Review of applied and tested control possibilities for energy flexibility in buildings

A technical report from IEA EBC Annex 67 Energy Flexible Buildings

Review of applied and tested control possibilities for energy flexibility in buildings

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Preface

The increasing global energy demand, the foreseen reduction of available fossil fuels and the increasing evidence off global warming during the last decades have generated a high interest in renewable energy sources. However, renewable energy sources, such as wind and solar power, have an intrinsic variability that can seriously affect the stability of the energy system if they account for a high percentage of the total generation.

The Energy Flexibility of buildings is commonly suggested as part of the solution to alleviate some of the upcoming challenges in the future demand-respond energy systems (electrical, district heating and gas grids). Buildings can supply flexibility services in different ways, e.g. utilization of thermal mass, adjustability of HVAC system use (e.g. heating/cooling/ventilation), charging of electric vehicles, and shifting of plug-loads. However, there is currently no overview or insight into how much Energy Flexibility different building may be able to offer to the future energy systems in the sense of avoiding excess energy production, increase the stability of the energy networks, minimize congestion problems, enhance the efficiency and cost effectiveness of the future energy networks. Therefore, there is a need for increasing knowledge on and demonstration of the Energy Flexibility buildings can provide to energy networks. At the same time, there is a need for identifying critical aspects and possible solutions to manage this Energy Flexibility, while maintaining the comfort of the occupants and minimizing the use of non-renewable energy.

In this context IEA EBC Annex 67 Energy Flexible Buildings was started in 2015 with the aim of gaining increased knowledge on the benefits and services the utilization of the Energy Flexibility in buildings may provide to the future energy networks. The present report is one among several outputs from IEA EBC Annex 67. For further information, please visit http://www.iea-ebc.org/projects/ongoing-projects/ebc-annex-67/.

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Contents

List of Figures

List of Tables

Abbreviations

Abbreviations	Meaning
AC	Alternating current
AHU	Air handling unit
ANN	Artificial neural network
BCVTB	Building control virtual test bed
BTM	Building thermal mass
CHP	Combined heat and power
COP	Coefficient of performance
DR	Demand response
DSM	Demand side management
FF	Flexibility factor
HVAC	Heating ventilation and air–conditioning
HP	Heat pump
KPI	Key performance indicator
MEF	Major Economies Forum (on Energy and Climate Change)
MPC	Model predictive control
MRE	Mean relative error
nZEB	Nearly zero energy buildings
P	Proportional (controller)
PCM	Phase change material
PI	Proportional-Integral (controller)
PID	Proportional-Integral-Derivative (controller)
PVT	Photovoltaic thermal hybrid solar collector
RBC	Rule-based control
RC	Resistance-capacitance
SC	Self-consumption
STG	Smart thermal grids
TES	Thermal energy storage
VAV	Variable air volume
ZEB	Zero energy buildings

1. Introduction

This report reviews the control strategies of energy flexible buildings, with a focus on heating[1] loads under different conditions. The conditions vary due to weather, occupancy and other factors that affect control. Control strategies and metrics are considered for both standalone buildings, *and* their interaction with the energy system. The aim is to transform building energy demand in order to increase efficiency of energy generation and transmission.

Typically the connected energy system is the electricity "grid"; with alternatives being natural gas and district heating networks. The limitations of the grid must be respected by both local producers and consumers. Metrics for grid interaction of individual buildings are included, however a review of building clusters is out of scope.

The report is organised as follows:
Section 2 presents an overview of building energy emphasizing dependency on the building type, its occupants and context. The motivation arising from significant building energy use, specificities of both energy vectors and energy systems are introduced. Two energy systems, electrical grid and district heating, are described and the role of demand response and energy flexibility is introduced.

Section 3 reviews control strategies, opening with control definitions and a critical review of control methods. Different control objectives are identified and compared, together with their constraints. The section explores the potential for optimising building energy use through model predictive control. Lastly, three modelling and simulation approaches are described (white box, grey box, black box) together with advanced mathematical techniques for control and decision making.

Section 4 reviews metrics and indicators to evaluate the results of control strategies. It distinguishes between voluminous monitoring data, computed metrics and high-level KPIs. Metrics and indicators reside in three categories. First, building energy *performance,* second, building energy *flexibility* and third, building *interaction* with it energy system. Energy system (grid) metrics used by transmission and distribution system operators are presented alongside building energy metrics. The contrast is important to understand potential field use of energy flexible buildings.

Appendix A contains the control classifications surveyed in the literature review. Appendix B records notes about simulation models and optimisation methods, in the context of energy flexible buildings.

[1] The focus on thermal aspects of energy use in buildings reflects the expertise of the authors of the present report. Other aspects (e.g. wet appliances, electric cars, etc. are therefore beyond the scope of this report, although the authors believe that they require further research.

Methodology of literature research

This literature research aims to present control strategies showing potential for demand side flexibility deployment in residential or commercial buildings. The control techniques and strategies discussed in this literature survey focus on the particular case of heating and cooling systems including heat pumps and thermal energy storage.

A classification of the literature is presented in Appendix A in the form of a spreadsheet where a number of parameters are assessed for each individual literature reference. The corresponding publications appear in the references at the end of each section.

2. Towards flexibility in energy demand

2.1 Energy use in buildings

Energy is consumed in a building for a variety of reasons related to human comfort and the purpose of the building. It depends on many factors, ranging from the building structure to its environment, as shown in Figure 1.

2.1.1 Key figures of energy use in buildings

A global picture of the energy use in buildings was drawn in a report from the International Energy Agency task-group on building energy efficiency (International Energy Agency, 2015). In this report, it was estimated that buildings worldwide consumed 120 EJ (33,3 ×10^(12) kWh) of energy in 2012. This is more than 30% of the total final energy use originating from human activity on earth, amounting for close to 30% of global CO2 emissions.

The same report highlighted that MEF countries (Australia, Brazil, Canada, China, the European Union, India, Indonesia, Japan, Korea, Mexico, Russia, South Africa, and the United States) are responsible for 73% of this global building energy consumption. Moreover, in these countries, a large share of energy use in buildings is used for the heating of space (36%) and water (18%).

