Forecast and control of heating loads in receding horizon

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FORECAST AND CONTROL OF HEATING LOADS IN RECEDING HORIZON

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Forecast and control of heating loads in receding horizon

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Abstract

Reducing the emissions of greenhouse gases from the energy sector is an essential component of mitigation of anthropogenic climate change. This is primarily addressed through energy efficiency (reducing the energy use for a given activity) and decarbonisation of the generating mix (reducing the emissions from each unit of energy consumed), which both come together with further socio-economic benefits. Recent developments in communication, computing and sensing have resulted in widespread availability of data and computational power, which opens the way to new solutions to this sustainable energy challenge – especially at the end-user level.

The work presented in this thesis concentrates on the use of mathematical modelling and optimisation for short-term forecast and predictive control of heating loads. For the control investigations, focus is made upon energy efficiency and carbon intensity, considering the specific application of heating in single family houses.

Forecast is an important tool for energy systems operation, as such systems often require a high level of reliability in their operation. At load level, the forecasts are essential inputs for predictive controllers, which are valuable for efficient and flexible load operation meeting the needs of end-users. At generation and network level, forecasts reduce the operational uncertainties and therefore the need for costly and inefficient operational margins to ensure security of supply. An application to district heating load forecast is introduced in the second chapter of this work, where a first contribution to evaluation of recursive least squares -based forecast of greenhouse heat load is presented. Moreover, forecast of disturbances for predictive control is presented, together with prediction methods to quantify the actual benefits from a controller change in practice.

Model predictive control is being increasingly recognised as a valuable control method to improve energy efficient and flexible heating operation. Its versatile optimisation mechanisms allow it to adopt a variety of strategies for optimising operation. However, trade-offs arise from these choices of strategy; for example between energy use, power cost, and carbon footprint. This is treated in the third chapter, which presents two examples of investigations on single family houses with electricity-powered heating in a Danish context.

An essential component of a model predictive controller is the control model. The identification of this model is currently the costliest part of the development, and a bottleneck to widespread implementation. A brief state of art analysis of model identification for building thermal dynamics is provided in the fourth chapter, together with an application to a real super-insulated single-family house.

Another essential aspect in economic formulations of predictive control is the price signal. When the aim is reducing of the carbon footprint, the dynamic carbon intensity of power is a particularly interesting candidate. This metric is studied in the fifth chapter, where the average carbon intensity of the power consumed is proposed as performance metric for flexible load operation. An application to single-family house heating in a Danish setting is then introduced to illustrate the concept.

Lastly, the final chapter concludes on the research and provides suggestions for future work in the field.

Resumé

For at begrænse den globale opvarmning er det nødvendigt at sænke udledningen af drivhusgasser fra energisektoren. Det kan primært gøres ved at bruge energi mere effektivt (bruge mindre energi på en aktivitet) og producere den på en måde der udleder mindre drivhusgas. Begge to bidrager også med mere social og økonomisk velfærd. I de seneste årtier det sket er det blevet mange fremskridt i kommunikation, databehandling og måling. Det har åbnet vejen til mere data og regne kraft, som kan bruges til nye løsninger for grøn omstilling, især på brugerniveau.

Dette projekt fokuserer på brug af matematisk modellering og optimering for kortsigtede prognoser og prædiktiv styring af varmeforbrug. Undersøgelser om varmestyring fokuserer på energiforbruget og de indirekte udledninger af drivhusgasser i parcelhuse.

Prognoserne er vigtige i energisystemerne for at sikre en yderst pålidelig drift. På brugerniveau er prognoserne nødvendige for prædiktiv styring, som forbedrer effektivitet og fleksibilitet af driften. Disse prognoser hjælper også på produktions og transport niveau, hvor de reducerer usikkerhederne og derfor behovet for en dyr og ineffektiv sikkerhedsmargen. En anvendelse af prognoser til drivhuses varmeforbrug introduceres i andet kapitel af dokumentet. Denne præstationsevaluering af rekursive mindste kvadrater er det første bidrag af forskningsarbejdet. Prognosemetoder præsenteres også for input data til prædiktivstyringssystemerne og evaluering af deres praktiske forbedring.

Modelbaseret prædiktivstyring bliver stadig mere anerkendt som en metode til at bruge energi mere effektiv og fleksibelt. Den bruger optimerings mekanismer som kan tilpasses til et stort udvalg af strategier. Alligevel er der kompromiser mellem strategierne, for eksempel mellem energiforbrug, omkostninger, og drivhusgas udledninger. Det er illustreret i det tredje kapitel, med to simuleringseksempler i parcelhuse med elvarme i Danmark.

I prædiktiv styring er det vigtig at have en god dynamisk model af systemet. Identificering af denne model er den dyreste del af udviklingsprocessen, og derfor en flaskehals for udbredt udvikling af prædiktiv styring. Det fjerde kapitel præsenterer en state-of-the-art analyse af dynamisk modellering for bygninger og opvarmnings systemer, sammen med en anvendelse til et ægte superisoleret parcelhus.

Prissignaler er nødvendige for økonomisk prædiktiv styring. Når det handler om at reducere udledninger af drivhusgas, kan det blive relevant at bruge det dynamiske udledningsfaktor (drivhusgas udledning per enhed af energi) som prissignal. Det introduceres i det femte kapitel, hvor den gennemsnitlig udledningsfaktor bliver præsenteret som mål for fleksible energiforbrugere. Konceptet illustreres derefter i et eksempel om opvarmning af et dansk parcelhus.

Det sidste kapitel konkluderer forskningen og åbner vejen til yderligere arbejde inden for prognose og prædiktiv styring af opvarmningssystemer.

Contents

"No matter what accomplishments you make, somebody helped you."

A. Gibson

Preface and acknowledgements

Although only one name appears on the front page of this thesis, it would never have been possible without the contribution and support of many. In fact, a comprehensive list of those would surely consist of more lines than the thesis itself. I will thus be brief for the sake of practicability, with the hope to be forgiven for the inherent unfairness.

Research hardly gets anywhere without a context, helpful guidance and feedback, human exchanges, and financial support. I would like to thank Per Dahlgaard Pedersen and Henrik Lund Stærmose from Neogrid Technologies ApS for offering me the opportunity to carry out my Ph.D. research with their company. I am also thankful to my main supervisors at Aalborg University, Rafael Wisniewski and Petar Popovski for their precious guidance, input, and feedback throughout the project. Moreover, I would like to thank Henrik Madsen and Peder Bacher from DTU Compute, as well as Laurent Georges from NTNU and Igor Sartori from SINTEF for allowing a couple of enriching external research stays to happen. When it comes to financial support of the project, I would like to acknowledge the European Union for funding the position through the AVANTAGE ITN project[1].

Work is done more happily and effectively when surrounded by kind and dedicated fellows. Here, I would like to thank the team at Neogrid and the fellows from the Control and Automation section at AAU for the numerous good times and experiences we shared in these years spent together. I am also thankful to the teams at DTU Compute as well as NTNU (and SINTEF) for their warm welcome and benevolence during my external stays. I would also like to thank my colleagues of the ADVANTAGE and CITIES projects, together with fellows of the IEA EBC Annex 67 for their friendliness and our inspiring exchanges.

We humans hardly achieve any demanding activity without love and support, all the less in sometimes alienating conditions. I am thus particularly

[1] ADVANTAGE was funded under EU's Seventh Framework Programme for research, technological development and demonstration under grant agreement no. 607774.

thankful to my close friends and family (including those who joined the choir invisible before these lines were completed) for their unconditional support and love. These have been invaluable for keeping the ship afloat throughout the journey, and a great life lesson for me. This thesis is consequently dedicated to them.

Pierre J.C. Vogler-Finck
Aalborg Øst, 21st February 2018

Part I

Introduction

"The question [of the energy transition] is much more fundamental [than a fuel shift]: it does not only involve the type of resources used, but also and above all their end-use, and the way they are consumed."

E. Lasida

1 Introduction

This chapter introduces the context of heating loads in energy systems, including the associated global climate concerns.

1 Global warming: a threat calling for an energy transition

In this section, the current energy system introduced in the context of global warming concerns.

1.1 Anthropogenic greenhouse gas emissions are endangering human prosperity and the biosphere

Since the industrial revolution in the XVIIIth century, humanity has become very reliant on fossil fuel combustion to sustain its economic activity. This combustion (together with other processes such as land use changes) releases significant amounts of *greenhouse gases* (GHGs)[1] in the atmosphere, which reinforce the natural greenhouse effect keeping the planet Earth warm enough to host life. Unfortunately, this reinforcement is such that the average global temperature is increasing. This phenomenon is known as *global warming*, which is one of the numerous dimensions of the *climate change* phenomenon.

[1] These are often referred to as "carbon", due to a strong focus on CO_2 . More details on GHGs is found in Chap. 5.

This change has a dramatic impact on the biosphere, which in turn affects human communities. Scientifically proven examples include threats to freshwater resources (putting water supplies at risk), agricultural yields (endangering food security), ice sheets and permafrost (negatively impacting the livelihood and economic activity of local populations), as well as marine ecosystems (jeopardizing livelihoods of fishing communities), among others. Further information on impacts is found in detailed reviews at global [1] and regional [2] levels. Due to the magnitude of these impacts, uncertainties, and the associated threats, anthropogenic climate change constitutes a transgression of the safe operating zone of the planetary system and an evolution into a so-called "zone of uncertainty" where risks for humanity are greatly increased [3, 4].

Growing awareness of this global climate threat in the recent decades led to the creation of the *International Panel on Climate Change* (IPCC) in 1988 to assess climate change and mitigation pathways from a scientific perspective [5]. Its work and conclusions are recognised by the United Nations Framework Convention on Climate Change (UNFCCC) in its *Paris Agreement*, a treaty ratified by 172 countries[2] which defines a common quantitative target of "[h]olding the increase in the global average temperature to well below 2 °C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 °C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change" [6]. It was however pointed out by critics that the resulting country pledges may be insufficient to reach the target [7], insufficiently ambitious, and lacking binding enforcement mechanisms.

1.2 The current energy sector is a major source of emissions

According to IPCC figures for the year 2010, the production of heat and electricity is responsible for 25% of humanity's GHG emissions, while other energy-related emissions accounted for 9.6 % [8, p.44] (i.e. 34.6 % of global emissions for the whole energy sector).

On a worldwide level over the last decades, economic growth (fast in some developing countries) and an increased share of coal in the global fuel mix have resulted in increasing global emissions. According to IPCC, this global increase was of 1.7 % per year for the period 1990–2000, and 3.1 % per year for the period 2000–2010.

Worldwide, the building sector is the largest single consumer of energy, covering over 30 % of total final energy demand [9, p.17]. This consumption

[2]The figure applies at the time of writing, as more countries have signed it but nt yet proceeded to ratification. These 172 countries include the European Union (EU), China, India, the United States of America (its federal government has however expressed a wish to withdraw from the agreement), Australia and Japan.

is dependent on the number of buildings, floor area, and number of appliances in buildings, which are all linked to socio-economic conditions. For the aggregate of the countries belonging to the Major Economy Forum on Energy and Climate Change (MEF - which includes the EU) over the period 2000–2012, it was observed that the total building energy demand increased (+12 %) jointly with floor area (+40 %), population (+11 %), gross domestic product (GDP) (+47 %), and number of households (+22 %) [9, p.15]. Most of this building energy demand is in the residential sector (around 70% for MEF countries in 2012 [9, p.18]).

For MEF countries, a majority of the overall energy used in buildings is used for heating of space (36 % in 2012) and water (18 % in 2012) [9, p.18]. It is therefore important to consider reducing energy demand of heating ventilation and air-conditioning (HVAC) systems. This is realised through energy efficiency measures, such as increased envelope insulation and use of heat-pumps. Here, policy, building regulations, and technological innovation play key complementary roles in driving the change.

1.3 Transitioning towards a low carbon energy system

Reduction in carbon emissions from energy use are addressed by two means: reduction of energy use and decarbonisation. The former is addressed by energy efficiency measures at all levels (i.e. from generation to consumption), which consist in reducing the amount of energy required for a given service (e.g. keeping a desired indoor temperature in a building). The latter is achieved by replacing conventional generation relying upon fossil fuels by renewable energy sources with low GHG emissions.

As highlighted by IPCC's report on mitigation of climate change [8], many renewable energy technologies have demonstrated great performance improvement together with decreasing costs in the recent years. Moreover, a growing number of them is becoming sufficiently mature to allow large scale deployment.

In fact, renewable energy is already growing in importance worldwide. Over the period 2010–2016, more new renewable capacity was installed (+118 GW/year) than fossil-fuel based generation (+113 GW/year), according to figures from the International Energy Agency (IEA) [11]. In its predictions after 2017, the IEA also envisions that installation of renewable generation will be significantly higher (+60 %) than for new conventional generation [11].

As a consequence of a shift to a low-carbon energy system and continued economic growth[3], electricity demand is expected to grow. A first driver should be the replacement fossil fuel heaters by electrical systems such as

[3]Assuming that the growth-seeking economic paradigm is continued and alternatives are not sought, while sufficient decoupling of economic activity and energy use is not achieved. More details on alternative economic pathways can be found in e.g. Jackson's works [12].

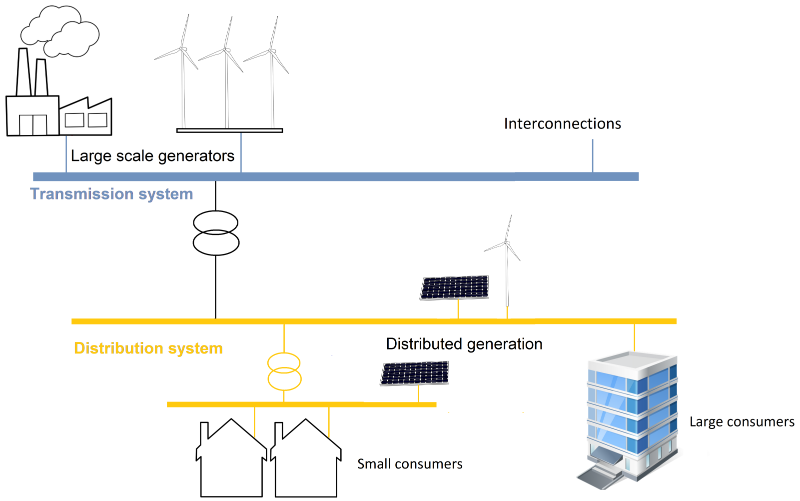

Figure 1.1: Structure of a power system. A similar structure applies in the case of district heating systems. (Cliparts taken from Openclipart [10])

heat-pumps, where a district heating option is not chosen. A second driver should be the replacement of petrol/diesel vehicles by electric ones. This increased electricity demand is however requiring planning as well as extension of the infrastructure at network and generation level.

