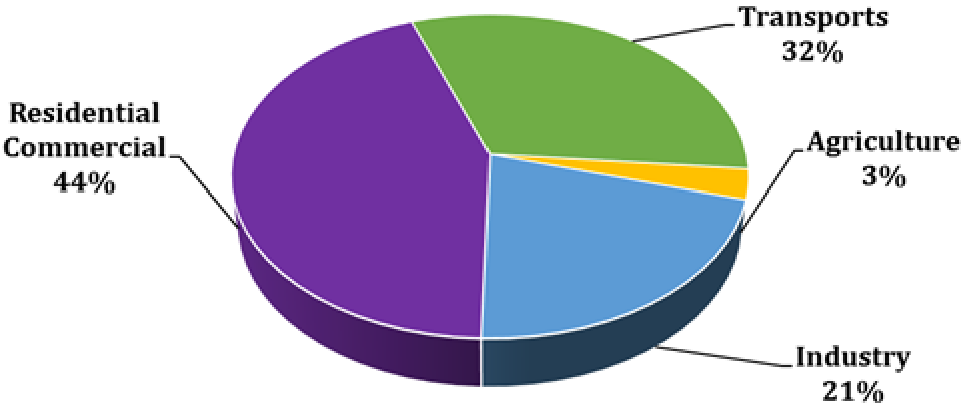


Fig. 1.1 Final energy consumption distributed by sector, France 2012 (source:Chiffres Clés 2012, Ministry of ecology, energy and sustainable development)

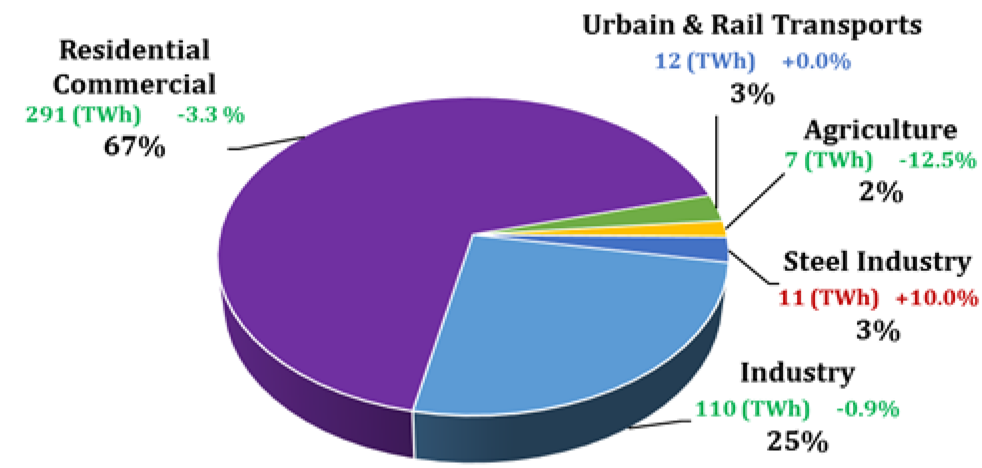


Fig. 1.2 Final electricity consumption distributed by sector, France 2012 (source:Chiffres Clés 2012, Ministry of ecology, energy and sustainable development)

Energy consumption of buildings is dedicated to guarantee occupants'comfort. Buildings consume energy in several ways which can be classified into 3 sectors:

- The heating/cooling energy;
- The lightening;
- Other domestic uses.

The building sector has a high attention in terms of energy consumption. Several studies and regulations have been set to reduce the building consumption. Raising awareness campaigns are done, insulation requirements and pricing plans were imposed to better control the energy losses and the consumption peaks [MP13a]. According to [ABG+10] and [Gel09], a considerable part of the energy consumed in the building sector is due to either bad insulation or bad control of the heating systems (unoptimized consumption). A study of the National Renewable Energy Laboratory (NREL) identifies the "lack of innovative controls and monitoring systems" as one of the principal challenges in achieving high energy efficiency in buildings [RGC+08] [FDT+13].

1.2 Motivations and challenges

Building conception is an important factor that affects the energy consumption and the comfort in the building. In the European context, this is one of the most important challenges to be worked out. Many tools were put in action to ameliorate the building energy behavior from the conception phase. However, this is not enough since the rehabilitation of the existing mass of buildings can be very expensive with a very long investment cycle. Moreover, there are other factors that can affect this behavior such as the technical as well as economic and regulatory issues to be integrated. Understanding the building heating system is challenging as well. The type of the heating system and its design affects enormously the energy consumption. Buildings with central heating systems could consume totally differently from those with individual heating systems. The same thing applies for the nature of the heating system (gas, electricity....). Furthermore, the regulation and planning of the heating system is highly important and can affect the energy consumption (use of building inertia, occupation planning , sun, energy pricing..).

1.3 Presentation of the problem: Building Heating consumption

Building energy performance is a major research topic nowadays. Integrating the knowledge obtained from these researches in the conceptual design phase of a building is indispensable. It can widely change the building thermal solutions. Building energy performance requires studying all factors affecting the building behavior.

1.3.1 Surrounding conditions

The energy consumption of a building is directly related to the geographical location of the building as well as the surrounding landscape. Each building is classified in a certain category of consumption according to meteorological data of the geographical location (base exterior temperature). This base exterior temperature is a key element when calculating the energy losses and needs. It represents the minimum exterior temperature that can be crossed down only once a year. The landscape effect on the other hand reflects whether the building is exposed or protected (trees, mountains, hills...). It also constitutes the building orientation and if it is sunlit or shaded. Another important condition is the altitude of the building. The altitude affects the exterior temperature as well as the basic exterior temperature. To take it into consideration, correction tables are used [MP13a].

Figure 1.3 shows the division of France according to the meteorological information. The data in this figure is supplied by Meteo-France weather stations. This division differs between winter energy needs $H1$, $H2$ and $H3$ as well as the summer thermal comfort a,b, c and d to end with 8 different climate zones.

1.3.2 Weather conditions

The following weather conditions are the key element of building energy consumption:

- Exterior temperature: The actual exterior temperature is determines the energy losses by conduction through the envelope as well as the losses by ventilation. It also has a great effect on the desired comfort temperature for the human body.

- Exterior humidity: The humidity effect is through the ventilation (exchange of the air between interior and exterior). It also might cause the condensation that can damage the envelope (case of hot humid conditions). With the new construction standards, a special importance is given to this aspect in order to avoid having this problem.

- Wind direction and speed: Which has the main role in heat losses through convection between the building envelope and the exterior air.

- Sun radiation: A building receives two types of sun radiation:

  - Direct radiation: which causes a considerable part of the solar gains;

  - Diffused radiation: this one depends on the sky clearness (cloudy, sunny ..).

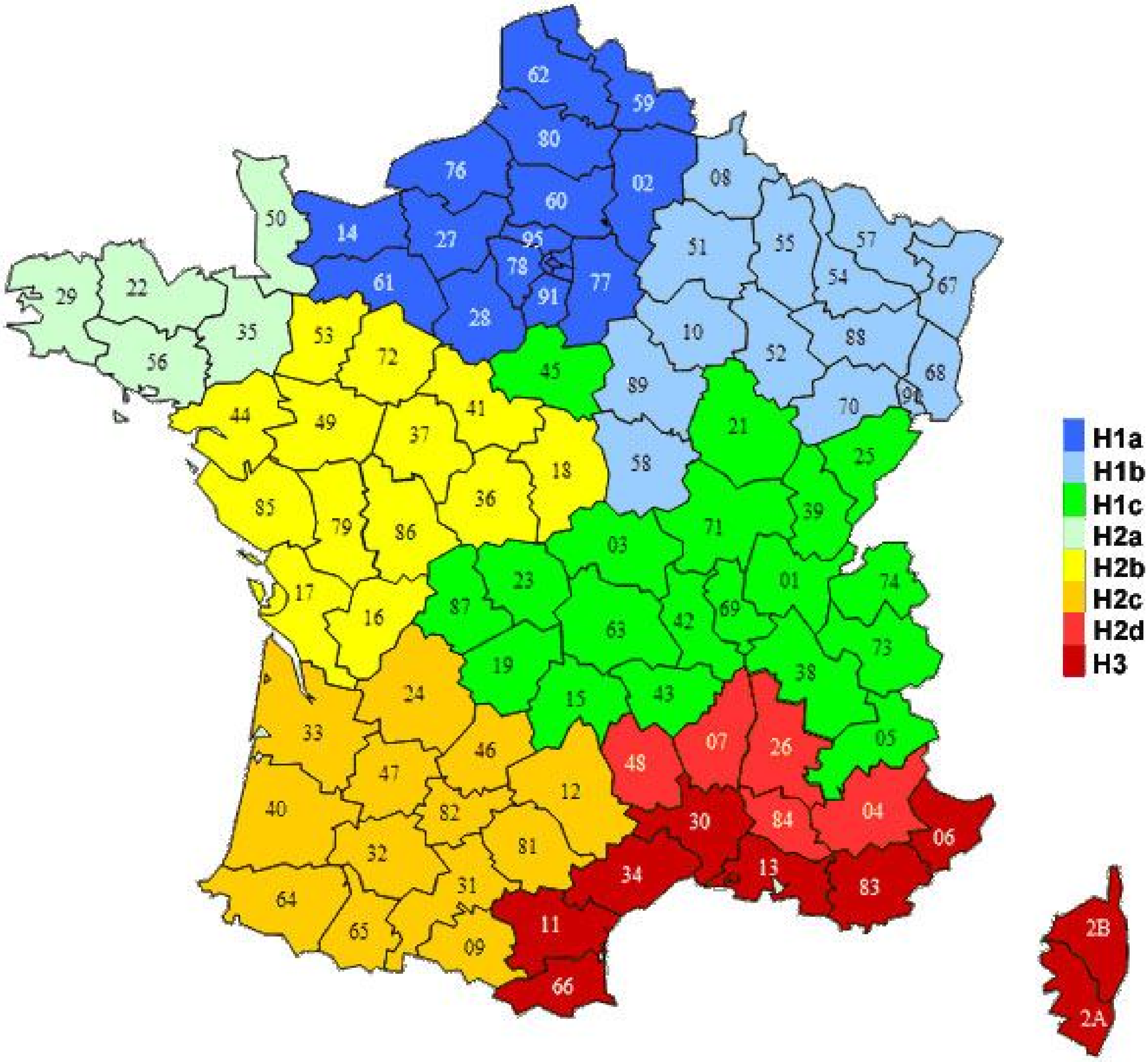


Fig. 1.3 Climate zones in France according (source RT 2012)

These two types of radiation depend on the day time and period of the year as well as the geographical data of the building location. The building orientation is the deciding factor of the received radiation on each part of the envelope regarding its position. The sun radiation is received through all parts of the envelope: Glazed surfaces and opaque ones. The difference is in the way and the speed of restoring the heat. While the effect of the radiation through windows is very quick, the one of the solar radiation on opaque walls is more delayed. Sun radiation and solar contributions are considered as ones of the most complicated factors to be taken into consideration while building a thermal model. The reason is the big uncertainty associated with these elements. Many studies were conducted regarding the solar contribution in details. (see [KF04], [DB13], [PLK96], [Hay79], [LL96]). It is important to mention that the sun radiation as one of the weather conditions is the most problematic element since it varies according to seasons as well as other weather conditions. Its effect depends as well on the following elements:

- The orientation of the building as well as the glazed façade and windows;
- The sunrise and sunset;
- The existence of curtains or stores and their properties;
- The date and time.

All the above weather conditions can be gathered to form what we call T_{eq} or the equivalent temperature (Air-Sun). This equivalent temperature will be used instead of the measured exterior temperature because it represents the people sensation to the exterior temperature.

1.3.3 Building inertia

Building inertia is a factor that has the largest influence on the building energy consumption. For a building that will be constructed, this inertia is easy to calculate. On the other hand, the determination of building inertia for an existing building is more challenging and almost impossible.

In most studies, building inertia is considered to be the speed of building reaction on any change in the outside conditions or perturbations. This reaction depends of course on the thermal properties of the building elements. Depending on the capacity of a certain element to stock the heat and transfer it. These elements include the envelope as well as the partitions.

1.3.3.1 Building envelope

The building envelope separates the interior (more or less stable conditions) from the exterior changing ambiance. This is the structure of the building which consists of different materials with different insulation. Building envelopes vary according to the area, the usage and the year of construction. The building envelope contains opaque walls as well as transparent surfaces where the solar radiation effect and the thermal transfers are stronger. However, no matter what materials are used, the building envelope is the overriding factor of the building thermal behavior and the energy consumption regarding that most heat losses take place through the envelope. These losses are either areal (take place through walls, ground, ceiling and windows) or otherwise linear or punctual and take place through thermal bridges. Thermal bridges happen wherever there is a rupture in the insulation, especially when the insulation is interior one. Figure 1.4 shows an example of different thermal bridges.

Figure 1.5 shows different insulation possibilities for the building envelope according to ADEME.

1.3.3.2 Internal partitions

By internal partitions we mean the interior walls that separate the space in a building. It is important to define the nature of these walls and whether they are light or not in order to define whether the building represents a mono-zone block or otherwise a multi-zones one. This is a very important information while modeling the building and designing the control scenarios.

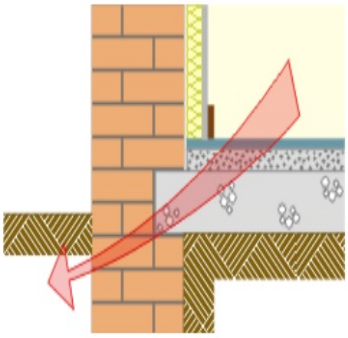
1.3.4 Ventilation system

Ventilation system is an important factor that can highly affect the building energy consumption. Ventilation can be natural or mechanical. It is essential in a building to have a sufficient ventilation rate to maintain the air quality for a hygiene and healthy environment.

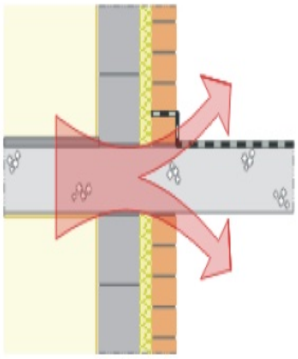
If natural ventilation happens through openings like windows and doors. It will cause a high loss in the energy due to the high rate of exchange of the air. On the other hand, the mechanical controlled ventilation (VMC) can ensure the desired rate of air exchange according to the norms. It can change according to the occupation rate. The VMC normally depends on one of the following two technologies:

- Simple exhaust ventilation system: which extracts the air from the humid areas (WC, bathroom and kitchen) of the building and injects the new exterior air in other pieces of the building. This type of ventilation is widely used in buildings since it is simple to install and less expensive. On the other hand, it is not considered as the best due to the energy losses that take place when extracting hot air and injecting the exterior cold air. Figure 1.6(a) shows a schema of an exhaust ventilation system.

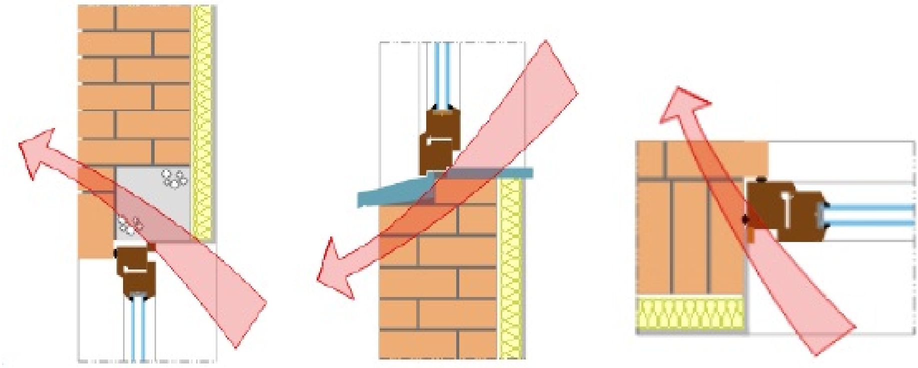
- Exhaust ventilation system with heat recovery: This system consists of two separated aeraulic circuits with a heat exchanger. The heat exchanger allows heating the exterior air before injecting it into the building through the extracted hot air. Some of these



(a) Foundation thermal bridge



(b) Balcony thermal bridge



(c) Joinery thermal bridges

Fig. 1.4 Examples of different thermal bridges in a building

systems efficiency is up to 90% which means a considerable reduction in the heat losses through ventilation. Figure 1.6(a) shows a schema of an exhaust ventilation system with heat recovery.

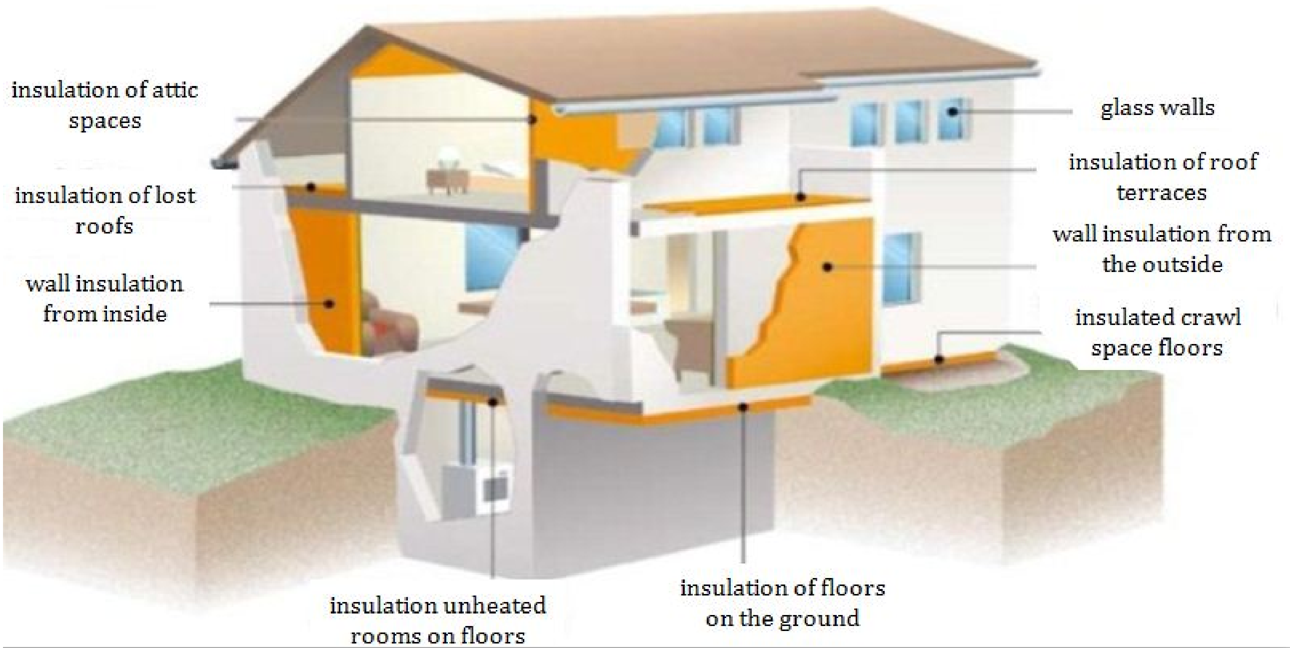


Fig. 1.5 Envelope insulation possibilities (source: ADEME)

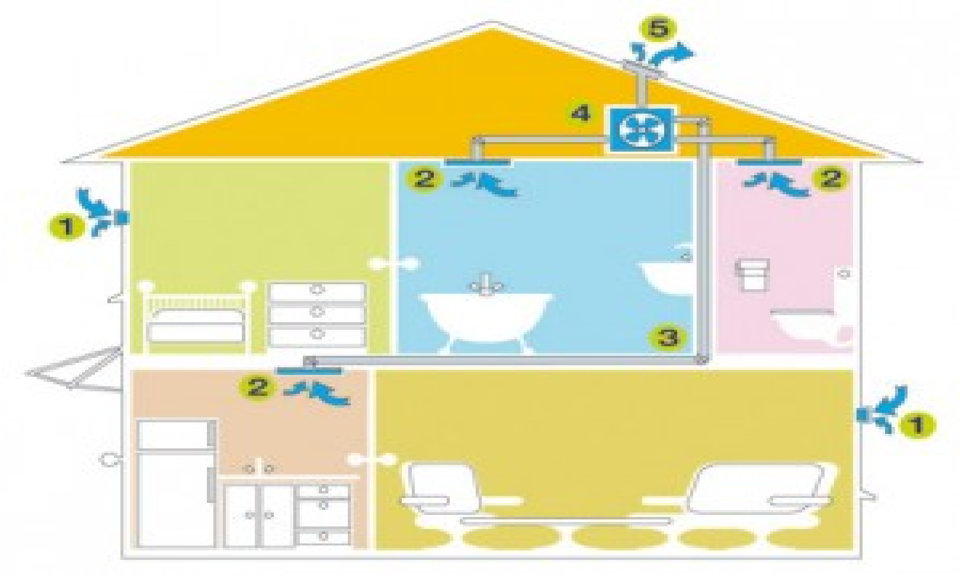
1.3.5 Internal Gains

Energy contributions are both the heating system contribution and the free energy gains. The free gains are important to take into consideration when designing the heating system. the existence of these contributions might change the heat balance in the heated local. There main sources for free energy gains are Internal gains: the internal gains are thrown up either from people (metabolic heat) or from lighting and equipments. These gains are defined in the norms according to the physical activities of people and the type of equipments and lights. However, these gains are considered as the disturbance of the system in most studies while there are rules to approximately calculate them when needed.

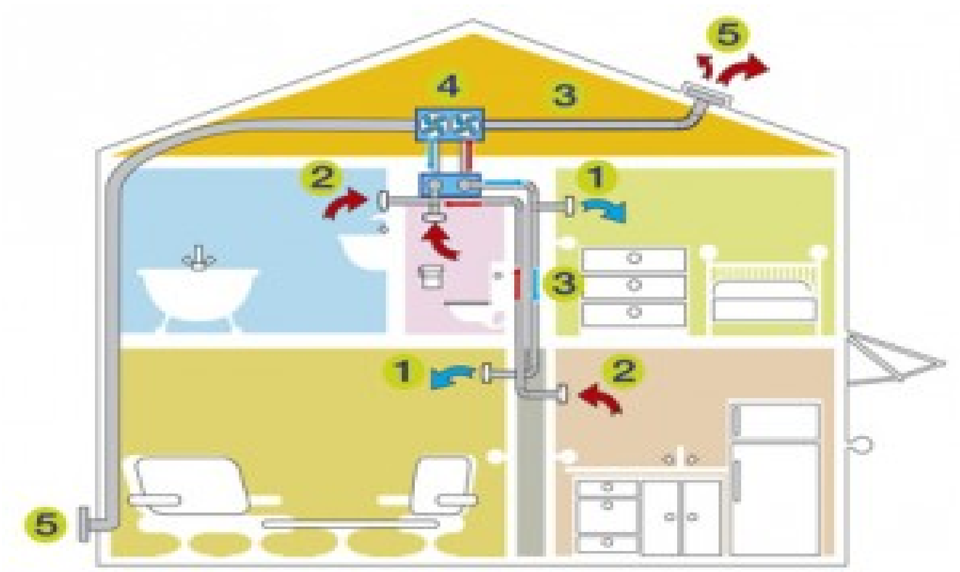
1.3.5.1 People heat gains

People presence is always associated with the sensible and latent heat production as well as Co_2 and humidity production. The quantity of the produced heat depends on:

1. The physical activities of the occupants (metabolic rate);
2. The air temperature and the relative humidity;
3. The individual's sex and age.



(a) Exhaust ventilation



(b) Exhaust ventilation with heat recovery

Fig. 1.6 Controlled ventilation systems

Two types of heat are generated by the occupants:

- Sensible heat gains (SHG): produced due to the temperature of human body. The produced heat can be calculated by equation 1.1.

$$Q_{ps} = N_p.F_u.q_s \tag{1.1}$$

- Latent heat gains (LHG): caused by the vapor production of the human body by respiration and transpiration. The produced heat can be calculated by equation 1.2.

$$Q_{pl} = N_p.F_u.q_l \tag{1.2}$$

where in equations 1.1,1.2:
N_p is the number of occupants.
F_u is the diversity factor and it depends the maximum conceptual capacity of the heated local.

$$0 \leq F_u \leq 1$$

$F_u = 0$ When there is no occupants. $F_u = 1$ When the conceptual maximum number of occupants are in the local.
q_s and q_l are the sensible and latent heat gain per person and are given in tables in the chartered institution of building services engineers CIBSE guide 2006 [GV86].

1.3.5.2 Lights heat gains

Light has also a considerable share of the internal free heat gains. It is considered that all the consumed energy in the lightening is transferred into heat either by the convection with the air or by radiation towards other objects or walls around. Lights emit only sensible heat. The heat released by lights can be expressed by equation 1.3.

$$Q_l = (W * 3.412) * F_u * F_s * CLF_h \tag{1.3}$$

where:
Q_l is the sensible heat gain from lights.
W is the lighting power output in Watts ($Btu/h = W * 3.412$).
F_u usage factor or percentage of maximum design for each hour of the day.

$$0 \leq F_u \leq 1$$

F_s service allowance factor (accounts for ballast losses in fluorescent lights and heat returned to return air ceiling plenum in the case of air light fixtures).
CLF_h Cooling Load Factor for a given hour. This depends on zone type, total hours that lights are on, and number of hours after lights are turned on.

1.3.5.3 Equipment heat gains

Equipment consists of three categories

- Electric resistance sensible load (ex. Toaster);
- Electric inductive sensible load (ex. Motor);
- Sensible and latent loads (ex. Electric or Gas Tea Kettle).

Two types of heat are generated by equipments:

- Sensible heat gains (SHG): produced due to the temperature of human body. The produced heat can be calculated by equation 1.4.

$$Q_{eq} = (W * 3.412) * F_u * F_p * CLF_h \tag{1.4}$$

  where:
  Q_{eq} is equipment sensible heat gain.
  W is equipment output in watts.
  F_u is the Usage factor or percentage of maximum design for each hour of the day.

$$0 \leq F_u \leq 1$$

  F_p is part load operating factor for motor type. Example, a compressor operating at 50% capacity might still use 80% of electric power.
  CLF_h is the cooling Load Factor (CLF) for given hour.

- Latent heat gains (LHG):latent heat gain from equipments is given in equation 1.5

$$Q_{eq} = Mw * Hfg * F_u * F_p \tag{1.5}$$

  where:
  Q_{eq} is equipment sensible heat gain.
  Hfg is Heat (btu/hr) required to convert 1 lb of water to steam.
  Mw Mass (lbs) of water converted to steam (evaporated or boiled).

1.3.6 Thermal Comfort

Thermal comfort is the key element that drives the temperature (wet and dry bulb temperatures) control system. It is essential and indispensable to achieve the occupants thermal comfort which can be expressed in two elements:

- A general wellness feeling
- The auto-regulation mechanism of the human body is in minimal level of activity that keeps the body temperature constant and comfortable

Static Thermal Comfort Thermal sensation differs between people even in the same environment. In other words, there is no absolute standard for thermal comfort. However, some norms have defined indicators to express the thermal comfort of occupants in a certain environment depending on the following six important factors:

- Interior air temperature;
- Relative humidity;
- Walls temperature;
- Clothing factor (Clo), this factor differs according to the clothes put on (1 clo = 0,155 $C.m^2/W$);
- Metabolism and activity type (M), which express the activity type of the human body and measured by W/m^2;
- Air velocity (m/s).

These factors were grouped to deduce the 'Predicted mean vote (PMV)' and 'predicted percentage of dissatisfied (PPD)' indicators which give measurements of thermal comfort.

1.3.6.1 Predicted mean vote (PMV)

This indicator was suggested by Fanger. It predicts the mean response of a group of people according to ASHRAE thermal sensation scale [DTN10]. It is expressed in equation 1.6:

$$PMV = [0.303exp(-0.036M) + 0.028]L = \alpha L \tag{1.6}$$

where L is the thermal load on the body. The values of PMV can be deduced from pre-calculated tables depending on the values of the above 6 factors. Values of PMV differ between -3 and $+3$ as in figure 1.7. To simplify the calculation of PMV, the Norm ISO 7730 proposes tables with PMV values deduced from values of different factors mentioned above.

Fig. 1.7 Values of PMV according to Fanger

1.3.6.2 Predicted percentage of dissatisfied (PPD)

This indicator predicts the percentage of people who felt discomfort and expressed dissatisfaction. PPD can be calculated according to PMV value using equation 1.7 or Figure 1.8

$$PPD = 100 - 95exp[-(0.03353PMV^4 + 0.2179PMV^2)] \tag{1.7}$$

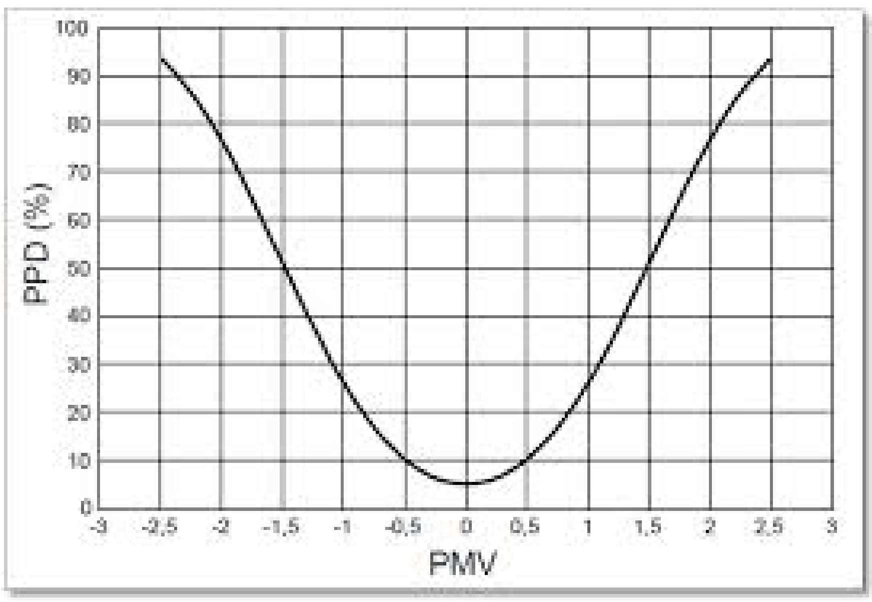


Fig. 1.8 Values of PPD according to PMV

In general, a certain percentage of around 10% of dissatisfied people is accepted in building conception phase.