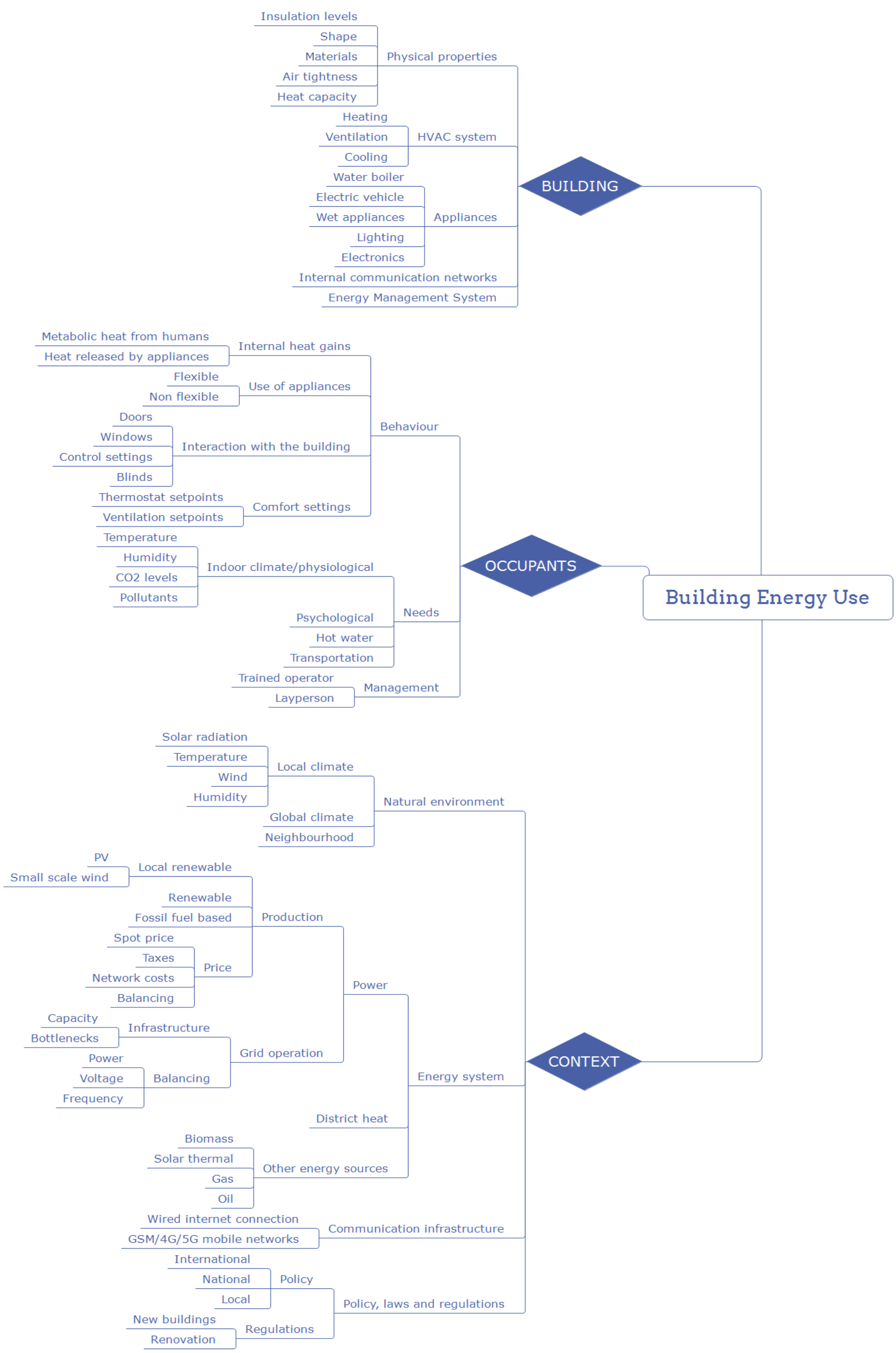

Figure 1. Insight into some of the different dimensions of use of energy in buildings for thermal management purposes.

2.1.2 Energy use in buildings

The final energy used in buildings is provided in a variety of forms: biomass, oil, coal, gas, electricity, heat (e.g. waste heat from other processes, or geothermal applications) and other renewable sources. Figure 2 presents the respective shares of each of those forms in the case of residential and services buildings, highlighting among others the importance of electricity, gas, coal and oil at a global level.

As the current paradigm focuses on the use of energy resources, the energy available as a by-product of activity within the building (e.g. heat originating from human metabolism) or its environment (e.g. solar heat gains) is typically not taken into account in most studies

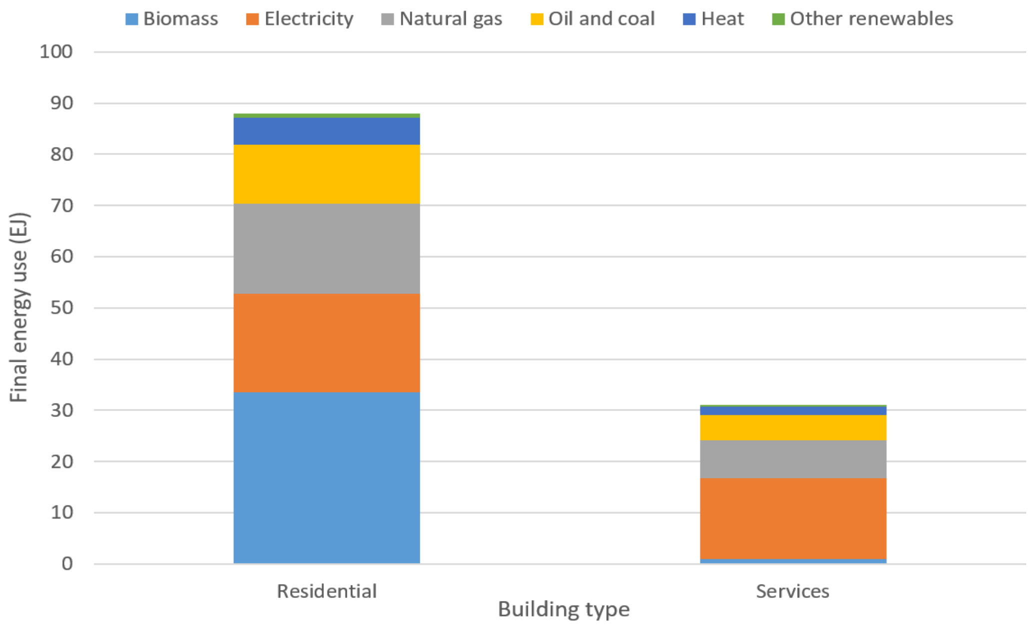

Figure 2. Estimations of global final energy use in buildings in 2012 (Data: (International Energy Agency, 2015)).

2.2 Supply systems supporting building energy demands

Energy is provided to buildings with a variety of supply systems, often through networks where the energy flow can be one or both ways (i.e. the building may either just receive, or both receive and deliver energy). In industrialised countries, typical supply systems are the power grid, district heating networks and gas grids.

Each of these supply systems has its specific operational needs and constraints, leading to different visions of flexibility and the need for it.

2.2.1 Electrical power system (grid)

In this part, electrical power grids are presented. A simplified visual overview of the structure of a power system is given in Figure 3.

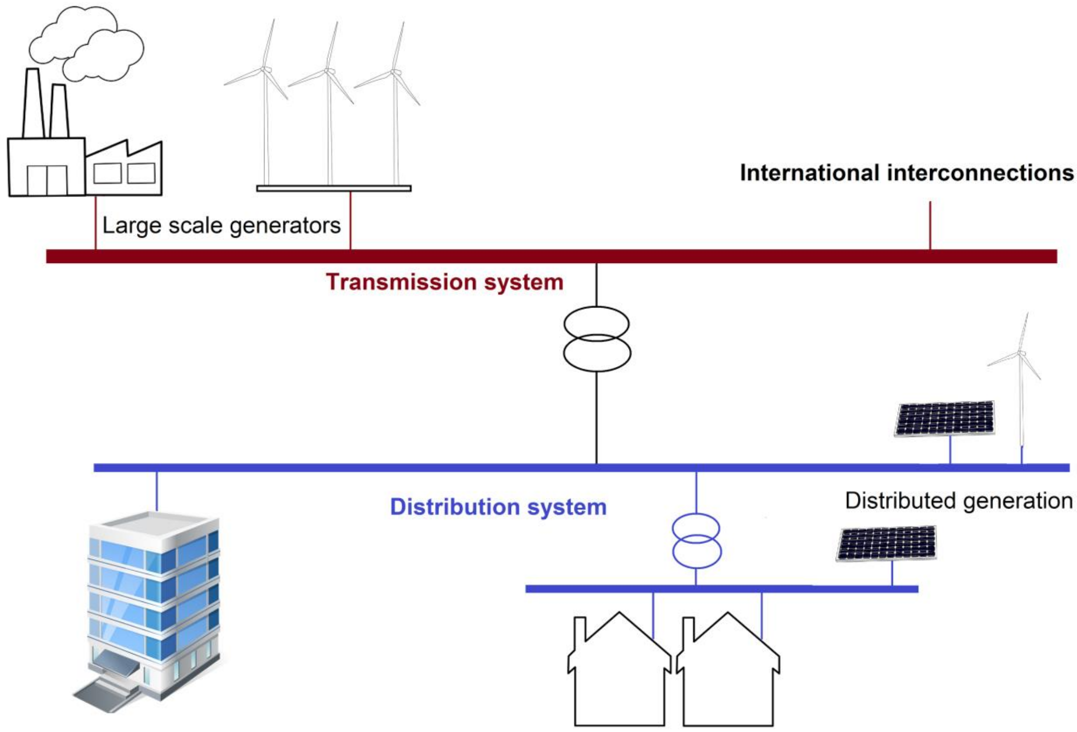

Figure 3. Simplified structure of a power system (cliparts from www.openclipart.org were used).

The transition to a sustainable power system

Historically, power systems have been developed with a centralised paradigm where the power would flow from large power plants to consumers. As conventional generation is more controllable than power from renewable sources, most of the control of the power balance was made on the production side. There has been little to no incentive for medium and small electricity consumers to adapt their energy use, beyond simple time of use pricing motivated by an economic interest for reducing the need to invest in additional infrastructure or load shedding at times when the system is getting over-stressed.

However, humanity has become more aware and concerned about the impact of its activity on the environment over the last decades. In particular greenhouse gases emissions from fossil fuel combustion which contribute to global warming are now receiving due attention. Therefore, an energy transition has started, where the aim is to move away from such fuels. In a system with higher shares of renewable energy production, power generation is expected to be made by smaller units distributed throughout the network. Consumers adjust to variable availability of the power. This distributed generation is, however, introducing a number of challenges in system operation (Pepermans *et al.*, 2005; Lopes *et al.*, 2007) that need to be addressed by means of changes in the way energy systems are operated, including more advanced control.

System operators, regulators and policy makers are working towards this energy transition, which requires a paradigm shift, with a pace and approaches differing among countries. Therefore, some control strategies and control types may not be implementable in some countries at a given point in time, due to technical limitations, differing contexts, and regulatory issues.