Decarbonisation may also lead to higher reliance on district heating, especially in densely populated areas. These district heating networks are expected to make increasing use of renewable energy and recycled heat. They should also become increasingly efficient through reduction of the supply temperatures as well as use of additional communication and optimisation. Moreover, integration with the power system is also considered, for example through use of heat-pumps. An example of a detailed framework for such future developments is the 4th generation district heating [13]. Here again, planning and extension of infrastructure will be necessary.

From an operational point of view, renewable generation is more variable in nature than conventional fossil-fuel based generation. Its deployment is thus requiring higher levels of flexibility on the load side and energy storage[4]. Especially in power systems, this forces to reconsider the traditional paradigm built upon central flexible plants providing energy to hardly flexible loads, by introducing a two-way communication. This communication is an essential part of the so-called "Smart-Grid" concept, which has recently

[4]A study of flexibility in future power systems is found in the review by Cochran et al. [14]. Furthermore, energy system flexibility measures for enabling high levels of renewable generation in power systems were reviewed by Lund et al. [15].

drawn extensive attention in the research community and energy sector.

2 Contributing to the energy transition by acting on the demand of buildings

This section introduces demand-side management and demand response, their importance, and contributions from the building sector.

2.1 Benefits and challenges of acting on the demand side

From an energy efficiency point of view, the most effective actions are often found at demand level. This is because of the inefficiencies of energy systems at extraction, conversion, transportation and distribution level. Such inefficiencies imply that each unit of energy saved at demand level results in a reduction of the production by more than one unit[5]. It is therefore very relevant to start by investing in energy efficiency at end-user level.

From a system operation point of view, extensive reliance on variable renewable energy sources requires more flexibility in the system – including on the demand side. Actions on the demand side are then of essential importance, using *demand-side management* (DSM) and *demand response* (DR).

Both DSM and DR are umbrella terms referring to all actions affecting the energy demand. The difference between them is that DSM focuses more on long term actions (including energy efficiency measures), while DR concentrates more on short term operational actions (so that it is sometimes considered as a sub-category of DSM). A reader interested in more details on DSM may refer to a reference article by Palensky and Dietrich [16], and the third section of a review by Lund et al. [15].

A critical review of benefits and challenges of DR in power systems was made by O'Connell et al. [17]. It highlighted that DR provides added flexibility to the system, which facilitates integration of renewable generation (even more than simple reliance on conventional generation for balancing) and reduces operating costs from reserves. Additionally, DR can be used for peak load reduction (therefore reducing generating capacity investment and high GHGs emission levels from peaking units) and congestion reduction on grids. Moreover, DR based upon variable tariffs has the potential to reduce cost at user[6] and societal levels, leading to increased welfare – although careful design of the price signal may be required to avoid undesirable side effects (e.g. congestions at network level). A higher overall reliability of the

[5] The actual ratio is very dependent on system characteristics, but typically varies from 1.05 to much higher values such as a factor 2 or more.

[6] Especially for flexible consumers, while non-flexible consumers may see increased costs.

system and reduced price volatility are also identified as extra benefits in a review by Albadi and El-Saadany [18].

The review [17] also highlighted a number of challenges for DR. The first one is the lack of appropriate market mechanisms in market structures, together with regulations and tariff structures. The second one is the difficulty of creating a business case for DR, due to the sharing of the welfare gain between a multiplicity of actors[7] and the difficulty to quantify it. The third is the competition against existing stakeholders (flexible generators). Lastly, end-user behaviour introduces a further challenge in terms of market modelling and participation to DR.

2.2 Demand-side management in buildings

In the case of buildings, DSM is divided between actions at a structural level (in architecture, construction and retrofits) and an operational level. The former is a long term action as the structure of a building is seldom modified over its lifetime, while the latter is typically acting in the short run (seconds to months) within the framework of DR.

At the structural level, several frameworks were proposed to address the reduction of the energy needs of buildings. Famous paradigms are *passive buildings*, *Zero Energy Buildings* (ZEB) [20], and more recently the *Zero Emission Buildings* [21] (which also accounts for life-cycle considerations such as materials, construction and deconstruction, on top of the operational phase). These frameworks are particularly useful and influential for design and construction of new buildings. Yet, with the low replacement rates in the building sector, the overall impact of such design changes is likely to be limited in the next few decades[8] during which retrofits on existing buildings should have a higher influence.

At an operational level (DR), a key aspect is the control of the building equipment. There is a significant potential for DR using appliances providing *energy* services[9] such as heating and cooling equipment, which can be often delayed without a strong impact on the building users' well-being.

DSM in buildings has received substantial attention, in particular for residential buildings. Residential demand response in smart grids was reviewed by Tarish Haider et al. [23], while techniques to support it were reviewed by Priya Esther and Sathish Kumar [24]. It is also important to remember that the value of residential DSM and its role is dependent on local/national con-

[7] An example for heat-pumps in the Danish case is found in the report of the iPower consortium [19].

[8] A reader interested in the impact of large scale rollout of ZEBs in a power system may be interested in the study on the Norwegian case by Lindberg [22].

[9] As opposed to *power* services where the service is instant (e.g. lighting), as pointed out by O'Connell et al. [17].

ditions[10].

3 Model-based optimisation: a technology to support demand-side management in buildings

In this section, model-based optimisation in buildings is presented.

3.1 Advances in computing, sensing and communication

Tremendous progress has been made in electronics in the recent decades, which has led to widespread access to low cost computation power, sensing equipment and communication technologies creating room for improvement in efficiency.

This has led to so-called "internet of things" (IoT) and "digitalisation" trends in industry, where data collection and exploitation has significantly grown as a revenue-generating activity. The result of these activities is often branded in popular terms as "smart" solutions, which are found in most sectors.

This trend has not excluded energy systems, where so-called "smart grids" and "smart heat networks" have become active research domains with a noticeable lack of consensus on the criteria required for the use of the qualifying adjective.

A similar phenomenon is observed in the building sector, with the "smart building" and "smart homes" trends. Buildings are now equipped with a large number of sensors (and actuators), estimated to be in the range of 200 (and 100) per 1000 m^2 of floor space [26].

These developments lead to strong opportunities for optimising operation, and improving the quality of the service (comfort in buildings, reliability in power systems) with decreased cost and environmental footprint.

However, they also lead to numerous challenges, including communication (in particular due to the large number of units and high desired reliability), interoperability (due to the lack of standards and variety of products on the market), data management (due to the large volumes of data – see Liu et al. [27] for an example in grids), modelling, and equipment maintenance.

3.2 Using modelling and optimisation to support system operation

Once data is available, it can be used to create models in an approach called *data-driven modelling* (or *system identification* in the field of control).

[10] This his illustrated in a comparative study of roles of households in future grids for Spain, Norway and Denmark [25].

This modelling is operated using a variety of techniques from the field of statistics (e.g. linear regression) and artificial intelligence (e.g. artificial neural networks). An application to modelling of building thermal systems is presented later in Chap. 4.

Once a model of the system is available, it can be used for optimising operation of the system, through *model-based control*. A typical example of such methods is *model predictive control* (MPC) where mathematical optimisation methods are combined with the modelling to achieve optimal operation (according to a certain criterion). In the last decade, MPC has gained considerable attention in the building HVAC [28] and energy research communities.

This MPC relies upon a *receding horizon* approach[11]. This means that at each instant when a control is computed, a prediction over a whole horizon of fixed length is made. This is similar to the behaviour of the Earth's horizon, which always remains at constant distance as one moves ahead, as pointed by Maciejowski [29]. This receding horizon idea is illustrated in Fig. 1.2.

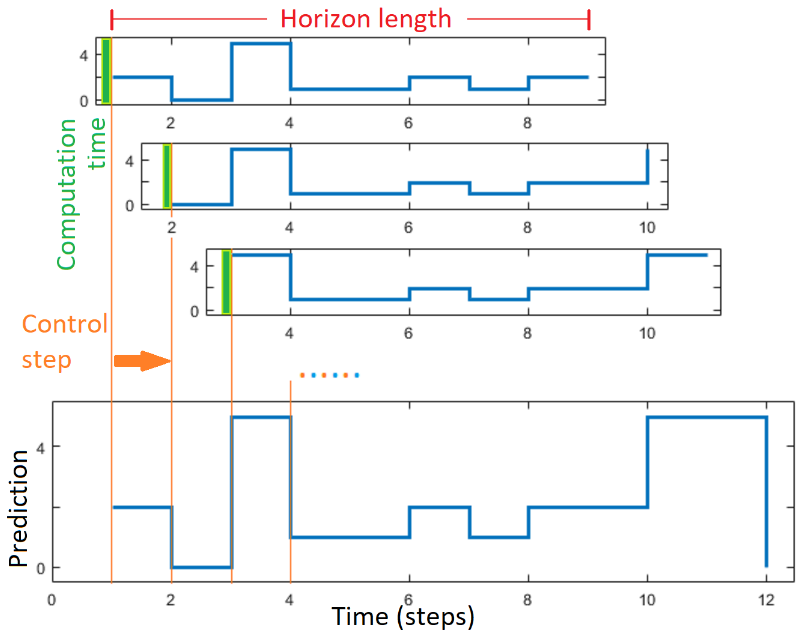

Figure 1.2: Illustration of the receding horizon concept

As exemplified in in Chap. 3 of this thesis focusing on MPC for building thermal systems, such modelling and optimisation can support energy efficiency and decarbonisation in energy systems. Thus, they can contribute to

[11]For this reason, MPC is sometimes also called "receding horizon control".

the transition to a sustainable energy future.

4 Thesis preview and contributions

In this section, the scope of the work and its contributions are presented.

4.1 Scope delimitation

The work focused on the applications of forecast and model predictive control to heating loads. Large industrial loads (greenhouses) were considered for forecast, and smaller residential loads (single-family houses) for model predictive control.

The work concentrated on the operation phase of the loads' life-cycle, using predictions in the short term spanning from minutes to days ahead. Structural changes such as envelope or heating hardware retrofit are out of the scope, and focus is restricted to changes in their controller.

Simple approaches were preferred, due to the industrial context of the research. Models were limited to linear models, which can be built using available tools and easily understood by industrial practitioners. For optimisation, only linear and quadratic programming were considered, as they are well known problems for which a variety of solvers (including open-source ones) are available.

Stochastic approaches to model predictive control were not considered in the work, for the sake of simplicity and usability in industry. However, it is important to know that these are increasingly used for their potential benefits in terms of robustness. Thus, a brief overview and references of such works are provided in the thesis, where relevant, to raise awareness on their possibilities.

4.2 Contributions

The contributions of the work are divided between load forecast, model predictive control (MPC), and control-oriented modelling.

Paper A [30] : An innovative method for automatic selection of model variables was developed for online short term load forecast. This method was based upon marginal root mean square error (RMSE) reduction and a recursive least square (RLS) method, with use of weekly curves and weather forecast. The practical performance of this method was demonstrated in the case of industrial greenhouses in a district heating system.

Paper B [31] : A comparison of performance of model predictive controllers with different formulations of the objective function was made, using an idealised case of a single-family house in Denmark with floor heating. This highlighted a trade-off between performance indicators, in particular energy consumption and carbon emissions. In particular, it was observed that energy optimisation and SPOT price optimisation failed to deliver the lowest possible carbon footprint.

Paper C [32] : A quantification of the carbon footprint reduction potential from MPC with different strategies, compared to thermostatic controllers was made. This was done in the specific case of 3 single-family houses using low inertia heating in a Danish environment. Simulations showed that MPC reduced energy consumption compared to thermostat. However, it was also observed that MPC would not deliver significantly better performances than a well-tuned PID control for such fast heating types. Similarly for the carbon footprint, MPC allowed reducing the overall footprint, as well as the average carbon intensity of the energy intake in the case of CO_2 (and in some cases SPOT price) optimisation. But it was also shown that these benefits from MPC were comparatively lower than those obtained by first lowering the thermostatic bounds by 1 °C (back to a standard value).

Paper D [33] : A simple dynamical model was identified on a real lightweight (wooden) super-insulated single-family house using fast acting electrical heaters. A grey-box modelling approach was taken, using a first order model, comparing results from the Matlab System Identification toolbox and the CTSM package. It turned out that both software packages yielded different model parameter values and uncertainty (although with similar magnitude), and that the sample time of the dataset affected these numerical values. Moreover, it was observed that this first order model captured well the main (slow) dynamics of the average temperature within the building. Lastly, experimental data was made public to allow benchmarking and further analyses.

"All models are wrong, but some of them are useful."

G.E.P. Box

2
Forecast of signals

1 Problem statement

A *forecast* is a prediction of a future event. It is based upon knowledge acquired through *past observations* and *experience*, as well as *current information* about recent conditions.

Energy systems rely extensively on forecasts for their planning and operation. Typical usages are in load, generation, and weather forecasts. Increasing reliance on variable renewable generation has drawn further interest in this field.

Forecasts are *uncertain* in essence, as they describe a future which has not yet happened and been measured. This results in different forms of forecasts, depending on how this uncertainty is considered. *Point forecasts* provide only the expected value of the predicted variable, therefore completely neglecting the uncertainty. *Interval forecasts* provide a range of values in which the predicted variable is expected to be, with a given confidence level. *Ensemble forecasts* provide a set of possible values of the predicted variable.

Forecasts can be used in either *online* or *offline* applications. In offline forecast, knowledge of a given set of past observations and experience is used, while updated current information is not available. This has the advantage that predictions can be made for any point in time, at the cost of not using all latest available information. In online forecast, predictions are updated on a regular basis as information about current conditions is incorporated in knowledge over time. This allows for regular model updates and use of the latest-available information. However, this prevents application to a distant future and cases where no knowledge of current conditions is available.

Formal problem definition

The aim is to build a predictor ($\hat{\mathcal{Y}}$) of observations ($\mathcal{Y}$), given some prior knowledge ($\mathcal{K}$), and expectations of the conditions ($\hat{\mathcal{V}}$). This predictor should minimise the mismatch between predictions and future observations over a given period ($\mathcal{T}$).