In other words, the set temperatures are designed with the hypothesis that 10% of the occupants will have a case of discomfort or dissatisfaction. ***Adaptive Thermal Comfort*** Adaptive approach derives from field studies, having the purpose of analyzing the real acceptability of thermal environment, which strongly depends on the context, the behavior of occupants and their expectations. ASHRAE has proposed an adaptive comfort level that depends on the exterior temperature to evaluate the acceptability of the ambiance. This level is more detailed in Chapter 4.

1.4 Building thermal modeling

Introduction

As mentioned in the former chapter, the knowledge of the building thermal behavior needs a lot of information about the building structure and conditions. The most important information are:

- Construction materials of walls, facades and ground;
- Insulation type (exterior or interior) and materials;
- Building type (architecture and usage);
- Orientation of glazed facades;
- Windows type;
- Building shape;
- Year of construction.

Figure 1.9[1] illustrates these factors.

As in the most part of cases these information are not available, an alternative can be applied to define the building behavior from experimental data. This alternative is thermal modeling and identification. Thermal modeling is one of the highest concerns in the field of building management and energy consumption. Researches around the world were conducted to develop appropriate thermal models.

[1]RT 2012, France

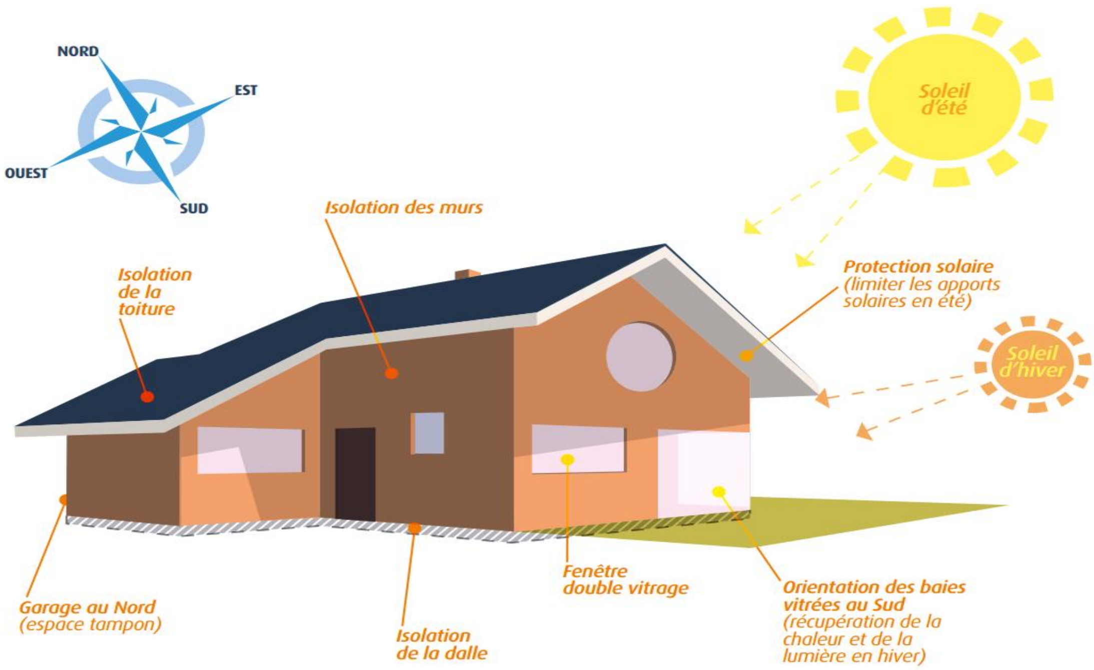


Fig. 1.9 Factors effect building thermal behavior (source RT 2012)

This section presents briefly existing methods of building thermal behavior identification and modeling. These methods can be classified into two categories: Static approaches and dynamic approaches.

1.4.1 Building thermal modeling

With the energy awareness revolution, the interest in defining the building thermal behavior in order to ameliorate its consumption appeared. When defining this behavior, some problems occur and can be classified as:

1. The lack of information about the building structure.
2. The uncertainty resulting from occupants behavior (machines usage, heating setting, activities and gains...etc).
3. Expensive and complicated experimental machines to explore the building materials and components.

To deal with this, thermal modeling replaced the traditional ways to discover the building behavior as a dynamic system that is affected by the weather as well as other conditions and disturbances. At the beginning, static models which are simple and elegant were adopted.

These were not fully adapted to the complexity of the building behavior. That is because they ignore the nature of the building transient behavior under the different thermal inputs. Moreover, they need a very long observation period to find the correlation and it doesn't allow the integration of the regulation system which is the most important actor in the thermal solution. All that leads to the need of a dynamic thermal model that can represent the thermal nature of a building to an accepted limit of credibility.

1.4.2 Static models

Static models express the building thermal behavior as a thermal balance between the energy needs to maintain the interior temperature in the building permanently equivalent to a set temperature. In other words, the energy needs from the heating system to maintain the set temperature must be equivalent to the energy losses with the exterior environment through the building envelope) [Ric91]. The thermal balance is expressed as in equation 1.8

$$Q = U(T_{int} - T_{ext}) - A_s I + \varepsilon \tag{1.8}$$

where:

- Q is the power needed to maintain the set temperature;
- T_{int} is the average interior temperature in the building $(°C)$;
- T_{ext} is the average exterior temperature $(°C)$;
- U is the coefficient of the global static losses $(W/°C)$;
- A_s is the equivalent south surface (m^2);
- I is the global south vertical radiation(W/m^2);
- ε is a factor that depends on the start and end time of the observation period and it is weighted by the inverse of the measurement time step (W).

Equation 1.8 can be adapted according to the precision needed and the data available. The term ε can be further developed by taking into consideration more gains to have better precision of calculations. It can be as well further simplified by ignoring ε and even the sun radiation and calculating the heat load as a function of the temperature difference between the interior and the exterior.

The most famous applications of this concept are:

1.4.2.1 Unified day degree method (DJU)

This method is mainly used by the professionals to quickly evaluate the heat losses through the building envelope. It accumulates the positive difference between the set temperature (set at $18 \circ C$) and the daily average of the exterior temperature for the whole year to obtain the number of the DJU. After that, the knowledge of the characteristics of the building envelope and gains allows the deduction of annual heat needs. This method is very practical and quick. On the other hand it is very simplified and needs a physical knowledge of the building (to calculate $U_{building}$).

1.4.2.2 Energy signature

Energy signature is a simplified method of static models that considers that the heat load is a function of T_{ext} while the interior temperature changes are negligible [LS03].

Equation 1.8 can then be simplified in equation 1.9 called building signature.

$$Q = \alpha + \beta . T_{ext} \tag{1.9}$$

The coefficients α and β can be calculated by linear regression using some registered measures of the studied building. In practical life, this same concept is used to control the boiler heating systems while the relation is between the departure water temperature (instead of the heat load) and the exterior temperature, and this is the "heating law".

1.4.2.3 Discussions

The static models are the first step to explore the building thermal characteristics through an observation period. They are widely spread between commercial actors. Yet they are limited by the following points:

- A relatively long observation period;
- The ignorance of the heating system nature;
- The ignorance of the transient behavior of the building.

From where appeared the necessity of dynamic thermal models.

1.4.3 Dynamic models

Dynamic thermal models can be classified into 2 categories:

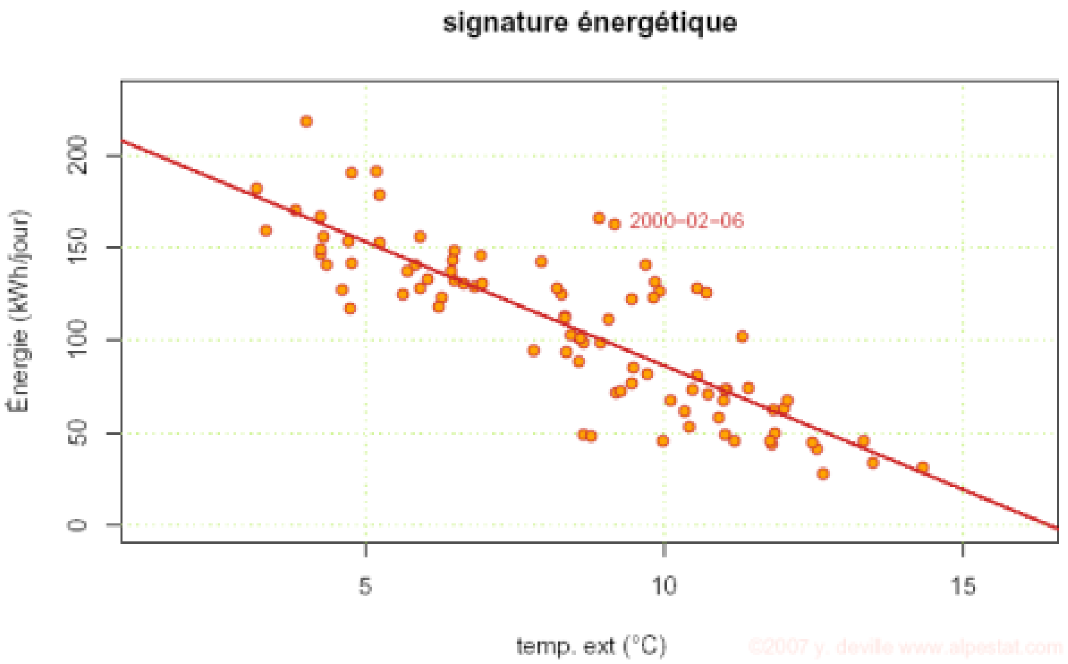


Fig. 1.10 An example of building energy signature

1.4.3.1 Physical models

Also known as detailed thermal models, these models depends on the deep knowledge of the physical characteristics of the building structure, materials and thermal transfers.

Thermal transfers have been the subject of many studies to identify and quantify them. The main thermal transfers that happen in a building are classified as the following:

1. Exchange with the exterior environment which is most effected by two main parameters:
   - Exterior temperature
   - Solar radiation
2. Heat exchange mechanisms between different surfaces and elements which are [RHC97]:
   - Conduction
   - Convection
   - Radiation

Physical models are either mono-zone where the temperature is supposed to be homogenous all over the modeled building or multi-zone models where several zones are identified according to the different temperatures and usages.

1.4.3.2 Reduced models

The simplified models consist of two main groups of building thermal modeling:

1. Models deduced by the simplification of detailed thermal models

   - Moore model reduction This method is by the simulation software used by Électricité de France (EDF) called PAPTER. It depends on the optimization of the poles and zeros placing in a way that maintains only the observable and commendable states.
   - Modal reduction This method consists of the representation of the building thermal system in the form of a state space (equation 2.1)

$$\begin{aligned} \dot{X} &= A*X+B*U \\ Y &= C*X+D*U \end{aligned} \tag{1.10}$$

     where:
     X is the vector of system internal variables known as state variables.
     Y is the measured output vector.
     U is the control input vector.
     $\dot{X}$ represents the differentiation with respect to the time t.
     A , B, C, D are the system parameters.
     The advantage of this method is that it conserves the representation of the original system time constants in the reduced models.

   Most building thermal systems can be represented by this form. This approach was used in the thermal regulations 2005 [MP13b].

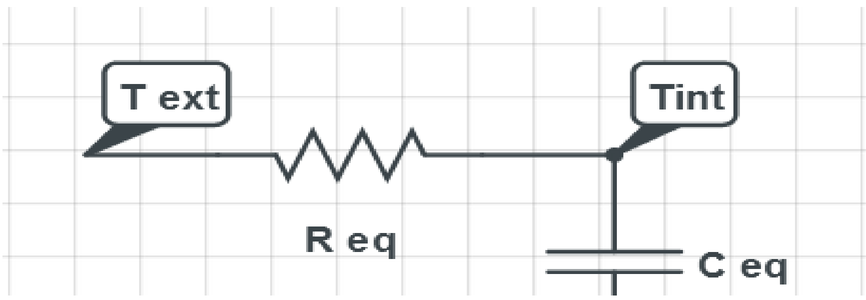
2. $R-C$ models These models were used by the thermal regulations $2000, 2005, 2012$. They consist of the representing thermal transfers in the building by electrical analogue of thermal capacities and resistances. In this analogy, the representation is done as in table 1.1

The choice of the number of resistances and capacities depends on the available data and priorities of modeling process. There are several possible choices according to the use. In

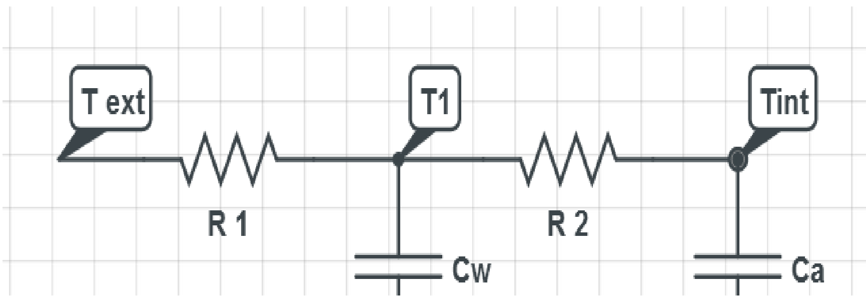
Table 1.1 Representation of building thermal factors in an electrical circuit

In the building	**In the circuit**
Heat flow	Electric current
Supplied heat flow	Current Generator
Thermal conductance	Electrical conductance
Set temperature	Tension generator
Thermal capacity	Electrical Condenser

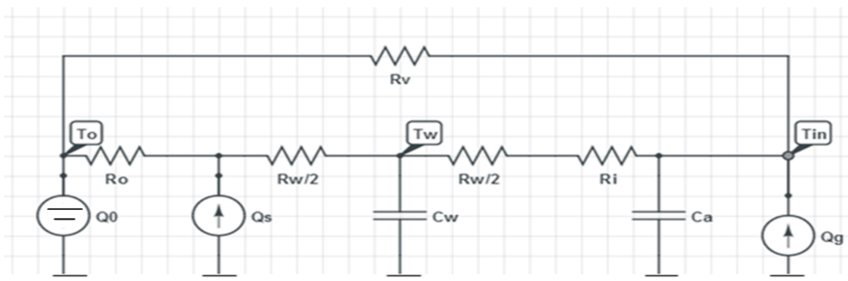
the bibliography, models with the forms (RC,R2C2,R3C2,R5C1,...etc) were found [Zay11] [DBMM10a]. Figure 1.11 shows an example of these models.



(a) R1C1



(b) R2C2



(c) R4C2

Fig. 1.11 Examples of RC system models

1.4.4 Inverse models

That is useful in the cases where we don't have enough data or even accessibility to certain physical phenomenons in the building. The inverse models allow the deduction of the phenomena or the cause starting from known measured input and output of the system. These methods are mainly used for the parameter estimation procedures.

The physical system can be represented by the schema in figure 1.12.

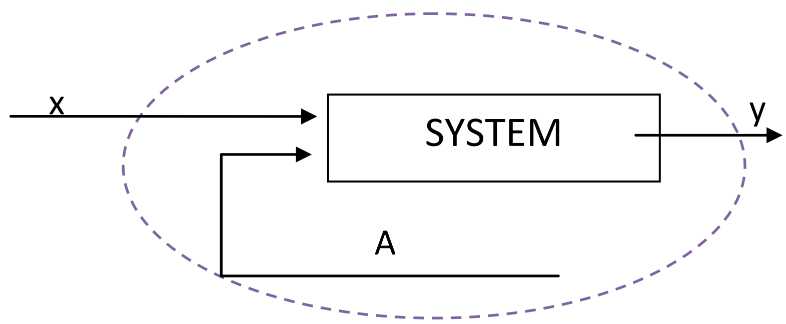


Fig. 1.12 General presentation for a physical system

As it is the opposite of the direct problem, the inverse problem consists then at defining the values of the unknown parameters A of the system knowing already the values of the output y. To solve this problem, the use of an identification method that allows to inverse the sense in figure 1.12.

In the next chapter, an explanation of the parameter identification process and the proposed methods is done.

1.5 Synthesis

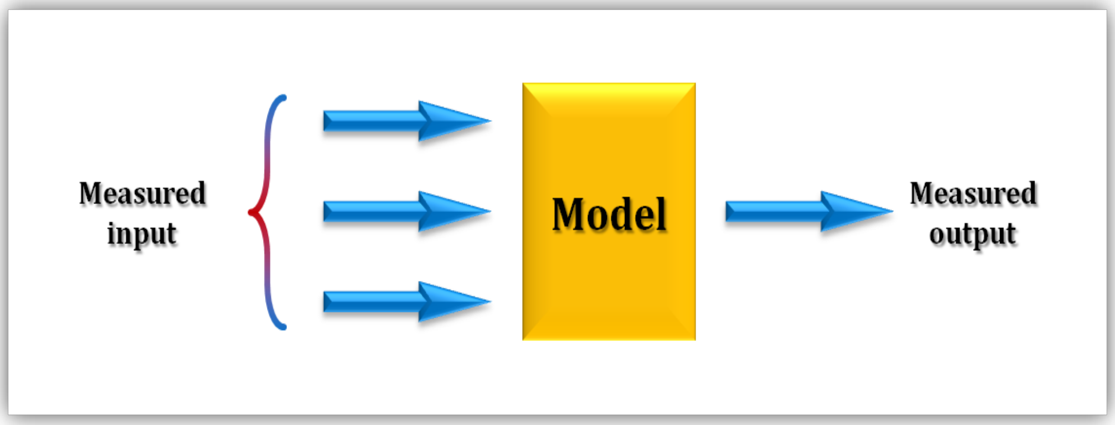
In this chapter, a synthesis of the whole problem of building energy consumption was presented. The understanding of the building thermal dynamics is one of the most important research domains nowadays. Thermal models and identification strategies are the most important features of these researches. Another aspect that is also important for the economy of building consumption is the control strategies. Most controllers use a thermal model to simulate the building temperature under different conditions. However, for the control process, simplified models are preferred to reduce the computation time. This indicates the need of reliable simplified thermal models. In this work, a simplified thermal model is proposed to be used in the control process. This model uses only the exterior temperature and the heating to simulate the resulting interior temperature. To calculate the parameters of thermal models, a new differential algebra based method is proposed as well. Afterwords comes the control process, the optimization of the consumption needs innovative control methods. Therefore, a new Monte Carlo based predictive control method is proposed to optimize the consumption. The main advantage of this method over other predictive optimized control methods is its simplicity. Finally a new real-time differential flatness control method is proposed. The software used in this work is MATLAB/SIMULINK for all the simulations.

1.6 Document organization

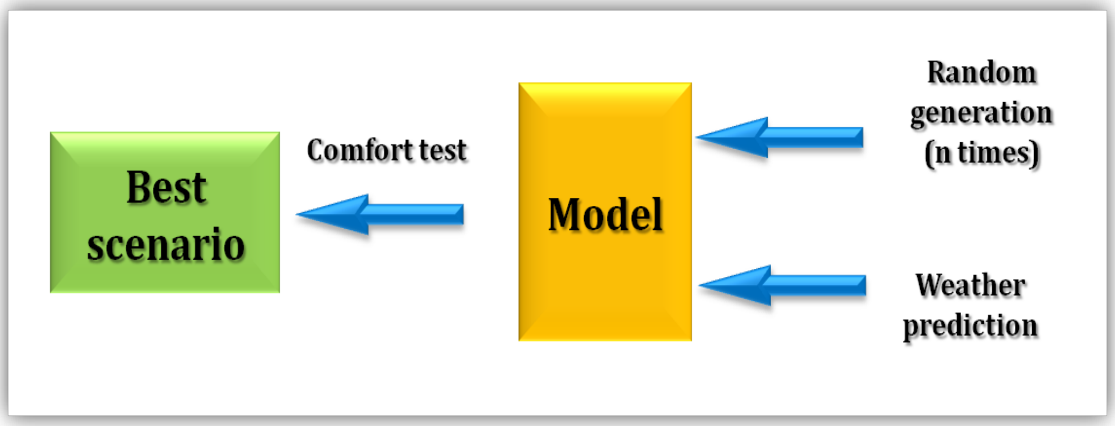
In chapter 2 of this thesis, an explanation of the retained thermal model is done as well as the used identification and parameter estimation methods and their application on a case study. Chapter 3 is a synthesis of the heating control systems and the different approaches used in the control optimization process. While in chapter 4 a presentation of the proposed Monte Carlo based control method is done with the application, results and discussions. Chapter 5 presents a first step towards the application of differential flatness real time control on the building heating system and finally chapter 6 is a general conclusion with the perspectives and future works.

These work will be used to accomplish the main proposed phases to guarantee the optimization of the control. These three phases are 1.13:

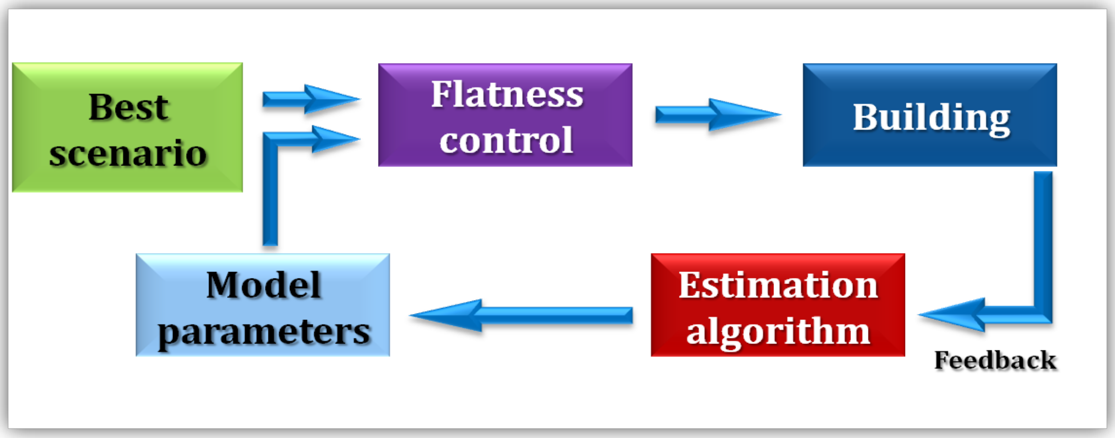
- Modeling phase: A simplified thermal model will be developed.
- Prediction phase: Choosing the best scenario of set temperature that guarantees economy.
- Real time control phase: Tracking the best scenario will be ensured by new real time parameter and control methods.



(a) Modeling Phase



(b) Prediction Phase



(c) Real-Time Parameter Estimation and Control Phase

Fig. 1.13 Proposed Optimization Process

Chapter 2

Building thermal identification and modeling

Introduction

In this chapter, a presentation for the retained thermal model is done. This thermal model was tested and validated on a case study. After the validation of the model, it was integrated in the proposed heating control method which will be presented in chapter 4. In the second section of this chapter, an advanced parameter estimation method is also presented and compared with another widely used method which is the Least squares parameter estimation method. A discussion is then done regarding the achieved work.

2.1 The retained thermal model: State space model

The first chapter shows the high diversity in existing thermal models. This diversity together with the absence of tools and criteria to compare these models makes it a hard mission to choose a certain model. That is why choosing a thermal model, in most cases, is derived by its later use. In other words, the choice of a thermal model is done as a function of the objectives of each work.

For this thesis, the main objective is to propose a heating control method that is able to:

- Maintain the thermal comfort;
- Optimize the energy consumption.

Regarding the intention to use the model for the control process, a choice of a simplified thermal model is taken.

2.1.1 Model formulation

The model used in this thesis is a state space model. Literature studies show that building thermal dynamics can be represented by a state space form [BSSM12] [HGP12]. A state space model consists of a set of differential equations derived from physical relations. Furthermore, to better integrate the model in the control process, the model is preferred to be simple [Fri12] [Fav13] [DBMM10b]. Hazyuk et al. [HGP12] conclude that a second order state space is well fitted to describe the building thermal behavior, more precisely for the control process. The output of the developed model is the interior temperature while there are three inputs:

- The outside temperature;
- The energy supplied by the heating system;
- The free gains (solar gains and interior gains).

It has the form in equation 2.1

$$\begin{aligned} \dot{X} &= A * X + B * U \\ Y &= C * X + D * U \end{aligned} \tag{2.1}$$

Where X is the vector of system internal variables known as state variables, Y is the measured output vector, U is the control input vector, $\dot{X}$ represents the differentiation with respect to the time t and finally A, B, C, D are the system parameters.

2.1.1.1 MISO system

This model is a mono-zone model that represents a building or an area in the building where the interior temperature is supposed to be homogenous. As the interior temperature is a main output, the system is designed to be a Multi Input Simple Output system (MISO) where:

- U is a presentation of the controllable source:'the energy supplied', together with uncontrollable entries represented by weather forecast and more precisely the exterior temperature and the solar gain which constitute the disturbance of the system.
- Y is the simple output representing the interior temperature in a certain zone.

However, it is important to mention that most industrial systems use the same inputs and outputs to regulate heating.

2.1.1.2 Model identification

As mentioned before, in order to identify the system parameters, information about the building materials, insulation layers and the thermal interaction between these materials are necessary. However, for the control process, the information about physical parameters of the model are not required, that's why a parameter estimation process is sufficient to identify the system model and use it in the control process [Lju98], [DLL14].

The identification process goes into two phases before it is ready to be integrated it in the control process.

- Learning phase: to estimate the model parameters depending on available data sets;
- Validation phase: to validate the estimated parameters using different data sets.

The data sets used in these two phases concern historical recorded data of interior, exterior temperatures and the associated supply of energy.

2.1.2 Case study

In our case, a model with the known parameters (material characteristics) built using COMFIE has served to establish a comparison basis for the parameter estimation process of the state space model used for the control. As a case study, an office building model is used. It is a two story brick building with an approximate ground area of $200m^2$. The walls consist of 4 layers and double glazed windows of $40m^2$ area. Table 2.1 shows the walls composition and characteristics, while the heat exchange with the ground is ignored supposing that the floor is well insulated. The building is considered as mono-zone so the temperature is homogenous in all parts of it. Analysis and identification of the model were conducted using MATLAB-SIMULINK.

Table 2.1 Wall specification

Wall layer	Density $[kg/m^2]$	Thickness $[m]$	Specific heat capacity $[J/kg.K]$	Thermal Conductivity $[W/mK]$
Plaster board	950	0.012	840	0.16
Insulation	25	0.2	1000	0.035
Air	1.4	0.05	1005	0.022
Brick wall	1700	0.15	800	0.84

The parameter estimation was done using a big set of inputs and outputs generated from the COMFIE model. This set was divided into two parts:

- 70% of the data was used in the learning process to deduce parameter values;
- 30% of the data was used to validate the obtained values;

We used the parameter estimation toolbox shown in figure 2.1 from MATLAB/SIMULINK to get the parameter values and validate them [BGL$^+$13] [RTTP14]. The parameter estimation method used in this toolbox is the least squares method.

Figure 2.2 shows some captures of the parameter estimation process using this toolbox. The process starts with initial values and then it applies a parameter estimation method to find the solution that makes measured and simulated outputs identical.

In the next section, a new parameter estimation method is proposed. A comparison between the new method and a classic recursive least squares method is done.

2.2 Advanced parameter estimation

The identification of the building thermal system is the most essential issue in the system optimal control [HK12], [NKB14]. Many methods have been developed in order to get a more reliable estimation of the system parameters which is the key element for an optimized control in terms of costs and comfort [KvSS13].From the last section, we can classify the model parameter estimation approaches in two categories:

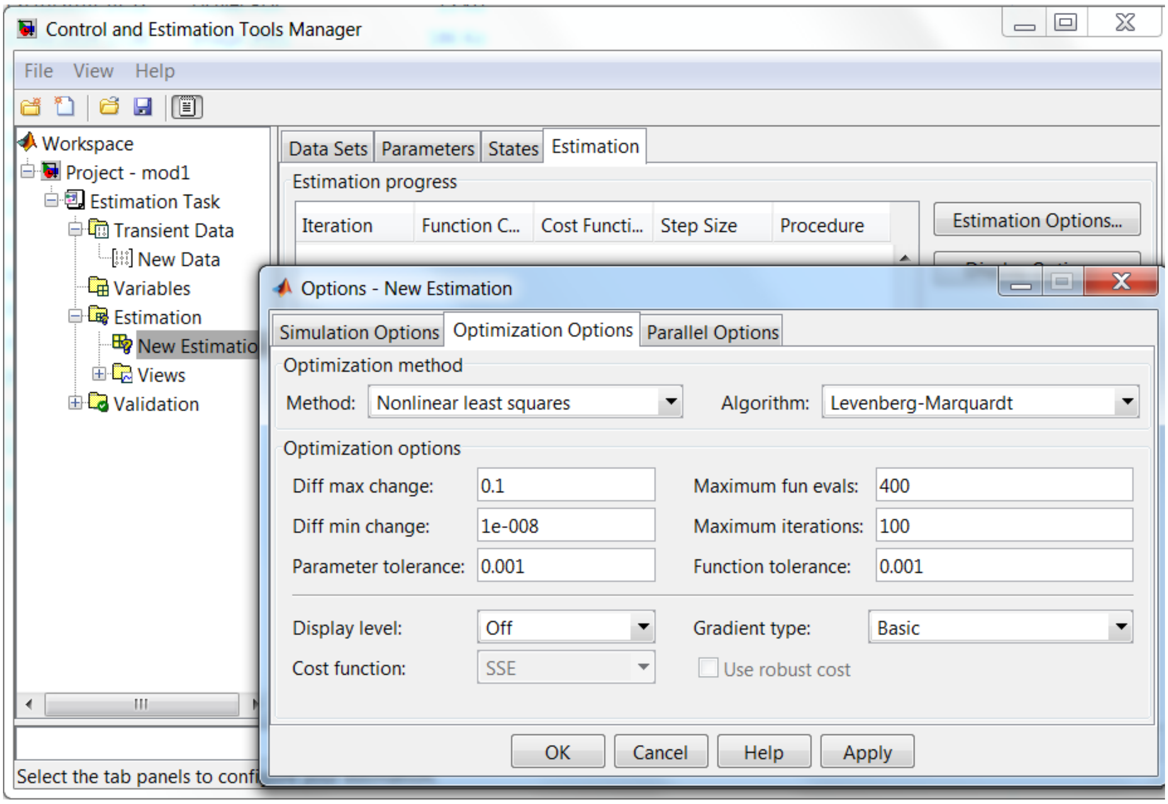


Fig. 2.1 MATLAB/SIMULINK parameter estimation toolbox

1. Forward parameter estimation method where:
   - Information and details about materials are known;
   - Model parameters are then directly calculated from these details and characteristics.
2. Backward parameter estimation method where:
   - Information and details about materials are not available;
   - Model parameters are then deduced from measured inputs and outputs of the system by one of the parameter identification methods.