Power systems specifics

It is important to understand that a power grid needs to operate under conditions that satisfy all consumers, producers and security constraints. In particular, the power system includes some very sensitive loads which can be affected by too low a power quality. This can, for example, lead to perturbed or interrupted operation or even destruction of appliances leading to large economic losses. Tight requirements are therefore enforced in operation of the power system, to ensure high power quality on the grid (Bollen *et al.*, 2000), through the use of a Grid code to be followed by any actor connected to the grid

As part of the transition to a sustainable energy future, integrating more variable generation is however introducing more pressure on meeting those requirements. Increased contribution from end consumers through demand response is seen as one of the enablers of acceptable operation of a system with higher shares of renewable generation, which is part of the so-called ‘Smart-grid’ paradigm (International Energy Agency, 2011).

Decisions in power system operation are made according to a simple hierarchy:

1. **Ensure stability and operation security of the system**: the power system is a complex and unstable system, where control must be made at all times to ensure its stability and secure operation.
2. **Ensure the provision of the power**: the power system is meant to meet electricity demand. It should therefore fulfil this role in accordance with the desired level of reliability.
3. **Operate in a cost efficient and sustainable manner**: efficient operation benefits the society as a whole by reducing the cost of power, both in financial and environmental terms.

In the case of demand response, most of the contribution to be made lies in improvement of the cost efficiency and sustainability of the power system operation.

There are numerous challenges in power system operation and management, which may be decomposed into the following entangled problematics (Machowski, Bialek and Bumby, 2008; Juelsgaard, 2014):

- **Security of supply**: the power should be provided in a reliable way, so that outages can be prevented whenever possible.
- **Balancing**: in a power system, generation and load must be equal at all times. The power market is designed to help matching them through a number of timescales (from years ahead when making generating capacity investment decisions to intra-day market where generation and consumption are adjusted in real time) and services. Imbalances are measured in frequency deviation that must be contained within a certain range, otherwise disconnections will occur to protect and stabilise the system.
- **Voltage regulation**: voltage needs to be kept within bounds in order to ensure quality of the power, which is made through adjustment of the grid topology and adjustment of the demand.

- **Peak load**: power systems are designed according to the maximum load on the system, although it may happen for only a few hours a year. For power generation, this means that the available capacity must be able to cover this peak demand. A high peak load requires heavy investment in production or storage capacity. And when it comes to transportation of power, a higher peak load translates into need for larger cables and transformers, which is also cost and resource intensive.
- **Losses**: whenever current flows in a conductor, losses occur in the form of heat proportionally to the square of this current. As this energy is wasted, it is of interest to reduce these losses in order to improve the system efficiency.
- **Congestion management**: the grid infrastructure (cable, transformers, etc.) is sized for certain operating conditions, keeping in mind that an oversized infrastructure is neither cost efficient nor environmentally friendly. At times with high system loads, congestions can occur if load (or local production) exceeds the capacity of the grid in a certain area. Congestion increases the power losses and reduces the lifetime of the equipment, so that there is much interest in reducing them as much as possible.

Power systems specificities

Demand response (DR, or Demand Side Response) is a generic term referring to all actions promoting a more active approach to energy consumption, where end consumers are responding to external factors such as incentives or other control signals. It is one of many aspects of demand side management, which is a broader term that also includes energy efficiency measures among others, as shown in Figure 4.

DR has been implemented into power grids for decades, with forms ranging from load shedding for blackout prevention, to time of use rates to reduce system peak load (O´Connell *et al.*, 2014). Nevertheless, progress in computation and communication technology has paved the way to more advanced possibilities for DR.

However, harmonised standards and protocols are still a technological barrier, while control and market structures for demand response are still an open research problem (O´Connell *et al.*, 2014).

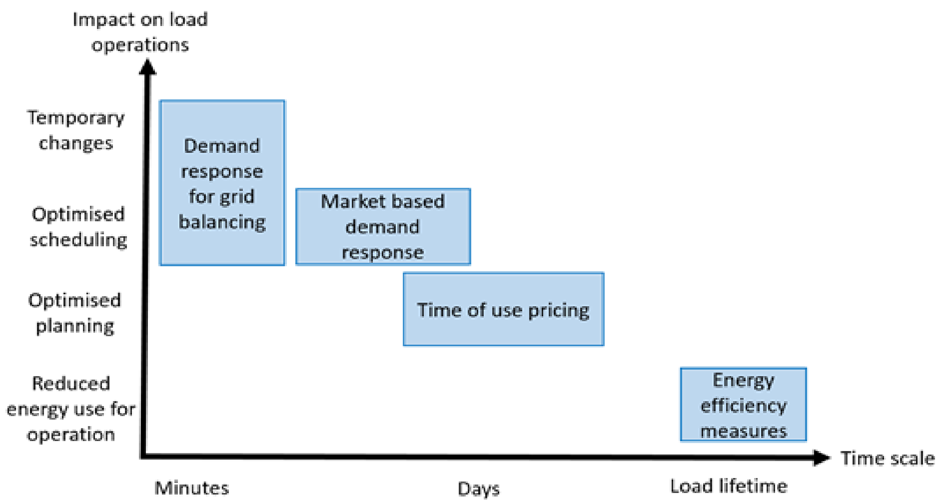

Figure 4. Categories of demand side management (adapted from (Palensky and Dietrich, 2011)).

2.2.2 District heating networks

Structure of a district heating network

District heating (DH) is a widespread means of efficiently supplying heat in densely populated areas (especially in urban areas of Northern countries - e.g. Stockholm and Copenhagen), by using hot water (or steam in early version) as a medium for transporting calorific energy. In DH systems, the network is separated in a transmission grid, usually at high temperatures and with larger pipes, and a distribution system with smaller pipes and at lower temperatures. There are heat exchanger substations for connecting the DH pipelines with the customer´s network (single buildings or apartment blocks) by extracting heat from DH water (Dahl, Brun and Andresen, 2017).

Heat can be produced from a variety of technologies, such as combined heat-and-power (CHP) plants, boilers using a variety of fuel depending on their availability and prices, renewable energy systems or heat pumps. In general, the water is forwarded to the customer at a temperature between 80°C and 120°C depending on the surrounding temperature, pressure, location and heat losses in the pipeline, whereas the return water temperature ranges from 45°C to 75°C. Figure 5 shows the working principle of DH (Fossum, 2012).

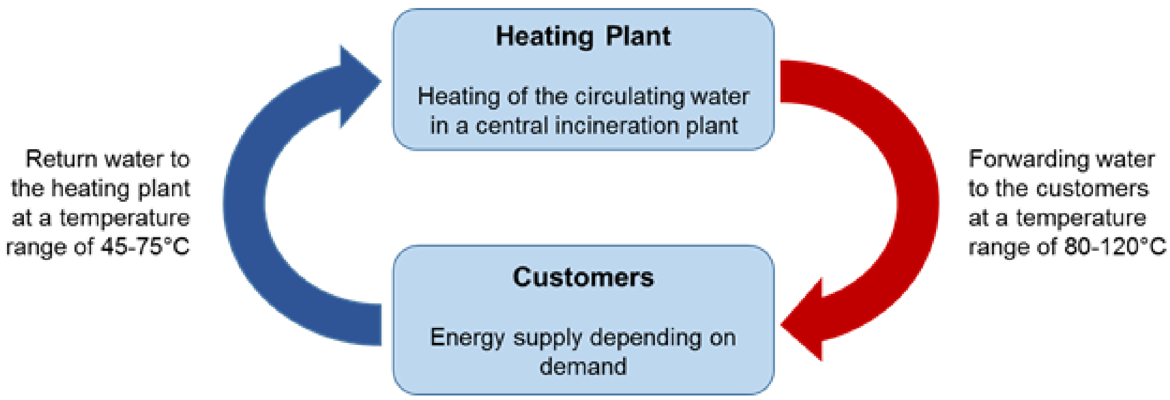

Figure 5. Working principle of district heating (Fossum, 2012).

The transition to a sustainable power system

Flexibility in building energy usage is of interest for district heating networks, especially in cold climates (Lund *et al.*, 2010). In future DH systems (as proposed by a 4th generation DH vision), one of the important features to enable more efficient operation of the system is intelligent control of building heating (Lund *et al.*, 2014). Typical properties of so-called ‘Smart Thermal Grids’ are presented in Table 1.

Table 1. Requirements of a Smart Thermal Grid (Schmidt, Fevrier and Dumas, 2013).

Property	Purpose
Flexible	- Short-term: adaptation to energy supply and demand - Medium-term: adaptation by adjusting temperature levels in existing networks and by installation of new distribution micro-networks - Long-term: adaptation by alignment of network development and urban planning
Intelligent	- Planning and operation - End-user interaction with the energy system (demand side management)
Integrated	- Urban planning and networks – electricity, sewage, waste, Information and communications technology (ICT), etc.
Efficient	- Optimization of technologies and cascade usage
Competitive	- Cost-effective, affordable
Scalable	- Neighborhood-level or city-wide application
Securing energy supply	- Use of local renewable energy sources

Figure 6 gives an overview of characteristics of a smart thermal grid.