In loose terms, this can be formally expressed by:

$$\hat{\mathcal{Y}} = \arg\min_{\hat{\mathcal{Y}}} \ Mismatch\Big(\hat{\mathcal{Y}}(\hat{\mathcal{V}}, \mathcal{K}, \mathcal{T}), \mathcal{Y}(\mathcal{T})\Big) \tag{2.1}$$

2 Brief overview of the state of the art

This section presents a brief overview of the different dimensions of the problem forecast, as well as a short analysis of the state of the art of forecasting approaches.

2.1 Evaluation of forecast performance

This subsection presents choices of 'Mismatch' functions to assess forecast performance. These are typically based upon the *forecast error*, which is difference between the observations (Y) and their prediction ($\hat{Y}$):

$$E \triangleq Y - \hat{Y} \tag{2.2}$$

This error is a random variable in essence, described by a *probability distribution*. It is therefore not directly measurable in practise, but can be observed through the *residuals*, which are a *realisation* of it. For an experiment with N measurements, these residuals (ϵ) are be computed *a posteriori* using:

$$\forall i \in \{1, ..., N\}, \ \ \epsilon[i] \triangleq Y[i] - \hat{Y}[i] \tag{2.3}$$

These residuals can then be used to *estimate* the properties of the error using statistical theory, in particular the *bias* (μ) and *standard deviation* (σ). In loose terms, the bias provides an answer to the question "What is the *average error* of the forecast?", while the standard deviation answers "How *uncertain* are the results of this forecast?". In practise, there is often a compromise between these two, known as the 'Bias-variance trade-off' in statistical theory.

Bias and variance are *estimated* using Eqs. (2.4) and (2.5), respectively[1]. A more visual approach is provided in Fig. 2.1.

$$\hat{\mu}(E) = \frac{1}{N}\sum_{i=1}^{N} \epsilon[i] \tag{2.4}$$

$$\hat{\sigma}(E) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (\epsilon[i] - \text{Bias}(E))^2} \tag{2.5}$$

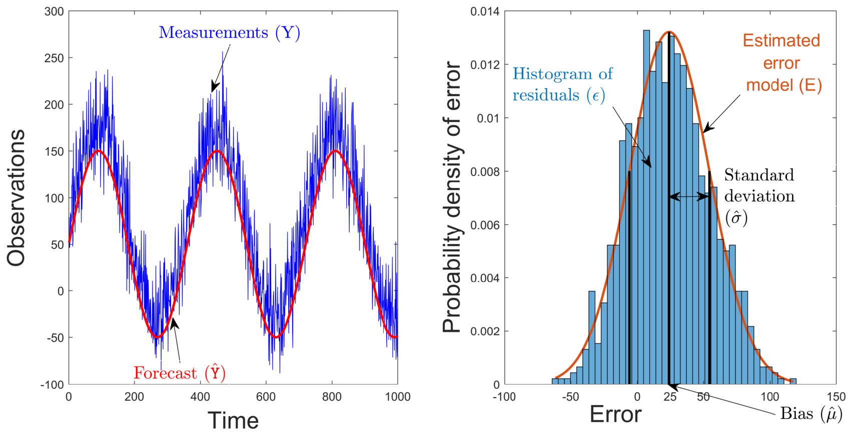

Figure 2.1: Visual summary of the concepts of forecast error, bias, standard deviation. An example of forecast is given on the left side, while the corresponding histogram of the error is given in the right plot.

The *distribution* of the residuals is a very informative indication, as it allows building confidence bounds for the forecast. Nevertheless, most applications use reduced metrics to describe the residuals, despite the loss of information. Such metrics are the mean absolute error (MAE), the root mean square error (RMSE), and the mean square error (MSE), which are defined in

[1]In many applications where the predicted variable evolves within a continuum (e.g. load, temperature, solar radiation), the error often-times follows a Gaussian distribution. This allows to estimate the probability distribution of the error directly from the estimated bias and variance.

Eqs. (2.6), (2.7), and (2.8), respectively.

$$\mathrm{MAE}(\epsilon) = \frac{1}{N}\sum_{i=1}^{N} |\epsilon[i]| \tag{2.6}$$

$$\mathrm{RMSE}(\epsilon) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \epsilon[i]^2} \tag{2.7}$$

$$\mathrm{MSE}(\epsilon) = \frac{1}{N}\sum_{i=1}^{N} \epsilon[i]^2 \tag{2.8}$$

Normalised metrics are also used for MAE, RMSE, and MSE, with a lack of consensus among practitioners regarding the choice of the normalisation factor (e.g. peak, average, or standard deviation of measured signal). It is is therefore recommended to pay particular attention to their definition when they are used, and defining them explicitly when using them in a publication. Another normalised metric commonly used is the *coefficient of determination* (R^2) defined in Eq. (2.9), which is to be maximised (with an upper limit of 1), contrary to the other metrics.

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \epsilon[i]^2}{\sum_{i=1}^{N} \left(Y[i] - \frac{\sum_{i=1}^{N} Y[i]}{N} \right)^2} \tag{2.9}$$

In some cases, such as application with a focus on robustness, it can be interesting to measure the largest forecast error, quantified by the *peak error* (PE) [34]:

$$\mathrm{PE}(\epsilon) = \max_{i \in \{1,\dots,N\}} \|\epsilon[i]\| \tag{2.10}$$

There is no consensus in the forecast literature on a 'best' error metric. Some practitioners argue that the MAE is preferable, as it is a non-ambiguous measure of average error, while the RMSE is influenced by error distribution and square root of number of residuals [35]. Others highlight that the RMSE is a better metric for normally distributed residuals, although the most common concern with this metric is its sensitivity to outliers [36] (which is even higher in the case of the PE).

Although not covered in more details here, other metrics are available, such as the Akaike Information Criterion (AIC), or correlation of the residuals with themselves or other variables (see textbooks from Madsen [37, Chap. 6] or Ljung [38, Chap. 16] for more details).

A remark on use of real life measurements

When it comes to use of real life data, an important issue is the case of corrupt data and *outliers*. Outliers are observation that are distant from others, either due to issues in the measurements or unusual behaviour. These (and their magnitude) can significantly affect the design choices and performance criteria for the forecasts systems. For example, approaches based upon square error are much more sensitive to large deviations than those relying on absolute errors.

2.2 Forecasting methods

This subsection presents a brief review of typical forecasting methods found in the literature, which allow to build this predictor $\hat{\mathcal{Y}}$.

Forecasting can be made in a number of manners, depending on the tools, computation capability, acceptable complexity, and information at hand. It can be either qualitative or quantitative. In this work, focus is made on applications of quantitative forecast to load, weather, occupancy, and price prediction.

The simplest kind of forecast consists in relying upon repetition of the conditions. This is sometimes referred to as *naïve* forecast, or *persistence*. Typical repetition periods used are day (e.g. tomorrow is the same as today), or week (e.g. next Monday will be the same as the past Monday) for human activities strongly affected by weekly patterns, such as occupation in office buildings.

Linear models are often used in forecasts. An example is linear regression, and its adaptive form using recursive least squares (RLS). Other examples are timeseries process models such as *auto-regressive* models with exogenous inputs (ARX), with moving average (ARMA), with moving average and exogenous inputs (ARMAX), or with integrated moving average (ARIMA)[2].

Alternatives are numerous, including (but not limited to) K-nearest neighbour, Markov chains, classification and regression trees, extremely randomised regression trees, genetic programming, Gaussian processes, and physics-based system identification. Recently, artificial neural networks (ANN) and support vector machines (SVM) have also received significant attention.

A short structured review of usages of these forecast methods to load, weather, price, and occupancy is provided in Tbl. 2.1.

When several methods are possible, it can often be valuable to combine them in order to improve performance [60, 73]. For such purposes, the *expert advice* method can be a versatile way to operate the combination [42]. A reader interested in other methods may also refer to the works of Genre et al. [74].

[2]A reader interested in more details can get further insight in the book by Madsen [37].

Table 2.1: Review of forecasting methods and examples of usage

Method	Load	Forecast application Weather	 Price	 Occupation
Naïve				
1 day repeat	[30]	[39], [40]	(CO_2 : [40])	
7 days repeat			(CO_2 : [40])	[41]
Linear regression			(CO_2 : [40])	
Multiple linear regression	[42, 43]			
ARX	[44, 45]	[46]		
Seasonal ARIMA	[47]			
Recursive least squares	[30, 48–50]			
Genetic programming	[51]			
Gaussian processes		[40]	(CO_2 : [40])	
K-nearest neighbour and Markov chain	[52]			
Classification and regression trees	[43]			
Extremely randomised tree regressors	[42]			
ANN	[42, 43, 51]	[53–56]		
- Multiple	[57]			
- combined with wavelet-based ...	[58, 59]			
multi-resolution analysis				
Neuro-fuzzy inference system	[60, 61]			
Adaptive neuro-fuzzy inference system	[62]			
SVM	[42, 43, 51, 63]		[64]	
System identification	[65]			
(Review)	[66–68]			
	[69, Chap. 5]			
(Review for ANN)	[70]	[71, 72]		

2.3 Selection of relevant knowledge for forecast

When building a forecast, one often has access to a variety of information (past observations, measurements, knowledge of physics, experience,...), which constitute so-called *prior knowledge* ($\mathcal{K}$).

A vast amount of information is contained in this prior knowledge. However, not all of this information is always relevant[3] for forecasting. In most cases, the practitioner makes decisions on relevance of information based upon his/her experience, or manual trial and error. Yet there are also cases when this is not desirable, so that automated methods are preferred.

This is illustrated in the case of loads in district heating systems. Heating loads often depend on ambient (outdoor) temperature, global sun radiation, wind speed, supply temperature of the water, time (hour, day, month), humidity, as well as some internal parameters (e.g. return temperature, flow rates) [30]. Moreover, lagged versions of these parameters can also have an influence for systems that are slow to react, such as those with a large thermal inertia. Therefore, these can be used as inputs ($\hat{\mathcal{V}}$) to a heat load predictor, when they are *available* and *relevant*.

The relevance of input information[4] can be assessed using statistical methods, or iterations with criteria on performance improvement. The basic principle here is that models should be as simple as possible (i.e. with the fewest explanatory variables) while integrating all the relevant information at hand. Two approaches are essentially available: *forward* and *backward* selection. In forward selection, inputs are added one by one to the predictor in a step-wise manner (model extension). A minimum number of inputs are used as a start, and only those additions resulting in improvement of the model are kept. Conversely, in backward selection, one starts by using all inputs at hand, and removing the irrelevant ones in a step-wise manner (model reduction).

Relevance criteria are typically based upon the model error (e.g. MAE, RMSE [30, 45], R^2 [60], MSE, ... as presented above), correlation of residuals and inputs [48], or statistical relevance (e.g. standard deviation or *p-value* of model parameters). Here, the advantage of simple metrics is that they can be used for automatic modelling, which is highly valuable in the context of 'smart' energy systems.

[3] Here, 'relevant' is used as a synonym for 'which leads to reduced forecast error or uncertainty when used in the model'.

[4] This is also referred to as 'features', or 'explanatory variables'.

3 Application to greenhouse heat load in district heating systems

This section summarises the context and findings of the work presented in paper A [30].

The work focused on point forecast of heat loads of individual large consumers (greenhouses) in a district heating system using a weather forecast service. An online adaptive approach was taken, using the framework of recursive least squares (RLS) with forgetting [37, Chap. 11]. Moreover, the study was carried out on historical data covering a period of 8 months for 5 greenhouses.

An automatic input selection algorithm was presented, based upon forward selection and a RMSE-based model extension criterion. Inputs variables were selected among weekly curves (sine waves of a period between 2 h and a week), and weather parameters (ambient temperature, global horizontal solar radiation, wind speed, humidity, and atmospheric pressure).

Results showed that an RLS-based forecast brought significant improvement compared to a 1 day persistence forecast. Moreover, adaptivity performed well at capturing recurring load profiles and accommodating the regular changes in operation, but not the fast frequency changes. This resulted in a RMSE of 8–20% of the peak load for predictions 1 to 48 h ahead.

In terms of model, it was observed that the relevant model inputs differed among greenhouses, where the only common relevant variables were time periods of a day (and fractions of it) and ambient temperature. This supports the value of automated selection of inputs for such individual loads.

4 Use of forecasts for predictive controller input

Predictive controllers such as MPC (introduced in Chap. 3), typically require forecasts of future disturbances on the system. Such applications are briefly reviewed in this section.

For weather forecasts, many studies used an embedded weather forecasting module (see examples in Tbl. 2.1). In this case, the methods presented in this chapter can be used.

Nevertheless, a widespread practise is to rely on external weather forecasting services [41, 75–78]. In this case, it is recommended to calibrate the ambient temperature using local measurements (if available) to obtain better accuracy [41].

Forecasts of price signals can be either acquired from third parties, or predicted by an embedded module. Occupancy (and related internal heat gains) forecast is made using embedded modules. Again, examples from the literature are found in Tbl. 2.1.

For predictive control application, a trade-off is therefore arising between use of an active communication link and reliance on external services when using third party forecast (often involving subscription fees), against higher sensing needs, computational load and lower forecast precision when using embedded forecasts.

5 Use of predictions for practical quantification of savings from a change of controller

Another application of forecast worth mentioning here is the estimation of a baseline consumption for controller retrofit[5]. Whenever a controller is changed with the aim to improve the efficiency of operation, it is essential to quantify the actual benefits in practice. This is a necessary consideration for business model development, as well as for meeting energy efficiency (or carbon footprint) targets within the regulatory frameworks[6].

Precise quantification of benefits is a difficult task, especially when it comes to energy savings in real buildings. This is because the energy use has a strong dependency on the weather and environment[7], as well as user behaviour[8]. Unfortunately, it is not obviously practicable to operate a building in the exact same conditions with both the previous and the new controller, as done in simulations. Therefore the consumption of the previous controller in the new conditions needs to be estimated.

5.1 Degree days methods

The industry standard method for evaluation of consumption of heating loads focuses on the use of energy per so-called 'heating degree day' (HDD)[9]. Degree days are a simple integration of the ambient temperature (T_a) below a base temperature (T_base) over a given period ($\mathcal{T}$):

$$\mathrm{HDD}(\mathcal{T}) = \frac{1}{24\ \mathrm{h}} \int_{\mathcal{T}} \max\Big(0,\ T_\mathrm{base} - T_\mathrm{a}(t)\Big)\ dt \tag{2.11}$$

[5]In fact, the considerations in this section are not limited to controller update, and can be applied for any type of retrofit (e.g. insulation improvement, window change).

[6]For example, the EU energy efficiency directive requires energy retailors and distributors to achieve a 1.5% reduction in energy use per year [79].