Nowadays, with the development of building information technologies and acquisition systems, the reasonable cost of sensing and computing devices justifies to carry out learning and calculating the system parameters instead of searching the physical characteristics [Moo12], [CA03], [DN12]. Moreover, the application of advanced control and operation strategies requires robust online system models [WS07], [LW14] which makes backward parameter estimation preferable to the forward one.

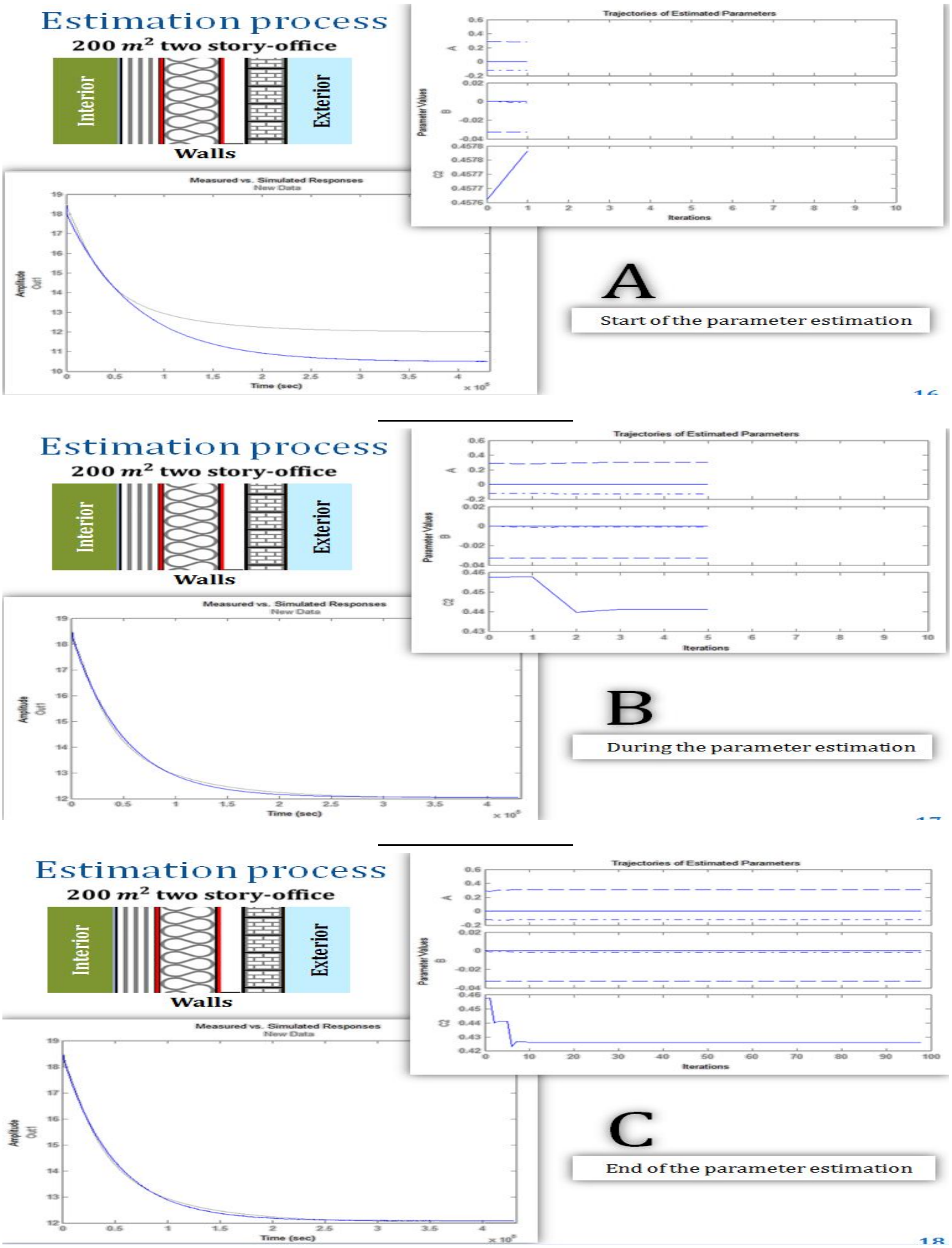


Fig. 2.2 The parameter estimation process

All these factors, make the backward parameter estimation widely common and efficient. Especially with the fact that materials can actually change their characteristics with time which leads to doubts in the forward parameter estimation results and reliability.
There are many methods for system identification that have been applied to identify the building thermal system such as statistical regression models, optimal control theory, artificial neural networks [KAS13], [NKB14]. Most of these methods are developed for an online estimation and measurements. As an example, Recursive Least squares method (RLS) that has reached a significant level of popularity and perfection in the field of parameter estimation [Str80]. In this section, a novel estimation method with algebraic flavor is proposed to be employed for the identification of building thermal system. This method will be evaluated by a comparison with the recursive least squares parameter estimation using an experimental example.

2.2.1 Formulation

The objective is to illustrate the principle of parameter estimation. Therefore, an energy signature model is used. Admitting that the change of the interior temperature is caused by both internal and external sources, e.g., mechanical cooling and heating, ventilation, solar radiation, heat conduction through walls and human factors [WS12]. And knowing that in most practical applications, the control of the heating system is based on the exterior temperature T_{ext} [KRF$^+$14], [KPH10]. Then the predicted exterior temperature and the desired set temperature simply define the quantity of energy needed depending on the building parameters and the heating system characteristics. The building thermal system can be simplified and represented in Figure 2.3, where T_{int}, the interior temperature, represents the system's output. Q $(Watt)$ and T_{ext} are the supplied power and the exterior temperature respectively.

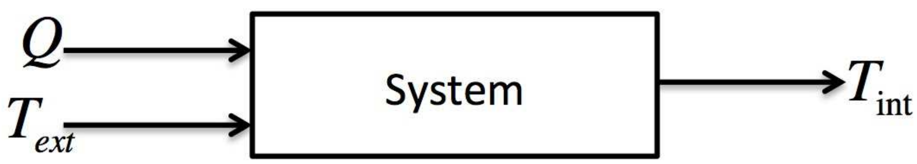


Fig. 2.3 Example of the studied system - MISO system

Therefore, the model retained in the last section can be rewritten according to the following logic. The ambiance temperature T_{int} in a certain zone/building can be expressed by the following simplified differential equation (5.10) [YHSP06], [BCC+11]

$$\dot{T}_{int} = -\theta_1 T_{int} + \theta_2 Q + \theta_3 T_{ext} \tag{2.2}$$

The question is then about the values of parameters θ_1, θ_2 and θ_3. These values are very problematic to evaluate since they reflect the overall behavior of factors affecting the temperature in a thermal zone. However, a reliable estimation of θ_1, θ_2 and θ_3 is the key element to represent the building thermal behavior. The proposed algebraic method of online parameter estimation was tested and compared with the widely used recursive least squares (RLS) parameter estimation.[1]

2.2.2 Differential algebraic methods

Differential algebraic as a parameter estimation method is used in many industrial applications, especially those with control objectives. It is widely being taught in Germany [ÅAB+01], [Dry13]. This method is normally used for the following three objectives [FJSR08], [CMP99], [FJM+05]:

- Parametric estimation;
- Fault diagnosis and fault tolerant control;
- Perturbation attenuation.

The main objective of the differential algebra, as a mathematical discipline, is to generalize the methods of commutative algebra to study systems with differential equation [Rit66], [Kol73].

2.2.3 Application to parameter estimation

In this section, an application of differential algebra on the thermal system is presented. The objective is to do a parameter estimation using this method.

[1]The solar gains are to be taken into consideration as well. We didn't include them because of the north location orientation of the studied room, otherwise $\theta_4 I$ is to be added in equation (2.3)

Rewriting the equation (2.2) in the operational domain (Laplace transformation)

$$sT_{int}(s) - T(0) = -\theta_1 T_{int}(s) + \theta_2 Q(s) + \theta_3 T_{ext}(s) \tag{2.3}$$

Deriving the above equation gives the following:

$$s\frac{dT_{int}(s)}{ds} + T_{int}(s) = -\theta_1 \frac{dT_{int}(s)}{ds} + \theta_2 \frac{dQ(s)}{ds} + \theta_3 \frac{dT_{ext}(s)}{ds} \tag{2.4}$$

The unknown parameters θ_1, θ_2 and θ_3 are obtained using the following differential operators
$\frac{d^2}{ds^2} = 2\frac{d}{ds} + s\frac{d^2}{ds^2}$, $\frac{d^3}{ds^3} = 3\frac{d^2}{ds^2} + s\frac{d^3}{ds^3}$,
and
$\frac{d^4}{ds^4} = 4\frac{d^3}{ds^3} + s\frac{d^4}{ds^4}$

$$\begin{pmatrix} -\frac{dT_{int}^2(s)}{ds^2} & \frac{dQ^2(s)}{ds^2} & \frac{dT_{ext}^2(s)}{ds^2} \\ -\frac{dT_{int}^3(s)}{ds^3} & \frac{dQ^3(s)}{ds^3} & \frac{dT_{ext}^3(s)}{ds^3} \\ -\frac{dT_{int}^4(s)}{ds^4} & \frac{dQ^4(s)}{ds^4} & \frac{dT_{ext}^4(s)}{ds^4} \end{pmatrix} \begin{pmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{pmatrix} = \begin{pmatrix} s\frac{d^2T_{int}(s)}{ds^2} + 2\frac{dT_{int}(s)}{ds} \\ s\frac{d^3T_{int}(s)}{ds^3} + 3\frac{d^2T_{int}(s)}{ds^2} \\ s\frac{d^4T_{int}(s)}{ds^4} + 4\frac{d^3T_{int}(s)}{ds^3} \end{pmatrix} \tag{2.5}$$

Multiplying both sides of the equation (2.5) by s^{-2} gives: [2]

$$\begin{pmatrix} -s^{-2}\frac{dT_{int}^2(s)}{ds^2} & s^{-2}\frac{dQ^2(s)}{ds^2} & s^{-2}\frac{dT_{ext}^2(s)}{ds^2} \\ -s^{-2}\frac{dT_{int}^3(s)}{ds^3} & s^{-2}\frac{dQ^3(s)}{ds^3} & s^{-2}\frac{dT_{ext}^3(s)}{ds^3} \\ -s^{-2}\frac{dT_{int}^4(s)}{ds^4} & s^{-2}\frac{dQ^4(s)}{ds^4} & s^{-2}\frac{dT_{ext}^4(s)}{ds^4} \end{pmatrix} \begin{pmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{pmatrix} = \begin{pmatrix} s^{-1}\frac{d^2T_{int}(s)}{ds^2} + 2s^{-2}\frac{dT_{int}(s)}{ds} \\ s^{-1}\frac{d^3T_{int}(s)}{ds^3} + 3s^{-2}\frac{d^2T_{int}(s)}{ds^2} \\ s^{-1}\frac{d^4T_{int}(s)}{ds^4} + 4s^{-2}\frac{d^3T_{int}(s)}{ds^3} \end{pmatrix} \tag{2.6}$$

According to the equivalence between time and operational domains and using Cauchy

[2]The multiplication by s^{-n} corresponds in time domain to multiple integration of order n: $s^{-n} \longrightarrow \int^{(n)}$. Furthermore, algebraic derivative $\frac{d}{ds}$ is equivalent to $(-1)^n t^n$.

rules, the parameters θ_1, θ_2 and θ_3 can be expressed as:

$$\begin{pmatrix} \theta_1 \\ \\ \theta_2 \\ \\ \theta_3 \end{pmatrix} = \begin{pmatrix} -\int_0^t (t-\tau)\tau^2 T_{int}(\tau)d\tau & \int_0^t (t-\tau)\tau^2 Q(\tau)d\tau & \int_0^t (t-\tau)\tau^2 T_{ext}(\tau)d\tau \\ \\ \int_0^t (t-\tau)\tau^3 T_{int}(\tau)d\tau & -\int_0^t (t-\tau)\tau^3 Q(\tau)d\tau & -\int_0^t (t-\tau)\tau^3 T_{ext}(\tau)d\tau \\ \\ -\int_0^t (t-\tau)\tau^4 T_{int}(\tau)d\tau & \int_0^t (t-\tau)\tau^4 Q(\tau)d\tau & \int_0^t (t-\tau)\tau^4 T_{ext}(\tau)d\tau \end{pmatrix}^{-1}$$

$$\begin{pmatrix} \int_0^t \tau^2 T_{int}(\tau)d\tau - 2\int_0^t (t-\tau)\tau T_{int}(\tau)d\tau \\ \\ -\int_0^t \tau^3 T_{int}(\tau)d\tau + 3\int_0^t (t-\tau)\tau^2 T_{int}(\tau)d\tau \\ \\ \int_0^t \tau^4 T_{int}(\tau)d\tau - 4\int_0^t (t-\tau)\tau^3 T_{int}(\tau)d\tau \end{pmatrix} \tag{2.7}$$

Note that the set of iterated time integrals are low pass filters which attenuate the corrupting noises, which are viewed as highly fluctuating phenomena.

2.2.4 Case study and instrumentation

Since the input - output needed to estimate parameters of this model are simply the exterior/interior temperatures together with the applied heating power. A real test room of $(1.7 * 3m^2)$ (Figure 2.4) was equipped with the necessary sensors to replace the COMFIE model input output used in the last section. The room is located in the $4th$ floor of the building of Polytech'Lille in Villeneuve d'ascq city in the north of France. It has only one exterior north oriented facade. The sensors used are:

- 2 sensors for the operative interior temperature (Air and wall surface temperatures) ;
- A sensor of exterior temperature.

The sensors acquisition frequency is 1 measurement each 30 seconds. The room was equipped as well by a heater with a maximum power of $2000watt$ and the possibilities of $750watt$ and $1250watt$. The interior temperature used in the calculations is the average of the 3 measured temperatures from the 3 sensors.

Applying the proposed parameter estimation approach on measures from this case study gives the simulated temperatures and estimated parameter values shown in figures 2.5, 2.6 respectively.

Fig. 2.4 Instrumented room with measurement sensors

From figure 2.6, we can notice that the estimated parameter values converge quickly towards a constant value and then slightly fluctuate around it.

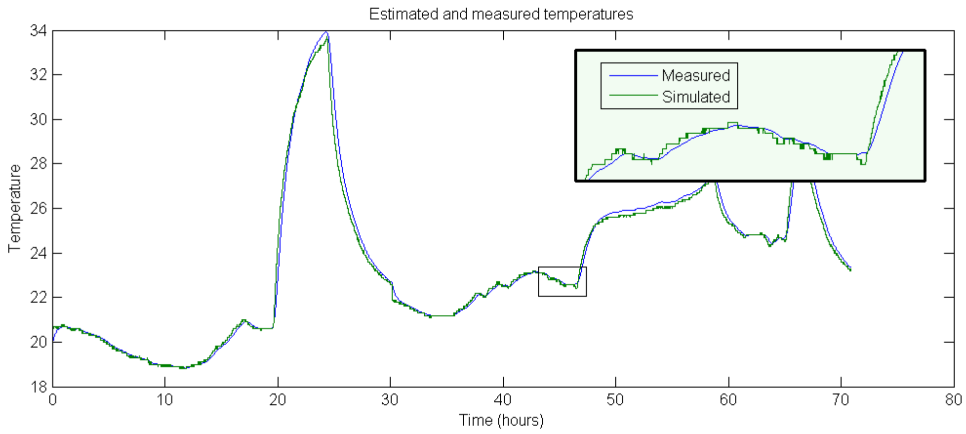


Fig. 2.5 Measured and estimated temperatures using algebraic method parameter estimation

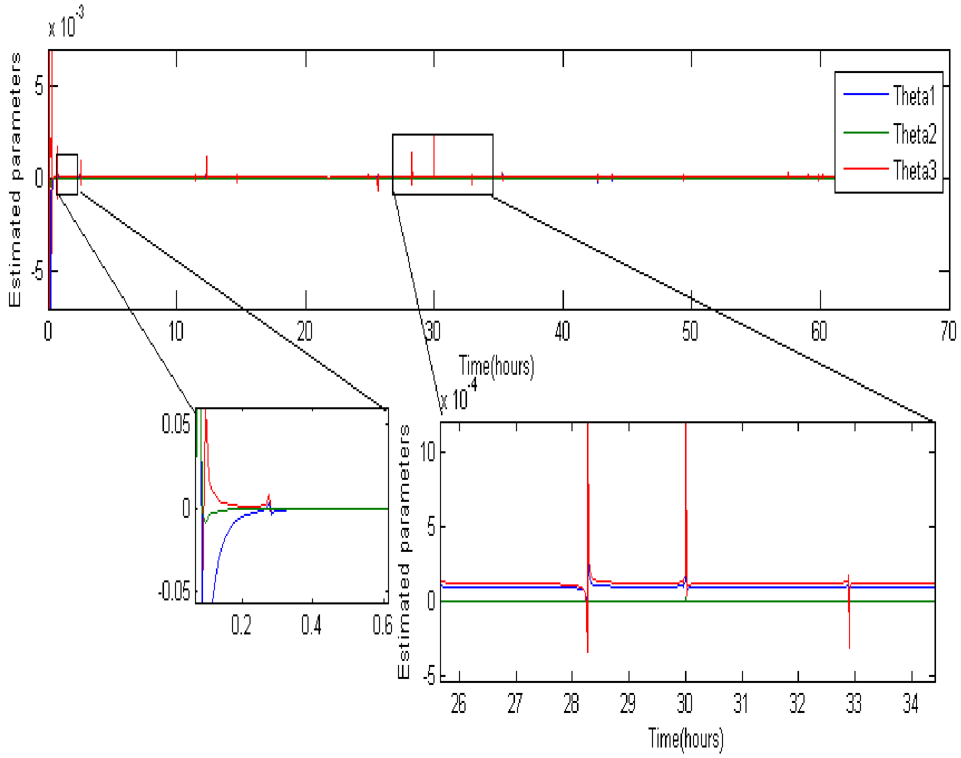


Fig. 2.6 Estimated parameters using Algebraic parameter estimation method

2.2.5 Comparative study: Least squares parameter estimation:

2.2.5.1 Offline estimation

Least squares method is one of the oldest parameter estimation procedures that can be applied to evaluate constants from experimental data. It proposes the evaluation of a set of parameters with the highest probability of being correct from a set of measured data [JF92] [GVL80].
Equation (5.10) can be put in the following matrix form.

$$\underbrace{\begin{pmatrix} y(1) \\ y(2) \\ y(3) \\ \dots \\ y(n) \end{pmatrix}}_{Y} = \underbrace{\begin{pmatrix} y(0) & Q(0) & T_{ext}(0) \\ y(1) & Q(1) & T_{ext}(1) \\ y(2) & Q(2) & T_{ext}(2) \\ \dots & \dots & \dots \\ y(n-1) & Q(n-1) & T_{ext}(n-1) \end{pmatrix}}_{\Phi} * \underbrace{\begin{pmatrix} \theta_1 \\ \\ \theta_2 \\ \\ \theta_3 \end{pmatrix}}_{\theta} \tag{2.8}$$

Where Y represents the output of the system i.e.T_{int}. The solution of 2.8 according to the least square method estimator is given by equation 2.9

$$\theta = (\Phi^T.\Phi)^{-1}.\Phi^T.Y \tag{2.9}$$

The resulting parameters' values are shown in table 2.2.

Table 2.2 Parameter values using offline least squares method

Parameter	$\theta 1$	$\theta 2$	$\theta 3$
Value using offline least squares method	$9.9 * 10^{-5}$	$8.19 * 10^{-7}$	$1.24 * 10^{-4}$

Figure 2.7 shows the measured temperatures together with the temperatures resulting from the application of the offline estimated parameters in the test room using the measure exterior temperature, interior temperature and the known energy consumption. It is obvious then during the phase:

- **Heating on:** the estimation is quite efficient. In this case the dynamic that represents the effect of the exterior temperature is almost negligible.

– **Heating off:** the estimation is not as efficient.

Table 2.3 presents the average error and standard deviation for the application of this estimation method on the case study.

Table 2.3 Error using offline LSM

Estimation average error	Standard deviation
0.52	1.369

The error is caused mainly because the unique estimated value is meant to represent all the complicated dynamics of the thermal system. That causes a compromise in order to find a global solution that applies for all conditions. To avoid this anomaly, an online estimation using RLS is done to improve the data fitting and ensure a proper estimation. RLS parameter estimation implies the change of these parameters with time. This means that the parameter estimated at time t should be computed as a function of the estimate at time $t-1$ and of the incoming information at time t [RLR96], [LW86]. There are different methods for the on-line parameter estimation using recursive least squares. For this work, we applied the RLS with Kalman filter [BKM14], [LD14].

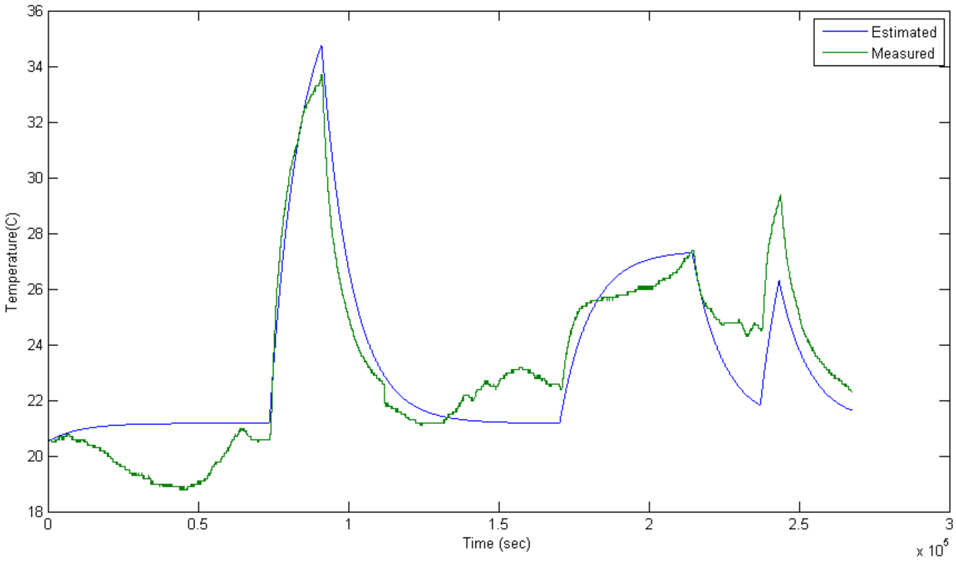


Fig. 2.7 Measured and estimated temperatures using least square method parameter estimation

2.2.5.2 Online estimation: Recursive least square parameter estimation

As mentioned before, the solution of the system using offline least squares parameter estimation is done by equation 2.9. Assuming that one additional observation becomes available, the problem is then to find $\theta(t+1)$ as a function of $\theta(t)$ and the observed $y(t+1)$ and $\phi(t+1)$. Defining $\Phi(t+1)$ and $Y(t+1)$ as:

$$\Phi(t+1) = \begin{pmatrix} \Phi(t) \\ \\ \phi^T(t+1) \end{pmatrix} \tag{2.10a}$$

$$Y(t+1) = \begin{pmatrix} Y(t) \\ \\ y(t+1) \end{pmatrix} \tag{2.10b}$$

and defining $P(t)$ and $P(t+1)$ as:

$$P(t) = \left[\Phi^T(t)\Phi(t)\right]^{-1} \tag{2.11a}$$

$$P(t+1) = \left[\Phi^T(t+1)\Phi(t+1)\right]^{-1} \tag{2.11b}$$

Doing some simple matrix manipulations gives the recursive least squares together with Kalman filter algorithm expressed in the following equation 2.12:

$$\theta(t+1) = \theta(t) + K(t+1)\left[y(t+1) - \phi^T(t+1)\theta(t)\right] \tag{2.12}$$

Where Kalman filter is given by:

$$K(t+1) = \frac{P(t)\phi(t+1)}{1+\phi^T(t+1)P(t)\phi(t+1)} \tag{2.13}$$

$$P(t+1) = P(t) - \frac{P(t)\phi(t+1)\phi^T(t+1)P(t)}{1+\phi^T(t+1)P(t)\phi(t+1)} \tag{2.14}$$

Figure 2.8 shows the estimated resulting temperatures from applying these equations on the same example together with the measured temperatures, knowing that the offline estimated parameters were considered as initial values for this estimation.

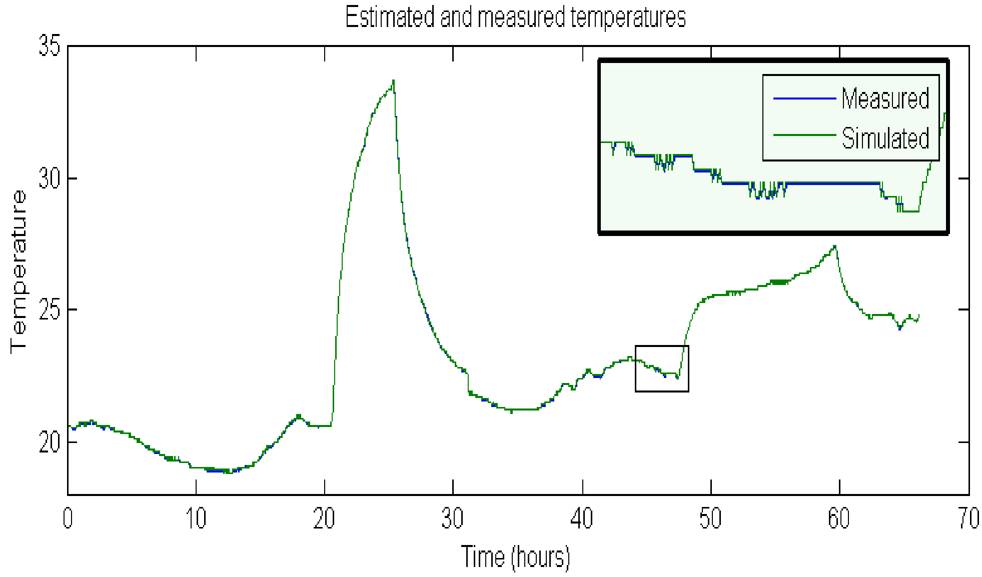


Fig. 2.8 Measured and estimated temperatures using RLS method parameter estimation

While figure 2.9 shows the estimated parameters and the associated heating. The heating is shown to emphasis the considerable change in the parameters values between heating On/Off cases. This switch can be translated in a multi-model representation in order to be able to simulate all the system dynamics since the proposed model is very simplified to reflect all these dynamics. The RLS estimated values of the parameters are not necessarily the real physical values. They are solutions that correspond to the problem in question at each time step.

2.2.6 Discussions

Table 2.4 shows an error comparison between RLSM and the algebraic method. The error in the RLSM is smaller. This is a logical result since the RLSM behaves as a model switch. IT doesn't apply any compromise to maintain a value or even a certain order of values. While on the other hand, the algebraic method stabilize on a certain value and doesn't switch.