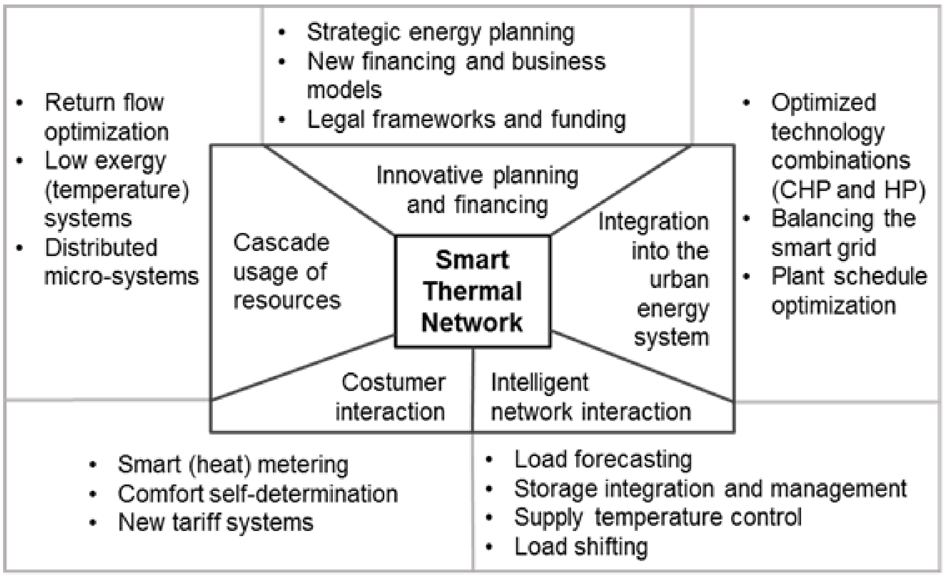

Figure 6. Characteristics of a smart thermal grid (International Energy Agency, 2014).

Challenges in district heating operation

There are many challenges in operation of district heating systems (Lund *et al.*, 2014), in addition to the security of supply and balancing (although less stringent than for power systems):

- **Reducing losses**: losses occur in the form of thermal losses and pressure drops. Thermal losses occur in the pipes, where a higher water temperature incurs higher losses. Thus the aim is to operate with lower water temperature. This also allows using renewable sources that provide lower temperatures (e.g. solar and geothermal heat).

- **Peak load**: the system is designed according to highest load levels. A reduction of the peak load would, therefore, allow to reduce the peak flow rate resulting in decreasing pressure drop values.

- **Integration within 'smart' energy systems**: district heat systems are expected to become increasingly coordinated with other energy networks. For example, combined-heat and power plants or use of large electrical heat pumps can allow dumping excess power at times of overproduction.

Other challenges to be overcome for a reasonable STG integration are (International Energy Agency, 2014):

- Cost-effective operation of district heating grids
- Supply of renewables to district heating and cooling (DHC) grids
- Planning and implementation of innovative networks
- Supply of (industrial) waste heat to DHC (district heating and cooling) networks

2.3 Definition of energy flexibility

A comprehensive definition of energy flexibility is hard to obtain, since researchers with different academic backgrounds may have different objectives when investigating energy flexibility. Therefore, this chapter provides just a short overview of a few definitions.

Energy flexibility can be seen as the **ability** to manage a building's demand and generation according to local climate conditions, user needs and grid requirements.

It can also be understood as a building **property**, if it is seen as the margin in which the building can be operated while respecting its functional requirements (Clauß *et al.*, 2017).

On the other hand, energy flexibility can be regarded as a **service** which can be provided. In that sense, energy flexibility will allow for demand side management/load control and demand response based on the requirements of the surrounding grids.

3. Literature review on applied control strategies

3.1 Terminology

For clarity, and because the present paper is not necessarily aimed at experts in control theory, some terms need to be defined clearly. A list of definitions is provided in the following Terminology section, and these terms have the corresponding meaning when used in the whole report. A general control scheme is also presented in Fig 7.

Controller: The controller is the physical representation of the control strategy monitoring the operation of a given plant (system). A control algorithm is implemented which executes the predefined control technique/method.

Plant (or system): the controlled system, in the present case most often consists of a HVAC component such as a heat pump for instance.

Control strategy: The control strategy is a high level approach to achieve identified objectives. It incorporates, inputs, outputs and constraints into a viable control method or more detailed technique.

Control method/technique: It should be noted that researchers assume that “control methods” and “control techniques” are interchangeable. In general, the development and implementation of control techniques aims to establish a framework to formulate the control strategy (Wang and Ma, 2008; Afram and Janabi-Sharifi, 2014) and to address control problems in a systematic way (Siddique, 2014).

Control objective: The goal or target aimed by the controller. This objective might be formulated explicitly or not. (Seborg *et al.*, 2011) defines the control objectives as: “the chief objective of the process control is to maintain a process at the desired operating conditions, safely and efficient, while satisfying environmental and product quality requirements.”

Examples of control objectives: reducing the operating cost, shave the demand peak etc.

Disturbance: External parameter affecting the behaviour of the system on a physical level, but without any possibilities of control (i.e. not a control input). Disturbances can be measured or not.

Examples of disturbances: ambient temperature, solar irradiance, wind speed, internal heat gains, hot water consumption etc.

Control inputs: The signals sent by the controller to the plant, in order to alter its operation. The control inputs are sometimes also named manipulated variables. Examples: on/off signal, temperature set-point etc.

Control outputs: The output parameter of the system that should be controlled (sometimes also named controlled variable). In most of the cases, the indoor temperature is the control output when dealing with climate control of buildings.

Control signals: Parameters supporting the control decisions made by the controller. The controller uses this information in its algorithm to determine the control inputs. Examples: electricity price, residual load, power measurement etc.

Constraints: The limits imposed on the control inputs, the control outputs or the operation of the system. In practice all processes are subject to constraints. Specific signals must not violate specified bounds due to safety limitations, environmental regulations, consumer specifications and/or physical restrictions. (Camacho and Bordons, 2007). Example of constraints: comfort temperature range, maximum power capacity of a heating system, slew rate of the system etc.

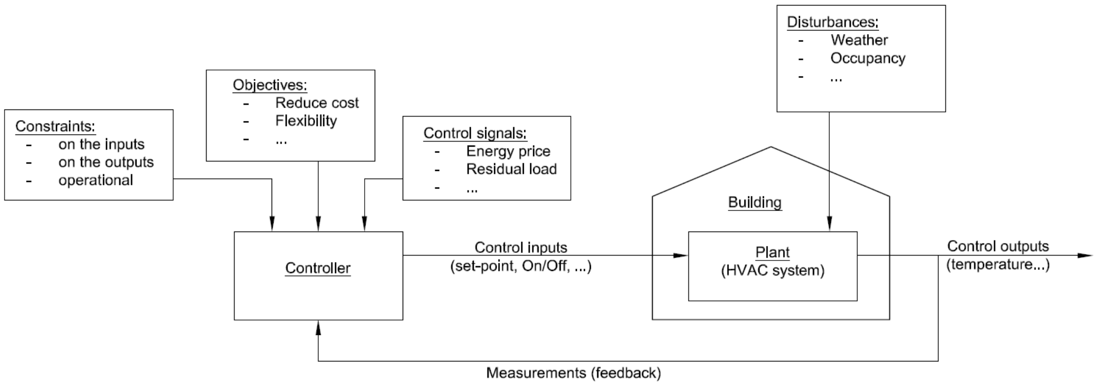

Figure 7. General scheme of a single-level control.

3.2 State-of-the-art control methods

This chapter starts with an overview of state-of-the-art control methods for HVAC systems and focus on the latest advancements, such as model-predictive control (MPC).

3.2.1 Terminology of control methods

There are two main types of control: (1) control of a single component, also known as local control, and (2) control of a whole energy system, also known as supervisory control. The local controller makes sure that the process is stable and a proper set-point is kept at all times, whereas the supervisory controller coordinates all the local controllers in a way that the overall operation of the energy system works smoothly (Naidu and Rieger, 2011a).

Control methods can be divided into hard control, soft control and hybrid control. Naidu et al. (Naidu and Rieger, 2011a) include classical controls in hard controls, whereas Afram et al. (Afram and Janabi-Sharifi, 2014) see classical controls as a distinct group of HVAC control methods. Dounis et al. (Dounis and Caraiscos, 2009) on the other hand only distinguish between classical controllers and optimal, predictive and adaptive controllers. An overview of different HVAC control methods is given in Figure 8.