[7]In technical terms, this is often referred to as 'boundary conditions'.

[8]This uncertainty from user behaviour is comparatively higher in cases with a limited number of occupants (e.g. single family houses), than cases with a large number of them (e.g. apartment blocks).

[9]In fact, a similar metric exists for cooling loads: the cooling degree day.

In Denmark, the Danish Technological Institute recommends using a base temperature value of 17°C [80], while some geographical areas have other default values. However, it is important to know that the base temperature differs among buildings/loads. The value of this base temperature should therefore be fitted to each application (whenever possible) and explicitly given in studies relying upon it, as it has a strong influence on the value of HDD.

For practicability, the integral in Eq. (2.11) is approximated by a discrete sum, where the ambient temperature is an average over a period (e.g. 1 day [81], or 1 h). The higher the length of this period, the less precise the metric, when the ambient temperature gets closer to the base temperature.

Then, the energy use over the period ($E(\mathcal{T})$) is normalised by these HDD for the period to obtain a consumption per degree day:

$$E_{\text{normalised}}(\mathcal{T}) = \frac{E(\mathcal{T})}{\text{HDD}(\mathcal{T})} \tag{2.12}$$

The underlying assumption is that the load is zero when the temperature is higher or equal to the base temperature (T_{base}), and that it is proportional to the difference between ambient and base temperature for lower ambient temperatures. This is represented in Fig. 2.2.

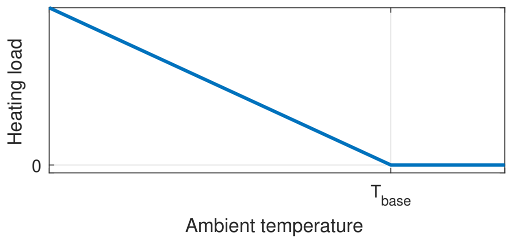

Figure 2.2: Energy consumption model with the heating degree day model

Clearly, this is a rather coarse simple approximation, although it works reasonably well for basic comparison of heat loads (as the highest sensitivity of heating loads often is on ambient temperature). For more precise comparison, it is important to ensure that environmental conditions are similar between the periods compared[10] [76]. Additionally, as pointed by Catalina et al. [83], the HDD measure tends to over-evaluate the energy demand and neglect important features of the building, such as its thermal inertia.

Examples of use of the heating degree day method in experimental comparison of controllers can be found in the works of Široký et al. [76], and De

[10]An example of issue with the HDD can be found in the project report "Smart Energi i Hjemmet" [82] where the authors consider the risk of a so-called 'warm winter effect' when considering a new controller in a warmer winter compared to baseline data.

Coninck and Helsen [41]. In the latter study, the limits of the degree day normalisation are observed, as the new controller would typically provide higher relative savings for higher degree days.

5.2 Regression based methods

A more precise approach to energy demand estimation is found in regression methods. These methods rely upon multiple linear regression (MLR) of the load, using observations of the weather (e.g. ambient temperature, solar radiation, wind speed, humidity) or time considerations (e.g. weekday/weekend) as explanatory parameters. In fact, these methods are very versatile in terms of the explanatory parameters that can be used, where simple quantitative criteria[11] allow to identify the relevant ones.

These methods are rather simple to use, and can be implemented using widespread data analysis software packages (e.g. R, Matlab, Microsoft Excel...). They have the advantage of being easy to interpret and provide an estimation of the uncertainty of the prediction. However, they are highly sensitive to outliers in the data[12].

An example of MLR is the fitting of a static heat load model using heat load transfer coefficient (UA), a solar gain (gA), and a wind-speed sensitivity (wA) [84]. In this case, inputs are indoor temperature (T_i, typically approximated by a constant when unmeasured), ambient temperature (T_a), global solar radiation (Φ_G), and wind speed[13] (W_s). In this case, the heat load (H) is modelled by:

$$H = \mathrm{UA}\ (T_\mathrm{i} - T_\mathrm{a}) + \mathrm{gA}\ \Phi_\mathrm{G} + \mathrm{wA}\ W_\mathrm{s} \tag{2.13}$$

5.3 Other methods

The previously introduced degree day compensation and regression analysis are the most widespread steady state methods to estimate energy demand. Nevertheless, a number of other methods can be used, for example modified and variable base degree day method, bin methods, ANN, and SVM.

A reader interested in finding out more about these may refer to the reviews of Zhao and Magoulès [68], Parks [86, p.10–11], and Yildiz et al. (focusing on building electricity demand) [67].

[11] For example the $\mathrm{p} - \text{value} < 0.05$ criterion for the coefficients in the regression

[12] In the case of many outliers, it can be better to use methods such as RANSAC or maximum likelihood.

[13] It is also possible to look at dependency on the product of windspeed and temperature difference (see Delff Andersen et al. [85], which also mentions a potential benefit from an exponent to the windspeed) or wind direction (see the study of Nielsen et al. [84] for more details).

"You have to learn the rules of the game. And then you have to play better than any[thing] else."

D. Feinstein

3 Model predictive control for heating of buildings

This chapter presents an overview of predictive control of heating in buildings, and relevant contributions of the research to this field.

1 Problem statement

This chapter deals with the problem of optimising the control of a building heating system. This is a decision problem, where one wants to provide an *optimal set of inputs* to the building affected by *disturbances* in order to ensure *satisfactory outputs*.

Typical inputs are heat, power, or temperature set-points. Disturbances are non-controllable factors, which can be divided into two types: *exogenous* (i.e. external factors) such as ambient temperature, solar radiation, wind speed, and *endogenous* (i.e. internal factors) such as heats gains from occupation. Outputs are typically temperatures, power, or heat.

Formal problem definition

Here, the problem is to compute an optimal input sequence ($\mathcal{U}$) over a period ($\mathcal{T}$), given an initial state of the system ($\mathcal{X}_0$), expectation of future disturbances ($\hat{\mathcal{V}}$), a price signal ($\mathcal{P}$), some prior knowledge about the sys-

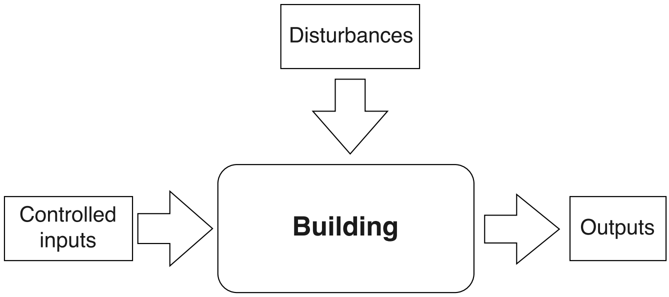

Figure 3.1: Schematic representation of the building

tem (typically summarised in the model $\mathcal{M}$), and a given objective allowing optimality to be well-defined.

$$\mathcal{U} = \arg\min_{\mathcal{U}} \; Objective(\mathcal{X}_0, \hat{\mathcal{V}}, \mathcal{P}, \mathcal{M}, \mathcal{T}) \tag{3.1}$$

2 Model predictive control of heating in buildings

2.1 Model predictive control

Model predictive control (MPC) is a control technique meant to *optimise* the operation of a system towards a certain objective, using a model predicting its future behaviour (hence the 'model predictive'). Here, the system will typically be a building and its heating equipment, while a typical objective will be minimising energy cost under thermal comfort constraints.

Although only the application of MPC to thermal systems is treated in this work, it is important to know that this control technique has numerous variants and can be applied to almost any field. A reader interested in an in-depth presentation of MPC may refer to Mayne's review [87], whose broad scope covers (among others) deterministic, robust, and stochastic MPC, as well as optimisation considerations. Moreover, a practical introduction to MPC (with Matlab examples) can be found in the textbook by Maciejowski [29].

A MPC controller is composed of several components: disturbances and price forecast modules[1], an optimiser, and a state estimator. This optimisation and state estimation require a simple dynamical model of the building. This is summarised in Fig. 3.2.

It is worth knowing that a number of alternative advanced control methods exist for building energy control, for example neural network control [54]

[1]These can also be provided by third parties, as highlighted in chapter 2

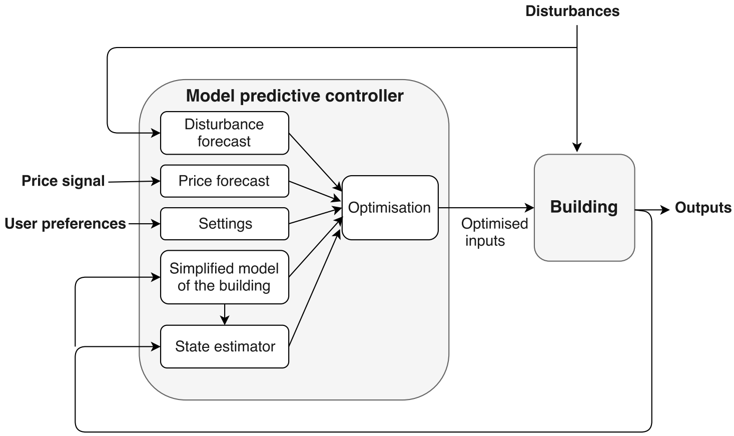

Figure 3.2: Structure of a model predictive controller for building heating

or batch reinforcement learning [88]. A reader interested in finding out more about alternatives may refer to the review by Shaikh et al. [89].

2.2 Structure of the optimal control problem

In the following, let us use a condensed notation for a series of consecutive values of a vector Z:

$$\underline{Z}[k, N_\mathrm{c}] = \Big(Z[k],\ Z[k+1],\ ...,\ Z[k+N_\mathrm{c}]\Big) \tag{3.2}$$

At a given time k, a control *decision* needs to be made for the inputs U to apply. Here, a number of parameters are taken into account in the decision (further details given in the next chapters):

- The *current state* of the system (X_init),
- Estimates of the *future disturbances* ($\underline{\hat{V}}[k, N_\mathrm{c}]$), such as environmental conditions or internal heat gains,
- Estimates of the future *control inputs* ($\underline{\hat{S}}[k, N_\mathrm{c}]$), such as power price, occupancy-related discomfort costs, or references to track [2].

This decision process results in a foreseen trajectory of the system. This trajectory consists of the *future controlled inputs* ($\underline{U}[k, N_\mathrm{c}]$) and *future states* of the system ($\underline{X}[k, N_\mathrm{c}]$), over a given number of steps ahead (N_c).

[2]Here, it is important to avoid confusion between control input $\hat{S}$ and controlled input U. The former is an information input to the decision process, while the latter is the output of the decision process.

Therefore, at the given time step k, a *finite-horizon optimal control problem* is to be solved. This problem is formulated in the following generic structure, named *optimal control problem*:

$$\min_{\underline{U}[k,N_c]} J\Big(\underline{X}[k,N_c],\ \underline{U}[k,N_c],\ \underline{\hat{V}}[k,N_c],\ \underline{\hat{S}}[k,N_c],\ k\Big) \qquad \text{(Objective)} \qquad (3.3)$$

$$s.t.$$

$$X[k] = X_{\text{init}} \qquad \text{(Initial state)} \qquad (3.4)$$

$$H\Big(\underline{X}[k,N_c],\ \underline{U}[k,N_c],\ k\Big) \in \mathcal{H} \qquad \text{(Constraints)} \qquad (3.5)$$

$$\forall j \in \{1, ..., N_c - 1\},$$

$$X[j+1] = F\Big(X[j],\ U[j],\ \hat{V}[j],\ k\Big) \qquad \text{(Dynamics)} \qquad (3.6)$$

Hereafter, only particular cases of this problem will be considered. This is to allow use of either linear programming (LP) or quadratic programming (QP) to solve the control problem. Both LP and QP are well-known optimisation methods with available solvers, which is an essential aspect for implementation. This results in restriction to:

- only linear and quadratic expressions of the objective function (J)
- linear forms of the state dynamics (F)
- the constraints (H, and $\mathcal{H}$) can be formulated with linear matrix inequalities (resulting in convex polytopes)

Quadratic formulations of the objective function are preferable to affine ones for control in buildings. This is because using the 1-norm will result in a so called bang-bang or idle control (due to the characteristics of LP problems where solutions always activate some of the constraints), while the 2-norm results in a more "smooth" control. This is discussed in the review of Cigler et al. [90] (referring to works by Rao and Rawlings [91], and Saffer and Doyle [92]).

In the case of ON/OFF heating systems, the input state is discrete[3]. This requires the use of mixed-integer optimisation (MILP or MIQP), which has a much higher computational complexity than its LP or QP counterpart. Tools for solving such problems are available.

2.3 Formulations of the objective function

In this subsection, different forms of the objective function (J) are presented. For the sake of simplicity, different expressions are presented separately here.

[3]Unless considering modulation by switching ON only for a fraction of the control step, which cannot be made with heat-pumps and devices operating in cycles.

However, it is important to know that these can be combined in *multi-objective optimisation* (for example by using weighted sums of these, as illustrated in Eq. (3.8)).

Optimising the cost of energy

First, a typical approach consists in focusing on the input itself over the optimisation horizon. For most applications, a simple linear expression of the objective can be used (Eq. (3.7)), which has the advantage of making the interpretation straightforward.

$$J\Big(\underline{X}[k,N_c],\ \underline{U}[k,N_c],\ \underline{\hat{V}}[k,N_c],\ \underline{\hat{S}}[k,N_c],\ k\Big) = \sum_{j=k}^{k+N_c-1} \hat{S}_{\mathrm{EN}}[j]U[j] \tag{3.7}$$

In most applications, the controlled input (U) corresponds to energy. In that case, the price signals ($\hat{S}_{\mathrm{EN}}$, a subcomponent of the control inputs $\hat{S}$) typically used are:

- A *constant* value, to equally penalise consumption at different times. This corresponds to an aim of minimising *energy usage*.
- A *primary energy factor* value, to reflect different energy conversion efficiencies between energy sources (e.g. gas, and electricity in the case of dual energy input). This corresponds to an aim of minimising the *primary energy usage* (often focusing on the non-renewable part of it).
- The *real time price of energy* (S_{RTP}), to encourage consumption at times with low prices. This corresponds to an aim of minimising *energy costs*. Some studies use time of use (ToU) prices, or day-ahead real time pricing (RTP) on the SPOT market.
  Here, it is important to know that SPOT prices are only a fraction of the final cost to the user while transportation costs, taxes, and other public services obligations constitute the largest part[4].
- The *carbon intensity* of the power consumed (S_{CO2}), to discourage consumption at times of high CO_2 emissions from generation. This corresponds to an aim on minimising the carbon footprint resulting from the energy generation.
- A scaled *grid load* (S_{load}), to reduce consumption at times of high load. This corresponds to an aim of *reducing the peak load*.