Table 2.4 Error using Algebraic and RLSM parameter estimation methods

	Estimation average error	Standard deviation
RLSM	0.012	0.231
Algebraic method	0.08	0.432

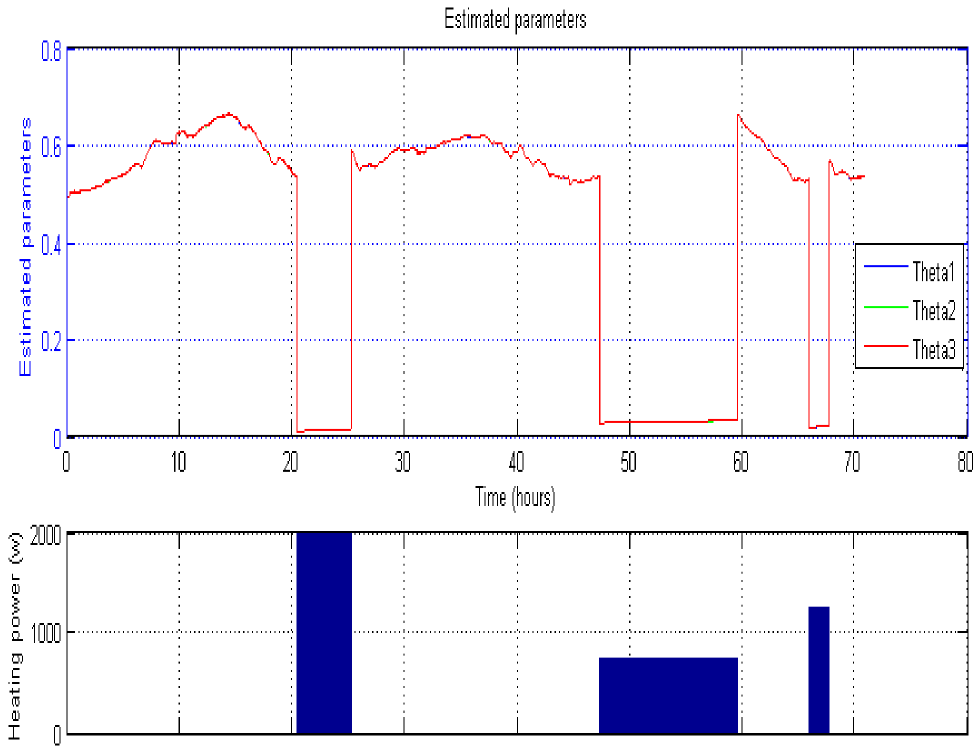


Fig. 2.9 Estimated parameters using recursive least square parameter estimation

As a conclusion, recursive least squares parameter estimation is a very efficient estimation that satisfies the control needs. It actually use the on-line estimation to reflect the dynamics of the problem in the shape of a multi-model to compensate the simplicity of the chosen model. On the other hand, the existence of a corrector (Kalman filter) means that the estimated values are solutions of the problem but are not necessarily the real physical values. Especially with the possibility of having more than one solution for the mathematical problem. The parameters' values in this case are simply values that can reproduce the building behavior discarding the problem of the offline estimation (with/without heating different dynamics). This on-line estimation multi-model result is completely reasonable as the estimated model is very simplified to be able to produce two different dynamics of such a complicated system.

Oppositely, the algebraic parameter estimation, tends to converge to a constant value and stabilize around it.

In both cases, the identified model parameters can be used in a real time control process. This is because constant parameters for such a simplified model can be misleading. However, with the least squares based estimation, it is important to differentiate two sets of parameters for two different dynamics.

Another use for the algebraic based parameter estimation is anomaly detection (for example: an open window). In other words, if a room is installed with measurement sensors, an online estimation of this type can point out problems whenever a considerable change in the values takes place.

In the next chapter, a synthesis of heating control methods is done. This synthesis aims to locate the proposed control approaches in the following chapter between the existing methods.

Chapter 3

Heating Control Methods

Introduction

With the significant attention given to the optimization of energy consumption nowadays, a lot of methods have been developed and proposed to be applied on the Heating, ventilation, and air conditioning (HVAC) control systems. This chapter presents, a synthesis of the mostly used control methods in building heating systems. The objective is to illustrate the existing techniques used in heating control in buildings in order to locate the proposed control methods in the next chapter between these methods.
As buildings are the highest energy consuming asset, the development and implementation of new control strategies is one of the quickly developing research and technology fields nowadays. Furthermore, the following two factors have helped to realize a revolution in the heating systems and control optimization by making robust systems much more easy to apply:

- The development of the data sector and processors with the high potential and possibilities of data processing and storage;
- The existence of communication protocols which allow the exchange of data between different elements of the system.

Therefore, a big variety of control methods is available nowadays. Starting from a classical on/off system to the artificial intelligence and expert system based control.

Before presenting the heating control methods, the objectives and priorities of these methods must be explained in order to understand the relation between the purpose, the design and used control.

3.1 Control priorities

It is obvious that a heating system control is normally dedicated to maintain a certain level of comfort and therefore to satisfy occupants. While on the other hand, an optimized control is designed not only to maintain the comfort, but also to reduce the consumption and the costs.
In this section, we will present these two objectives as the key leaders of a heating control process.

3.1.1 Thermal comfort

As mentioned in the first chapter, the thermal comfort is defined by several indicators such as the interior temperature, the relative humidity, the air velocity .. etc. Hence, the interior temperature (operative) is considered as the main indicator of thermal comfort in most practical applications.

It is delicate to define the comfort temperatures because it highly affects the energy consumption and it depends on different factors as:

- The building usage;
- The exterior temperature;
- The activities of occupants (in the occupation periods);
- The internal heat gains.

Some scientific works studied the determination of optimal environment in buildings considering energy consumption and human comfort [ClB$^+$11] or in a certain type of buildings as the study related to office buildings optimal working environment in [DLL14] [VCi$^+$14] and the study about residential buildings in [PdVH$^+$08]. Many tools were developed to calculate the comfort level. Some of them depend on the PMV method explained before and others calculate the comfort using the operative temperature as a simple function to the exterior temperature. A study of the American

Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) has proposed PMV-based method with the simplified relation 3.1 to define a 90% and 80% acceptability range where people feel comfortable as a function of the exterior temperature [BdD01a] [BdD01b] [YYCL03].

$$\text{The 90\% acceptability level} \begin{cases} T_{90(min)} = 0.31 * T_{ext} + 15.3 \\ T_{90(max)} = 0.31 * T_{ext} + 20.3 \end{cases} \tag{3.1}$$

$$\text{The 80\% acceptability level} \begin{cases} T_{80(min)} = 0.31 * T_{ext} + 14.3 \\ T_{80(max)} = 0.31 * T_{ext} + 21.3 \end{cases} \tag{3.2}$$

With a so-called comfort temperature in equation 3.3. This temperature is normally used as a set temperature for control systems.

$$T_{comfort} = 0.31 * T_{ext} + 17.3 \tag{3.3}$$

3.1.2 Energy Pricing

The objective is to minimize the energy consumption and cost. The energy consumption is the integration of the power supplied over time. In France, the electricity subscription is priced depending on the supplied power $P(watt)$ and the consumed energy $Q(kWh)$. A day time is also priced into two types: peak hours and normal hours. Table 3.1 shows an example of a dynamic pricing plan of the electricity in 2014 in France $(euro/kWh)$. Thereby the timing of consumption must be well planned in order not to exceed the maximum power supplied on one hand and to minimize the consumption cost on the other hand.

3.2 Existing control methods

After defining the main leaders in a control process, a presentation of existing control method is done. Figure 3.1 shows a diagram of all different types of heating con-

Table 3.1 Hours classification according to the price of kWh in France 2014

	Normal hours	**Peak hours**
Hour	22h00 - 06h00	06h00 - 22h00
Price (TTC) euro/KWh	0.1044	0.1510

trol methods. The most common methods for the control of energy in buildings are [MOAC03] [PEG+10a]:

3.2.1 On/Off system

They are either controlled according to the room temperature error (equations 3.4, 3.5) or otherwise by a pre-scheduled plan to switch the system on and off.
This pre-scheduled plan can be either daily or in some special cases it depends on the season. In other words, the system goes on at the beginning of the heating season and of at the end of it. Haniff et al. [HSY+13] present all different scheduling techniques and arrange them into three different categories:

- Basic scheduling: with simple on/off;
- Conventional scheduling with strategies as pre-heating or pre-cooling in order to shift the demand from the peak hours;
- Advanced scheduling with a bit more complicated scheduling taking into consideration factors like occupancy, comfort and peak hours. This has a higher potential to reduce consumption.

$$e = T_{set} - T_{room} \tag{3.4}$$

and:

$$S = f_{on-off}(e) \tag{3.5}$$

Where e is the temperature error and S is the heating device state.

This type of control is the simplest and it doesn't take into consideration any of the building's dynamics.

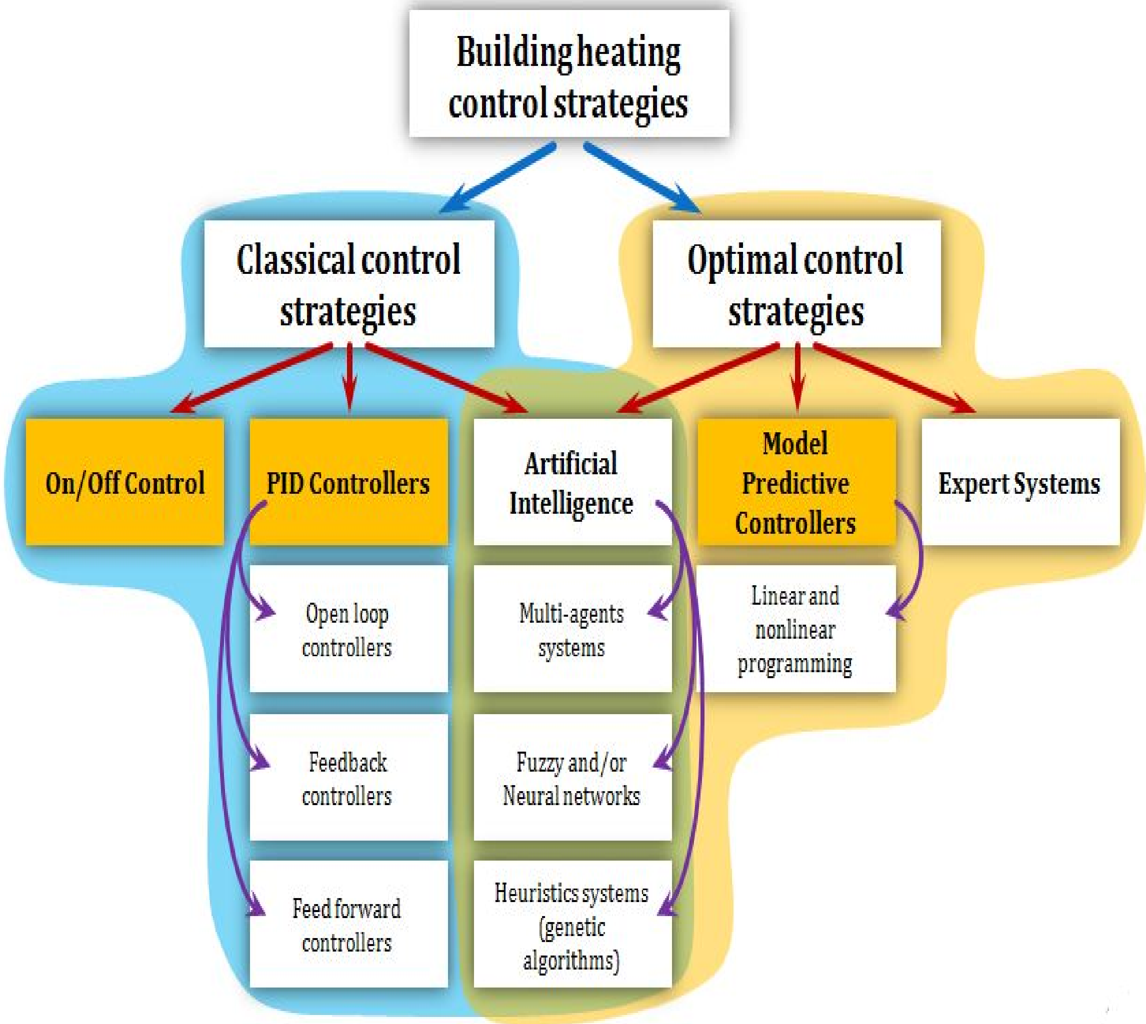


Fig. 3.1 Methods applied on heating control

3.2.2 Proportional Controls

Also called "weather compensated control", This system aims at eliminating the cycling associated with on-off control. It includes an effector device (heater) and a controller. The temperature of the heating medium (water for example) is controlled on a proportional relationship according to the outside temperature (equation 3.6) [EF92]. This control method, as the former one, doesn't take into consideration the building dynamics either. Though it is famous for its easy tuning [PŠFC11].

$$E = f(T_{exterior}) \tag{3.6}$$

Where E is the energy input signal.

3.2.3 PID control

PID is a very popular controller in heating applications [NAE11]. It combines proportional control with two additional adjustments (error integral and derivative), which helps the unit automatically compensate for changes in the system.

Figure 3.2 shows the design of a PID controller which can be written in equation 3.7.

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{d}{dt} e(t) \tag{3.7}$$

Where:

- K_p is the proportional gain, first tuning parameter.
- K_i is the integral gain, second tuning parameter.
- K_d is the derivative gain, third tuning parameter.
- e is the error between the set temperature and the measured one.
- t is the time (present).
- τ is the integration variable, it changes between 0 and t.

The first term $K_p e(t)$ is called the proportional gain. It produces output which is proportional to the error e. This proportional gain normally contributes the bulk of the output change. The second term $K_i \int_0^t e(\tau) d\tau$ is called the integral gain, it tackles at the same time the magnitude of the error together with its duration. Its main mission is to accelerate the movement towards the set point by summing up the offset that occurred over time and should have been corrected in previous steps. It avoids the residual steady state error that might happen with a simple proportional controller but risks causing an overshoot to the set point value if it is not well tuned. The last term $K_d \frac{d}{dt} e(t)$, is called the derivative gain and it is important to improve the settling time and stability of the system. On the other hand, it is rarely used in real life applications because of the high frequency gain and noise it might cause [ACL05a].

In a nut shell, PID can be expressed as a function of error and error history (equation :3.8).

$$E = f(e, history) \tag{3.8}$$

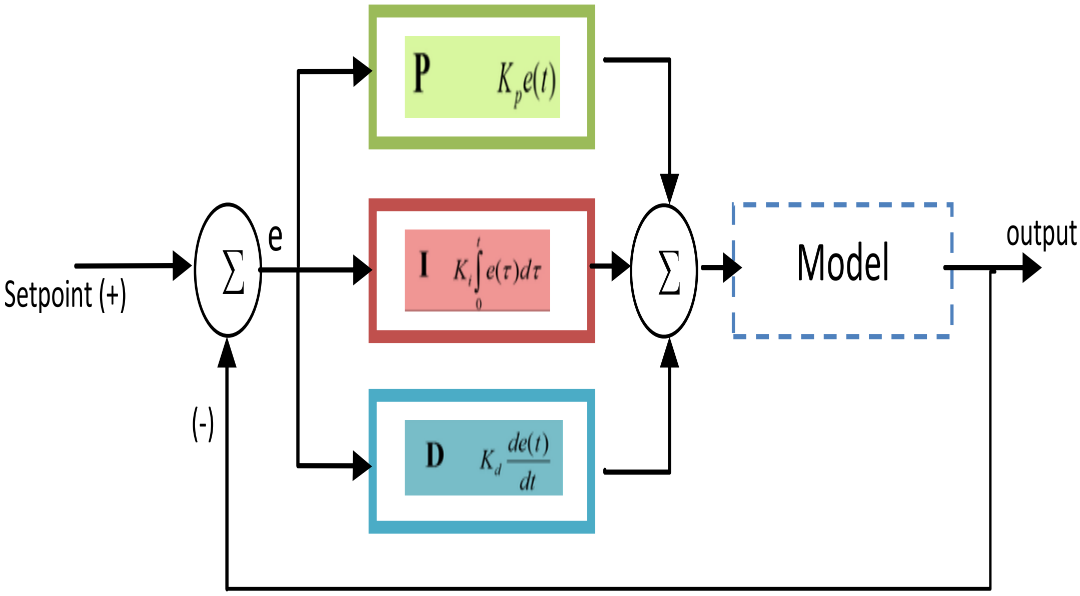


Fig. 3.2 PID controller block diagram

PID controllers are robust and allow accurate tuning, but they cannot reflect the outside temperature effects [PiFC11] [LAC06] [ACL05b] [PEG$^+$10b]. Another limitation of a PID is its complicated tuning when it comes to a multi-input multi-output (MIMO) system regarding the high number of factors that must be taken into consideration. From where the need of a control method that takes into consideration, at the same time, the multi factors, the history, the error and the system dynamics.

3.2.4 Model predictive controllers (MPC)

Model predictive controllers (MPC) can be expressed in equation 3.9.

$$E = f(e, history, T_{exterior}, building\ dynamics) \tag{3.9}$$

This method is considered as a powerful framework for the optimization of the buildings heating consumption as a constrained minimization problem considering both comfort requirements and limited capacity of the heating system. Model predictive control is considered as an ideal framework to tackle this problem [MRRS00]. This approach depends on generating a heating plan for an upcoming prediction horizon which is a receding horizon where only the first step of the predicted plan is applied to the system while all other inputs are used only to make good decisions at the current time step. This requires an important computation power and a reliable weather prediction. However, nowadays with the powerful computation powers and the possibility to do the computation in external places such as clouds, MPC becomes more doable [Zav12] [OPJ+12] [PEG+10a] [PEG+10b]. Model predictive controller employed in building heating control use normally two main information:

- Weather prediction (exterior temperature mainly);
- Building thermal model.

Many other intelligent predictive controllers were developed but MPC still have an important location between them.

3.2.5 Hybrid and soft control

Hybrid and soft control are all controllers based on Fuzzy logic and Artificial neural networks (ANN). They can merge more than one control technique at the same time. For example, a fuzzy-PID is a PID that depends on Fuzzy logic to auto tune its gains. The hybrid and soft control methods profit from advantages of many methods by gathering them in a new controller [KX12] [LD05] [Rie08] [YD10].

3.3 Prediction and control horizon

Most advanced HVAC systems are predictive controller. A prediction horizon is normally longer or equal to the control horizon. A prediction horizon refers to the time for which the control output is computed while on the other hand a control horizon refers to the time where the control signal is computed [AJS14].
The prediction horizon for the control plan differs according to the building inertia (thermal mass) and time constant. It is evident that in buildings with high inertia, the time constant is long which leads to slow heat dynamics. Oppositely, this is not the case in buildings with low inertia. Referring to the discussion about the prediction horizon length in [OPJ+12], a prediction horizon of 24 hours is the most common in heating control applications [OPJ+12] [Zav12].

3.4 Conclusion

As presented in this chapter, HVAC systems' control vary from very basic ones to high technology with the application of the most intelligent and expert methods ones. Though, there is always limitations related either to high simplicity and neglecting system dynamics, or to high complexity resulting from considering so many factors in the optimization procedures. In the next chapter, a new predictive control approach is presented. This approach is model based and robust. It has the same aim as model predictive control but without the complexity of mathematical optimization procedures. This new approach will be compared to a PID controller as it is considered as one of the most efficient, robust and widely used control method in the domain.

Chapter 4

The proposed control method

Introduction

This chapter presents a new control approach based on the application of Monte Carlo method, i.e., randomly generating sequences of the heating system states, testing these sequences then choosing the best one for the heating according to the least consumption or the least price. The method is based on exploiting the following three elements:

- The building inertia;
- The occupation profile;
- The dynamic pricing.

4.1 Monte Carlo based control method

The proposed control method represents a constrained optimization problem as in the model predictive control. This optimization concerns the minimization of energy consumption and cost. The simplicity of the optimization process is the main advantage of the proposed approach over MPC. The energy consumption of this approach can be expressed as a function of many factors as in equation 4.1

$$E = f(e, occupation, pricing, T_{exterior}, buildingdynamics, heatingsystem) \qquad (4.1)$$

4.1.1 Methodology

For a given heating system with M possible states, the method depends on generating different heating scenarios. This scenario generating is supposed to be random using a multiplication factor α to vary the supplied power at each time step and create a sequences (scenario). This multiplication factor α takes values as in equation 4.2.

$$\alpha \in [0; M-1] * \frac{1}{M-1} \text{with } M \geq 2\ M = 2 \text{ is the case of On/Off heating system} \quad (4.2)$$

These generated scenarios will pass by three steps 4.1:

1. Application to the thermal model using weather prediction;
2. Checking the thermal comfort condition;
3. Price calculation.

Finally the most economic sequence between the accepted ones will be applied.

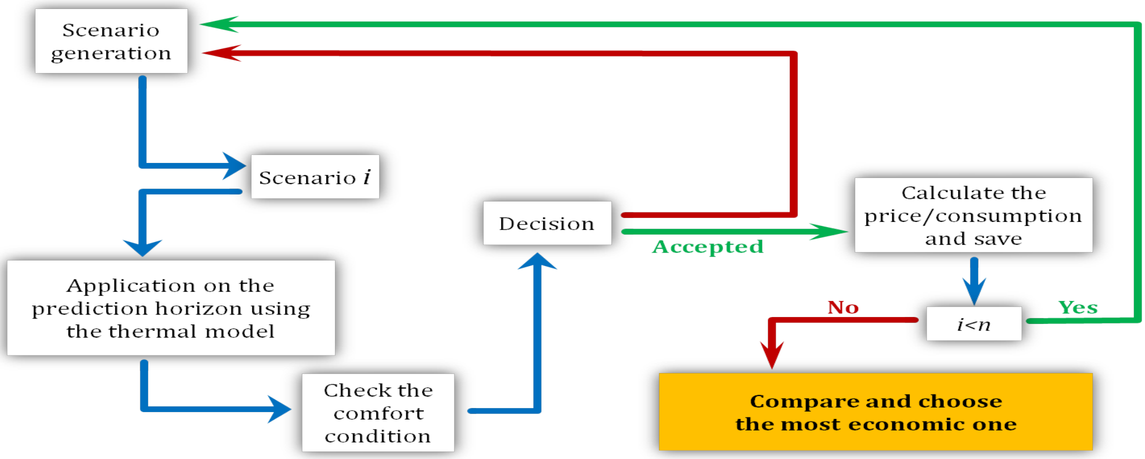


Fig. 4.1 The Methodology of the Monte Carlo Based Proposed Method

4.1.1.1 The problem formulation

As mentioned before, it is a constrained optimization regarding:

– The thermal comfort of occupants;

– The limited heating power;

– The dynamic pricing policy.

Supposing that we have n thermal zones, M heating system states and K time steps Δt, then the optimization problem concerns finding the best combination of a sequence $\alpha_i(k)$ over the study period $K * \Delta t$ that satisfies the minimization function in equation 4.3.
For a zone i, the cost function is expressed as:

$$minG_i = \sum_{k=1}^{K} c_i(k) * Q_i(k) \tag{4.3}$$

where:
$Q_i(k)$ is the consumption of zone (i) over a period Δt and $Q_i(k) = P_i(k) * \Delta t$;
$c_i(k)$ is the unit cost of zone (i) consumption over a time step k

subject to:

$$\begin{cases} P_i(k) = \alpha_i(k) * P_{max}, \\ Q_i(k) = P_i(k) * \Delta t, \end{cases}$$

where:
$\alpha_i(k)$ is a random number where: $\alpha_i(k) \in [0; M-1] * \frac{1}{M-1}$
$P_i(k)$ is the supply power for zone (i) over a period Δt

Maintaining the comfort condition:

$$T_{i(min)}(k) \leq T_i(k) \leq T_{i(max)}(k) \tag{4.4}$$

where $T_{i(min)}(k)$ and $T_{i(max)}(k)$ are the minimum and maximum accepted interior temperature at a certain step k. These temperatures must be predefined according to the

occupation profile and to the standards.
Note that in the special case where the unit cost $c_i(k)$ is a constant which value is one, the function will correspond to a minimization of energy consumption as well as the cost.

The minimization will be done by choosing the best (cheapest) sequence of $\alpha_i(k)$ that fulfills the conditions of the problem.

4.1.1.2 The comfort priority

The condition imposed in equation 4.4 is meant to maintain comfort. This condition implies having an accepted range of temperatures rather than a fixed set temperature (as proposed in section 3.1.1). In the case where the temperature is tending to cross this range (whether up or down), a certain value of α will be imposed to make sure the sequence will still be valid. If this is impossible, the whole sequence will be excluded.

Figure 4.2, illustrates the difference between an accepted and rejected sequence.

To reduce simulation time and reduce the number of excluded sequences, the following two actions are added to the problem.

$$\begin{cases} \text{if: } T_{i(min)}(k) \geq T_i(k) \text{ then regenerate } \alpha_i(k) \\ \text{if: } T_{i(max)}(k) \leq T_i(k) \text{ then } \alpha_i(k) = 0 \end{cases} \tag{4.5}$$

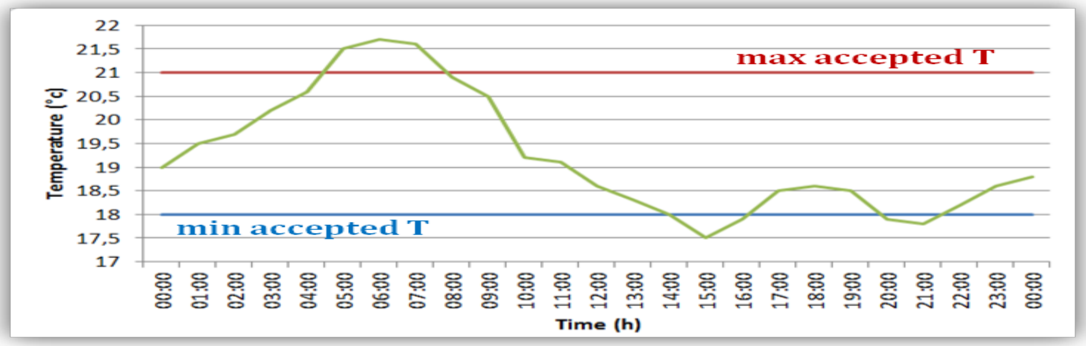
4.1.2 Case study

This method was tested using the model proposed in section 2.1 and the building described in table 2.1 supposing that it is an office building. Two heating systems have been used to test this method. The first heating system has 3 states ($M = 3$):

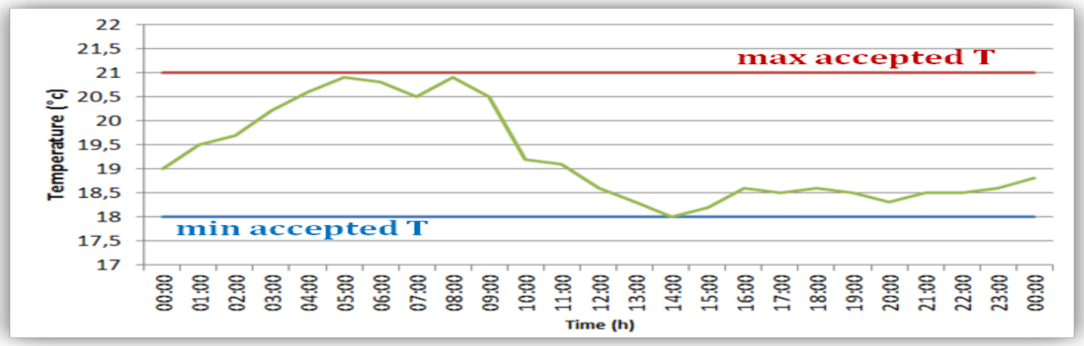
1. On: 100% of the maximum power
2. 50% of the power
3. Off: no power

And the second one has 5 states ($M = 5$).

1. On: 100% of the maximum power
2. 75% of the power



(a) Example of an excluded scenario



(b) Example of an accepted scenario

Fig. 4.2 The difference between an excluded sequence (a) and an accepted sequence (b) according to the set temperature conditions

3. 50% of the power
4. 25% of the power
5. Off: no power

4.1.2.1 The chosen prediction horizon

Referring to the discussion handled in section 3.3, the prediction horizon for the control plan differs according to the building inertia (thermal mass) and the building's time constant. It is evident that in buildings with high inertia, the time constant is long which leads to a slow heat dynamics. On the other hand, this is not the case in buildings with low inertia. For this study, a prediction horizon of 24 hours was chosen for the following two reasons:

– To exploit the dynamic pricing of the electricity;

– As the heating plan is made using weather predictions, 24 hours horizon seems to be reasonable in terms of weather prediction certainty.

This choice was also made in other studies [OPJ+12] [Zav12] [OPJ+12]. While the choice of midnight as a simulation start point is only a hypothesis made for this study. The prediction horizon and the start time can be easily changed and adapted according to the building requirements.
The simulation time step is 5 minutes while the control is conducted with a time step of 30 minutes to avoid the continuous change of the heating system state (unless in urgent cases when the temperature crosses the comfort limits).

4.1.2.2 The chosen thermal comfort level

Figure 4.3 shows an example of a designed comfort range for an office building. It is essential to note that the thermal comfort in an occupation period in not to be compromised. While on the other hand, in the no-occupation period, we authorize a higher heating to benefit of the cheap price of the energy. Afterwords, according to the building time constant, the building will keep a certain level of comfort for a certain period (due to this higher heating). This period depends on the building inertia and is taken into consideration.