Classical control refers to the most commonly used control techniques, such as on/off control, P, PI or PID control. An on/off controller regulates a process within a predefined lower and upper threshold so that the process stays within these boundaries. P, PI and PID controllers modulate a controlled variable by using error dynamics, so that accurate control is achieved. Research related to PID controllers focuses on auto-tuning or optimal tuning methods of these controllers (Afram and Janabi-Sharifi, 2014).

Hard controllers follow the theory of control systems based on nonlinear control, robust control, optimal control, adaptive control and MPC (Naidu and Rieger, 2011a; Afram and Janabi-Sharifi, 2014). Hard controllers are usually rather straightforward to analyse. They have a predictable overall behaviour and stability and usually a low to moderate computational burden of practical algorithms (Ovaska, VanLandingham and Kamiya, 2002).

Soft control systems are based on fuzzy logic, neural networks or genetic algorithms.

Hybrid controls are a combination of hard and soft control techniques and benefit from the advantages of each of them. The soft control is usually applied for supervisory control, whereas the hard controller is used for local control (Afram and Janabi-Sharifi, 2014) even though MPC can be used for supervisory control, too. A summary of the most common control methods is given in Table 2.

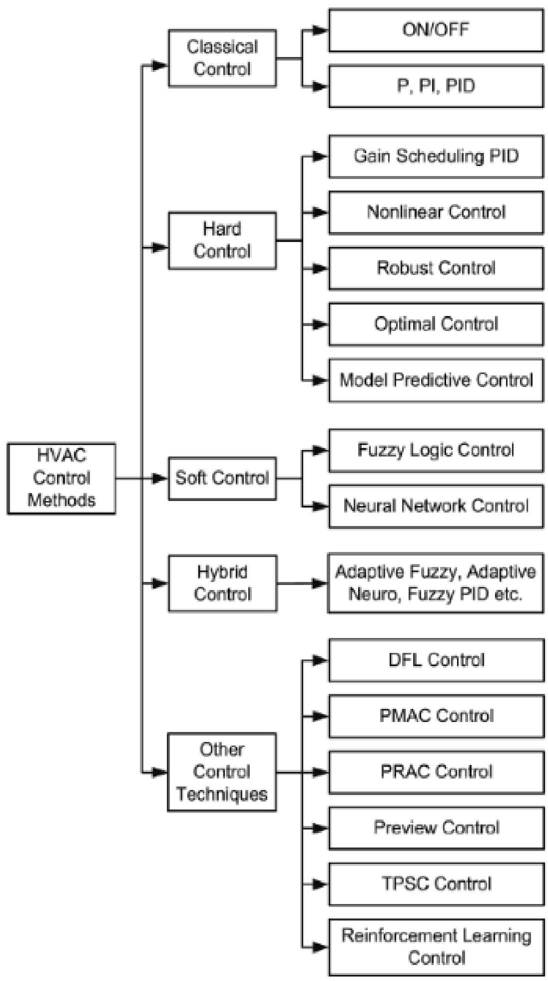

Figure 8. Overview of control methods for HVAC systems (Afram and Janabi-Sharifi, 2014).

Table 2. Summary of the most common control methods.

Type of controller	Working principle	Implementation maturity	References
Thermostatic on/off control	Regulates a process within a predefined lower and upper threshold so that the process stays within these boundaries	State-of-the-art in buildings	(Dounis and Caraiscos, 2009; Naidu and Rieger, 2011a; Afram and Janabi-Sharifi, 2014; Yu *et al.*, 2015)
P, PI, PID control	Modulate a controlled variable by taking into account error dynamics	State-of-the-art in buildings	(Dounis and Caraiscos, 2009; Naidu and Rieger, 2011a; Afram and Janabi-Sharifi, 2014; Yu *et al.*, 2015)
Gain Scheduling PID	Controlling non-linear systems by a family of linear controls which are used to control different operating points of the non-linear system	State-of-the-art for hydronic-radiator-based HVAC systems	(Leith and Leithead, 2000; Afram and Janabi-Sharifi, 2014)
Non-linear	A control law (derived from Lyapunov´s stability theory, feedback linearization and adaptive control techniques) for reaching a stable state of the non-linear system while keeping the control objectives	State-of-the-art for AHUs and cross-flow water to air heat exchanger	(Afram and Janabi-Sharifi, 2014)
Robust	Controller works well for changing parameters as well as time-varying disturbances / Considers model uncertainty and non-linearities of the system	State-of-the-art for supply air temperature, supply airflow rate and zone temperature control	(Naidu and Rieger, 2011a; Afram and Janabi-Sharifi, 2014)
Optimal	Solves an optimization problem (optimizing a cost function) → minimization of energy consumption and control effort, maximizing thermal comfort	State-of-the-art for active TES, energy optimization for HVAC systems, VAV system control, building heating and cooling control	(Naidu and Rieger, 2011a; Afram and Janabi-Sharifi, 2014)
Adaptive	Controller learns to adapt to changes and learns from the characteristics of a building or/and environment by self-regulation	Used for single cases, but not widespread/ Used for AHUs with VAV	(Dounis and Caraiscos, 2009; Naidu and Rieger, 2011a; Yu *et al.*, 2015)
MPC	Applies a system model for predicting future system states and optimizes a cost function over a sliding planning horizon / Takes into account disturbances and constraints	Applied at building design stage, but not yet widespread for practical operation	(Naidu and Rieger, 2011a; Afram and Janabi-Sharifi, 2014)
Neural Network	A mathematical representation of neurons relating inputs and outputs as a huge network / Black-box modelling technique / A controller which is tuned/trained on the performance data of a system / Fits a non-linear mathematical model to the historical data	For fan control of an air cooled chiller and for AC setback time based on the outdoor temperature	(Naidu and Rieger, 2011b; Afram and Janabi-Sharifi, 2014)
Fuzzy Logic	Control actions as if-then-else statement / Methodology to represent human knowledge and reasoning by remembering rules and functions / Can be applied as supervisory control in combination with a local PID controller	Used in AHUs	(Naidu and Rieger, 2011b; Afram and Janabi-Sharifi, 2014)
Reinforcement Learning (RL)	Optimal control actions are learned from past system interactions / model-free & model-based RL	Used for single cases, but not widespread	(Yang *et al.*, 2015; Wei, Wang and Zhu, 2017)

3.2.2 Strengths and weaknesses of different control methods

On/off controllers are not able to control dynamic processes with time delays. A good performance of PID controllers is ensured only if the operating conditions do not vary from the tuning conditions (Afram and Janabi-Sharifi, 2014). Gain-Scheduling PID shows improved stability compared to “normal” PID controllers (Leith and Leithead, 2000), but it is necessary to spot the linear regions and to develop a logic for switching the regions. Manual tuning of the PID controller is required and can be laborious.

Hard controllers are a common technique in control system design. Nonlinear control is effective, but requires a rather complex mathematical analysis when designing the controller as well as an identification of stable states. Optimal and robust control can handle time-varying parameters and disturbances, but robustness is difficult to obtain because of varying conditions for HVAC systems in buildings. According to (Afram and Janabi-Sharifi, 2014) specification of additional parameters is required for hard controllers and thus an integration in HVAC systems may be difficult or impractical.

Soft controllers are not very common in real building applications. Neural-networks -based control systems need an extensive amount of historical data for training purposes, in order to cover a wide range of operating conditions. Similarly, fuzzy logic controllers require an extensive knowledge of the building operation under different conditions.

Hybrid controllers inherit the benefits and weaknesses of both hard control and soft control systems.

3.3 Control strategies for heating and cooling using MPC

Some of the main challenges facing a HVAC system are non-linear dynamics, time-varying dynamics, time-varying disturbances and supervisory control. MPC is a control method that overcomes these problems.

(Afram and Janabi-Sharifi, 2014) summarise main features of MPC:

- MPC is not a corrective control, but anticipates future system evolution
- An integrated disturbance model can handle disturbances in an explicit manner
- It has the ability to explicitly handle uncertainties and constraints
- It is capable of dealing with processes with time delays
- Energy saving strategies can be integrated in the controller formulation
- Multiple objectives can be achieved by using appropriate formulations of the cost function
- MPC can be used for supervisory as well as local control
- Explicitly includes the prediction of occupant behaviour, equipment use and weather forecasting

The reviews of (Dounis and Caraiscos, 2009; Naidu and Rieger, 2011a, 2011b; Afram and Janabi-Sharifi, 2014) include several metrics for comparing the performances of different controllers. However, they do not consider the potential for flexibility deployment in details.