[4]In the Danish case in 2014, the decomposition at household level was the following: SPOT price 17.3%, Value Added Tax (VAT) 20%, Taxes 36,5%, Public Service Obligations (PSO) 8.3%, Energy Saving Effort 0.8%, Transport (TSO) 3%, Distribution (DSO) 14.1% – according to the Danish Intelligent Energy Alliance (Intelligent Energi) [93]

- A *tax/subsidy cost* (S_{PSO}), to account for tax related to local policies (e.g. a constant value from city concession [64], or mixture of SPOT price and wind generation to model the effect of public subsidies to renewable power [94]).

These differing concerns can in fact be combined together. This was done in past works in the field [64, 94–96], resulting in a penalty signal in the form of a weighted sum (Eq. (3.8) – where $< Z >$ designates the average of Z).

$$
\begin{aligned}
S_{\mathrm{EN}}[k] = \alpha_{\mathrm{p}} \frac{S_{\mathrm{RTP}}[k]}{< S_{\mathrm{RTP}} >} + \alpha_{\mathrm{CO2}} \frac{S_{\mathrm{CO2}}[k]}{< S_{\mathrm{CO2}} >} \\
+ \alpha_{\mathrm{load}} \frac{S_{\mathrm{load}}[k]}{< S_{\mathrm{load}} >} + \alpha_{\mathrm{PSO}} \frac{S_{\mathrm{PSO}}[k]}{< S_{\mathrm{PSO}} >}
\end{aligned} \tag{3.8}
$$

Another case worth mentioning here concerns water-based heating systems, for which keeping the lowest possible supply temperature is essential to reduce the thermal losses (and keep a high COP, when using a heat pump). In such cases, the input (U) can be the supply temperature. This was addressed by Lindelöf et al. [56], who used minimisation of the sum of supply temperatures. Another approach used by Verhelst et al. [97], is to explicitly account for the dependencies of the COP to operating conditions (e.g. compressor frequency, ambient temperature, supply temperature) in the objective function.

A summary of these different possibilities is given in Tbl. 3.1.

Table 3.1: Penalty signals found in the literature

U	$\hat{S}$	References
Energy	Constant	[31, 98]
	(Non renewable) primary energy factors	[99, 100]
	Energy price	[31, 41, 94–96, 101–105]
	Carbon intensity of power	[31, 94–96]
	Scaled grid load	[64, 94, 96]
	(Weighted sum of above-mentioned)	[64, 94–96]
Flow temperature	Constant	[56]

Optimising the thermal comfort

Another optimisation approach consists in the tracking of a temperature reference. This can be made using either affine, or quadratic measures of the discomfort.

In such cases, the input signal ($\hat{S}$) typically consists of an *occupancy signal* ($\hat{S}_{\mathrm{OCC}}$) and a *reference* to be tracked ($S_{X_{\mathrm{ref}}}$).

Affine discomfort is expressed using a simple linear penalisation of the deviation from the reference (β is a vector of weights for the different states to be tracked). This method is used in previous works [31] (which implicitly assumed permanent occupation), and results in the following form:

$$J\Big(\underline{X}[k,N_{\mathrm{c}}],\ \underline{U}[k,N_{\mathrm{c}}],\ \underline{\hat{V}}[k,N_{\mathrm{c}}],\ \underline{\hat{S}}[k,N_{\mathrm{c}}],\ k\Big) = \sum_{j=k+1}^{k+N_{\mathrm{c}}} \hat{S}_{\mathrm{OCC}}[j]\ \|\beta^{\mathrm{T}}\Big(X[j]-S_{X_{\mathrm{ref}}}[j]\Big)\|_1 \tag{3.9}$$

Quadratic discomfort is expressed using a simple quadratic penalisation of the deviation from the reference. This method was used by Lindelöf et al. [56], De Coninck and Helsen [41], Verhelst et al. [97] (where permanent occupancy is implicitly assumed), and Salque et al. [53] (where an exponentially decreasing weight factor is added, to reduce the importance of predictions far ahead). It is expressed by:

$$J\Big(\underline{X}[k,N_{\mathrm{c}}],\ \underline{U}[k,N_{\mathrm{c}}],\ \underline{\hat{V}}[k,N_{\mathrm{c}}],\ \underline{\hat{S}}[k,N_{\mathrm{c}}],\ k\Big) = \sum_{j=k+1}^{k+N_{\mathrm{c}}} \hat{S}_{\mathrm{OCC}}[j]\ \|\beta^{\mathrm{T}}\Big(X[j]-S_{X_{\mathrm{ref}}}[j]\Big)\|_2^2 \tag{3.10}$$

Alternatives relying upon more complex comfort metrics exist. In particular, some based upon the PMV/PPD have been used in MPC [5] (see references [55, 107] for more details). PMV/PPD are however resulting in a non-linear comfort function, which is outside the scope of this thesis.

Alternative forms of objective functions

For peak load reduction for large buildings, Corbin and Henze [108] proposed to use power as an input (U), and consider the *maximum of a moving average of the load* (over n steps). This results in the objective function form given in Eq. (3.11).

[5] Predicted mean vote (PMV) and predicted percentage dissatisfied (PPD) are more detailed comfort metrics, forming the basis for the thermal comfort standard ISO 7730 [106]. When using these, the computational burden can be reduced by applying the convexified approximation found in the works of Cigler et al. [107].

$$J\Big(\underline{X}[k, N_c],\ \underline{U}[k, N_c],\ \underline{\hat{V}}[k, N_c],\ \underline{\hat{S}}[k, N_c],\ k\Big) = \max_{j \in \{k+1,...,k+N_c-n+1\}} \frac{\sum_{i=j}^{j+n-1} U[i]}{n} \quad (3.11)$$

Achieving flexible energy consumption

The above objective functions either enforce flexible energy usage or do not.

Objective functions using price, primary energy[6], carbon intensity, and grid load optimising (as well as their combination) promote flexible energy usage. When using them, the flexibility of the thermal mass is unlocked and utilised to provide some kind of service to the energy network.

Energy optimisation (in the sense of a constant cost over time), flow temperature, and comfort optimisation are widespread building-centred optimisation objectives. These 'selfish' approaches completely ignore the grid conditions (or even local production), and therefore do not include any consideration of energy flexibility. As such, they are unsuited to applications where energy flexibility is needed.

However, where energy flexibility is important, the building-centred strategies can be useful to create a baseline load shape against which to assess energy flexible usage. A typical example of this is the pricing of the provision of energy flexibility at a given instant.

2.4 Constraint formulations

In this subsection, constraints on the optimisation (H) are presented.

In the simplest case, range constraints are used for inputs and states - i.e. $\forall j \in 1, ..., N_c$:

$$X_{\min}[j] \leqslant X[j] \leqslant X_{\max}[j] \quad (3.12)$$

$$U_{\min}[j] \leqslant U[j] \leqslant U_{\max}[j] \quad (3.13)$$

In such cases, these constraints are convex and straightforwardly translated to linear matrix inequalities, which are 'easy' to handle in optimisation and compatible with linear and quadratic programming. Moreover, the use of time varying bounds allows for a variety of use cases, including accounting for occupancy, or wish to avoid running the heating at night[7].

[6]When using dynamic primary intensity factors reflecting the energy mix from the grid.

[7]This was identified as a desirable feature by Hansen in an interview [109], as well as by Molderink et al. for noise prevention [110].

In some cases, such as optimisation of use of ON/OFF heating devices, inputs can only take a discrete number of values, resulting in a constraint such as i.e. $\forall j \in 1, ..., N_\mathrm{c}$:

$$U[j] \in \{U_1, ..., U_n\} \tag{3.14}$$

This results in a different type of optimisation (MILP or MIQP, as highlighted earlier), which is a NP-hard non-convex problem.

Softening of the state constraints

The constraints presented in Eq. (3.12) and (3.13) are designated as *hard constraints*, in the sense that they can not be violated. Therefore, it can happen that the optimisation problem is *infeasible* – for example in the unlikely case that the indoor temperature would fall below the minimum allowed temperature. This would cause the controller to crash, which is obviously not desirable (all the more that these cases can correspond to critical events where it is important to react).

In practical deployments, it is therefore important to *soften* the constraints which do not correspond to physical limits[8]. This can be operated by reformulating the problem to allow violation of the constraints at a high cost.

For example, the softening of the constraint in eq. (3.12) would result in its replacement by, $\forall j \in 1, ..., N_\mathrm{c}$:

$$X_\mathrm{min}[j] - \xi[j] \leqslant X[j] \leqslant X_\mathrm{max}[j] + \xi[j] \tag{3.15}$$

$$\xi[j] \geqslant 0 \tag{3.16}$$

while the objective function would be updated to (omitting some of the arguments for the sake of brevity):

$$J^{(\mathrm{upd})}\Big(..., k\Big) = J\Big(..., k\Big) + \rho \sum_{j=k}^{k+N_\mathrm{c}-1} \|\xi[j]\|_2^2 \tag{3.17}$$

where ρ is a 'large' weight penalising the deviation. For using LP in optimisation (rather than QP), the 2-norm squared can be replaced by a simple 1-norm.

2.5 Estimation of initial state and system dynamics

Together with objectives and constraints, there is also a need to account for the dynamics of the system. This requires a dynamical model of the system, which will be introduced in the upcoming chapter 4.

[8]For example, indoor temperature bounds corresponds to preferences, whereas the maximum power to a heater is physically limited by its rating.

State estimation

The initial state of the system (X_{init}) is computed from measurements using *state estimation*. This is needed because all the states of a model are seldom measured (or even measurable[9]) and subject to noise. Moreover, in real systems, it can also happen that measurements are occasionally missing or corrupted, in which case the estimation can still allow the system to run.

This state estimation from measurements creates a *feedback loop* in the control, which ensures the stability of the system. Therefore, in control terms, MPC essentially is a *closed-loop* control, which combines feedback and feedforward (through the use of predicted disturbances $\hat{V}$).

In practise, a *Kalman filter* is used for this initial state estimation, as it provides an optimal reconstruction of the state (for linear systems with normally distributed process and observation noises [37, Chap. 4]). Further details on the Kalman filter and its implementation can be found in Madsen's [37, Chap. 10] and Ljung's [38, Chap. 4] textbooks.

Modelling of system dynamics

The description of the system dynamics allows predicting the future behaviour of the system. It is an essential part of the MPC controller.

These dynamics are traditionally described using a discrete time *state space model* of the system, which describes the dynamics of the system. Creating such a model is a task called *model identification*, which is described more in details in the next chapter.

In order to use LP or QP optimisation, a linear state space model is required. For such a model, the function F is takes the form

$$X[j+1] = AX[j] + B_{\mathrm{U}}U[j] + B_{\mathrm{V}}\hat{V}[j] + \epsilon_{\mathrm{P}}[j] \tag{3.18}$$

and an observation equation is added

$$Y[j] = CX[j] + \epsilon_{\mathrm{O}}[j] \tag{3.19}$$

where $(A, B_{\mathrm{U}}, B_{\mathrm{V}}, C)$ are the state space model matrices, ϵ_{P} the process noise, ϵ_{O} the observation noise, X the states, U the controlled inputs, $\hat{V}$ the estimated disturbances, and Y the observations.

3 Review of applications of MPC on real buildings

[9]For example, envelope temperature in a lumped grey-box model cannot be directly measured.

3.1 Experiments

Investigations of model predictive control have been made in the recent years, on both large office buildings and residential buildings. A few examples are presented in this subsection.

Lindelöf et al. have investigated the performance of a MPC controller using ANN on 10 Swiss residential buildings, and observed an average of 28% energy savings in the period with significant variations from one house to another. These savings originated from the capability of accounting for future climate conditions (including solar gains). [56]

The OptiControl project[10] investigated the performance of MPC on part of an office building in Basel (Switzerland) [78, 111], leading to reduced energy use and high comfort compared to a rule-based controller (RBC)[11]. It concluded that the required engineering work (modelling, controller development, training of operator, installation and hardware, and data/forecast management) was too high to justify widespread adoption of MPC on the sole basis of the resulting cost savings. However, it was also emphasised that this conclusion was conditioned by current energy prices, the tools currently available, and the type of building. [99]

Extensive investigations of MPC were also made on a university building of the Czech Technical University in Prag [75, 76]. Savings in the range of 20% were observed in the experiments, compared to the initial heating curve control. Moreover, modelling was identified as the most demanding and costly part of the implementation of MPC. [112]

De Coninck and Helsen investigated the performance gains of MPC on a medium-sized office building in Brussels (Belgium). A reduction of the cost in the range of 30% and primary energy use of around 20% were observed, compared to the initial RBC. Comfort was also observed to be higher or equal when using MPC instead of RBC. [41]

A vast amount of literature is available for applications of MPC in simulation works, as presented in the review by Shaikh et al. [89]. Typical examples of simulation packages used for investigation of MPC are (among others) TRNSYS, Dymola, Matlab/Simulink, EnergyPlus[12], and IDA-ICE[13].

[10] A large project involving industrial and academic partners, more details on: `http://www.opticontrol.ethz.ch/`

[11] RBC is a type of controller based on simple rules of the type, which is the state of art in building control systems.

[12] EnergyPlus can be coupled with Matlab, Simulink, Dymola using the BCVTB toolbox [113].

[13] At the time of writing, IDA-ICE did not have an easy way to interface to Matlab and other optimisation packages. However, this may appear in future versions.

3.2 Benefits and drawbacks from predictive control

As highlighted in an extensive review by Afram and Janabi-Sharifi, MPC was generally observed to lower the energy consumption, be more robust to disturbances, have a more consistent performance in varying conditions, and a better transient response, compared to most other control techniques [28].

Moreover, MPC is naturally well suited to applications where storage is given.

Drawbacks of MPC are its high costs originating from engineering (modelling, design, and maintenance), data management (forecast and data storage), added hardware (sensing and data collection), and operator training (in the case of large buildings with a building manager). A reader interested in more details may refer to the case study on an office building by Sturzenegger et al. [99].

The performance of MPC is conditioned by a number of factors, with a cumulative impact on the overall performance of the controller [28, 41]:

- the mismatch between the model and reality,
- the accuracy of the disturbance forecast (e.g. weather and occupancy),
- the chosen sampling time and prediction horizon,
- the precision of the state estimation.