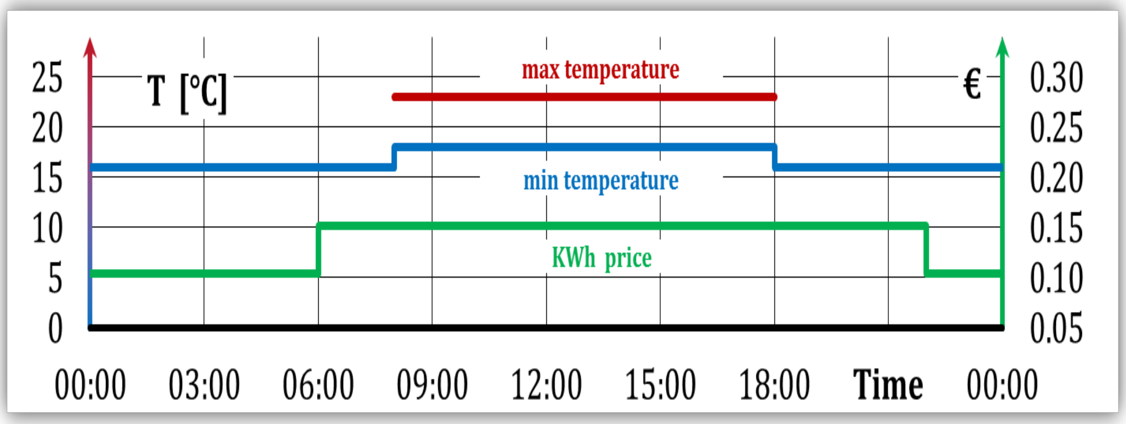
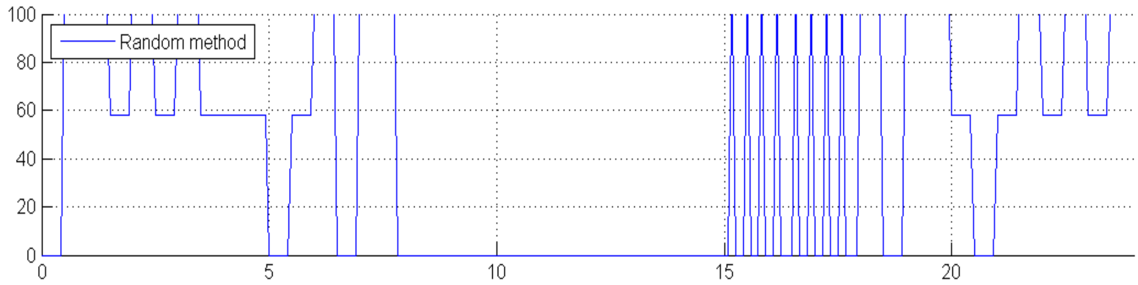


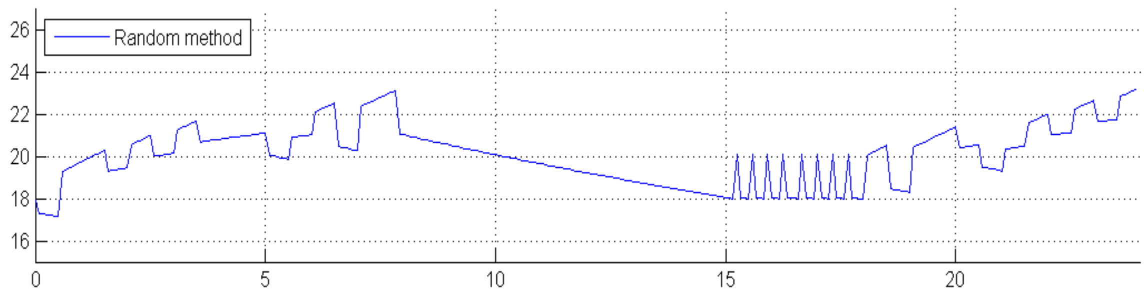
Fig. 4.3 An example for the chosen temperature interval for an office building

The pricing plan in table 3.1 is used in this example. Thereby the timing of consumption must be well planned in order not to exceed the maximum power supplied on one hand and to minimize the consumption cost on the other hand.

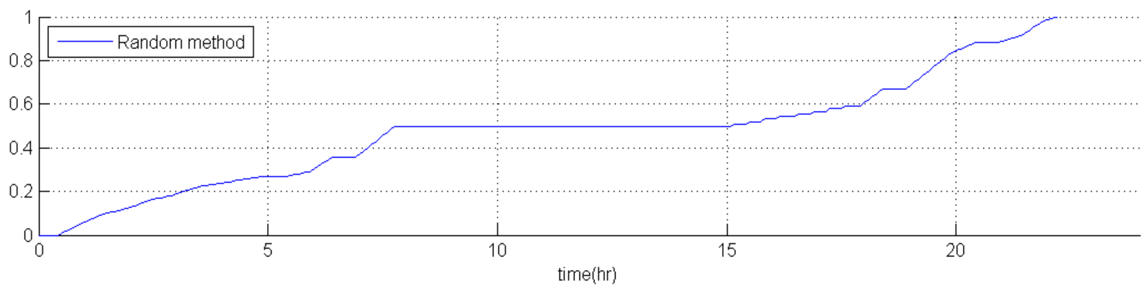
Running the simulations for a certain number of times (the more times it is repeated, the higher are the chances to get a better solution) will give us more possibilities of the heating plan. For each sequence, we will have the associated consumption and price as in figure 4.4. Depending on these results, we can then choose the sequence that fulfills our defined criteria.



(a) Used percentage of total power



(b) Associated interior temperature



(c) Accumulated Energy Cost

Fig. 4.4 Example of a building energy consumption, price and temperatures

4.1.2.3 Comparison of the proposed method with the pid method

As mentioned in section 3.2.3, a PID controller was used as a comparison base to show the efficiency of the proposed method.

A PID controller needs a defined profile of set temperatures which can not be expressed by intervals. So, for a justified comparison, we used the minimum level of the interval designed for the building as a reference set temperature for the PID (which means a PID is based on a minimum level of comfort). In this case, the PID is sure to minimize the energy consumption as it is working for a minimum level of comfort. However, a PID controller doesn't take into consideration the pricing policy. Here appears the advantage of the proposed system that can provide a better solution in terms of price and consumption timings[1].

Figures 4.5 and 4.6 show the energy consumed using both methods together with the associated temperatures. The simulation is applied on the two mentioned heating systems $M = 3$ and $M = 5$. From the figure we can see two obvious advantages of the proposed method:

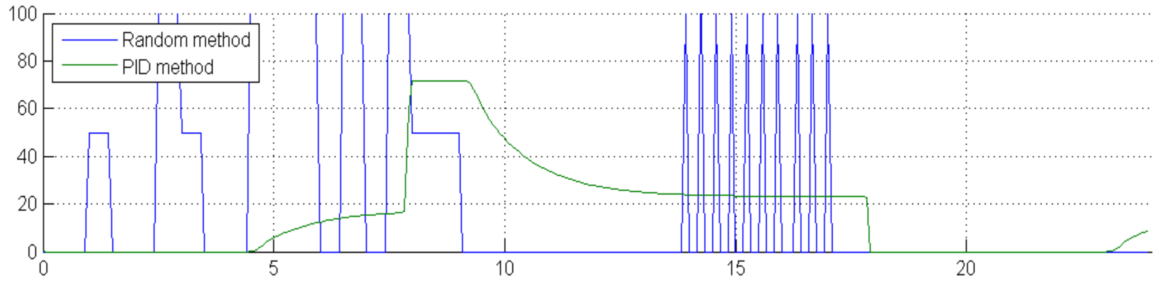
- An energy shedding is performed by exploiting the building inertia (avoid heating in the peak time);
- Due to this shedding of energy and the re-distribution of the load considering the dynamic pricing, the price of consumed energy is less than the PID method consumption price.

Table 4.1 shows some chosen iterations from a simulation done 2000 times (with the heating system of ($M = 5$)). The table shows that the least price is not necessarily associated with the least consumption. While on the other hand, two different iteration with exactly the same amount of consumption don't necessarily have the same price (iterations 16,102). This is of course due to the dynamic pricing.

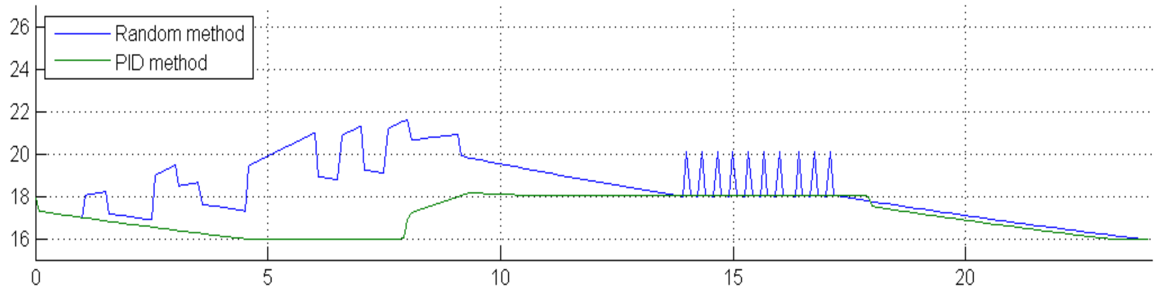
Table 4.1 Some iterations from 2000 iteration made, consumption - price comparison

Iteration number	Total consumed energy as a percentage of the PID consumption	Price as a percentage of the PID price)
3	158,71	107,38
16	198,9	144,96
102	198,9	137,8
1371	154,4	125,17
1578	131.2	91.78

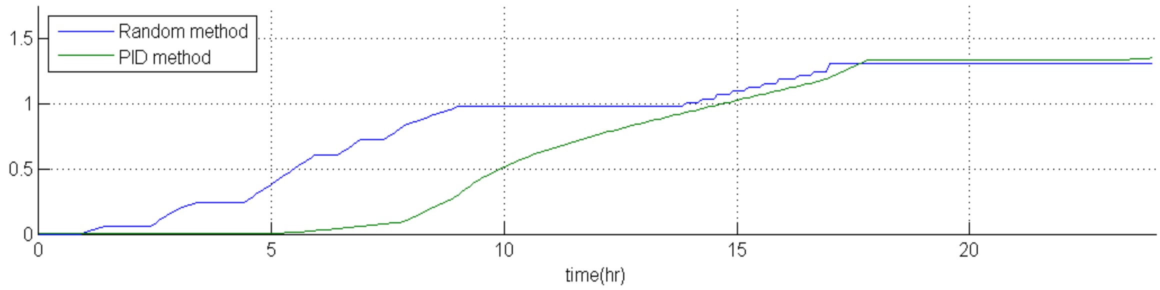
[1]That depends on the heating system capacity as well as the building inertia



(a) Used percentage of total power



(b) Associated interior temperature



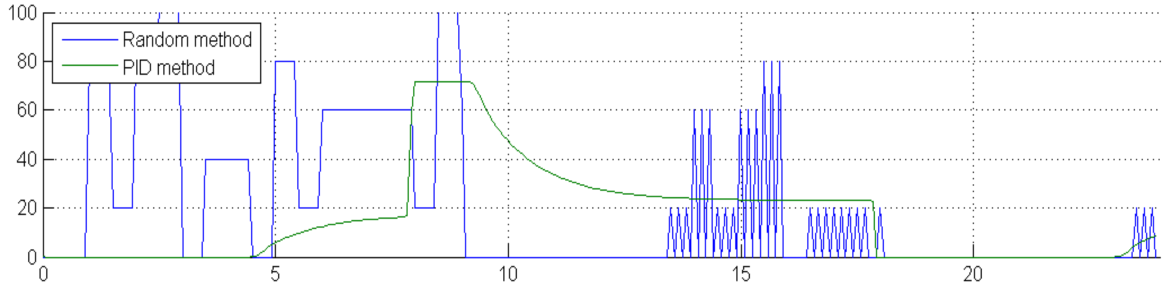
(c) Accumulated Energy Cost

Fig. 4.5 A comparison of the energy consumption between the traditional PID system and the proposed random method (M=3)

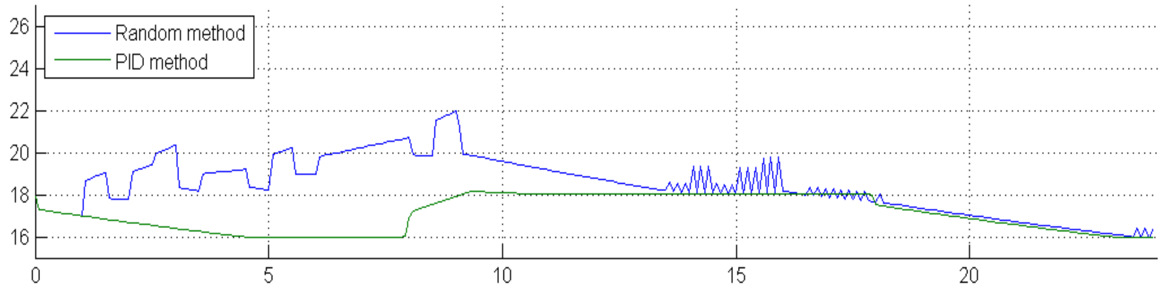
4.1.2.4 Comfort quantification

In order to better judge the results of both methods, a quantification of the comfort was done using the concept of 90% and 80% satisfaction proposed in ASHRAE (see chapter 4). The percentage of time where the temperature is in the 90% acceptability range as well as the 80% acceptability range was calculated for both control methods. Table 4.2 shows the results of this comparison.

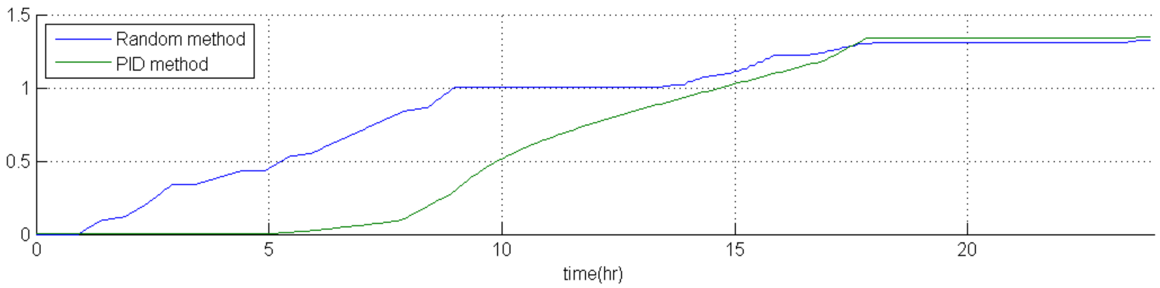
From the table and the figures we see that the MC based method can keep a higher comfort level for a longer period and a lower cost. This is due to exploiting the pricing differences.



(a) Used percentage of total power



(b) Associated interior temperature



(c) Accumulated Energy Cost

Fig. 4.6 A comparison of the energy consumption between the traditional PID system and the proposed random method (M=5)

4.1.2.5 Case of low inertia

Efficiency of the proposed method is less obvious in the case of low inertia buildings because the heat can't be stocked for a relatively long time to be used afterwords. Figure 4.7 shows a heating plan for a building which has the same dimensions as the one studied before, but with a smaller time constant. From the interior temperature graph we can see that a fluctuation in the temperature is probable to happen due to the low insulation and change in the heating state. At 6.00 pm, both the PID and the random methods have the same cost while the comfort the proposed method provides is better than the PID.

Table 4.2 Comfort indicator

Satisfaction percentage	90% satisfied	80% satisfied
MC-based Optimization Method	85.76%	14.24%
Traditional PID	43.5%	56.5%

4.1.3 generalization to multiple zones

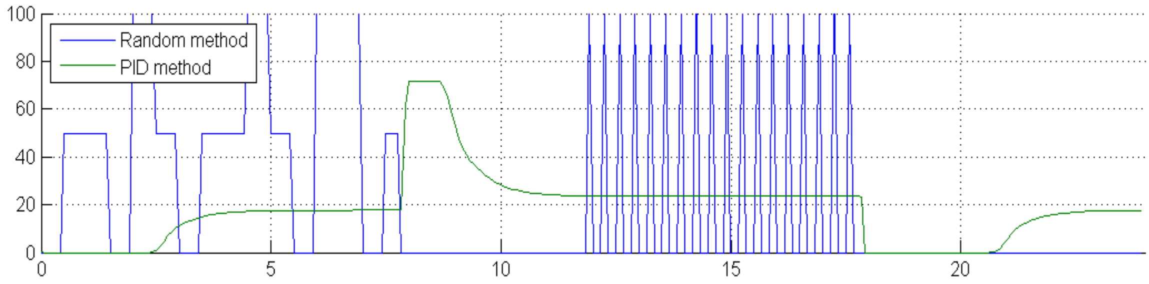
If we have n thermal zones, then the approach applied will remain the same with one more condition regarding the partition of energy source between these zones (as the power source is limited):

$$\sum_{i=1}^{n} P_i(k) \leq P_{max} \Longleftrightarrow \sum_{i=1}^{n} \alpha_i(k) \leq 1 \tag{4.6}$$

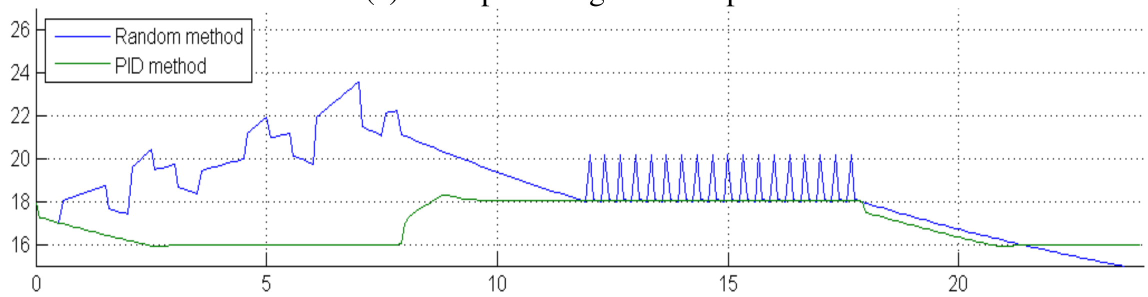
The minimization will be done by choosing the best (cheapest) sequence of $\alpha_i(k)$ that fulfills the conditions of the problem. The multi zone can be generalized for the case of multi buildings. Consequently, the system can take advantage of different occupation profiles to design the thermal comfort (example in figure 4.8) as well as the heating scenarios. This concept might be very interesting in urbain systems with one energy source and different types of buildings.

4.1.4 Discussions

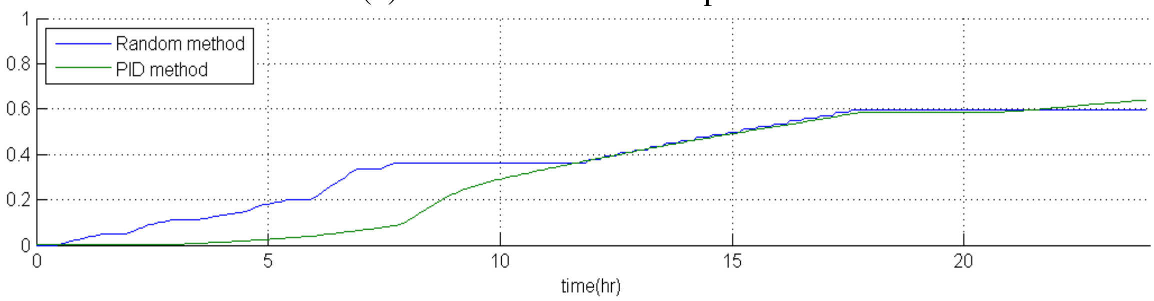
As the MC based method uses a comfort level as limits of the optimization problem, the comfort is guaranteed at each moment of the occupation period. However, a higher heating is authorized in the no-occupation period to make advantage of the cheap power pricing. This will also cause a shifting of the energy consumption and reducing the peak loads. The building relatively slow heat dynamics help keeping the comfort in the occupation period, even if the heating is off because of the expensive price [HPMJ12]. In other words, we benefit of the building thermal time constant which helps to maintain an acceptable level of comfort for a certain period. Meanwhile, heating can be reduced or even shut down to avoid consumption in peak hours [FDT+13] [Pir13]. The application of this method results in a best heating plan for the prediction horizon period (between all tested plans). Which constitutes the necessity



(a) Used percentage of total power



(b) Associated interior temperature



(c) Accumulated Energy Cost

Fig. 4.7 A comparison of the energy consumption and price between the PID and the proposed method

of a large number of sequences to insure having an optimal plan which again explains the need of a simplified model to reduce the computation time.

The fact that the heating plan is designed in advance for the whole prediction horizon constitutes another advantage of this method over the MPC. This is the possibility to have a global solution over the prediction horizon while it is not the case in the MPC as it is a sliding horizon (sliding window over the prediction horizon).

However, the problem of a reliable weather prediction is still present and open for discussion. That is why, in real application, instead of using the optimal heating plan, a use of the resulting simulated temperature from this plan is advised. A simple PID can be used to ensure following and monitoring this optimal temperature plan. As

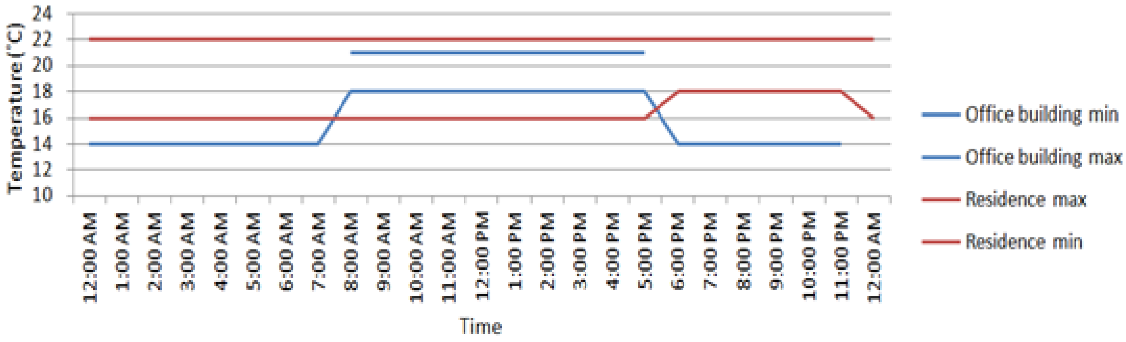


Fig. 4.8 An example for the chosen temperature interval for an office building

a result, errors caused by different weather conditions from the simulated ones are avoided (return the problem into a closed loop system 4.9). Moreover, a smoothing for the plan is possible in order to reduce temperature fluctuation (Figure 4.10).

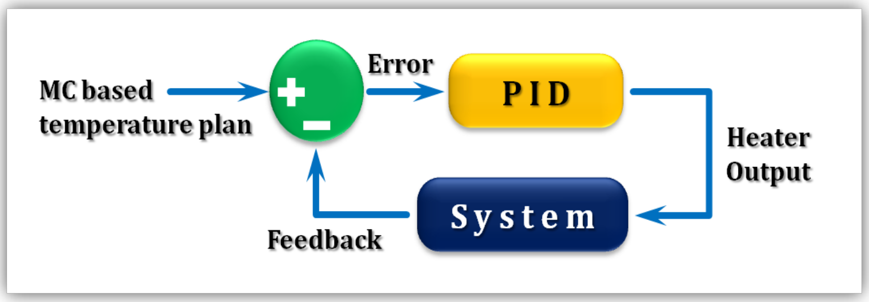


Fig. 4.9 Closed loop structure

This last idea of using a real time controller to apply the optimal plan generated by the MC based control approach has lead to a research in the real time control approaches. In the next chapter, the application of flatness based control is proposed to be applied in the heating control. This is a new control approach that has been proposed 15 years ago and that is being developed and applied to all different control problems.

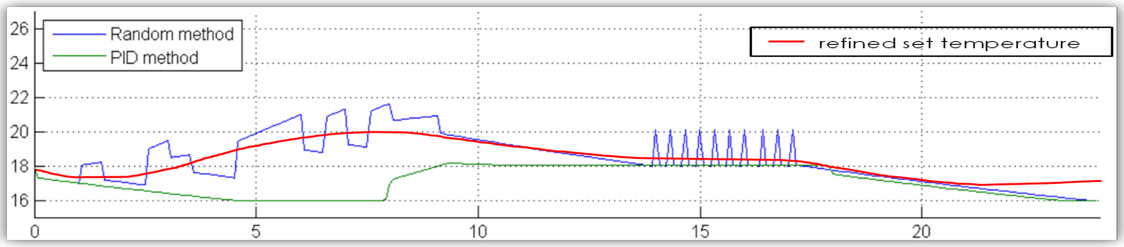


Fig. 4.10 Smooth optimal temperature plan

Chapter 5

Real time temperature control using differential flatness

Introduction

Real-time indoor temperature control is tackled in this chapter, applying the concept of differentially flat systems. Such modern control scheme is characterized by the fact that the whole system behavior is described by the trajectory of a so-called "*flat output*" and a number of its successive time derivatives.

5.1 Differentially flat systems

This chapter proposes employing a new approach to control the building heating system. This approach has several advantages in terms of simplicity, robustness against perturbations and optimization. It applies the concept of differential flatness to ameliorate and optimize the energy consumption in the building [FLMR92] [FLMR95].

Differentially flat systems were introduced more than 15 years ago using the formalism of differential algebra [Mar92] and was later expressed using Lie-Bäcklund transformation [FLMR99].

The flatness-based control methods are expected to play a very significant role in high technology applications in the next few years, similar to what happened for nonlinear control in the last decade [SRA04]. The main property of the flat systems is that all the state and input variables can be expressed directly as a so-called "flat output" and a number of its time derivatives (without integration of any differential equations).

More precisely, the entire system behavior is determined by the trajectory of a finite collection of quantities: flat outputs. This leads to a simple and elegant trajectories design. For a given system, the number of flat outputs is equal to the number of the system inputs.

5.1.1 Flat Systems Definition

In this section, a definition of flatness for state-space control system is presented. Considering the system defined using the following equation:

$$\dot{x} = f(x,u); \quad x \in R^n, \;\; u \in R^m \tag{5.1}$$

where $x = (x_1, x_2, ..., x_n)$ vector of state variables and $u = (u_1, u_2, ..., u_m)$, m scalar control. The system (5.1) is flat *if and only if*, there exist m real smooth functions $h = (h_1, h_2, ..., h_m)$ depending on x and a finite number of u derivatives, β, that, generically the solution (x,u) of the square differential-algebraic system $(t \mapsto y(t)$ is given)

$$\dot{x} = f(x,u), \quad y(t) = h(x,u,\dot{u},...,u^{(\beta)}) \tag{5.2}$$

does not involve any differential equation and thus it is of the form:

$$x = \Phi(y,\dot{y},...,y^{(\beta)}), \quad u = \Psi(y,\dot{y},...,y^{(\beta+1)}) \tag{5.3}$$

where, Φ and Ψ are smooth functions [1], and β is some finite number [Rou05]. The quantity y is of fundamental importance: it is called "*flat output*" or linearizing output. In the control language, the flat output y, as the inverse of $\dot{x} = f(x,u), y = h(x,u,\dot{u},...,u^{(\beta)})$ has no dynamics [IMDL86] [Rou05].

Differentially flat systems are very useful in the situations where the explicit generation of trajectories is required. Since the behavior of the flat systems is determined by the flat outputs, we can plan the trajectories in the outputs space and then connect these to appropriate inputs.

More precisely, from the trajectories of the flat outputs y, we can deduce immediately

[1] A smooth function is a function that has continuous derivatives up to some desired order over some domain

the trajectories of the state x and the input u variables. Applications of the flatness concept to problems of engineering field have grown steadily in recent years and a variety of case studies have been shown to be flat and flatness based controllers based on trajectories generation by polynomial interpolation. Afterwords, closing the loop on the obtained trajectories have been developed.

5.1.2 Trajectories planning for Flat systems

The main advantage of flat systems is their ability for solving control problems. The synthesis of control laws is divided into: "*trajectories planing*" corresponding to the *open-loop control* synthesis and "*trajectories tracking*" which corresponds to the *closed-loop control* design.

For flat systems there is a systematic method for trajectories planning [RWW03]. Often these trajectories are required to parametrize a finite time transition between two stationary regimes. This equilibrium can be computed (locally) from the following relations:

$$u = \Psi(y, \dot{y}, ..., y^{(\beta+1)})$$

by substituting $y^{(i)} = 0, i > 0$. They are, thus, specified by constant values of the flat output.

The transition between two states is determined by choosing a reference trajectory for the flat output, and y being differentially independent. The trajectories of its components can be chosen independently, and freely. In principle, any sufficiently smooth curve $t \mapsto y_i^*(t)$ may be used. A particularly simple method uses polynomials to define reference trajectories. Then the coefficients of the polynomials, follow from the initial $(t = 0)$ and final values $(t = T)$ of y by solving a linear system of equations. [RWW03] explains the exact method of coefficients calculation.

5.1.3 Trajectories tracking for Flat systems

For flat systems, trajectories planning may be achieved using endogenous feedback. Thus, for a given system with y as flat output, corresponding to the state x and the input u, as measured variables, and y^* as the reference trajectory of the flat output, we can then write:

$$\varepsilon_i = y_i - y_i^*; \quad i = 1, ..., m \tag{5.4}$$

and construct an endogenous dynamic feedback in such way that the system is written as follow:

$$\nu = y_i^{(\beta+1)} \tag{5.5}$$

If we put:

$$\nu^* = y_i^{*(\beta+1)} \tag{5.6}$$

then the error equation becomes:

$$\varepsilon^{(\beta+1)} = \nu - \nu^* \tag{5.7}$$

It is then enough to put for each component:

$$\nu_i = \nu^* + \sum_{j=0}^{\beta} k_{i,j}\varepsilon^{(\beta)}, \quad i = 1, ..., m \tag{5.8}$$

where, $k_{i,j}$ are the control gains chosen such that the m polynomials $s^{\beta+1} - \sum_{j=0}^{\beta} k_{i,j}s^{(\beta)}$ all have the roots with strictly negative real part:

$$\varepsilon_i^{(\beta+1)} = -\sum_{j=0}^{\beta} k_{i,j}.\varepsilon_i^{(j)}; \quad i = 1, ..., m \tag{5.9}$$

In this way, the output y, and all of its time derivatives up to order $\beta + 1$, will converge to their reference values. Using the equations (5.3), we can ensure that all the original systems' variables (state x and control u variables) will converge exponentially to their references.

5.2 Building thermal system model and case study

This paper is concerned about employing the differential flatness approach to the control of the heating system and optimize the consumption. As mentioned in chapter 2, building thermal behavior can be simplified and represented in equation (5.10), where

T_{int}, the interior temperature, represents the system's output. Q $(Watt)$ and T_{ext} are the supplied power and the exterior temperature respectively. The application is done on the same test room described in chapter 2 section 2.

$$\dot{T}_{int} = -\theta_1.T_{int} + \theta_2.Q + \theta_3.T_{ext} \tag{5.10}$$

2

5.3 Flatness based control of the building heating

Considering the above equation (5.10), where the main objective is to control the ambiance temperature T_{int}. The system is flat with $F = T_{int}$ as a flat output. The state T_{int} and the control $Q = u$ variables can be expressed in the form of this flat output and its time-derivative up to one.

$$T_{int} = F$$

$$u = \frac{1}{\theta_2}\left[\dot{F} + \theta_1 F - \theta_3 T_{ext}\right] \tag{5.11}$$

The expression of the state variable allows choosing a suitable trajectory of the ambiance temperature (the flat output). The equation of the control (input) variable allows adding additional constraints to this ambiance temperature trajectory. This means that all important properties of the system (5.10) are contained in such a differential parametrization.