The research on MPC has intensified during the last decade. It is well understood and proven that this control method can achieve energy savings while maintaining or even improving thermal comfort requirements in buildings. Researchers show different approaches for applying MPC for controlling HVAC systems in buildings in combination with thermal energy storages in order to deploy the demand side flexibility that a building may offer. Table 3 presents an overview of recent research activities regarding MPC and other predictive control methods.

Table 3. Selected examples on MPC research.

Reference	Title	Results
(Fiorentini *et al.*, 2015)	Hybrid model predictive control of a residential HVAC system with PVT energy generation and PCM thermal storage	The COP of the conventional heat pump air conditioning system is 2.1 and any higher COP was assumed to be an improvement to the system. The average COP for cooling applying the PVT system as well as the PCM material are 6.2 and 2.7 respectively. Therefore, it is proven that the controller leads to an improved system performance.
(Halvgaard *et al.*, 2012)	Economic Model Predictive Control for building climate control in a Smart Grid	The electricity costs were decreased by 25-35% compared to a conventional heat pump control.
(Kandler, Wimmer and Honold, 2015)	Predictive control and regulation strategies of air-to-water heat pumps	The two controllers lead to a decrease of up to 40% of total run-time of the heat pump (per year) compared to a state-of-the-art non-predictive controller, as well as less overproduction. Total costs were nearly halved by running the heat pump during the day, at times of photovoltaic overproduction and lower electricity prices.
(Arnold and Andersson, 2011)	Model Predictive Control of energy storage including uncertain forecasts	It is proven that the further the forecasting period, the more efficient the storage devices can be operated, in case the storage capacities are big enough. The deviations within load forecasts can be reduced from 15% to 2.5% and thus show that the MPC can lead to more accurate predictions.
(Kajgaard *et al.*, 2013)	Model Predictive Control of domestic heat pump	It is found that the controller avoids using electricity during the most expensive hours. If the deviation from the indoor temperature set-point is about 0.93°C, cost savings of 7% can be achieved. For higher cost savings the difference from the set-point temperature has to be increased much more which would lead to higher thermal discomfort.

Reference	Title	Results
(Lindelöf *et al.*, 2015)	Field Tests of an Adaptive Model-Predictive Heating Control System	The adaptive MPC led to energy savings of up to 25% at constant thermal comfort (rather constant indoor air temperature). The SH energy consumption vs. ambient temperature is a linear dependency and therefore, if the slopes of the indoor temperature of the two controls are compared, the difference of the slopes yields the relative energy savings of one controller against another.
(Sayadi, S., Tsatsaronis, G., Morosuk, 2016)	Reducing the Energy Consumption of HVAC Systems in Buildings by Using Model Predictive Control	The energy use is reduced by 43% and 31% during two measurement periods after having implemented the MPC.
(Jin *et al.*, 2014)	Model Predictive Control of Heat Pump Water Heaters for Energy Efficiency	It is possible for the MPC to identify when draws of hot water are likely to happen and to respond appropriately, day to day variations in hot water consumption are however not well captured. Preheating of the hot water before a draw allowed the heat pump to meet the load so that the electric back-up heaters were not used. Compared to the baseline, the MPC achieves about 180 kWh of energy savings per year, which corresponds to about 20 USD/year (prices of 2014).

MPC can be applied for design purposes as well as for experiments. The results for both show advantages of the MPC over classical HVAC system control.

(Huang, 2011) shows that the control signal for zone temperature regulation is much smoother when using a MPC compared to a PI controller. Zone temperature regulation has also been investigated by (Moroşan *et al.*, 2010) who simulated the performance of a PI controller and a distributed MPC. The MPC achieved 13% energy savings and a 37% improvement of the thermal comfort. More studies are presented in the review paper (Afram and Janabi-Sharifi, 2014).

The zone temperature is also the typical control variable in experiments. (Hong et. al, 2007) implemented a MPC into a HVAC system and showed an improved robustness as well as greater tracking performance of the MPC compared to a PID controller. (Aswani *et al.*, 2012) implemented a learning-based MPC into a heat pump test facility at a university and showed that the energy consumption can be reduced by 30 to 70% compared to on/off control.

Economic MPCs (Halvgaard *et al.*, 2012) include electricity prices from the day-ahead market into the cost function and suggest an optimized schedule for electricity consumption over the planning horizon based on these prices. Energy consumption is shifted to periods with low electricity prices. For instance, the controller of a heat pump can compute an optimized schedule for the compressor based on dynamic electricity prices as well as weather conditions (outdoor temperature and solar radiation).

3.4 Control strategies for heating and cooling using Reinforcement Learning (RL)

As explained in previous sections, recent research in the building control community has mostly focused on MPC. This is mostly driven by the ability of MPC based controllers to achieve predefined and easily understandable objectives. However, recently reinforcement learning (RL) based controllers have shown remarkable progress in achieving state of the art results in many difficult and previously unsolvable domains (Lai, 2015; Mnih *et al.*, 2015; Silver *et al.*, 2016).

Some pioneering work on the suitability of applying RL methods to building control appeared in (Liu and Henze, 2006). However, much of the work in reinforcement learning for building control since then has focused on primitive algorithms such as Q-learning and SARSA (Barrett and Linder, 2015; Yang *et al.*, 2015; Ali and Kazmi, 2017). These algorithms have well-documented shortcomings which have been systematically addressed in state of the art algorithms since then. Very recently, some studies have started to appear where advanced RL controllers are applied to building control (Yang *et al.*, 2015; Wei, Wang and Zhu, 2017).

RL based control operates differently than traditional MPC even when solving the same problem. This distinction is best understood by classifying RL algorithms into two further subclasses: model-free and model-based RL. In this section, we explain the core differences between model-based and model-free RL and how they relate to MPC. We also present an example formulation for reinforcement learning based control to buildings. The interested reader is referred to (Sutton and Barto, 1998) for a broad yet readable overview and (Wiering, Marco; van Otterlo, 2012) for a comprehensive review of RL algorithms.

3.4.1 Model-free RL

Model-free RL is, in many ways, the polar opposite of model predictive control. In model-free RL, unlike MPC, the controller neither possesses nor learns a system dynamics model. Rather, it learns optimal control actions directly from its past interactions with the system. While such an RL controller can be designed to optimize any objective function, motivating an RL controller is done differently than in the case of MPC.

The model-free RL controller fundamentally works as follows: it observes the system state, its own actions and the reward it obtains from the environment. Its task is to maximize this reward stream over time by choosing appropriate actions. This is complicated by the delayed reward problem (i.e. actions chosen at an earlier point can influence rewards much later in time). Nevertheless, the controller improves the actions it takes through interaction with the environment over time. In most real world problems, defining the controller's reward function can be challenging because of competing objectives (e.g. energy minimization vs. occupant comfort etc.)

Advantages and disadvantages of model-free RL

Model-free RL based controllers can be extremely lightweight when compared to their MPC counterparts. This is because, in the absence of a model, the controller simply learns a mapping between possible states and optimal control actions which maximizes its rewards over time. During operation, the RL agent not only executes this optimal control action but also updates its mapping which can make it robust to non-stationarities in the operational environment. The allure of faster computation and increased robustness can make these controllers better suited to many practical problems when compared with classical MPC controllers.

Model-free controllers however suffer from significant limitations. Foremost amongst these is the curse of dimensionality. Furthermore, as alluded to earlier, learning in environments with delayed rewards can also be challenging for these controllers. This means that, in a reasonably complex state-space, the controller will require an inordinate amount of data before it can discover the optimal policy. This also means that their 'sample complexity' is usually much lower than their model-based counterparts i.e. they require more data to attain a similar level of control. Furthermore, exploratory actions are often required by the RL agent to discover the optimal policy but such actions can directly lead to occupant discomfort. While solutions or workarounds for these problems have been developed in many domains, extensive research has to be carried out for building control to ensure their feasibility.

3.4.2 Model-based RL

Model-based RL is in many ways closer to classical MPC and can draw many parallels to data-driven MPC. Model-based RL is used extensively in robotics and other disciplines where decision making needs to happen in real-time with limited and noisy sensing data. These algorithms can perform as well as MPC while also offering the potential to greatly reduce computational complexity.

The biggest difference between model-based RL and data-driven MPC is twofold. The first is an explicit exploratory strategy whereby the controller is incentivized to explore the state-space better to discover potentially rewarding strategies. The second, and arguably more important, is the use of policy-side learning to speedup computation. In traditional MPC, depending on its current observed state, the controller solves an optimization problem. If the controller revisits the same (or a similar) state, it will optimize the same optimization problem again before executing control. Policy-side learning means that the model-based RL controller learns from solving these optimizations over time and does not need to repeatedly optimize. Rather, learning allows it to increase generalization, thereby drastically reducing the computational load once a stable policy has been learnt. This is usually done by learning the Q-value of different state-action couplings through a function approximation algorithm such as Gaussian Processes, neural networks or random forests (Hester and Stone, 2013; Gal, Mcallister and Rasmussen, 2016).