This emphasises the existence of multiple points of failure for achieving the highest possible MPC performance.

Despite concluding on a lack of economic viability in its use case, the OptiControl project highlighted that MPC developments have an important synergy with RBC. This is because on a mathematical level, there is equivalence between finding optimal rules in a large decision space and solving the MPC problem. In other words, an in-depth study of MPC on a given building should allow deriving a reduced set of relevant rules and parameters for a RBC. [111]

4 A simulation study on a Danish single family house

In this section, the contribution of the research in the field of MPC are briefly introduced.

4.1 Study on an idealised house with floor heating

This subsection summarises the work from paper B [31].

Methodology and context

In the study, a low energy single family house with floor heating was simulated for a period of 2 months in the winter, using historical data from Denmark.

Six different MPCs were compared, with different strategies minimising: energy use, spot price of power, CO_2 emissions from power, non-renewable energy use, non-renewable energy use with incentive to balance excess wind power, and deviations from the set-point. All controllers were based upon LP optimisation, and using the same simplified model as was used for simulating the house (leading to an ideal case).

All six controllers were compared using a common set of key performance indicators: energy consumption, non-renewable energy consumption[14], CO_2 emissions from power generation, cost of energy (based upon SPOT price), integral deviation from the set-point, and comfort violations (using a degree hour criterion).

Outcomes

The study demonstrated the flexible behaviour of price, renewable power and CO_2 optimisation, were the thermal mass of the building was activated through automatic deviation of the indoor temperature from its set-point. Conversely, energy and comfort optimisation did not activate this thermal mass. For any controller, the comfort bounds were never significantly violated.

Then, a number of trade-offs between the strategies were observed. A first important side effect from flexible energy use was the increase in total energy consumption by 3.5–5.2 %, compared to energy or comfort optimisation. On the other hand, CO_2 emissions were observed to be 7–12 % lower for the CO_2 optimising controller than for the others (including energy minimisation), with energy and comfort optimisation being the most carbon intensive.
Moreover, it was observed that spot price optimisation does not provide a significant cut in CO_2 emissions compared to energy optimisation and that its cost reduction would be minor for the end consumer. This challenges a common belief that price optimisation leads to minimised emissions, as renewable generator bid in the power market at zero marginal price.

4.2 Extensive study with low inertia heating

This subsection summarises the results in paper C [32] which are relevant to MPC (the results on carbon intensity will be presented later in chapter 5).

[14]Better indicators would in fact be the fraction of power not originating from renewable generation, or non-renewable primary energy consumption.

Methodology and context

The study considers three single family houses of identical shape, but different construction years (1970, 2010, and 2015 – therefore with differing insulation standards). These were simulated for a period of one year, using historical data from Denmark. Heating was made using low inertia electrical heating, and occupation of the 4 inner rooms was simulated using predefined schedules.

Different controllers were evaluated on each of the houses: 2 thermostatic controllers (with normal and high lower temperature bound), and 4 MPCs (minimising energy, CO_2 emissions, spot price, or deviation from indoor temperature set-point) which were combined with a dispatcher to ensure comfort within each of the rooms.

Performance was assessed using common performance indicators for each of the houses and controllers over a heating season: energy consumption, indirect CO_2 from power use, and integrated discomfort. Energy and discomfort indicators were evaluated with monthly granularity.

Outcomes

It was observed that MPC would provide limited benefits for low inertia heating. In comparison, lowering the thermostat lower bound by 1 °C (in the case that occupants would have set it higher than needed) would in fact have provided more energy savings and reduction of the carbon footprint.

Predictive controllers resulted in lower energy consumption (within 7–12% for energy optimisation, and 2–9% for price and CO_2 optimisation), and lower carbon footprint (within 7–12% for CO_2 and energy optimisation, with lower benefits from price optimisation) compared to thermostatic control. In terms of comfort, it happened that CO_2 and price optimisation resulted in uncomfortable over-heating (especially for the older house), while comfort optimisation (minimising the deviation from the set-point) resulted in equivalent or worse comfort than energy optimisation.

From an energy and carbon perspective, only energy and CO_2 optimising formulations of the predictive control problem were observed to be relevant, whereas spot price and comfort optimisation were not seen to bring further value.

"The goal of an identification procedure is, in loose terms, to obtain a good and reliable model with a reasonable amount of work."

L. Ljung

4

Control-oriented dynamical modelling of the thermal dynamics of buildings

1 Problem statement

This chapter deals with the problem of building a suitable model for the thermal dynamics of a building. This model is meant to be used to support MPC, which was presented in the previous chapter[1].

A dynamical model is a mathematical entity describing the behaviour of a system. It provides an estimation of the outputs, given inputs and disturbances to this system. Often, the structure of such a model comprises a number of parameters (such as a model order or physical parameters).

In the case of buildings, common inputs are temperature set-points, heat and power, depending on what actuators are available to the controller. Ordinary outputs are indoor temperature or power/heat load. Disturbances fall into two categories: *exogenous* disturbances originating from outside the building, and *endogenous* disturbances from within the building – as high-

[1]It is worth knowing that dynamical models are also valuable for a variety of other important applications. Examples of such alternative applications are energy performance assessment [114], building characterisation [115, 116], fault detection and diagnostic [117] (including on the HVAC equipment [118]), and performance monitoring [119].

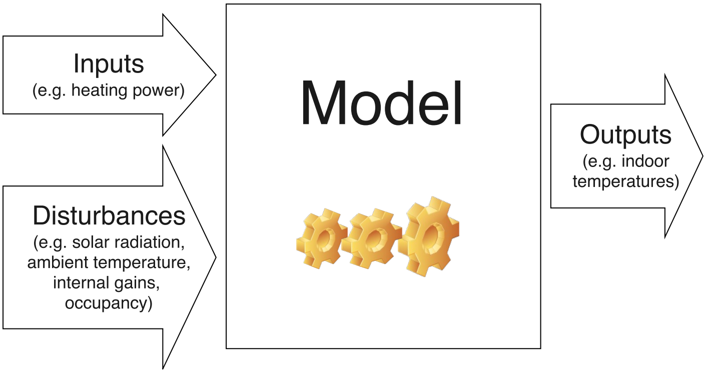

Figure 4.1: Schematic representation of the model

lighted by De Coninck and Helsen [41]. Typical examples of exogenous disturbances are ambient temperature[2], solar radiation[3], and wind speed [85], while common endogenous disturbances are occupation, internal heat gains, and plug loads.

This illustrated on Fig. 4.1.

Formal problem definition

The problem is somewhat similar to the forecast problem (see Eq. (2.1)). However, the focus is on the model ($\mathcal{M}$), rather than the result of its predictions ($\hat{\mathcal{Y}}$) of observations ($\mathcal{Y}$), given knowledge of the inputs and disturbances ($\hat{\mathcal{V}}$) over a determined period ($\mathcal{T}$). Here, a time (or budget) constraint ($\mathcal{C}$) for the modelling task, as well as prior-knowledge ($\mathcal{K}$) can act as limits in the decision space.

The task can therefore be expressed as the resolution of a constrained optimisation problem:

$$\begin{aligned} \mathcal{M} &= \arg\min_{\mathcal{M}} \; Mismatch\Big(\hat{\mathcal{Y}}(\hat{\mathcal{V}},\mathcal{T}),\mathcal{Y}(\mathcal{T})\Big) \\ s.t.& \\ &\mathcal{C}\;,\;\;\mathcal{K} \end{aligned} \tag{4.1}$$

[2]Dry-bulb air temperature

[3]Here, the global horizontal value [120] or projection onto a particular plane [85] are mostly used.

2 Dynamical modelling of the thermal behaviour of buildings

This section presents the framework for building a suitable dynamical model for MPC (corresponding to the prior Eq. 3.6, and Eq. 3.18 for the linear form).

Model categories

These models can be of different types, falling in 3 categories: white-, grey-, and black-box modelling. White-box modelling relies simply on physical principles and prior knowledge to describe the system's dynamics. Conversely, black-box modelling relies upon observations of the system to infer a description of the dynamics while not directly using any prior knowledge of the system (other than the limited observations). Lastly, grey-box modelling somewhat combines both approaches by providing a simplified parameterised physical description of the dynamics, whose parameters are identified using the observations. It is therefore sometimes called "semi-physical modelling".

For these reasons, white-box modelling is referred to as *forward* modelling, while grey- and black-box correspond to *inverse* modelling.

For each of these categories, a variety of methods are available. White-box models often rely upon simulation softwares (e.g. TRNSYS [121], Energy+ [122], IDA ICE [123]). Grey-box models traditionally rely upon equivalent resistance-capacitance (RC) networks [120], with either a deterministic or stochastic description (depending on the type of differential equations adopted). Black-box models are often built using regressive methods (e.g. ARX [124], ARMAX [125]) [126], artificial neural networks (ANN) [53, 127], subspace identification methods[4] (4SID) [112, 125, 129, 130], or other methods. A summary of the most common methods is given in Fig. 4.2. For a more detailed insight in dynamical models for building modelling, the reader may refer to the reviews of Atam and Helsen [131], Foucquier et al. [132], and Li and Wen [133].

Criteria for usability in control

Here, the focus is on *control-oriented modelling*, as the aim is to obtain a model to use in MPC. Beyond a satisfactory of the dynamics of the system, this requires that the model is *observable*, of *low complexity*, and requiring low solver time when used in optimisation [134]. *Robustness* of the models is an additional important feature.

[4] In fact, 4SID can even be extended to use prior information [128].

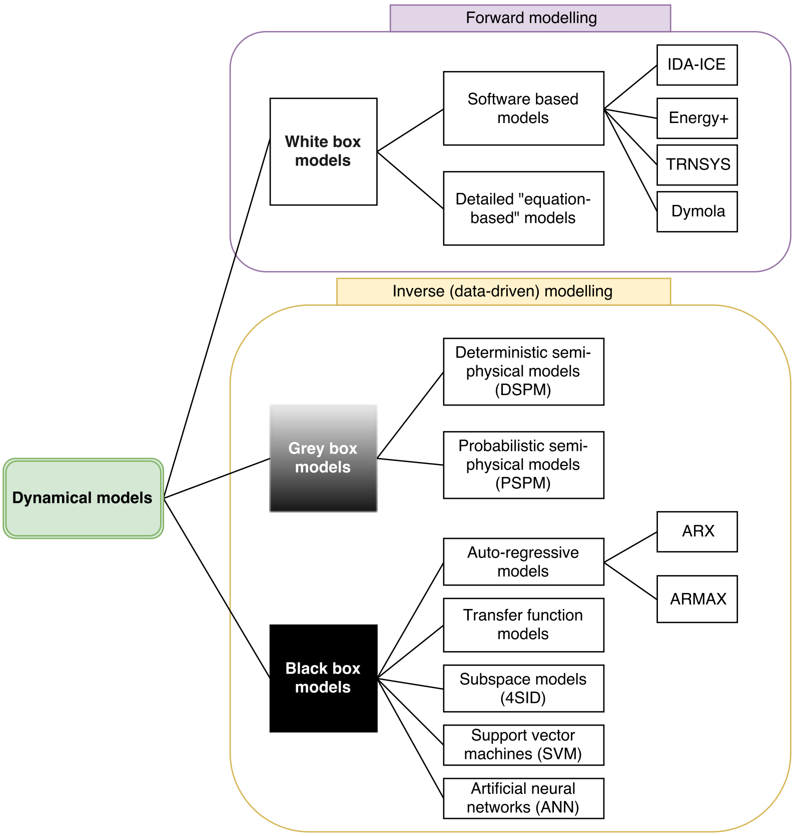

Figure 4.2: Main approaches for dynamical modelling

Observability is important, because the initial state of the system needs to be estimated at each step using observations.

Low model complexity is needed, because the model needs to be usable in optimisation (which is not straightforward with non-linear models) and should be identifiable with reasonable amounts of data and efforts.

Low solver time (in optimisation) is needed in order to converge to a solution faster than the length of a control step.

Lastly, robustness is important as it ensures that the model will describe well the dynamics of the system under any operating conditions (e.g. cold winter, as well as warmer days).

White-box models typically fail to meet these conditions, due to their high complexity. They are therefore not used in control. On the other hand, grey- and black-box models are more simple to build and often to use in optimisation, but their robustness requires particular attention. This robustness issue is due to the use of a limited dataset, which often only covers a reduced range of operating conditions.

Experimental data collection to support modelling

For grey- and black-box modelling, a crucial aspect is the dataset used for modelling. This dataset should be *rich* enough, in terms of information. First, this requires sufficient variations in the inputs and disturbances to ensure that the range of operating conditions is covered. Second, these inputs and disturbances should have a low cross-correlation, in order to be able to distinguish their influence[5]. Third, the output should also exhibit sufficient variations to allow identification of the dynamics.

In fact, data obtained under normal closed-loop operation is hardly rich enough for model identification. Pseudo random binary sequences (PRBS) [38, Sec. 13.3] can be used as an input to help meeting these conditions. Nevertheless, such an open-loop control is hardly compatible with comfortable occupation of the building (unless specific precautions are taken [135]). A number of such applications of PRBS to real building modelling are found in the literature [85, 105, 120, 136, 137].

When carrying out experiments, an important issue is the presence of noise, which can later impact the quality of the models derived[6]. Such noise can originate from uncalibrated sensors (resulting in a bias), limited precision of indoor temperature sensors (high quantisation steps in the range of 0.3 °C), as well as human interaction with the building – among others.

Detailed considerations concerning the experimental design are found in

[5] This is because data-driven modelling relies upon correlation analysis between inputs and outputs.

[6] For grey-box model, parameters values and confidence intervals can be affected, as shown by Reynders et al. [138]

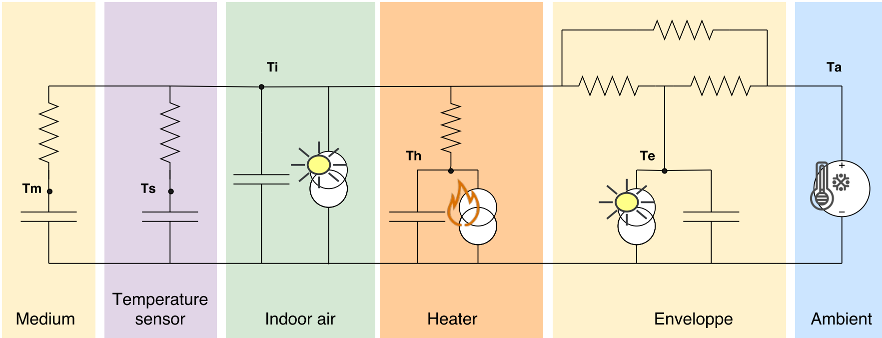

Figure 4.3: Example of a complex building model in RC-network form (structure from [120]). The pictograms on generators correspond to the inputs/disturbances that are modelled (solar radiation, heat, and ambient temperature) while the states (temperatures) are annotated on the corresponding node of the diagram.