5.3.1 Trajectory planning for the heating system: open loop design

Equation (5.11) corresponds to the open loop control algorithm. In order to close the loop, a trajectory is needed. A so-called 'trajectory' of the flat output F represents simply a set temperature.

This control method is originally studied in this work to ensure the optimal temperature trajectory resulting from the MC based method proposed in chapter 4. However,

[2]Values of parameters θ_1, θ_2 and θ_3 define the relations and thermal transfers between the evolution of the interior temperature and the inputs of the system. They are supposed to be constant and known, either from physical information or using a parameter estimation method (chapter 2).

an explanation of the commonly used trajectory planning method follows in order to tackle the whole new approach.
For this section, a presentation of the typically used method to define a trajectory of the flat output.

According to 5.11, this trajectory must have smooth derivatives up to order two. From the initial and final conditions of the desired interior temperature $(F(t_i) = F_i,\ \dot{F}(t_i) = 0)$ and $(F(t_f) = F_f,\ \dot{F}(t_f)) = 0)$, this reference trajectory for the ambiance temperature (flat output) can be built using a polynomial interpolation because of the reduced computational effort in the real time environment [SRA04]. Indeed, at the system equilibrium points the constant values of the output variable $(y(t))$ and the flat output, $F(t)$, perfectly coincide. Instead of the original problem, the equivalent problem of controlling and transferring the flat output F, between the given initial and final values, is tackled.
The goal is then to transfer the flat output F between the values $F^*(t_i) = F_i$ and $F^*(t_f) = F_f$. Using the polynomial interpolation, this is accomplished by prescribing the following desired trajectory for the flat output F:

$$F^*(t) = \begin{cases} F_i & \text{for } t < t_i \\ F_i + (F_f - F_i)\varphi(t, t_i, t_f) & \text{for } t_i \le t \le t_f \\ F_f & \text{for } t > t_f \end{cases} \tag{5.12}$$

where $\varphi(t, t_i, t_f)$ is a polynomial function of time, exhibiting a sufficient number of zero derivatives at times, t_i and t_f, while also satisfying: $\varphi(t_i, t_i, t_f) = 0$ and $\varphi(t_f, t_i, t_f) = 1$ (Figure 5.1).

The studied system has four conditions, that's why a degree of 3 polynomial is needed [RWW03] [SRA04]:

$$\varphi(t) = \begin{cases} 0 & \text{if } t < t_i \\ 3\left(\frac{t-t_i}{t_f-t_i}\right)^2 - 2\left(\frac{t-t_i}{t_f-t_i}\right)^3 & \text{if } t_i \le t \le t_f \\ 1 & \text{if } t > t_f \end{cases} \tag{5.13}$$

Using the expression of the control variable in (5.11) with relation (5.12), the nominal

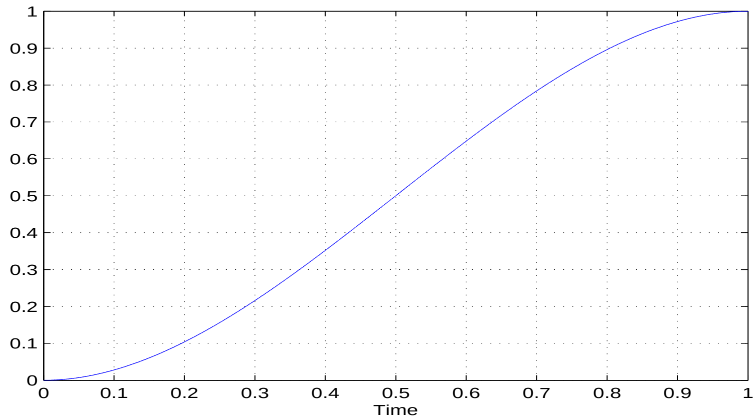


Fig. 5.1 Polynomial function φ

open loop control can be calculated[3]:

$$u^{\star} = \frac{1}{\theta_2}\left[\dot{F}^{\star} + \theta_1 F^{\star}\right] \tag{5.14}$$

5.3.2 Trajectory tracking: closed loop design

Due to the possible parameter variations and disturbances in the building thermal behavior, together with the changes in the heating conditions, the open loop control is not sufficient to control such system. To ensure a steady state and reduce the influence of the disturbances, the thermal building control has to be operated in a closed loop (5.2). Using the flatness-based open loop algorithm (5.14), an additional feedback can

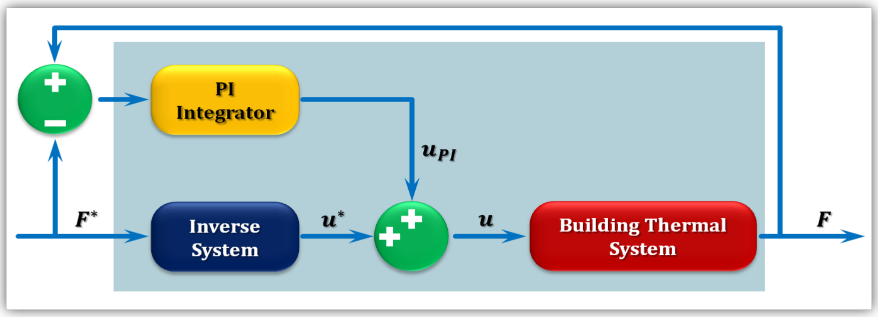


Fig. 5.2 Closed loop structure

[3]In the nominal context we do not introduce the external temperature considered as perturbation.

be determined in order to achieve the desired dynamic behavior and to compensate the external disturbances. The closed-loop control schema including the flatness-based loop can be obtained as follow:
For $(\dot{F}(t))$ in (5.11), a new input is defined: $\nu = \dot{F}$. By replacing this variable in the equation of u in (5.11), the system is transformed into the following form:

$$\nu(t) = \dot{F}^*(t) - k_1(F(t) - F^*(t)) - k_2 \int (F(t) - F^*(t))dt \tag{5.15}$$

where k_1 and k_2 are parameters that must be selected to satisfy the desired performances of the closed loop system and to ensure asymptotically stabilization of the input variable. The final control law u is then:

$$u(t) = \frac{1}{\theta_2}\left[\dot{F}^*(t) - k_1(F(t) - F^*(t)) - k_2 \int (F(t) - F^*(t))dt + \theta_1 F - \theta_3 T_{ext}\right] \tag{5.16}$$

[4]

5.4 Numerical simulations

For the system shown in Figure 2.3 and described by equation (5.10), the control objective is to maintain the indoor thermal comfort during the occupation period (for this application $T_{int} = 20\ °C$). Figure 5.3, shows the exterior temperature time evolution. While figure 5.4 shows the control signal time evolution for the proposed controller together with a PID controller.

In the case with no special control (other than personal control from the occupant), the indoor (interior) temperature varies in a random way depending on the internal and external factors including perturbations. This case does not necessarily ensure comfort for the occupant of the room. Moreover, it causes a lot of energy losses because of the overheat and coldness cases resulting from the building slow dynamics. Considering a comfort range of $20 \leqslant T_{int} \leqslant 22$[5]. Figure 5.5 shows that, in spite of the existing uncertainty and the real data which are corrupted by noises, the designed controller ensure the tracking of the desired reference. The control signal evolution Figure 5.6, corresponding to the supplied power Q which respects the following con-

[4] The feedback in (5.16) depends, as usual in flatness-based control, on the derivative of the flat output and not on the state variables.

[5] Other values could be defined easily.

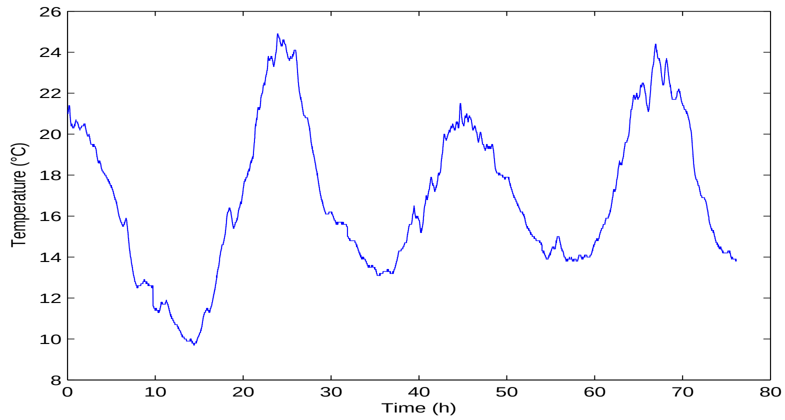


Fig. 5.3 Exterior temperature time evolution

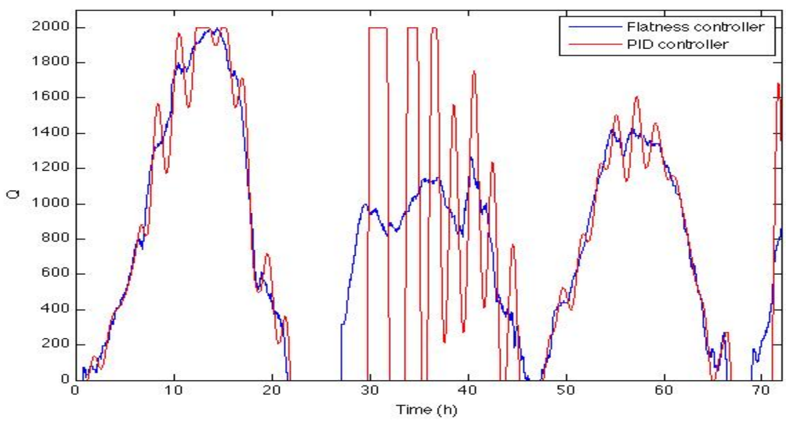


Fig. 5.4 Control signal time evolution (flatness controller - PID controller

straints ($0 \leqslant u \leqslant 2000\ (Watt)$), varies accordingly which ensure an optimal use of this energy.

Even if the output variable T_{int} is corrupted by additive noise (Figure 5.7), the interior temperature will still follow the desired trajectory which demonstrate the robustness of the proposed controller.

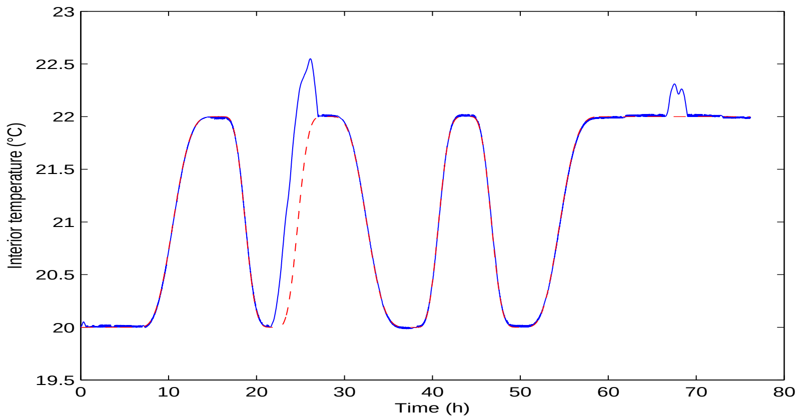


Fig. 5.5 Interior temperature time evolution: control case

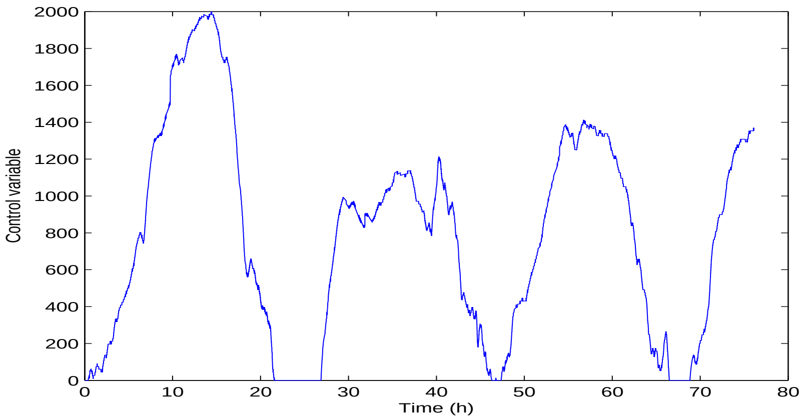


Fig. 5.6 Control signal time evolution

5.5 Conclusion

In this work, a new control algorithm based on the concept of differential flatness is successfully applied to building thermal system. The main advantage of this method is that the whole system variables (state and control) are described through the flat output and a number of its time-derivatives. Such method which does not need any integration seems to be more adequate for indoor temperature control and prediction in spite of existing uncertainties and noisy data. However, the proposed algorithm guarantees having solutions in order to ensure a high quality of comfort for the users.

Furthermore, this method can be coupled with the online algebraic parameter esti-

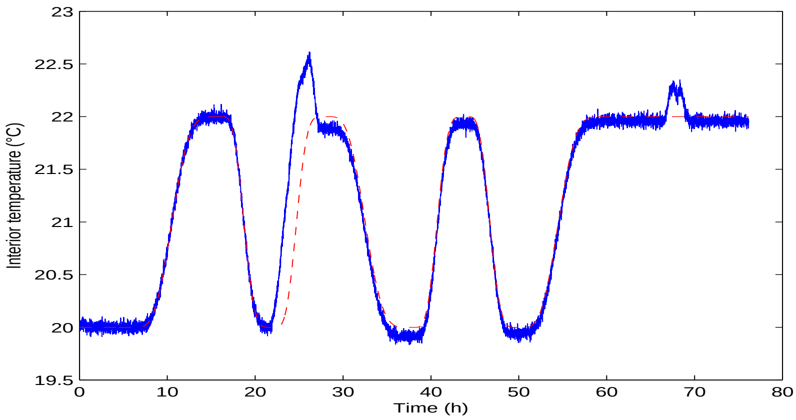


Fig. 5.7 Interior temperature in noisy environment

mation method (Chapter 2) to achieve full monitoring and control in real time and at the same time avoid any errors or anomalies caused be either model failure or wrong weather predictions 5.8.

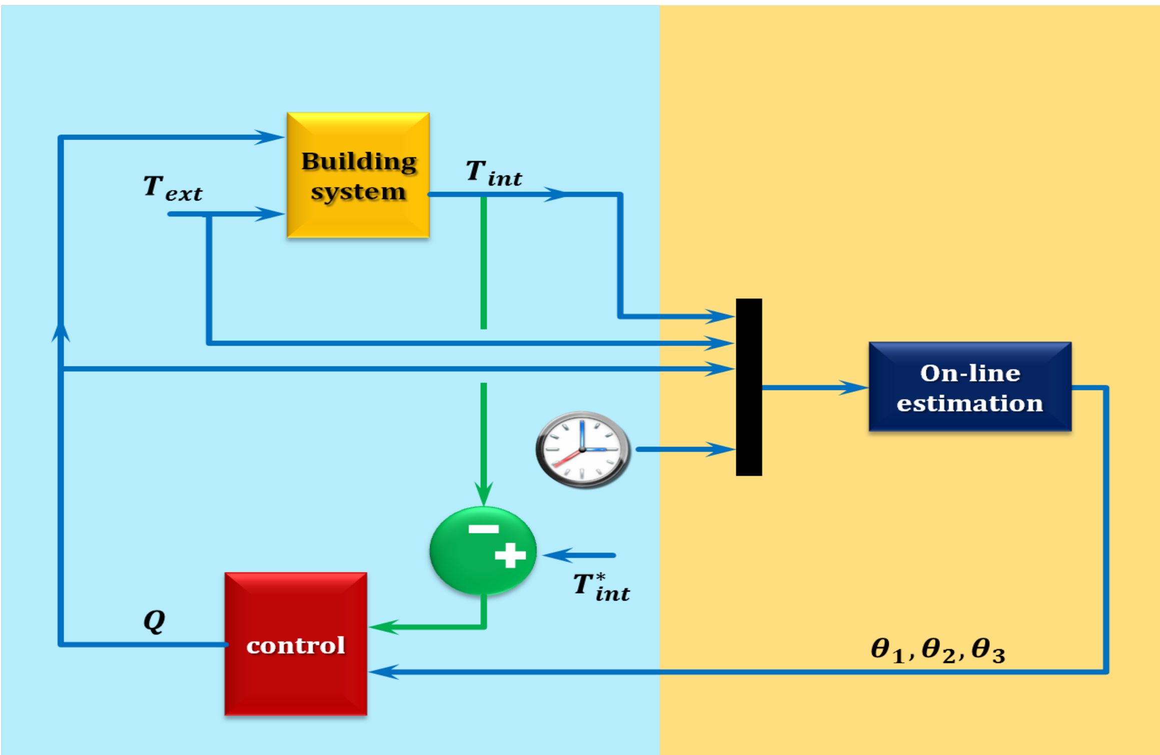


Fig. 5.8 Real time monitoring and control process

Conclusion

With the high attention to raise awareness about energy consumption, a lot of methods and strategies are put in action. These strategies and methods are adopted on all levels starting from the highest ones represented by governments through intermediate levels like communities and research centers and ending by the last level in the hierarchy represented by the individuals themselves. The governments main role is to raise awareness and impose regulations (energy pricing policies, carbon tax and RT 2012 as examples), while communities and research centers propose solutions to facilitate and guarantee the energy economy. And finally the individuals are responsible of applying the regulations and improving their own behavior regarding energy consumption.

Many researches have been conducted regarding the understanding of the building thermal behavior as well as developing optimal control strategies. This understanding of the building thermal behavior is represented by thermal models. Identification of thermal models using measured data (backwards approach) is nowadays more common and reliable than the traditional way (forward approach starting from material and compositions). Furthermore, it is less expensive considering the technology revolution and the reasonable prices of measurements and data processing. However, identification process is still a big research theme. Moreover, if the model is developed for control reasons, simplified models are preferable. This leads to the compromise between taking all factors into consideration from one side, and the simplicity needed for the control process from the other side. Here comes the need for a simplified model that reasonably reflects the building dynamics and behavior and can be easily integrated in the control process. This work is a control oriented research that went into the following 4 steps:

– As a first step, a research in the existing thermal models was done to finally retain a simplified thermal model and develop it to be able to represent the building thermal behavior. This simplified model has the form of a MISO system with the exterior temperature and the heating as inputs, and the interior temperature as the output. The model was tested using several data sets. The validation of the model was successful and it was done using different data sets from those used for the estimation.

– After developing the model and estimating its parameters using the parameter estimation toolbox in MATLAB/SIMULINK, a research is done through the different parameter estimation methods and the application of a new algebraic based method is proposed. This algebraic based estimation was less efficient than the recursive least squares estimation with Kalman filter (in terms of error). On the other hand, as the algebraic method doesn't have a corrector (as in recursive least squares), parameter values tend to converge to a certain value and stabilize around it. This has the potential to serve into a default detection model and is considered as a future work.
  This on line estimation is important in the case of real time control to make sure the estimated values are not misleading the results.

– The third step was a proposal of a new Monte Carlo based (MC-based) heating predictive control approach. This approach employs the building model, the occupation profile and the dynamic energy pricing to optimize the energy consumption. It has an advantage over the traditional model predictive controllers (MPC) regarding its simplicity (no mathematical optimization processes). The proposed method resulted in interesting heating plans in terms of consumption economy and load shifting at the same time.
  The following points appeared to be essential to get an optimal plan:
  * Generating a relatively high numbers of plans (to cover more possibilities);
  * Designing an appropriate comfort level;

  However, applying this plan without monitoring in real time constitutes an open loop control case. Therefore, we started the research for a real time control method to ensure the optimal plan application (closed loop).

– A research into real time control of the temperature, lead to the differential flatness control. This type of control appeared only 15 years ago. A new control algorithm based on the concept of differential flatness is successfully applied to building temperature control. The main advantage of this method is that the whole system variables (state and control) are described through the flat output and a number of its time-derivatives. Moreover, it guarantees having solutions in order to ensure a high quality of comfort for the users.

Further developments have to be considered as the continuation of this work. The generalization of the proposed MC-based control approach on the urban scale to optimize the total consumption must be the next step. Moreover, a further consideration of the effect of the type of heating system and their own inertia (electricity, gas based, collective, individual..) is important to allow applying the method on all heating systems. On the other hand, improving the proposed real time control and applying the free model control (which is based on the flatness control) are also in the perspectives of this work to facilitate the practical applications.

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Appendix A

Publications

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A simplified building thermal model for the optimization of energy consumption: Use of a random number generator

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ABSTRACT

This paper proposes a new method for an optimal control of the heating system at the building scale. This control is a new approach of energy planning that aims to decrease the heating consumption/expenses over a defined prediction horizon while respecting the occupants' thermal comfort. It employs a simplified building thermal model to simulate the building thermal behavior taking into consideration the weather predictions. This approach is based on the application of Monte Carlo method, i.e., a random generator for the heating system scenarios. The aim is to determine the optimal heating plan for the prediction horizon that fulfills the constraints regarding the thermal comfort of occupants and the minimization of the energy consumption/expenses together with achieving a load shedding.

1. State of art

1.1. Introduction

Energy is considered nowadays as one of the most challenging issues. In cold climates, heating is responsible for approximately 50% of the total final energy consumption [1]. According to ADEME and INSEE [2,3], buildings account for the highest energy consuming assets with 44% of the total energy consumption and 19% of the green house gas emissions in France. Strategies have been set in order to reduce the energy consumption. These strategies contain regulations to ameliorate the building thermal performance. Starting from January 2013, the thermal regulation reference (*RT*2012) is put in action in France. This reference includes many obligatory and complementary requirements that guarantee the conventional interior temperature and the reduction of energy consumption. It concerns building cold bridges (thermal bridges), building air-tightness (air permeability) and building thermal characteristics [2,4]. Moreover, insulation requirements and pricing plans have been developed to reduce the energy losses and the consumption peaks. According to [5,6], a considerable part of the energy consumed in the building sector is due to either bad insulation or bad control of the heating systems (unoptimized consumption).

A study of the National Renewable Energy Laboratory (NREL) identifies the "lack of innovative controls and monitoring systems" as one of the principal challenges in achieving high energy efficiency in buildings [7,8]. The control of energy in buildings uses mainly one of the following systems [9,10]:

- On/Off system: traditional systems.
- Proportional controls: this system aims at eliminating the cycling associated with on-off control. It includes an effector device (heater) and a controller. The heating power is controlled on a proportional relationship according to the temperature of the controlled medium [11].
- PID control: this method is popular in heating control. It combines proportional control with two additional adjustments (error integral and derivative), which helps the unit automatically compensate for changes in the system. PID controllers are robust and allow accurate tuning, but they cannot reflect the outside temperature effects [10,12–14,10]. Fig. 1 shows a block diagram of a PID controller. Wemhoff [15] concludes that a good calibration of proportional coefficients can reduce the system energy

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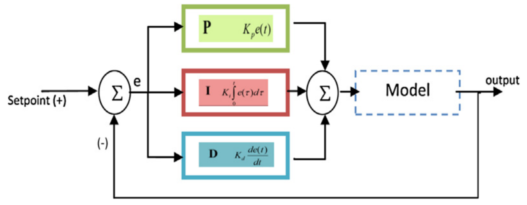


Fig. 1. PID controller block diagram.

consumption by up to 29% and can improve meeting temperature set points by up to 45%.

- Model predictive controllers (MPC) [10,16]: this method is considered as a powerful framework for the optimization of the buildings heat consumption as a constrained minimization problem considering both comfort requirements and limited capacity of the heating system. MPC is considered as an ideal framework to tackle this problem [17,18]. This approach depends on generating a heating plan for an upcoming prediction horizon which is a receding horizon where only the first step of the predicted plan is applied to the system while all other inputs are used only to make good decisions at the current time step. This requires an important computation power and a reliable weather prediction. However, nowadays with the powerful computation powers and the possibility to do the computation in external places such as clouds, MPC becomes more doable [19,20]. Castilla et al. [21] concludes that the non-linear MPC approach is able to maintain thermal comfort inside a comfort zone even in the presence of disturbances, and to minimize the energy consumption derived from the use of the HVAC system around a 53%, in comparison with other approaches.

1.2. Main idea of the paper

This paper presents a control approach that has a constrained optimization problem as in MPC. The optimization concerns the minimization of energy consumption by exploiting the occupation profile, the dynamic pricing and the building inertia (thermal mass).

This approach is based on the application of Monte Carlo method, i.e., randomly generating sequences of the heating system states, testing these sequences then choosing the best one for the heating according to the least consumption or the least price. The simplicity of the optimization process is the main difference between the proposed approach and MPC. Since the method is based on the use of three elements: the building inertia, the occupation profile and the dynamic pricing, it could lead to a higher heating consumption in the case of no-occupation. This allows shifting the energy consumption to the cheap pricing period. By doing this, we benefit of building slow heat dynamics to turn off the heating during the expensive pricing period maintaining the comfort needed in the occupation periods [22]. In other words, we benefit of the building thermal time constant which helps to maintain an acceptable level of comfort for a certain period. Meanwhile, heating can be reduced or even shut down [23,24]. The application of this method results in a heating plan which is optimal for the prediction horizon period (between all tested plans). Which constitutes the necessity of a large number of sequences to insure having an optimal plan.

Table 1
Hours classification according to the price of *kWh* in France 2014.

	Normal hours	Peak hours
Hour	22:00–06:00	06:00–22:00
Price (TTC) euro/kWh	0.1044	0.1510

2. Objectives

The thermal comfort is defined by several indicators such as the interior temperature, the relative humidity and the air velocity. Hence, the interior temperature is considered nowadays as the key element in building's heating. The thermal comfort temperature varies between day and night or according to the building usage [25,26]. A study of the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) proposed an interval of accepted indoor temperature according to the exterior one [26,27]. It is delicate to define the comfort temperatures because it highly affects the energy consumption and it depends on different factors as:

- the building usage;
- the activities of occupants (in the occupation periods);
- the internal heat gains to be considered.

Some scientific works studied the determination of optimal environment in buildings considering energy consumption and human comfort in a building [28] or in a certain type of buildings as the study related to office buildings optimal working environment in [29,30] and the study about residential buildings in [31]. Fig. 2 shows an example of a chosen comfort interval for an office building. It is essential to note that the thermal comfort in an occupation period in not to be compromised. While on the other hand, in the no-occupation period, we can authorize a higher heating to benefit of the cheap price of the energy. Afterwards, according to the building thermal constant, the building will keep a certain level of comfort for a certain period. This period depends on the building inertia and is taken into consideration.

After defining this comfort level, the objective is to minimize the energy consumption and cost. The energy consumption is the integration of the power supplied over time. In France, normally the electricity subscription is priced depending on the supplied power $P(watt)$ and the consumed energy $Q(kWh)$, a day time is also priced into two types: peak hours and normal hours. Table 1 shows the considered dynamic pricing of the electricity in 2014 in France ($euro/kWh$). Thereby the timing of consumption must be well planned in order to not exceed the maximum power supplied on one hand and to minimize the consumption cost on the other hand.

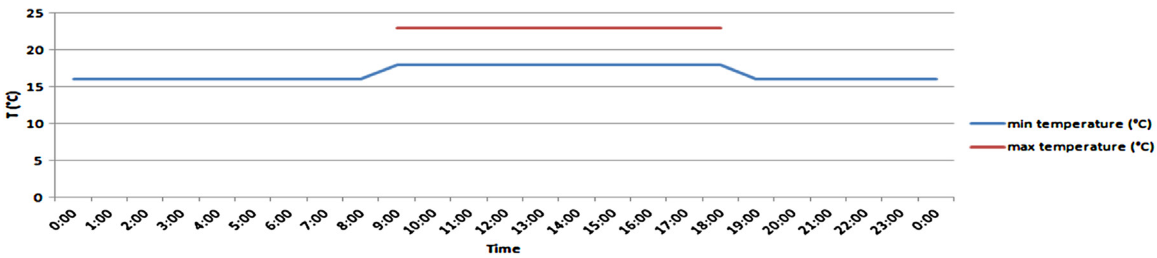


Fig. 2. An example for the a chosen temperature interval for an office building.

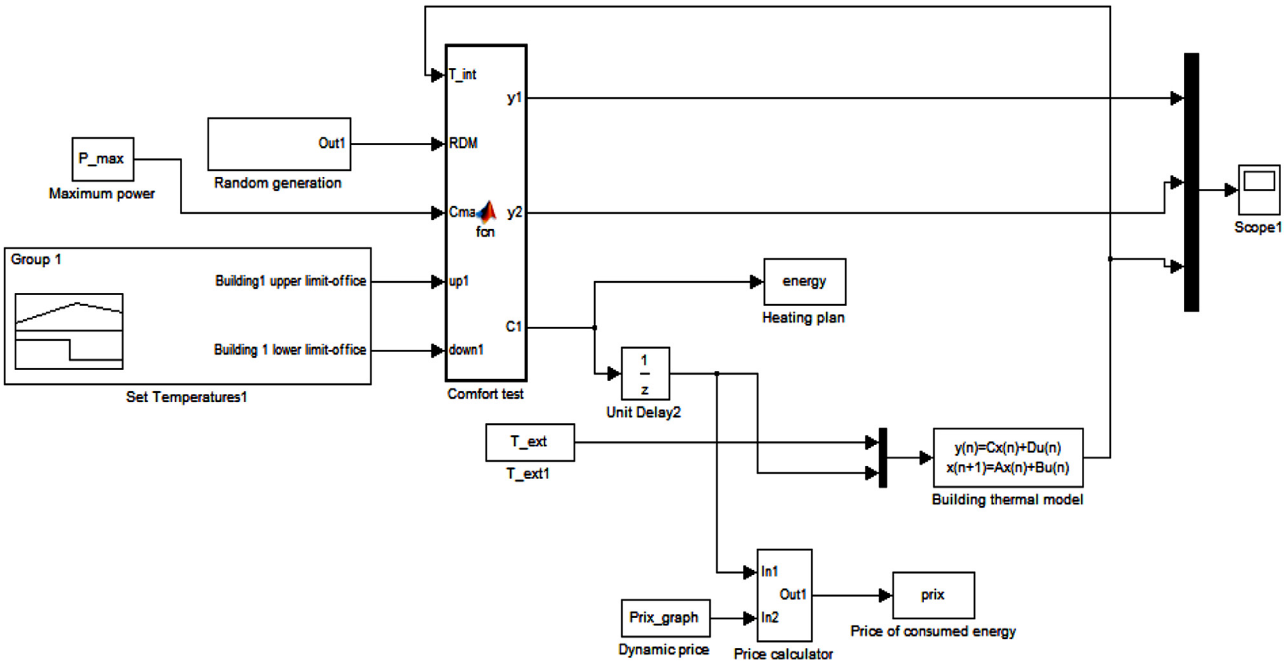


Fig. 3. The coupling of the building model with the proposed control system.