Advantages and disadvantages of model-based RL

The biggest advantage of model-based RL is its compatibility with existing MPC controllers. By offering similar or better performance at (asymptotically) reduced computational loads, it can contribute to the next generation of controllers. At the same time, some additional concerns arise, primarily because of the additional system complexity which can potentially increase the likelihood of a failure.

In addition, depending on the size of the state-space, policy-side learning can be a formidable undertaking requiring substantial amounts of computational resources before convergence. This is usually not a concern in building control. Once the controller has learnt an appropriate mapping, the computational requirements are much lower than with conventional MPC. Policy-side learning also offers additional advantages. For population-based optimization schemes such as genetic algorithms, it can also quickly enable agents to discover feasible and often near-optimal solutions with limited computational requirements. While exploratory steps can likewise improve the asymptotic performance of the controller, they come with the increased risk of lost user comfort, as with model-free controllers.

3.4.3 Formulation of RL control

As opposed to MPC where an explicit objective function is defined, RL controllers usually employ a reward (or penalty) function. Depending on the state of the system, the controller is either rewarded or punished for the states of the system. The controller, over time, learns to select the actions which maximize this reward stream. This can include delayed reward schemes where the agent is rewarded or punished only once a trigger occurs (for instance loss of user comfort). The assignment of reward is thus a challenging problem for the agent as it does not know a priori which control actions led to it. This has to be learnt through repeated interactions with the system.

Most commonly, reinforcement learning controllers assume that the Markov property holds (i.e. the system and its future evolution can be perfectly characterized by knowledge of its current state). This leads to the formulation of a Markov Decision Process (MDP); M = {s, a, T, R} (Sutton and Barto, 1998). Here, s is the system state and a corresponds to the controller's actions. T signifies the transition function which defines a future state, s', given a current state, s, and an action, a. R is the reward the controller receives as a consequence at every time step and has to be crafted by a human designer.

In many practical cases, the actual state of the agent can be hidden from the controller. This partial observability can be because of sensing limitations (for example inadequate temporal or spatial resolution, corrupted or missing sensor data etc.) or unexpected changes to the agent's environment (for example a context change caused by a refurbishment or change of tenants in a building etc.). In this case, the problem can be formulated as a partially observable Markov Decision Process (POMDP). Formulating and solving a POMDP is a more challenging problem and is beyond the scope of this report.

Concrete examples applied to practical control problems can be found in (Ruelens *et al.*, 2015) and (Yang *et al.*, 2015).

3.4.4 Multi-agent reinforcement learning

Conventional reinforcement learning formulations work well in the context of controlling a single device in a building. However, scaling to multiple devices or buildings in the context of an entire grid brings additional challenges. These are related to how well the agents can cooperate and address game theoretic concerns of cooperation and competition to arrive at optimal strategies.

Traditional approaches to solving the problem include centralized planners which decide on the control actions for all flexible devices. These approaches can quickly become intractable as the number of controllable devices increases. A more computationally tractable approach to solving the problem is through decentralized algorithms such as dual decomposition and ADMM. However, these can suffer from convergence issues under certain conditions and, more importantly, the inherent stochasticity in both device response and human behaviour leads to frequent re-planning which increases computational load.

Multi-agent reinforcement learning offers a potentially attractive alternative to these problems (Tan, 1993; Shoham, Powers and Grenager, 2003). These can be both centralized and decentralized. Joint action learning (JAL) is an example of this paradigm where each agent learns the consequences of its actions in conjunction with other agents' actions (Banerjee and Sen, 2007). This implies observability of other agents' actions. Where this is not possible, the agents can treat other agents' actions as unobserved in their learning and planning, however this can lead to greater data requirements to achieve the same performance.

3.5 Control objectives, inputs, disturbances, constraints, and signals

The aim of the applied control strategies presented in this report is to improve the energy flexibility, or implement demand-side management (DSM). However, this objective remains general, and DSM can take several forms, such as load-shifting, peak shaving etc. For this reason, this section intends to identify more precisely objectives that were addressed by the different control strategies, as well as other parameters taken into account (disturbances, constraints, control inputs and signals) in their design.

This identification process is not always straightforward. In MPC and optimal control, the objective function is explicit: its expression represents the quantity that the control should optimize, for instance, the energy cost. This function can also contain multiple terms that represent multiple objectives, which are balanced with appropriate weights. In rule-based controls (RBC), the final objective is more difficult to identify, and is not always explicitly mentioned in the reviewed papers. A certain method is often analysed under different angles (impact on the energy use, comfort, flexibility etc.), without a clear statement of the goals to achieve. There can also be a short-term goal (e.g. shifting loads to a certain time of the day), and a more general goal on the long-term (e.g. enabling the integration of more RES in the grid).

Because of this conceptual difference, these two types of control (RBC and MPC) have been separated when analysing their respective objectives. The constraints, control inputs disturbances and signals present similarities and therefore have been reviewed jointly. It should be noted too that there is not always a consensus on the boundaries between these different elements, as different works would address these with different approaches. For instance, comfort can be considered as an objective (minimize discomfort) or as a constraint (with boundaries for the indoor temperature for example).

3.5.1 Control objectives

In rule-based controls

The most simple flexibility objective consists in load shifting according to a predefined fixed schedule. Regular daily peak periods can usually be identified in a national energy grid. The controller can therefore try to avoid or force the operation of the systems during fixed hours. For instance, (Lee, Joo and Baek, 2015) use set-point modulation to reduce the energy use during the grid peak hours (14 to 17 in summer and 17 to 20 in winter). (Carvalho *et al.*, 2015) completely shut down the heat pump during peak hours (9:00 to 10:30 and 18:00 to 20:30). Fixed scheduling can also be used to force the charging of a TES tank, like presented by (De Coninck *et al.*, 2010). In another study, (De Coninck *et al.*, 2014) used clock control, raising the DHW heating set-point from 12:00 to 16:00 in order to reduce PV curtailing losses at that time because a heat pump can be run to charge the DHW storage. Overall, fixed scheduling strategies are simple and easy to implement, and they can already achieve a substantial performance. However, the fixed schedule cannot adapt to changing conditions in the daily profile of the grid.

Another objective targeted by RBC strategies is **peak shaving**, i.e. the reduction of the demand peak, in order to support the grid operation. In these cases, the power exchange of the building with the grid is monitored, and thresholds can be defined both for the import and export (when a production unit is present, i.e. when the customer is a prosumer) of power. When the thresholds are passed, an action is taken by the controller to stop or force the operation of the mechanical systems, and thus limit the peak to the predefined threshold. For instance, (Dar *et al.*, 2014) set an import limit of 2500 W and an export limit of 5000 W in a nZEB equipped with a PV system, while (De Coninck *et al.*, 2010) present a similar "grid-load strategy", with both import and export thresholds set at 3500 W.

Certain control strategies aim at **reducing the energy costs** for the end-users. In general, these approaches rely on time-varying energy prices, and the controller aims at operating the energy-using systems during low-price periods, or at avoiding their operation during high-price periods. Identifying the thresholds for low and high-price periods therefore becomes the key elements of these RBC strategies. (Schibuola, Scarpa and Tambani, 2015) proposes two different approaches in this regard: the first one analyses the price data of two entire years (2012 and 2013), and fixes thresholds based on this distribution. The second approach compares the current electricity price with the forecasted price over the next 12 hours, hence relying on prediction data rather than on past data. (Le Dréau and Heiselberg, 2016) also based their approach on recorded past data: their thresholds were calculated using the first and the third quartiles from the price distribution of the two weeks prior to the current moment.

Finally, other rule-based controls aim **at improving the use of energy from renewable energy sources** (RES). This can be done at the scale of the building with a local generation unit (in the case of a prosumer), where the objective consists in improving the self-consumption. It can also be done at the scale of the overall power grid, which means the control relies on the analysis of the residual load calculated at a national level. The methods employed can then take different forms. The heating systems can be switched on simply when the local PV are generating electricity (Schibuola, Scarpa and Tambani, 2015), or when this production exceeds the non-heating loads (Dar *et al.*, 2014). Thus a thermal storage is charged to temperatures which are higher than the usual set point. This leads to a better coincidence between production and demand. (De Coninck *et al.*, 2014) use a different trigger for the activation of DSM: voltage measurement. Their study works on the assumption that an excess PV production induces an increase of voltage of the distribution feeder. The voltage is therefore monitored, and when it surpasses a defined value (around 250 V), the set-point for the DHW tank is raised in order to utilize more electricity and avoid the curtailment of PV production due to inverter shutdown. (Miara *et al.*, 2014) use the residual load profile at the national level to design their own ToU signal and thus use energy at times of low residual load.