Ljung's reference textbook [38, Chap. 13] (for theoretical considerations), and a report by the IEA EBC Annex 58 [115] (for a more practical and building-oriented approach, although more focused on characterisation than control-oriented modelling)

Grey-box model structures from the literature

The literature contains a large number of generic grey-box model structures for the thermal dynamics of a building. These range from a simple first order model to advanced models containing more than five states (see the example in RC-network form in Fig. 4.3).

Detailed possibilities of model structures in RC-network form are found in the works of Bacher and Madsen[7] [120], Berthou [126], De Coninck et al. [134], Thavlov and Bindner [139], Ferracuti et al. [140], Li et al. [130], and Vivian et al.[8] [141].

2.1 Identification and validation of a model

The first step in modelling is to choose a modelling approach and model structure. The approach is typically one of those previously summarised in Fig. 4.2, where the model structure comprises the inputs, outputs, disturbances, and parameters.

[7]Structural identifiability was however not considered in the study of Bacher and Madsen.

[8]The models from the VDI 6007 and ISO 13790 standards used in the study of Vivian et al. have some identifiability issues due to their numerous parameters and resistances in series.

Identification of a dynamical model

Once this model structure is chosen, the model needs to be *identified*. This can be realised using *prediction error methods* (PEM), *maximum-likelihood estimation* (MLE – for parameterised models), or least squares estimation (LSE). In the case of PEM, a particularly interesting approach is the so-called "MPC relevant identification" method (MRI), which minimises a multi-step ahead prediction error[9] [144, 145].

A key issue in identification is model *identifiability*. In the case of parametric models, this means that there is only one parameter vector that represents best the observation data. This can be checked through sensitivity analysis of the parameters, for example by using the standard deviation, p-value, or the Sobol indices [146] (as done by Berthou [126]) of the parameters.

Validation of a dynamical model

After a model is identified, it needs to be *validated*. This validation can either be made by predicting the behaviour on new validation data, or by operating residual analysis. Residual analysis can be made by looking at the cumulated periodogram, the cross-correlation with inputs, and the autocorrelation of the residuals, as exemplified in the works Bacher and Madsen [120] or Prívara et al. [147].

On the one hand, the use of validation data reduces the risk of over-fitting of the model, at the cost of reducing the dataset available for training the model or collecting new data. On the other hand, residual analysis allows to use the full dataset (or avoid collecting new data), and obtain a deeper understanding of further possibilities to improve the model.

2.2 Selection of a model among a set of candidates

Given a number of different identified models of varying inputs and/or structure, an important issue is the selection of the model that represents the system best. Such a problem is called *model selection*, and can be addressed using a variety of methods presented below.

Prívara et al. [147] introduced an iterative two stage process. First, appropriate disturbances are selected. Then, a preferable model complexity (e.g. its order) is selected. In both cases, it is proposed to operate the model selection using likelihood ratio tests (for models identified using MLE) or a test based upon the cumulative periodogram.

For nested grey-box models (i.e. where a model is an extension of another) identified using MLE, Bacher and Madsen proposed a forward selection approach based upon likelihood ratio tests [120]. In such a case, an extension of

[9] An enhanced version of the algorithm was developed by Potts et al. [142]. Another interesting extension is the combination with partial least squares, presented by Prívara et al. [143].

a model is selected if and only if it (1) increases the likelihood of the model on the training data and (2) is the extension that provides the highest increase of this likelihood.

A limitation of pure forward selection is that insignificant parameter may be kept, according to Andersen et al. [85]. It is therefore recommended to consider backward selection on the resulting model to remove potential useless terms.

2.3 Tools for identification

Several software packages are now available for data-driven modelling.

A first possibility is the MATLAB System Identification toolbox [148]. It is capable of identifying both discrete and continuous time models, for either grey- or black-box models, with deterministic or stochastic approaches.

Another possibility is the CTSM package for R [149], which has gained popularity in the field of building thermal dynamics in the recent years with a growing number of applications [85, 85, 120, 138, 139]. This package exclusively operates with continuous time stochastic models. Although particularly suitable for grey-box modelling, it may also be applied for black-box modelling approaches from the field of timeseries analysis.

Both CTSM and the MATLAB toolbox have the capability to deal with both linear and non-linear models. In both cases, a sensitive issue in grey-box model identification is the choice of a suitable initial parameter vector (as the non-convexity of the optimisation does not yet seem to be fully accounted for).

Other possibilities of software packages are LORD [150] and TMB[10] [151].

Recently, some toolboxes have been developed to automate an increasing part of the modelling process [134, 152]. However, full automation of the modelling task does not seem to have yet been achieved by any tool.

3 A case study on a super-insulated building

This section summarises the work from paper D [33].

Methodology and context

This work is a case study of a super-insulated residential building in Norwegian climate: the LivingLab at NTNU, which was designed to be a zero-emission building[11]. A dedicated controlled excitation experiment was made upon the building, over a total duration of 24 days.

[10] At the time of writing, no published work on building thermal dynamics seems to have used the TMB package.

[11] Accounting for emissions from materials, construction, and operation.

Heating was ensured by a unique central electrical radiator operated according to a PRBS, while the building was unoccupied to avoid noise from human behaviour.

After processing, a simple first order model was identified from the data. This model used ambient temperature, global horizontal radiation, heat from appliances and ventilation as inputs, building-averaged indoor temperature as a state, and had 3 identifiable parameters. This identification was made using two different software packages: CTSM and the MATLAB System Identification toolbox. Results on reduced parts of the dataset, as well as data with different sample times (5, 15, 30, and 60 min) were compared.

Outcomes

It was first observed that significant indoor temperature variations occurred between different zones of the building with the chosen heating configuration (especially with closed doors to the bedrooms), as well as between different heights. In fact, the difference between the lowest and highest temperature measurement was as high as 10 °C in some occasions.

Despite these inhomogeneities, a single equivalent average temperature was used to model the indoor temperature in the first order model. In such a case, it was observed that the first order model trained on a week of data with a 15 min sample time would provide a reasonable model for the main trend of this average temperature. Increasing the length of the training dataset was however found to provide some improvement in the model, while increasing the sample time of the data reduced the quality of the model.

When it comes to the values of the parameters identified by the software packages, disparities were observed both between the software packages and between the sample times used for the data for a given software package. However, for a given sample time, there was always an overlap between the 95% confidence intervals of the parameters identified by the software packages.

Lastly, in order to stimulate further analysis (and potential model benchmarking) on the data, the dataset was published on an open-data platform [153].

"What we measure affects what we do; and if our measurements are flawed, decisions may be distorted."

J.E. Stiglitz, A. Sen & J.-P. Fitoussi

5 Carbon intensity of power: a control signal and performance metric for flexible loads

This chapter introduces the carbon intensity metric, and possibilities of usage in control and performance assessment. Here, it is important to note that "carbon" is meant as a synonym for "greenhouse gas emissions".

In this work, a deliberate choice is made to transfer the full responsibility of the emissions of the energy production, conversion, transmission and distribution to the end-consumer (together with their moral burden). This is motivated by a user-centric perspective adopted here, where the energy system is only seen as an essential means to deliver services fulfilling human needs (such as maintaining a comfortable indoor temperature in buildings).

At this point in time, the dynamic carbon intensity signal is only available for some power systems. Therefore this work focuses on the sole case of power systems. Nevertheless, such a framework can in fact also be applied to other systems (e.g. district heating systems) provided that such information becomes available in these.

1 The carbon intensity metric

This section presents the carbon intensity metric. The reader is hereby advised that this metric is still very flawed at the time of writing. Nevertheless, the intention here is to open directions for future usages of it and push the debate further.

1.1 A common metric for greenhouse gas emissions linked to energy production

The *carbon intensity* of energy is defined by the amount of greenhouse gas emissions per unit of energy. It is sometimes also called *emission intensity* or CO_2 *intensity*. These emissions can be either direct (e.g. combustion), or indirect through the necessary processes to obtain this energy (e.g. flooding of an area causing plant decay, fuel extraction and refining).

The most common greenhouse gases are carbon dioxide (CO_2), methane (CH_4), nitrous oxides (N_2O), and fluorinated gases such as SF_6, NF_3, hydrofluorocarbons (HFCs – also responsible for ozone layer depletion, and therefore regulated by the Montreal protocol) and perfluorinated compounds (PFCs).

Each of these chemical species has a different impact on the atmosphere's greenhouse effect, measured by its *global warming potential*[1]. These potentials are expressed in CO_2 equivalent (unit: $kgCO_{2,eq}$ or similar), which provides a (simplified and approximate) common emission parameter.

Different generation technologies have different emission intensity, as illustrated in Tbl. 5.1. For a given technology, there is also a high uncertainty on this emission factor, for a considerable number of the plant's life-cycle details including construction process, fuel characteristics, and plant efficiency to name a few.

In energy systems where production is increasingly made by renewable energy, large variations of the emission intensity of energy can occur over time due to fluctuations in the energy mix[2], as illustrated in Fig. 5.1. It is therefore becoming important to consider such dynamical variations.

1.2 Intensity at end-user level

From an end-user perspective, most of the emissions from energy use are of indirect type (except from direct combustion, e.g. for heating purposes), as emissions occur in geographically distant places. This complicates the process of building quantitative awareness of the impact of the energy usage,

[1]A review of these was made by IPCC in a report [154, p.710–720]

[2]More details for recent years in Denmark are found in paper C.

Table 5.1: Typical greenhouse gas emissions from different power generation technologies used in Scandinavia. Figures from IPCC (accounting for lifecycle emissions and albedo) are presented together with data from Danish TSO (focusing solely on emissions from combustion with a coarse quantification of renewables) for 2016 and other sources

Source	Carbon intensity (g CO_2 eq/kWh)				
	IPCC [155]			Scandinavia	
	Min.	Median	Max.	DK [156]	NO
Power generation					
Coal (pulverized hard -)	740	820	910	851	
Gas (combined cycle)	410	490	650	440	
Biomass (co-fired)	620	740	890		
Biomass (dedicated)	130	230	420	3	
Solar PV (rooftop)	26	41	60	0	
Solar PV (utility)	18	48	180		
Wind (onshore)	7	11	56		
Wind (offshore)	8	12	35		
Hydropower	1	24	2200	0	2.4 [157]
Nuclear	3.7	12	110		
TSO emissions					
SF-6 leak				0.37	

and requires the use of information technology – especially when considering dynamical variations.

At end-user level, the energy is typically provided through a network[3] (e.g. district heating network, power grid) in which the energy is a compound of the energy produced by different units. In such a case, this energy physically originates from a mix of all these generators and not only a conveniently selected set of them[4]. Moreover, with regional connections, there is a need to consider not only the national energy mix but also the mix of all other regions interconnected with the system.

An important consideration remaining is the efficiency of the network. The lower the losses in a network, the lower the production required to meet a given demand – as expressed in Eq. (5.1). It is therefore important to remember this network efficiencies in footprint considerations, although its influence is typically within model uncertainties. However, this efficiency also comes with significant variations from one system to another, so that use of local data is important[5].

[3]Off-grid autonomous installations are out of the scope of this work

[4]Such a claim is often made in marketing for so-called "green power" contracts, which only ensure that as much energy is bought from renewable sources as was used by the consumer over a long period. To some extent, the critic could also apply to regional divisions of carbon intensity.

[5]In the case of Denmark (a country with rather high efficiency), efficiency of the power grid

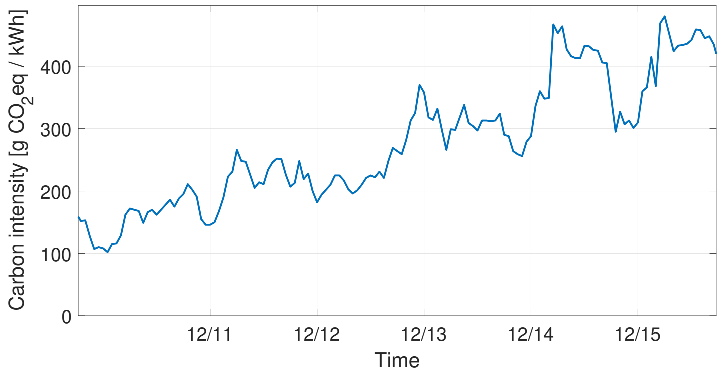

Figure 5.1: Variations in the estimated carbon intensity of the power in the Danish transmission system over a selection of days in December 2015 (data: Styr din Varmepumpe [158])

$$\text{Carbon intensity at user level} = \frac{\text{Carbon intensity from production mix}}{\text{Network efficiency}} \tag{5.1}$$

2 Average carbon intensity: a new performance metric for energy-flexible operation

In energy efficiency and carbon footprint assessment, typical performance metrics are the total energy consumption and carbon footprint, respectively. However, in the case of energy flexible loads, it can also be interesting to evaluate how 'well' the load is shifted to times with lower carbon intensity. A simple approach to such a quantification is to compute the *average carbon intensity* of the power consumed by the load over a period ($\mathcal{T}$), using Eq. (5.2).

$$\text{Average carbon intensity } (\mathcal{T}) = \frac{\text{CO}_2 \text{ emissions}(\mathcal{T})}{\text{Energy use}(\mathcal{T})} \qquad [\text{gCO}_{2,\text{eq}}/\text{kWh}] \tag{5.2}$$

On a mathematical level, this metric is no more than a simple cross-correlation between load and carbon intensity, normalised by the total load over the period – with a simple physical interpretation.

is around 97% at transmission level, and 95% at distribution level [156], while district heating networks have efficiencies around 80%.

By comparing this average value to the statistical properties of the carbon intensity signal over the period, it is possible to quickly characterise the flexible operation using only aggregate data, rather than the detail of the timeseries (once the total footprint is computed using these). This can therefore be a means to carry out a low-cost partial assessment of flexibility over a long timescale[6], without requiring the prior splitting of high and low price hours (as often done in typical approaches [159, 160]).