3. The building thermal model

A literature studies show that building thermal dynamics can be represented by a state space form [32,33]. A state space model consists of a set of differential equations derived from physical relations.

It has the form in Eq. (1)

$$\begin{aligned}\dot{X} &= A \times X + B \times U \\ Y &= C \times X + D \times U\end{aligned} \tag{1}$$

where X is the vector of system internal variables known as state variables, Y is the measured output vector, U is the control input vector, $\dot{X}$ represents the differentiation with respect to the time t and A, B, C, D are the system parameters.

In order to identify the parameters of the state space, information about the building materials, insulation layers and the thermal interaction between these materials are necessary. However, for the control process, the information about physical parameters of the model are not required, that's why a parameter estimation process is sufficient [34,29]. In order to better integrate the model in the control process, the model is preferred to be simple [35–37]. Hazyuk et al. [33] concludes that a second order state space is well fitted to describe the building thermal behavior, more precisely for the control process. The model used in this article is a second order state space. The output of the developed model is the interior temperature while there are three inputs: the outside temperature, the energy supplied by the heating system and the free gains (solar gains and interior gains).

The controllable source is the energy supplied, while weather forecast will be used to integrate the exterior temperature and the solar gain as uncontrollable entries of the system. However, most industrial systems use the same entries to regulate heating. The model is supposed to be a mono-zone model that represents a building or an area in the building where the interior temperature is supposed to be homogenous. The model will go into two phases before integrating it in the control process.

- Learning phase: to estimate the model parameters depending on available data sets;
- Validation phase: to validate the estimated parameters using other data sets.

The data sets used in these two phases concern historical recorded data of interior, exterior temperatures and the associated supply of energy. In our case, a model with the known parameters (material characteristics) built using COMFIE has served to establish a comparison basis for the parameter estimation process of the state space model used for the control. The parameter estimation was done using the same inputs and outputs. The comparison was achieved to make sure of the validity of this model [38].

The developed model used in the control process is a second order state space model which is likely to be used for the control functions regarding its simplicity [35,39]. The model was tested for several examples and it is compatible with the proposed control regarding its simplicity and sufficient representation of the building thermal behavior.

As the exterior temperature and the solar gains are very unpredicted sources those constitute the disturbance of the system, the prediction of the heating plan is made for 24 h horizon to have a reasonable weather prediction certainty. Anyway, in case of different weather data, a recalculation of optimal plan can be done or even a PID controller may be used as a complementary controller together with the predicted control plan to avoid having discomfort caused by incorrect prediction.

4. Control method assumptions and heating plan generation

As mentioned before, the energy source chosen for this study is the electricity. As the electricity has a maximum possible supplied power for n zones, the sum of allowed power at each time step for all the zones must be equal or less than the maximum. Fig. 3 represents the flow chart of the method.[1]

[1] This procedure is useful in the cases like the contracts with the electricity companies because it gives a solution for the over consumptions problems where the energy becomes extremely expensive.

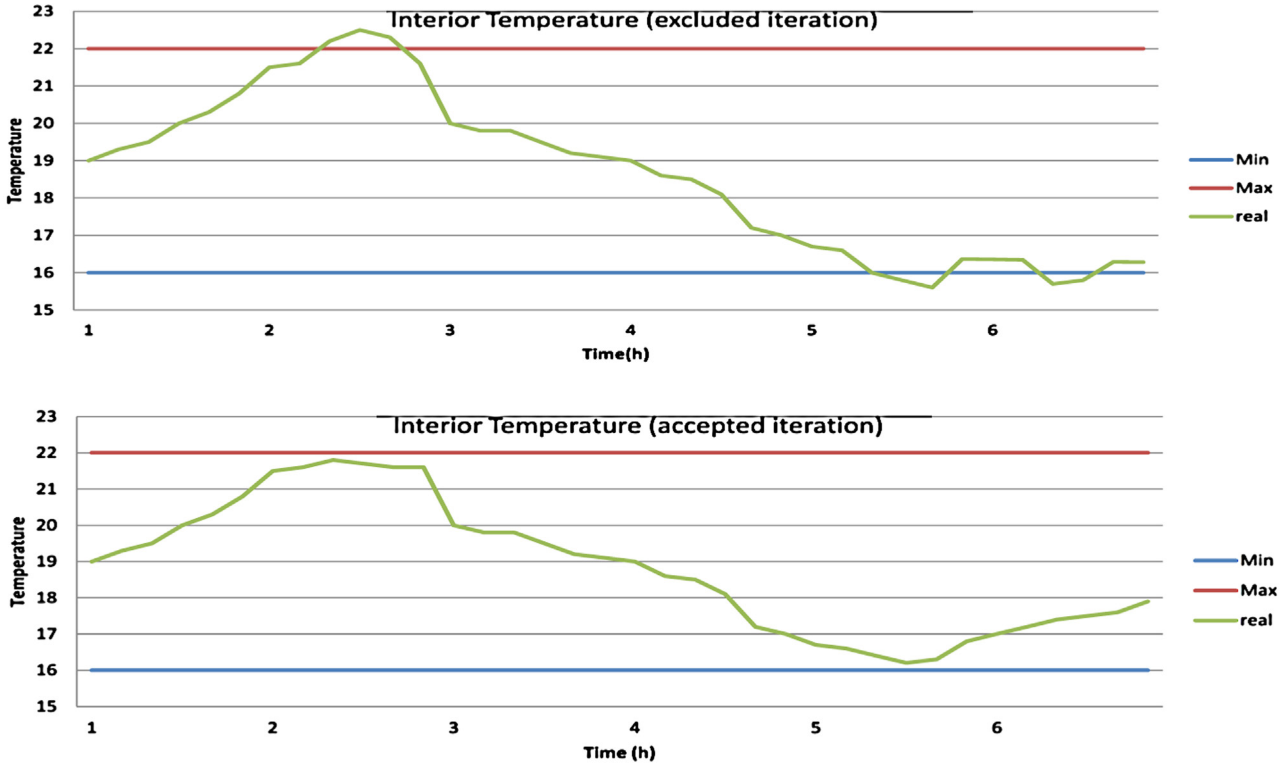


Fig. 4. The difference between an accepted and an excluded sequence according to the set temperature conditions.

The heating system is not an On/Off system. It can change state between M number of states. These states depend on the nature of the heating system and the possibility to control it. In this paper, we consider three states. However, it is possible to add more states. The considered three states are:

(1) On: 100% of the maximum power
(2) 50% of the power
(3) Off: no power

Concerning the distribution of the energy in the case of multi-zones or multi-buildings, it is assumed that one zone can receive at a certain time step 100% of the supplied power. This assumption is useful when buildings in the complex have different usages (residential, office, educational, etc.) and needs.

As the proposed heating system has M possible phases (3 in this study 100%, 50%, 0%) and in order to explore several heating possibilities, a method is proposed to generate heating scenarios. This method depends on randomly generating numbers α with M possible values (states) at each time step to create sequences. These sequences will be simulated using the simplified thermal model then controlled regarding the comfort level and finally the cheapest accepted sequence in terms of comfort will be retained.

4.1. The prediction time horizon

The prediction horizon for the control plan differs according to the building inertia (thermal mass) and time constant. It is evident that in buildings with high inertia, the time constant is long which leads to a slow heat dynamics. On the other hand, this is not the case in buildings with low inertia. Referring to the discussion about the prediction horizon length in [20], a prediction horizon of 24 h was chosen [20,19]. Moreover, the following two reasons have enforced this choice:

- To exploit the dynamic pricing of the electricity [40];
- As the heating plan is made using weather predictions, 24 h horizon seems to be reasonable in terms of weather prediction certainty.

While the choice of midnight as a start point is only a hypothesis made for this study. The prediction horizon and the start time can be easily changed and adapted according to the building requirements.

4.2. The optimization problem

This is a constrained optimization regarding: the thermal comfort of occupants, the limited heating power and the dynamic pricing policy.

Supposing that we have n thermal zones, M heating system states and K time steps Δt.

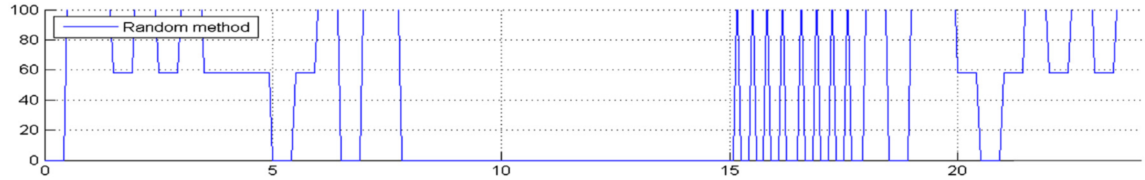
The optimization problem concerns finding the best combination of a sequence $\alpha_i(k)$ over the study period $K \times \Delta t$ that satisfies the minimization function in Eq. (2). For zone i, the cost function is expressed as:

$$\min G_i = \sum_{k=1}^{K} c_i(k) \times Q_i(k) \tag{2}$$

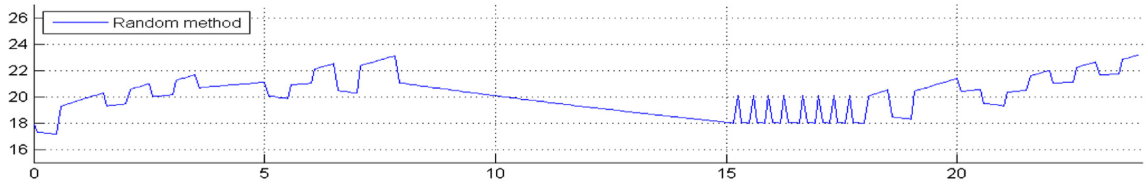
where $Q_i(k)$ is the consumption of zone (i) over a period Δt and $Q_i(k) = P_i(k) \times \Delta t$; $c_i(k)$ is the cost of zone (i) consumption over a time step k.

subject to:

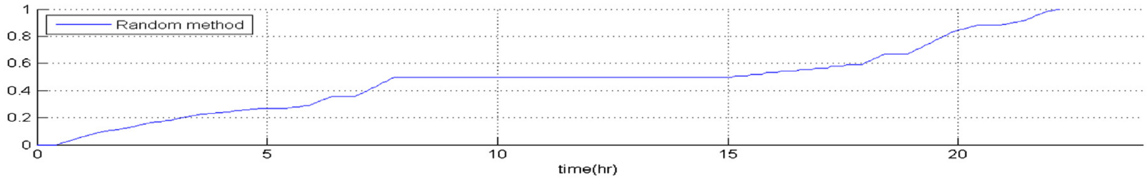
$$\begin{cases} P_i(k) = \alpha_i(k) \times P_{\max}, \\ Q_i(k) = P_i(k) \times \Delta t, \\ \alpha_i(k) \in [0; M-1] \times \dfrac{1}{M} \end{cases}$$



(a) Used percentage of total power

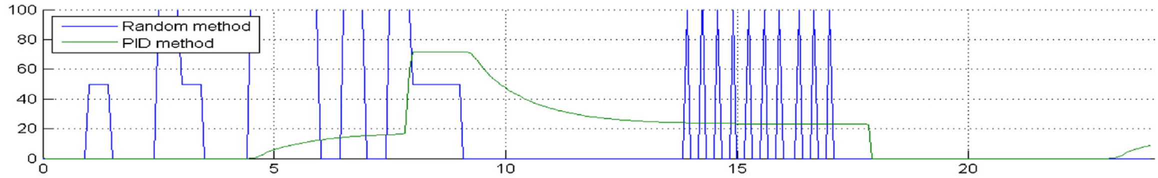


(b) Associated interior temperature

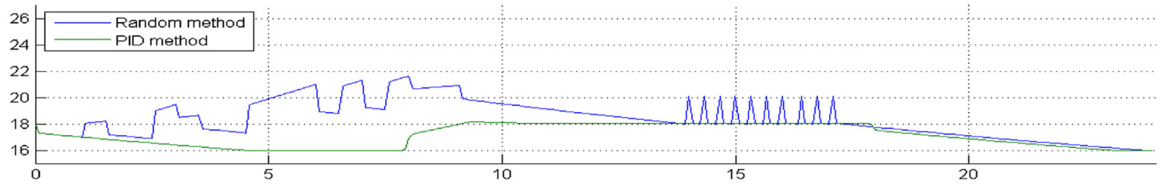


(c) Price in Euros for the simulation period

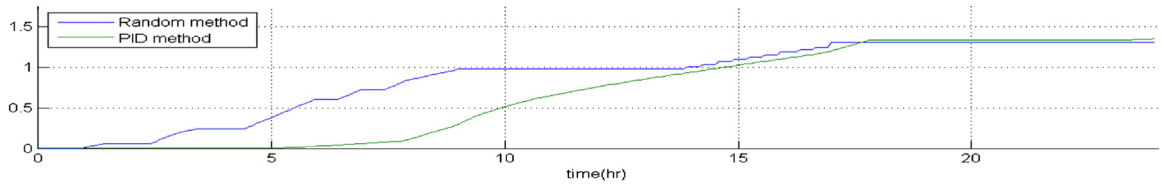
Fig. 5. Example of a building energy consumption, price and temperatures.



(a) Used percentage of total power



(b) Associated interior temperature

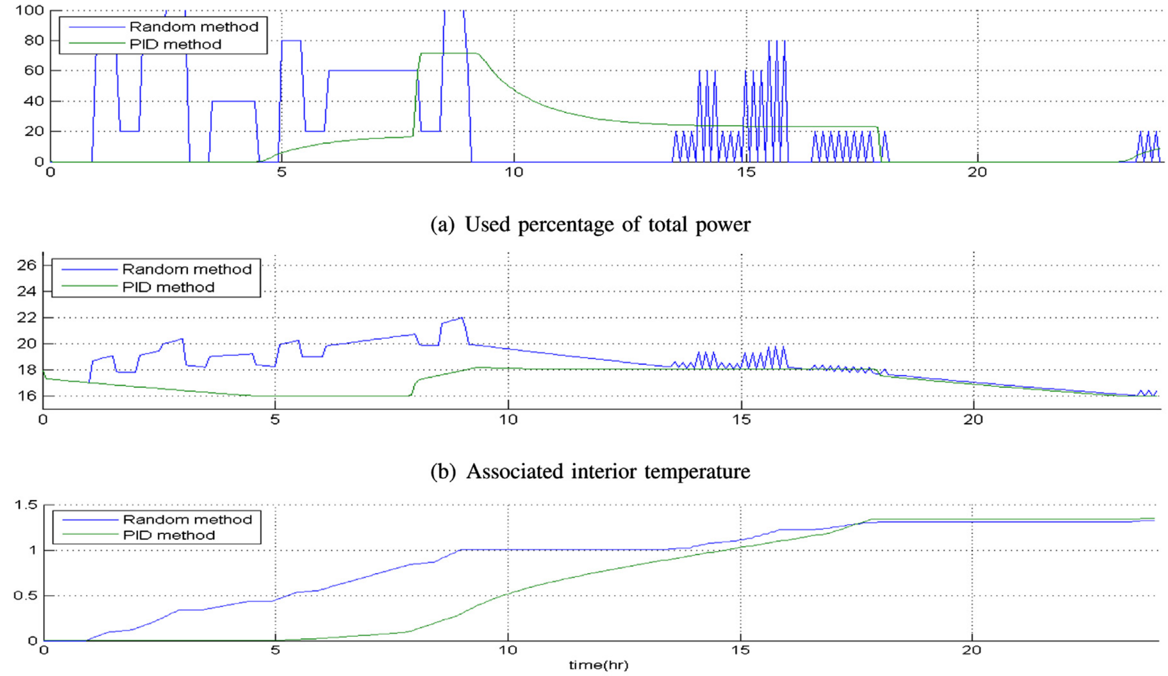


(c) Price in Euros for the simulation period

Fig. 6. A comparison of the energy consumption between the traditional PID system and the proposed random system ($M = 3$).

Table 2
Wall specification.

Wall layer	Density (kg/m^2)	Thickness (m)	Specific heat capacity (J/kg K)	Thermal conductivity (W/mK)
Plaster board	950	0.012	840	0.16
Insulation	25	0.2	1000	0.035
Air	1.4	0.05	1005	0.022
Brick wall	1700	0.15	800	0.84



(a) Used percentage of total power

(b) Associated interior temperature

(c) Price in Euros for the simulation period

Fig. 7. A comparison of the energy consumption between the traditional PID system and the proposed random system ($M = 5$).

where $\alpha_i(k)$ is a random number where: $\alpha_i(k) \in [0\,; M-1] \times (1/M)$; $P_i(k)$ is the supply power for zone (i) over a period Δt.

Maintaining the condition:

$$T_{i(\min)}(k) \le T_i(k) \le T_{i(\max)}(k) \quad (3)$$

where $T_{i(\min)}(k)$ and $T_{i(\max)}(k)$ are the minimum and maximum accepted interior temperature at a certain step k and knowing that the interior temperature $T_i(k)$ meets Eq. (1). For n thermal zones, we add the following conditions considering that the power source is limited:

$$\sum_{i=1}^{n} P_i(k) \le P_{\max} \Leftrightarrow \sum_{i=1}^{n} \alpha_i(k) \le 1 \quad (4)$$

Note that in the special case where $c_i(k)$ is a constant witch value is one, the function will correspond to a minimization of energy consumption as well as the cost.

The minimization will be done by choosing the best (cheapest) sequence of $\alpha_i(k)$ that fulfills the conditions of the problem.

To make sure that the defined thermal comfort is respected and to exclude all unsatisfactory sequences and reduce the calculation time, additional conditions will be added. These conditions must be designed to overcome the comfort limit cross. For our example we chose the following:

$$\begin{cases} \text{if:} \quad T_{i(\min)}(k) \ge T_i(k) \quad \text{then regenerate} \quad \alpha_i(k) \\ \text{if:} \quad T_{i(\max)}(k) \le T_i(k) \quad \text{then} \quad \alpha_i(k) = 0 \end{cases} \quad (5)$$

This condition will be applied respecting the priority of zones. A certain zone i is named prior when it's temperature is closer to the defined limits. Which means that the priority is dynamic depending on the most critical interior temperature. Fig. 4, illustrates the difference between an accepted and rejected sequence.

5. Case study

As a case study, an office building model is used. It is a two story brick building with an approximate ground area of 200 m^2. The walls consist of 4 layers and double glazed windows of 40 m^2 area. Table 2 shows the walls composition and characteristics, while the heat exchange with the ground is ignored supposing that the floor is well insulated. The building is considered as mono-zone so the temperature is homogenous in all parts of building. Analysis of the model and the application of the control method were conducted using MATLAB-SIMULINK.

The simulation time step is 5 min while the control is conducted with a time step of 30 min to avoid the continuous change of the heating system state (unless in urgent cases when the temperature crosses the comfort limits).

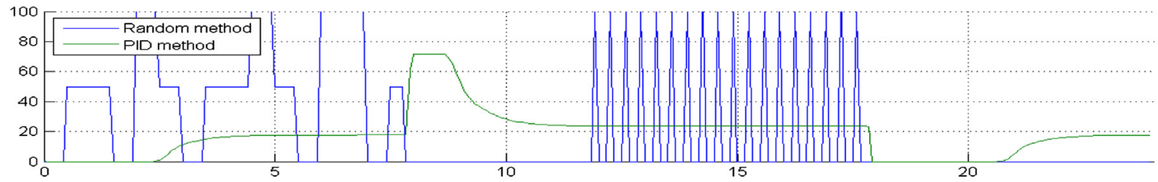
As a first step, the proposed method was tested on the described building supposing that it is an office building. Based on this, a comfort level was designed as in Fig. 2.

Running the simulations for a certain number of sequences (the more times it is repeated, the higher are the chances to get a better solution) will give us more possibilities of the heating plan. For each sequence, we will have the associated consumption and price as in Fig. 5. Depending on these results, we can then choose the sequence that fulfills our defined criteria.

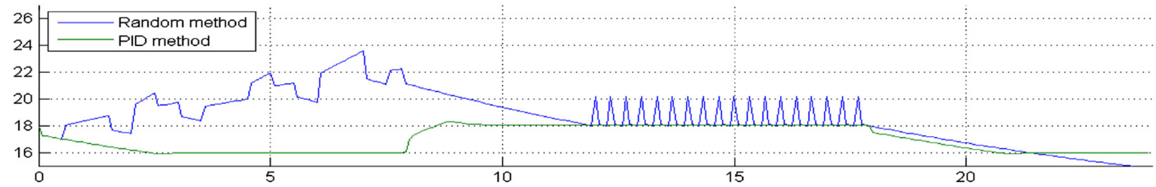
6. Comparison of the proposed method with the pid method

To show the efficiency of the proposed method, it is compared to the PID method which is largely used in heating control.

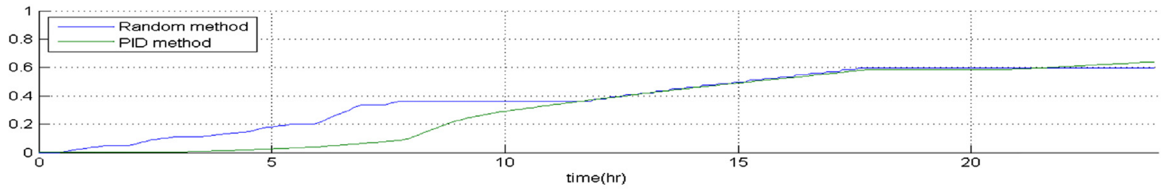
For the PID controller, we need a defined profile of set temperatures which can not be expressed by intervals. So for a justified comparison, we will use the minimum level of the interval designed for the building as a reference set temperature for the PID (which means a PID is based on a minimum level of comfort). In this case, the PID is sure to minimize the energy consumption.



(a) Used percentage of total power



(b) Associated interior temperature



(c) Price in Euros for the simulation period

Fig. 8. A comparison of the energy consumption and price between the PID and the proposed method.

A PID controller does not take into consideration the pricing policy. Here appears the advantage of the proposed system that can provide a better solution either in terms of price or consumption timings.[2]

Figs. 6 and 7 show the energy consumed using both methods together with the associated temperatures for two heating systems different in terms of number of states M. From the figure we can see two obvious advantages of the proposed method:

- An energy shedding is performed by exploiting the building inertia (avoid heating in the peak time);
- Due to this shedding of energy and the re-distribution of the load considering the dynamic pricing, the price of consumed energy is less than the PID method.

Efficiency of the proposed method is less obvious in the case of low inertia buildings because the heat cannot be stocked for a relatively long time to be used afterwords. Fig. 8 shows a heating plan for a building which has the same dimensions as the one studied before, but with less insulation (smaller time constant). From the interior temperature graph we can see that a fluctuation in the temperature is probable to happen due to the low insulation and change in the heating state. At 6.00 pm, both the PID and the random methods have the same cost while the comfort the proposed method provides is better than the PID.

7. Conclusion and future work

This paper presents a new control approach that depends on Monte Carlo method to generate an optimal heating plan. This approach is a minimization problem that has as constrains: the building inertia, the energy dynamic pricing and the thermal comfort of occupants.

These constrains allow a load shedding by distributing the consumption over the off-peak hours. This approach has advantages in terms of simplicity, computation power, time and efficiency. We applied this system on many types of buildings with various inertia. The obtained financial economy was up to 5% compared to the PID method (that has as set temperature the minimum limit of the proposed thermal comfort interval which leads to a lower comfort level). The method was adapted as well for n zones and a relatively high potential economy was obtained. This method is seen to be integrated in the heating control system of the building as well as in the consumption planning system (Building Management System BMS). It is also foreseen to be developed for an urban systems scale where the coupling of buildings with different usages and occupation profiles is possible. A further study to the application of this method in an urban system is in the perspective.

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Paper ID: C-109E
Title: Optimization of District Heating Consumption Using Random Heating Scenario Generator

Dear Ms. Ola ALHAJ HASAN,

I'm pleased to inform you that your paper" **Optimization of District Heating Consumption Using Random Heating Scenario Generator**" had been accepted by 2014 International Conference on Power and Energy Systems Engineering (CPESE2014), it will be published in "Applied Mechanics and Materials" [ISSN:1660-9336, Trans Tech Publications], which is indexed by Elsevier. Scopus and Ei Compendex (CPX), Cambridge Scientific Abstracts (CSA) , Chemical Abstracts (CA) , Google and Google Scholar, ISI (ISTP) , Institution of Electrical Engineers(IEE), etc.

Yours Sincerely,
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Conference Secretary of CPESE2014

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Optimization of District Heating Consumption Using Random Heating Scenario Generator

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Keywords: Smart grid, Optimization, energy, control, thermal model.

Abstract. This paper proposes a new method to optimize the control of the heating system of a district in a way that fulfills the thermal regulations and comfort in the whole district from one side and guarantees the minimization of the energy consumption (and bill) from the other side. This new method depends on coupling buildings with different functionalities and needs. A heating plan for the coupled entities will be generated afterwards. This plan makes advantage of the difference in occupation timing of the buildings and has as constraints the thermal comfort of the occupants and the maximum available energy. This heating plan takes into consideration the building inertia to design the supply plan and maintain the constraints.

Introduction

Buildings account for the first energy user in France with 44% of the total energy consumption and 19% of the green house gas emissions (ADEME and INSEE [1,2]). A National Renewable Energy Laboratory (NREL) study identifies the lack of innovative controls and monitoring systems as one of the principal challenges in achieving high energy efficiency in buildings [3,4]. District heating is a mechanism that distributes heat to multiple buildings from a central plant [5]. It is a very important technique that provides several buildings so-called a district with the energy needed to satisfy their needs and minimize the losses and the green gas emissions [6,7]. On average, over 80 per cent of heat supplied by district heating originates from renewable energy sources or heat recovery (i.e. from electricity production or industrial processes) [8]. However, in the case where the heat source is gas, the relation between the produced heat in the boiler level with the energy delivered to the building level makes the problem more complex and further study is needed [9,10].

Most of the cold developed countries are now heading towards the application of this concept regarding its high efficiency, easy operation and the relatively low cost compared to the individual heating systems. Figure 1 shows the countries the most using this technology in Europe [8,11].

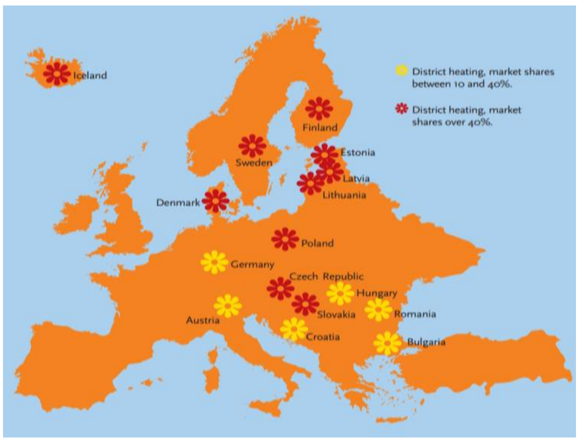

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Fig. 1: The use of the district heating technology in Europe [11]

This paper proposes an approach that helps to further reduce the total energy consumption in the district. It is focused on the case of electrical heating system. The main idea is to achieve a load shedding regarding the occupancy profiles and the building type (office, education, residence). The application of this approach on gas based heating system will be discussed in later publications and studies.

Generation of heating scenarios (plans)

The main goal of the district heating is to avoid losses caused by the individual energy generation or planning. The proposed approach generates heating plans (scenarios) for the entire district after clustering its buildings. A building clustering is done depending on the building occupation period. The occupation difference is an important feature that helps reducing the consumption peaks and assigning energy to different clusters according to the needs and usage. This will result in an energy shedding and the total energy consumption can be reduced. In the special case when the energy price is not constant, a cost minimization is done together with the consumption minimization.

The generation of heating scenarios will have as conditions the thermal comfort in each building as well as the building's inertia. This is taken into consideration through the thermal model designed for each building. For the work of this paper, we use a simplified thermal model to simulate the building thermal behavior.

In order to clearly explain the proposed method, an example of two buildings (or two clusters of buildings) with one energy source is studied. These two buildings are supposed to be a residential and an office building. The set temperature is designed as a comfort level expressed by the minimum and maximum accepted temperatures for users in each building. Figure 2 shows an example of a comfort level. These comfort levels are based on two main conditions:

1- The thermal comfort is a priority in the occupation period of any building. That is why in the occupation period, the ambiance temperature has to be within this level;
2- The minimum and maximum temperatures differ according to the building nature, usage and the internal gains. Fig. 2 shows one possible example of two building comfort levels; of course it can be changed according to building conditions.