This metric is used for quantification of controller performance in paper C, where its value is computed for different predictive controllers and thermostatic control. This simulation study was carried out on three simulated houses of differing age and with low inertia electrical heating in a Danish environment using a year of historical data. Its usage allowed highlighting that energy optimisation increased this average intensity slightly (+0.4–1.2 %) compared to a baseline thermostatic operation, while it was reduced for SPOT price (-0.4–2.5 %) and CO_2 optimisation (-2.8–4.3 %) compared to the same baseline. This information was a useful complement to the total energy use and total footprint for each of the controllers.

3 Use of carbon intensity in model predictive control

Whenever an estimation of the dynamic carbon intensity of energy is available (together with a short-term forecast of its future values) its usage is possible in control. As seen earlier in subsection 2.3, the dynamic carbon intensity of energy can be used as a price signal in MPC of loads. In such a case, it can be used either on its own, or combined with other price signals (see Eq. (3.8)).

3.1 Advantages and drawbacks

Direct usage of the carbon intensity in MPC of heating in individual houses was used in simulations in a Danish setting with results described in papers B and C . These studies showed that such a control has the potential to reduce the carbon footprint of heating in individual houses, although the reduction is small when only exploiting the thermal mass of rather lightweight buildings.

Nevertheless, it may happen that the total footprint increases compared to pure energy optimisation, when the model in MPC is insufficiently accurate (as occurred in paper C for the house from 1970). This is because the total energy use is often increased when shifting energy over time, although the

[6]The idea presented here works with any type of price signal, and is not limited to carbon intensity used here as a concrete example.

Table 5.2: Correlation coefficients between real time price, carbon intensity, wind, and load on the Danish power grid (2013–2014 figures from Knudsen and Petersen [95], 2015 data (january–november) from Styr din Varmepumpe [158])

	2013			2014			2015		
	CO_2	Load	Wind	CO_2	Load	Wind	CO_2	Load	Wind
Price	0.41	0.67	-0.48	0.57	0.62	-0.34	0.61	0.58	-0.38
CO_2		-0.05	-0.79		0.13	-0.81		0.32	-0.34
Load			0.04			0.09			0.13

total footprint of the predicted consumption is lower. Therefore, accuracy of the model prediction should be given great attention.

The advantages of CO_2 optimisation in MPC are multiple. First, it allows to optimise directly on an estimate of the CO_2 intensity rather than proxies such as the SPOT price of energy. Second, it promotes the consumption of renewable power and dissuades the consumption of fossil-fuels – which should improve correlation between the load and availability of renewable power. Third, the availability of the carbon intensity metric allows to easily raise quantitative awareness of the footprint and educating the user about the importance of flexibility).

On the other hand, such a control also comes with drawbacks. First, there is a need for a reasonably precise dynamic carbon intensity metric, which requires input data with a precision seldom found or even available[7]. Second, the quality of the dynamical model in MPC is key in ensuring actual footprint reduction compared to energy optimisation, as the accuracy of the predictions becomes even more important. Third, it may also increase load in the critical peak hour (a tendency observed in [95]) or coordination of loads which could cause congestions in networks.

3.2 Correlation between price and carbon intensity

The cross-correlation between the real time market prices (e.g. SPOT price) and the carbon intensity of energy is often rather limited, despite low marginal costs of renewable generation. An historical quantitative illustration for Denmark is given in Tbl. 5.2 below, and plotted for a short period in Fig. 5.2.

In practise, this low correlation can lead to limited benefits of implementing price optimisation when it comes to carbon footprint.

The study of paper B found only a minor decrease in the total carbon footprint of heating for spot price optimisation, compared to energy optim-

[7] Here, the reader is reminded of the uncertainties in Tbl. 5.1, and the approximations and lack of consensus on methodologies highlighted in paper C.

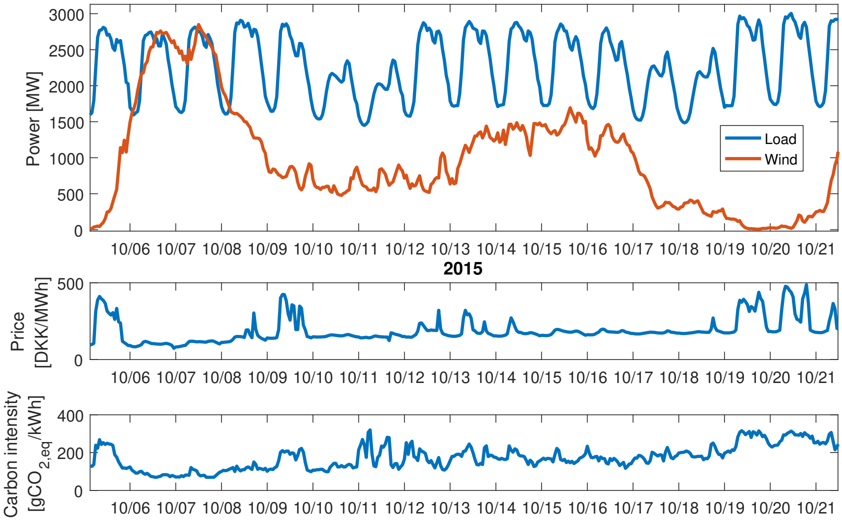

Figure 5.2: Dynamics of wind generation, load, spot price, and carbon intensity on the Danish grid over a period in October 2015 (data: Styr din Varmepumpe [158])

isation. This improvement was well below what could be achieved with CO_2 optimisation.

In the study of paper C, spot price optimisation led to reduced average carbon intensity compared to energy optimisation, but far from the full potential of CO_2 optimisation. Nevertheless, its total carbon footprint was higher than that of both energy and CO_2 optimisation.

3.3 Limits of the approach and further investigations

It is important to bear in mind that little research has yet been done in this field. Hence, further work is needed before drawing any robust conclusion about practical benefits and impacts presented in this section.

Regarding future work, an important discussion is needed on whether to use the *average* or the *marginal* dynamic carbon intensity. All the works in this thesis have focused on the former, while the latter is in fact more relevant for DSM considerations. This limitation is due to the difficulty to compute the marginal intensity without extensive knowledge of the system, and the lack of this parameter in the datasets supporting the study.

"The best way to predict the future is to invent it."

A. Kay

6 Conclusions and perspectives

This chapter concludes the introduction of the collection of papers by summarising contributions and proposing directions for future research.

1 Summary of findings

This work focused on short-term forecast and predictive control of heating loads, using historical data from Denmark.

A study of recursive least-squares with forgetting demonstrated that this method is well-suited to the load prediction for large customers with variable activity such as greenhouses. An automated modelling was proposed in order to facilitate cost-effective identification of models on individual loads.

Two simulation studies of model predictive control in Danish single family houses were then carried out. These demonstrated that the formulation of the objective functions in the predictive controller has an impact on the overall performance, resulting in trade-offs between energy use, carbon footprint, and energy cost. Such differences were due to the fluctuations of the SPOT price and carbon intensity of the power, as well as the reduced correlation between these signals. In future applications, it is therefore recommended to test such different objectives functions to evaluate these trade-offs prior to actual deployment.

A new performance metric for flexible load operation was introduced, corresponding to the average carbon intensity (or any other price signal) of the power consumed. This metric seems well-suited to price-responsive flexible loads, and complements the usual total energy consumption metric. This average intensity metric also has the advantage to allow assessment of the long-term value of load flexibility, as well as being simple to compute.

Regarding control-oriented modelling of thermal loads, it was noted that (at the time of writing) there is no fully automated tool for identifying a dynamical thermal model of a building. Therefore, engineering work is required to build this model, which increases the cost of the controller to a point where it may not be cost competitive for small buildings. This is a bottleneck for widespread implementation of model predictive control [131].

2 Suggestions for future research

Directions for future work are numerous in the domains touched upon in this work.

In terms of short term load forecast, comparison of the performance of recursive least squares with other techniques could be taken further. Combinations of different forecasts (e.g. using expert selection methods) would also be valuable, to assess whether this provides significant added value.

For control in individual buildings, more work needs to be done in comparing the performance of different controllers (including of different types) on a building[1]. In particular, the sensitivity of the performance changes on the building type, structure, and usage should be assessed more in depth. Further research suggestions on MPC of HVAC systems are proposed in the review by Afram and Janabi-Sharifi [28].

Some additional research is also needed on cooperative control of individual buildings within a neighbourhood. This has already been partially covered through the use of aggregators for centralised control, but room for research remains for distributed control and considerations of unreliable communication. Further propositions for residential DSM are given by Priya Esther and Satish Kumar [24], while Fischer and Madani provided recommendation for research on heat-pumps in Smart-Grids (with a scope ranging from individual units to aggregates of them) [162] .

Regarding modelling, further research should be made to achieve automation of the dynamical building modelling process, and alleviate the cost bottleneck of this phase for buildings with low and medium energy costs (such as houses and small offices), taking advantage of the recent steps in this direction. Update of the model over time should also be investigated.

The field of the use of dynamic carbon intensity in MPC and footprint assessment is still in its infancy. There is therefore considerable room for research on this level, including on refining the carbon intensity metric itself.

[1]This is also highlighted by Nägele et al. [161].

Different countries, systems, and types of flexible loads would most likely yield a variety of results. Moreover, introducing considerations of dynamic marginal carbon intensity of the energy adds further room for valuable research.

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Part II

Papers

Due to copyright reasons, this part only contains the full references to papers mentioned in the first part of this thesis.

Appendix A

Online short-term forecast of greenhouse heat load using a weather forecast service

Full reference:

Vogler-Finck P.J.C., Bacher P., Madsen H., Online short-term forecast of greenhouse heat load using a weather forecast service, Applied Energy, 2017, Vol. 205, pp. 1298–1310
http://dx.doi.org/10.1016/j.apenergy.2017.08.013

Appendix B

Comparison of strategies for model predictive control for home heating in future energy systems

Full reference:

Vogler-Finck P.J.C., Pedersen P.D., Popovski P., Wisniewski R., Comparison of strategies for model predictive control for home heating in future energy systems, Proceedings of the IEEE PowerTech conference, June 2017, Manchester (UK), 2017

http://dx.doi.org/10.1109/PTC.2017.7979747

Appendix C

Carbon footprint reduction of dwelling heating operation using model predictive control — A simulation study in Danish conditions

Full reference:

Vogler-Finck P.J.C., Wisniewski R., Popovski, P., Carbon footprint reduction of dwelling heating operation using model predictive control — A simulation study in Danish conditions, (Submitted to) Sustainable Cities and Society, 2018

Appendix D

Inverse model identification of the thermal dynamics of a Norwegian zero-emission house

Full reference:

Vogler-Finck P.J.C., Clauß J., Georges L., Sartori I., Wisniewski R., Inverse model identification of the thermal dynamics of a Norwegian zero-emission house, (will be published in the) Proceedings of the Cold Climate HVAC Conference 2018, Kiruna, 2018

Part III

Appendix

Comprehensive list of publications

Journal articles

– Vogler-Finck P.J.C., Früh W.-G., Evolution of primary frequency control requirements in Great Britain with increasing wind generation. International Journal of Electrical Power & Energy Systems. `http://dx.doi.org/10.1016/j.ijepes.2015.04.012`
— Vogler-Finck P.J.C., Bacher P., Madsen H., Online short-term forecast of greenhouse heat load using a weather forecast service. Applied Energy 2017;205:pp. 1298–310. `http://dx.doi.org/10.1016/j.apenergy.2017.08.013`.
— Vogler-Finck P.J.C., Wisniewski R., Popovski P., Reducing the carbon footprint of house heating through model predictive control – A simulation study in Danish conditions. (Submitted to Sustainable Cities and Societies).

Conference papers (peer-reviewed)

— Vogler-Finck P.J.C., Pedersen P.D., Popovski P., Wisniewski R., Comparison of strategies for model predictive control for home heating in future energy systems. IEEE PowerTech, Manchester: IEEE; 2017, pp.1–6. `http://dx.doi.org/10.1109/PTC.2017.7979747`.
– Clauß J., Finck C., Vogler-Finck P.J.C., Beagon P., Control strategies for building energy systems to unlock demand side flexibility – A review. Building Simulation Conference 2017, San Francisco: 2017. `http://hdl.handle.net/10197/9016`
— Vogler-Finck P.J.C., Clauß J., Georges L., Sartori I., Wisniewski R., Inverse model identification of the thermal dynamics of a Norwegian zero emission house. Cold Climate HVAC, Kiruna: Springer; 2018 (accepted).
– Clauß J., Vogler-Finck P.J.C., Georges L., Calibration of a high-resolution dynamic model for detailed investigation of the energy flexibility of a zero emission residential building. Cold Climate HVAC, Kiruna: Springer; 2018 (accepted).

Dataset

– Vogler-Finck P.J.C., Clauß J., Georges L., A dataset to support dynamical modelling of the thermal dynamics of a super-insulated building. Trondheim: 2017. `http://dx.doi.org/10.5281/zenodo.1034819`.

Presentations

International conferences

– Model Predictive Control for energy efficient house heating: a simulation study of benefits in a Danish environment. Young Researchers: Energy Efficiency + Biomass - World Sustainable Energy Days, Wels: 2017.
– Comparison of strategies for model predictive control for home heating in future energy systems. — IEEE PowerTech, June 2017, Manchester
– Online short-term heat load forecast – An experimental investigation on greenhouses — 4th Generation District Heating Conference, September 2017, Copenhagen

Workshops presentations

– Towards optimised control of heating in households — CITIES WP3 Flexibility and Buildings workshop, DTU Lyngby, September 2015
– Predictive control methods for individual buildings — IEA EBC Annex 67 working meeting, October 2016, Bolzano Prediction of heat load of greenhouses in a district heating system — CITIES internal project partners meeting, DTU Lyngby, October 2016
– Online prediction of heat load - A case study of greenhouses in a district heating system — CITIES workshop on use of smart-city data, January 2017, Aarhus
– Model predictive control for efficient building heating in the 'smart-grid' — Advantage workshop at the IEEE PowerTech, June 2017, Manchester
– Introducing model predictive control (MPC) and grey-box modelling to enable it - Practical experience with the LivingLab — Zero Emission Neighbourhoods in Smart Cities project workshop, November 2017, Oslo.

Posters at conferences and workshops

– Towards the next generation of building heating control — MCAA satellite event to the European Science Festival 2016, Manchester
– Comparison of control objectives for model predictive control of heating in 'Smart homes' — ADVANTAGE research seminar, October 2016, London
– Model predictive control of heating for sustainable home heating — Workshop on Integrating Communications, Control, and Computing Technologies for Smart Grid (ICT4SG) at the IEEE International Communication Conference, May 2017, Paris

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