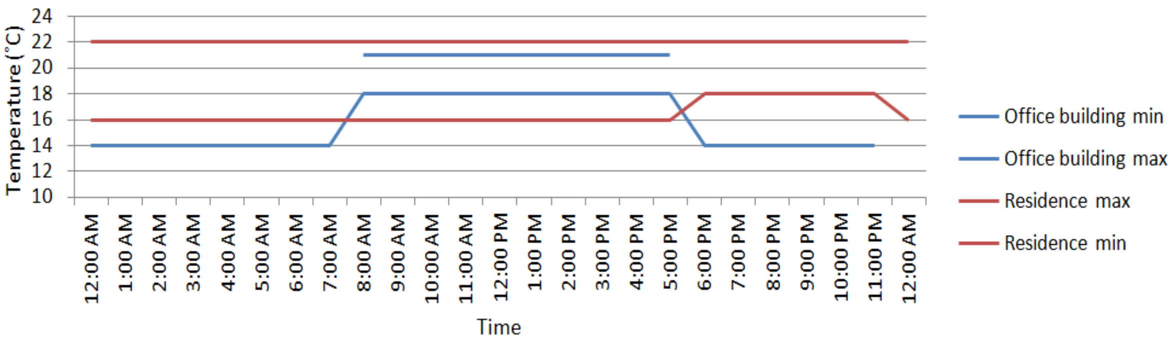

Fig. 2: An example of a comfort level for residential and office buildings

The heat plan is designed according to this thermal level by randomly generating many heat plans and then choosing the optimal one that meets the conditions to be applied.

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The optimization

The optimization concerns finding the best sequence α_i of energy partition between buildings which satisfies the minimization of the cost function expressed by eq. (1)
For n buildings or thermal zones and over a period ($K * \Delta t$):

$$\text{Min}\, G_i = \sum_{k=1}^{K} \left(\sum_{i=1}^{n} c(k).\, \alpha_i(k).\, P_{max}\right).\, \Delta t \tag{1}$$

Where: $c(k)$ is the energy price at time step k, P_{max} is the maximum available power for the whole district. Subject to:

- Thermal comfort condition, eq. (2). This thermal comfort is expressed by a minimum and maximum accepted temperature designed for a certain building regarding the thermal regulations and the occupants' needs (example in Figure 2);

$$T_{i\,(min)}(k) \leq T_i\,(k) \leq T_{i\,(max)}(k) \tag{2}$$

- Limited available power

$$\sum_{i=1}^{n} \alpha_i \leq 1 \tag{3}$$

The dynamic priority of buildings

If the random assignment for a set of buildings is always done in the same order and regarding the power distribution condition in eq. (3), that means that buildings don't have equal chances to keep their comfort levels. This will exclude a lot of iterations because the temperature in one or more building is out of the defined comfort level. Dynamic priority for buildings can help avoiding this problem. So at each time step, the system will define the building (or cluster) with the most critical temperature and give it the priority (the first random number will be assigned to it).

Doing the simulation so many times gives more scenarios of the heating plan. For each plan, there is the consumption and the price for each building and the total consumption - price for both buildings together.

Comparison between the proposed system and a PID controller

To show the credibility of this method, a comparison with a PID control system is done. A PID controller is commonly used nowadays to control heating systems [12]. Figure 3 shows the total consumption for both buildings over one day time using the proposed method and a PID controller.

Table 1. Energy price according to the time

	Normal hours	Peak hours	High peak hours
Hour	1h - 8h	9h - 16h 22h - 24h	17h - 21h
Price (Euro/kWh)	0.0864	0.1275	0.255

The energy price considered in this example is shown in table 1.

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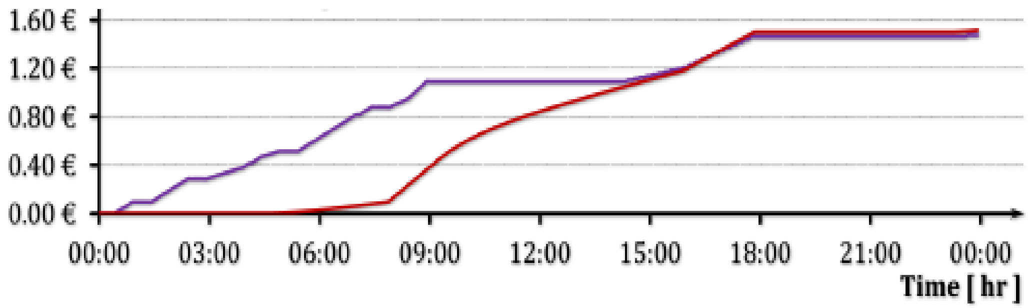

Fig. 3 Comparison of energy consumption for two buildings using the proposed method and the PID controller (Economy 4.6%)

Conclusion and future work

In this paper, a new method to optimize energy consumption is presented. This method depends on a new planning approach for the heat consumption and distribution that has the same mission as the predictive controls with some advantages in terms of simplicity and efficiency. The chosen plan makes advantage of the building inertia and the difference in the occupation profiles of the buildings to better distribute energy. Moreover, the thermal comfort of users is guaranteed due to the defined comfort level. At the same time, a load shedding is automatically done.

Applying this method on the district scale is easier than applying the optimization complex methods where lots of data is needed. The efficiency of this method was tested on an electrical heating system both on a building scale or district scale (several buildings). While for a boiler system, it is in the perspective to achieve a further study to adapt the method on the complexity of the system regarding the relation between the water inlet and outlet temperatures and the response time.

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Use of a random number generator and a simplified building thermal model for the optimization of energy consumption

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RESUME. Ce document propose une nouvelle méthode de gestion optimale de contrôle du système de chauffage. D'une part, ce système assure le confort thermique des occupants, d'autre part, il garantit la réduction de la consommation en énergie et par conséquent l'abaissement de la facture énergétique. Cette méthode est basée sur l'utilisation d'un générateur de nombres aléatoires pour le système de chauffage et d'un modèle thermique simplifié de bâtiment. La priorité pour cette génération concerne le confort thermique. Ensuite, l'analyse des séquences de production permet la détermination du contrôle optimal, au regard de la consommation en énergie ou du prix de celle-ci. Puis, cette séquence constituera le plan de chauffage pour le jour suivant. L'avantage de l'utilisation de cette méthode est son aptitude à employer la capacité thermique du bâtiment (inertie) d'une manière optimale en stockant la chaleur dans la structure du bâtiment et en l'utilisant ultérieurement, lorsque l'énergie sera plus coûteuse. Par ailleurs, coupler la consommation aux variations de prix de l'énergie permet de donner des moments privilégiés de chauffage quand l'énergie est moins chère. Cela signifie qu'un délestage d'énergie est automatiquement réalisé, contrairement aux PID existants et aux autres moyens de contrôle traditionnels qui utilisent l'énergie sans se soucier des heures de pointe ou des prix. Il est également important de préciser que cette méthode permet de trouver une solution optimale en testant un grand nombre d'itérations, signifiant qu'une optimisation est effectuée en commençant par des données médiocres.

MOTS-CLÉFS. confort thermique,gestion optimale,control de chauffage, délestage d'énergie

ABSTRACT. This paper proposes a new method for an optimal management of the control of the heating system. This system fulfills the occupants' thermal comfort from one side and guarantees the minimization of the energy consumption and the energy bills from the other side. This method is based on the use of both a random number generator for the heating system states and a simplified building thermal model. The priority for this generation concerns the thermal comfort. After that, analysis of the sequences outputs allows the determination of the optimal with regard to the energy consumption or price. Then this sequence will be the heating plan for the next day. The advantage of using this method is its ability to employ the building's thermal capacity (inertia) in the best way by stocking the heat in the building structure and using it later when the energy is more expensive. Moreover, coupling the consumption with the energy changing price helps giving heating preferred timings when the energy is cheaper which means that an energy shedding is automatically done contrary to the existing PID and other traditional controls that use the energy regardless the peak hours or prices. It is also important to mention that this method gives the possibility to find an optimal solution by testing a large number of iterations meaning that an optimization is done starting from very poor data.

KEYWORDS. Energy consumption control, random selection, energy optimization, comfort level, energy shedding

1 Introduction

Energy is considered nowadays one of the most challenging issues. The diminution of the fossil fuels resources together with the green house gas effects caused by burning them, make it crucial to reconsider the energy consumption as well as the emissions. In cold climates, heating is responsible for approximately 50% of total final energy consumption exploited in heating systems (Rezaie et Rosen (2012)). In France, buildings account for the highest energy consuming assets with 44% of the total energy consumption and 19% of the green house gas emissions according to ADEME and INSEE (Rouquette (2012), Carassus (2006)). Many strategies have been placed in order to reduce the energy consumption. Insulation requirements and pricing plans have been set to better control the energy losses and the consumption peaks. However, a considerable part of the energy consumed in the building sector is wasted either because of the bad insulation or because of the bad control of the heating systems (low efficiency, unoptimized consumption).

A study of the National Renewable Energy Laboratory (NREL) identifies the “lack of innovative controls and monitoring systems” as one of the principal challenges in achieving high energy efficiency in buildings (Richter et al. (2008), Fuchs et al. (2013)).

Existing controls use most likely one of the following systems(Mendes et al. (2003), Yahiaoui et al. (2006))

- On/Off system : traditional systems
- Proportional Controls : designed to eliminate the cycling associated with on-off control.
- PID control : combines proportional control with two additional adjustments, which helps the unit automatically compensate for changes in the system. (Naughton et al. (2011))
- Intelligent predictive controllers(Paris et al. (2010))

This paper aims to find a method to optimize the energy consumption by exploiting the building inertia (Thermal mass) in the best way and at the same time put constraints regarding the timing of consumption depending on the pricing plans as a reference which normally reflects the peak hours. Applying this, needs a model that reflects the building thermal behavior. We chose a simplified model to be to better integrate it in the control system (Berthou et al. (2012)) and to be able to do fast calculations which allows doing a large number of simulations, this mono-zone model is adjustable according to the available data used as entries. In literature studies, the problem of available data appears frequently when building a thermal model. That is also the reason why the model is preferred to be simplified according to the disposable data. At the same time, the entries chosen in this study are exterior temperature and the amount of energy (Including the solar gains and the heat flux from the heating system). The exterior temperature will be integrated in the model through a weather station forecast and the mission is to define the optimal amount of energy. This study proposes to control the central heating system depending on one indicator which is the interior temperature through defining an accepted level of thermal comfort. The coupling of energy consumption and price gives heating priority timings when the energy is cheaper, the stocked heat in the building structure (inertia) will then be re-pumped when the energy is expensive and the heating is off (Fuchs et al. (2013), Pirouti (2013)). This depends of course on the building insulation and thermal properties. This strategy will help avoiding consumption peaks or over consumption in the cases where there is a maximum consumption limit.

This new method depends on the concept of randomly generating many sequences of the heating system states, and then choose the best iteration according to the least consumption, the least price or both. The advantage of this method is that it can be actually applied to any heating system because the only information needed about the heating system is the utmost amount of kWh that can be provided whether it is the electricity or a boiler based system. This will also guarantee not to exceed the maximum allowed (in an electricity contract for example) no matter what happens. So the control system will find a solution to achieve the desired set temperature without exceeding the maximum allowed which means that a shedding of the energy is automatically being done. Another advantage to be mentioned is the fact that applying this method will guarantee having a relatively energy saver scenario (according to probability laws) of the heating system without the need to apply any mathematical based optimization processes.

2 OBJECTIVES

Thermal studies are dedicated to make sure that the building ambiance meets the thermal comfort. The latest is defined by several indicators such as the interior temperature, the relative humidity, the air velocity .. etc. Hence, the interior temperature is considered nowadays as the key element in heating studies and HVAC systems to express the thermal comfort. To achieve thermal comfort, a set temperature must be met. This set temperature varies between day and night or according to the building usage (Klein et al. (2011)).

Therefore, in this study, instead of defining a set temperature, we assumed an interval of temperatures that assures the thermal comfort. This interval will be designed according to three items :

- The building usage
- The thermal comfort of occupants (in the occupation periods :The 90% acceptability range)
- The internal heat gains to be considered

After defining this comfort level, the objective is to minimize the energy cost and consumption which is the integration of the power supplied over time.

Table 1 shows the considered hourly price of the electricity in France (Euro/kWh). In this study, the heating source in considered to be Electricity which is the case in special complexes as Eco-cities or small complexes with two or three buildings. While for the future work we will move on to consider a gas-based heating system as well.

	Normal hours	**Peak hours**	**High peak hours**
Hour	1h - 8h	9h - 16h 22h - 24h	17h - 21h
Price euro/kWh	0.0864	0.1275	0.255

TABLE 1: Hours classification according to the price of kWh

3 CONTROL METHOD ASSUMPTIONS AND HEATING PLAN GENERATION

The proposed method is expressed in the flow chart shown in figure 1 Where n is the number of thermal zones, M is the number of heating system phases

- K is the number of the time steps Δt that correspond to the total simulation period and k is the time step

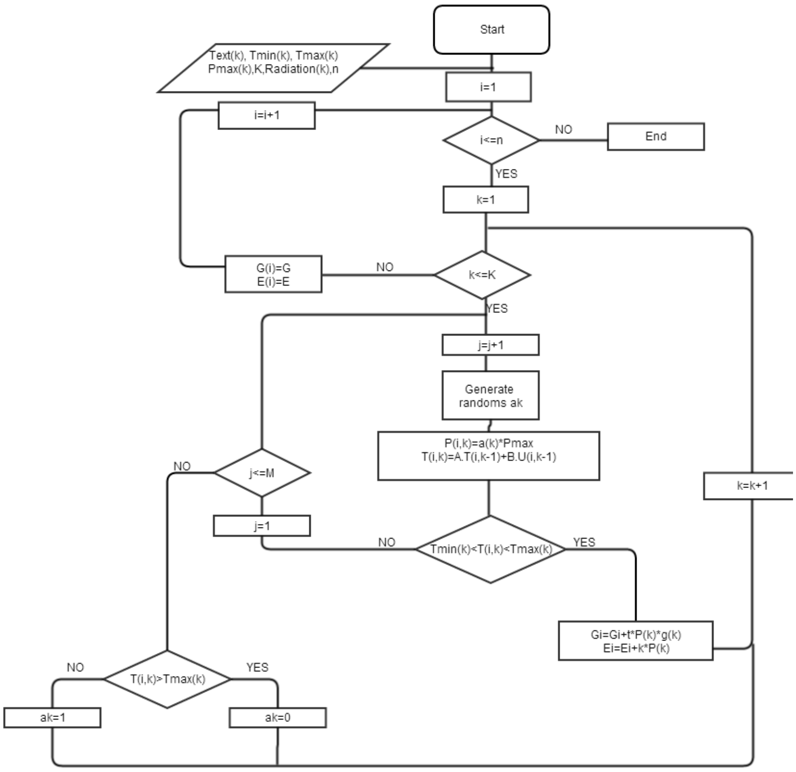

FIGURE 1. The control method flow chart

- $P_i(k)$ is the supply power for zone(i) over a period Δt
- $Q_i(k)$ is the consumption of zone(i) over a period Δt and $Q_i(k) = P_i(k) * \Delta t$;
- $c_i(k)$ is the cost of zone(i) consumption over a time step k
- $\alpha_i(k)$ is a random number where : $\alpha_i(k) \in [0; M-1] * \frac{1}{M}$
- M is the number heating system states

The optimization problem is Concerned by finding the best combination of a sequence $\alpha_i(k)$ over a study period $K * \Delta t$ that satisfies the following :
For building i case, the cost function is expressed as the following :

THE OPTIMIZATION PROBLEM :

$$minG_i = \sum_{k=1}^{K} c_i(k) * Q_i(k) \qquad (1)$$

Note that in the special case where $c_i(k)$ is a constant witch value is one, the function will correspond to a minimization of energy consumption as well as the cost.
subject to :

$$\begin{cases} P_i(k) = \alpha_i(k) * P_{max}, \\ Q_i(k) = P_i(k) * \Delta t, \\ T_i(k) = A_i * T_i(k-1) + B_i * U_i(k-1), \\ \alpha_i(k) \in [0; M-1] * \frac{1}{M} \end{cases}$$

Maintaining the condition :

$$T_{i(min)}(k) \leq T_i(k) \leq T_{i(max)}(k) \tag{2}$$

For n buildings, we add the following conditions considering that the power source is limited :

$$\sum_{i=1}^{n} P_i(k) \leq P_{max} \Longleftrightarrow \sum_{i=1}^{n} \alpha_i(k) \leq 1 \tag{3}$$

The minimization will be done by choosing the best (cheapest) sequence of $\alpha_i(k)$ that fulfills the conditions of the problem.

3.1 Boundary conditions :

To make sure that the defined thermal comfort is respected and to exclude all unsatisfactory iterations and reduce the calculation time, additional conditions will be added. These conditions must be designed to overcome the comfort limit cross, for our example we chose the following knowing that it can be changed depending on M and the building dynamic :

$$\begin{cases} \text{if : } T_{i(min)}(k) \geq T_i(k) \text{ then } \alpha_i(k) = 1 \\ \text{if : } T_{i(max)}(k) \leq T_i(k) \text{ then } \alpha_i(k) = 0 \end{cases} \tag{4}$$

This condition will be applied respecting the priority pf buildings. A certain building is named prior when it's temperature is closer to the defined limits. Which means that the priority is dynamic depending on the most critical interior temperature.

4 Case Study

As mentioned before, the simplified thermal model was designed and learned using data taken from COMFIE as a valid thermal modeling software.

The historical weather data was taken as well from COMFIE, noting that for the application of the method, the predicted exterior temperature can be searched directly from any weather website or weather station. A recalculation must be anticipated in case there is a significant difference between the weather forecast and the real weather conditions to avoid any comfort failures. The analysis of the model and the application of the control method was done using MATLAB-SIMULINK which is a perfectly adapted environment for control systems.

As a case study, an office building model was built in COMFIE and used. It is a two story brick building with an approximate ground area of $200m^2$. The walls consist of 4 layers and double glazed windows of $40m^2$ area. Table 2 shows the walls composition and characteristics, while the heat exchange with the ground is ignored supposing that the floor is well insulated. The building is considered as mono-zone so the temperature is homogenous in all parts of building.

Wall layer	Density $[kg/m^2]$	Thickness $[m]$	Specific heat capacity $[J/kg.K]$	Thermal Conductivity $[W/mK]$
Plaster board	950	0.012	840	0.16
Insulation	25	0.2	1000	0.035
Air	1.4	0.05	1005	0.022
Brick wall	1700	0.15	800	0.84

TABLE 2: Wall specification

Furthermore, as mentioned before, the energy price is directly integrated so the price of the consumed energy will be calculated in the same loop for each iteration. Figure 2 shows how the building model was integrated in the control loop. The simulation time step is 5 min while on the other hand the control is done with a different time step of 30 minutes to avoid the continuous change of the heating system state(unless in urgent cases when the temperature crosses the comfort limits).

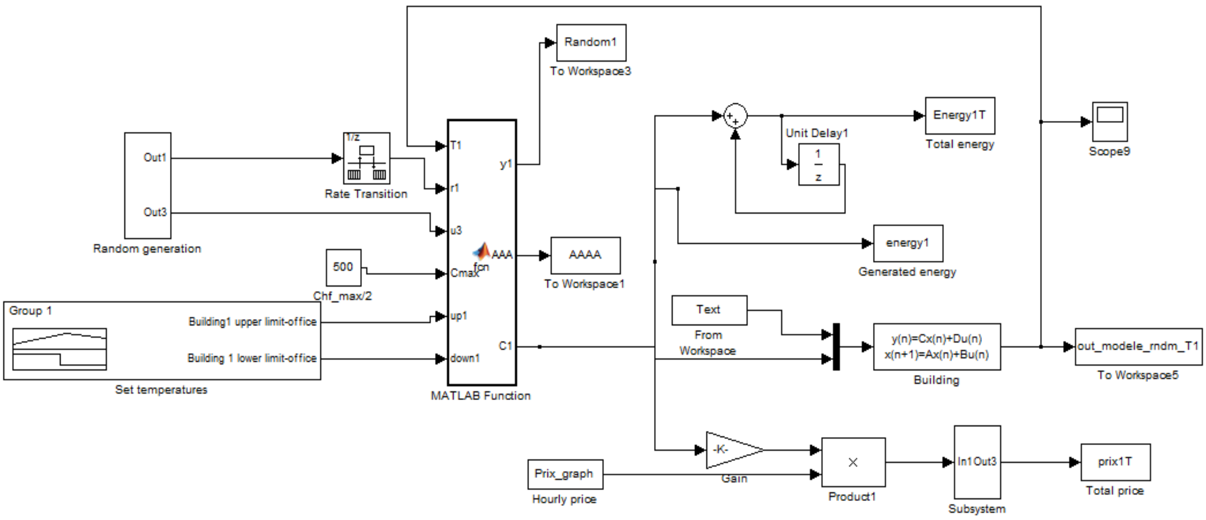

FIGURE 2. The coupling of the building model with the proposed control system

5 A COMPARISON OF THE PROPOSED METHOD WITH A TRADITIONAL PID SYSTEM

To see how efficient is the proposed method, it is necessary to compare it to another traditional method. The one we chose for this comparison is one of the most used methods to control the heating systems nowadays which is a PID controller. The choice was built regarding that the PID is in the middle between the primitive On-Off control and the intelligent predictive methods.

For the PID controller, we need a defined profile of set temperatures which can not be expressed by intervals. So for a justified comparison, we will use a reference set temperature taking into consideration that a PID is always sure to stick to it (when well designed). To do the comparison, we will consider the minimum level of the interval designed for the building considering it as a set temperature (which means we have a minimum level of comfort). Another important note is that a PID controller needs a system with the ability to work with different percentages which needs valves and maintenance costs. In this case, the PID is sure to consume the minimum energy possible but it is not necessarily the minimum price. Moreover, it doesn't take into consideration the peak hours. And here appears the advantage of the proposed system that can provide a better solution either in terms of price or consumption timings [1].

Both methods were applied with the same set of entries (exterior temperature and initial interior temperature) on the building represented by the simplified model, for the proposed method we ran the simulation 2000 times while for the PID one simulation is enough.

Figures 3, 4 shows the energy consumed using both methods together with the associated temperatures (For 2 cases : M=3, M=5). From the figure we can see two obvious advantages for the proposed method :

- An energy shedding is done by exploiting the building inertia heating (avoid heating in the peak time)
- Due to this shedding of energy, the price of energy is less than the one of PID (because the energy is more expensive in the peak time)

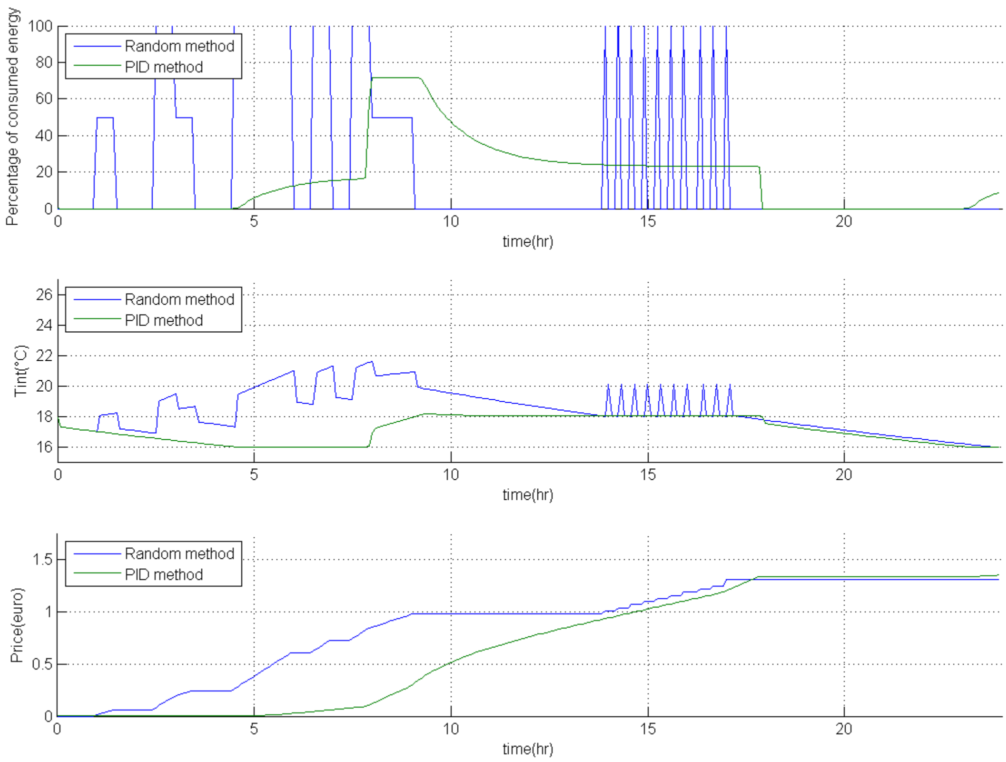

FIGURE 3. A comparison of the energy consumption between the traditional PID system and the proposed random system(M=3)(4.6% less expensive)

Table 3 shows some chosen iterations from a simulation done 2000 times. From the table, it is obvious that the least price is not necessarily associated with the least consumption. While on the other hand, two different iteration with exactly the same amount of consumption don't necessarily have the same price(terations 16,102).

6 Discussions

The proposed method is very effective if the simulation is repeated for a large number of iterations. So that there is a real need for a powerful machine to make sure of having a sufficient number of iterations. On the other hand, even the mathematical detailed optimization method, need the same powerful machines with the advantage for our method that we can build the model

1. That depends on the heating system capacity as well as the building inertia

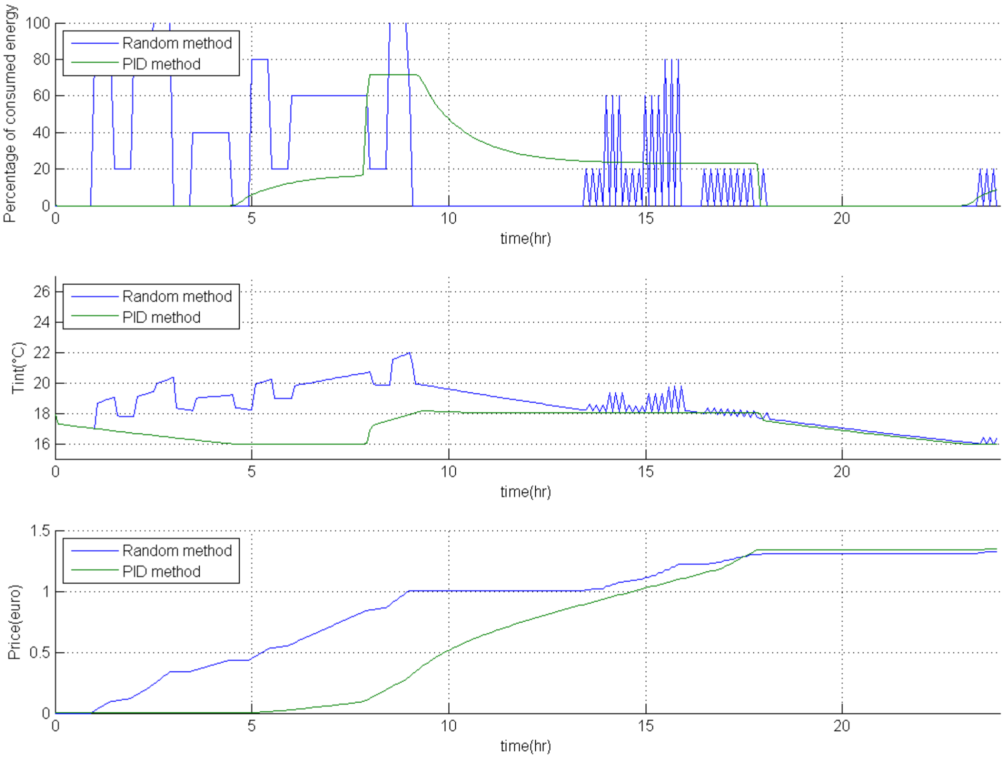

FIGURE 4. A comparison of the energy consumption between the traditional PID system and the proposed random system(M=5)(1.75% less expensive)

Iteration	Total consumed energy (% of PID)	Price (% of PID)
3	158,71	107,38
16	198,9	144,96
102	198,9	137,8
1371	154,4	125,17
1578	131.2	91.78
PID	100	100

TABLE 3: Some iterations from 2000 iteration made, consumption - price comparison

starting from the available data while for mathematical optimizations, details about the building and data are needed. Another advantage of this method is that some iterations will actually have the same consumption but different prices or the other way around which means that in fact we can get a better solution.

As the simulation will be done taking into consideration the limited available power, no over consumption can happen. That is simply because the system will automatically adapt to get the desired temperature in each time step considering the maximum power available. A traditional control system uses the energy when it is needed disregarding the price (the example of PID) while in this approach, a load shedding is automatically done.

The most important advantage of this method is its potential to do the energy consumption plan for more n buildings (urban scale) unlike many other control methods.

7 Conclusion and future work

In this paper, a new approach to optimize energy consumption is presented. This approach has some advantages in terms of simplicity and efficiency as explained before. Moreover, the thermal comfort of users is guaranteed due to the thermal intervals at the same time where a load shedding is automatically done. However, further developments can be done to improve the method and guarantee the optimization. One of these developments is to add the condition to use less energy when it is more expensive. This will minimize the cost of the energy.

A procedure to apply the best iteration as a heating plan for the next day will be foreseen together with a real time monitoring and correction one. Finally, this method will be generalized to be applied on more than one zone or building. In this case, more conditions should be set in terms of maximum available power and comfort scenarios. Doing that will facilitate employing this approach on a traditional district heating system (boiler system) which has different levels of energy distribution to be added as conditions as well as other limitations and constraints regarding the distribution network. The same approach with more constraints can be applied regarding that the available maximum capacity for each system is the one of the higher level system.

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