In optimised control and MPC

As recalled in the introduction of this section, the objective is easier to identify for MPC configurations, since it is explicitly formulated in the cost function that the controller optimizes. In the reviewed papers, one sort of MPC clearly stands out: **Economic MPC (EMPC)**, where the objective is to **reduce monetary costs**. This method utilizes the variation of energy prices in time to perform a cost optimization. The objective function Je can for example take the following form, taken from (Masy *et al.*, 2015):

$$J_e = \sum_i p_{el}(i)\, \dot{W}_{el}(i)$$

Where $\dot{W}_{el}$ is the manipulated variable (the heat pump power in this case), p_{el} is the electricity price (varying in time according to different tariffs). The optimization process then minimizes this cost function over the receding horizon, logically leading to monetary savings.

Even though the formal objective is to reduce the costs, this method will implicitly result in load shifting towards periods of lower energy prices. Depending on how the price profile is constructed, this load shifting can constitute a valuable form of energy flexibility. A similar cost function is used in (De Coninck and Helsen, 2016) (considering also a term for the cost of natural gas), (Halvgaard *et al.*, 2012; Zong *et al.*, 2012; Ma, Qin and Salsbury, 2014; Mendoza-Serrano and Chmielewski, 2014; Sichilalu and Xia, 2015; Bianchini *et al.*, 2016; Santos *et al.*, 2016) (including the monetary benefits of selling PV electricity) and (Oldewurtel *et al.*, 2013). As it appeared from the survey, EMPC seems to be a dominant form of MPC in studies of energy flexibility in buildings.

Comfort can also constitute an objective of MPC, or more precisely the **minimization of thermal discomfort**. The objective function can for instance take the following form, taken from (De Coninck and Helsen, 2016):

$$J_d = \sum_i \theta_{OCC}(i)(T_{zon}(i) - T_{set}(i))^2$$

Where θ_{OCC} is an occupancy factor (0 or 1), T_{zon} is the actual zone temperature, and T_{set} is the tracked set-point temperature. By minimizing this term, the optimization problem will reduce the difference between the actual and the desired temperature (set-point), hence improving the comfort conditions. (Masy *et al.*, 2015) use the same principle but with a slightly different formulation. (Váňa *et al.*, 2014) introduce two different comfort ranges in their objective function:

$$J_d = \sum_k (|Q(y_k - z_k)|_2^2 + |Q^c(y_k - z_k^c)|_2^2)$$

Where y_k represents the zone temperatures from system states, z_k represents soft comfort constraints (comfort range 1) that can be violated from time to time, while z_k^c represents soft comfort constraints (comfort range 2) that should not be violated at almost any cost. The hierarchy between comfort ranges 1 and 2 is realized through the weight matrices Q and Q^c. It should be noted that comfort is often also implemented in the form of constraints (see following paragraph).

In some cases, the objective function includes a term for the reduction of the energy use. For instance, (Sturzenegger *et al.*, 2013) present an MPC which aims at minimising the non-renewable primary energy use. The formulation is the following:

$$J_{pe} = \sum_k c_k^T u_k$$

Where c_k is the cost vector (depending on the systems efficiency) and u_k the manipulated variables (or control inputs). c_k puts different weight on the energy consumption depending on the operating conditions, which leaves room for a minimisation of non-renewable primary energy.

Few articles use a term for **peak shaving** within their objective function. Notably (Ma, Qin and Salsbury, 2014) present the following formulation:

$$J_p = \sum_k D_c(k)\ max\{P(k)\}$$

Where D_c represents the peak demand cost, and P is the average power consumption during the time interval k. In this way, the peak power is penalized in the objective function, therefore the MPC will try to reduce it, leading to peak shaving.

Reducing the CO2 intensity is another objective that may be implemented in MPC. (Dahl Knudsen and Petersen, 2016) notably introduce the following term:

$$J_c = \sum_k e_k u_k$$

Where e_k is a vector representing the prediction of the CO2 intensity associated with the electricity production (i.e. the amount of CO2 equivalent emissions per unit of energy, expressed in gCO2eq /kWh). The MPC optimization will therefore intend to minimise the total CO2 emissions incurred by the energy used for operation of the building.

Finally, other terms can be introduced in the objective function **to increase the robustness** of the control. They do not represent a flexibility objective in their own, but enable a smoother operation of the systems. For example, (Váňa *et al.*, 2014) introduce the following term:

$$J_r = \sum_k \delta\ |u_k - u_{k-1} - p_k|_2^2$$

Where δ is a penalty factor and p_k a slack variable. Introducing such terms in the objective function enables to avoid too drastic changes in the control inputs, and decreases the sensitivity to model mismatch and imperfect disturbance predictions. (Santos *et al.*, 2016) and (Halvgaard *et al.*, 2012) also introduce slack variables in order to soften the constraints imposed on the output, and thus enable the optimisation to always find a solution outside the strict range, although at the cost of a certain penalty.

Finally, it is important to mention that these different objectives can be combined in a single objective function. Most papers use linear combinations of the different terms, setting different weights to put more emphasis on certain aspects of the optimisation. For instance, (Masy *et al.*, 2015) and (De Coninck and Helsen, 2016) present a global objective function of the form $J = J_e + \alpha J_d$, which is an EMPC but also taking into account discomfort term J_d with weight α.

3.5.2 Control constraints

As recalled by (Camacho and Bordons, 2007), in practice all processes are subject to constraints: a heating system cannot provide more heat than its maximum thermal capacity, or a ventilation system cannot provide more air than the capacity of its fans. Limits can also be set for safety or constructive reasons. The control algorithm needs to know these boundaries in order to yield physically meaningful solutions to the numerical optimisation problem in the case of MPC (e.g. exclude negative flow rates).

A distinction can be made between the constraints implemented on the control inputs and the control outputs (or system states). The first type can always be respected, since the controller decides the control inputs, therefore it can choose them within the defined boundaries. In the case of MPC, the constraints on control outputs and states must be anticipated beforehand, since these variables depend on the behavior and inertia of the modelled plant, as well as disturbances. Therefore, imposing hard constraints on these outputs and states may lead to infeasibility of the receding horizon optimisation (Löfberg, 2012), which is why these constraints are usually softened in practise.

It should be kept in mind that adding constraints to an MPC problem, even though it is probably necessary in the kind of applications reviewed in this report, makes it impossible to find an explicit solution of the optimization problem. Therefore, numerical methods must be used.

The **constraints on the control inputs** mostly represent the **physical limitations** of the devices in use. For instance, (Dahl Knudsen and Petersen, 2016) bound the power of the heating system to 0–0.5 kW, and (Masy *et al.*, 2015) to 0–3 kW, which corresponds to the devices used in their respective studies. The MPC controller can then pick a thermal power within this interval at every time step. In (Oldewurtel *et al.*, 2013) and (Sturzenegger *et al.*, 2013), the MPC also controls blinds or ventilation, therefore constraints are also imposed on these systems (e.g. minimum and maximum air supply temperature, non-closed position for the blinds during occupancy hours to guarantee some daylighting). A minimum air ventilation flow rate is also implemented as a constraint for health reasons, to guarantee air renewal indoors.

Time constraints can also be applied to the inputs of the control strategies. In (Le Dréau and Heiselberg, 2016), the DSM activation can only last for a predefined amount of hours. In (Carvalho *et al.*, 2015), the systems can operate only between a start hour and a stop hour which are fixed beforehand. In (Dar *et al.*, 2014), a minimum cycle length is imposed to the heat pump, and in (Santos *et al.*, 2016) and (Halvgaard *et al.*, 2012) the successive changes in the control inputs are penalized. These methods enable to avoid frequent cycling that may reduce the lifetime of the equipment.

As for the **constraints on control outputs**, they include almost in every case reviewed a **temperature comfort range** (as defined in the standards EN 15251 (CEN, 2007) or ASHRAE 55 (ASHRAE, 2013) for instance). This range can apply to indoor operative temperature: for example, 22-25°C in winter and 22-27°C in summer mentioned by (Sturzenegger *et al.*, 2013), 21-24°C in (Ma, Qin and Salsbury, 2014), 20-22°C in (Masy *et al.*, 2015). The constraints can be relaxed during non-occupancy periods: in (Hong *et al.*, 2012) and (Masy *et al.*, 2015), the problem is unconstrained when the building is not occupied. (Halvgaard *et al.*, 2012) changes the constraints at night, with a minimum output temperature of 18°C, while this lower bound is set to 21°C during daytime. The temperature constraint can also be formulated as a set-point around which a dead band is applied. For instance in (Schibuola, Scarpa and Tambani, 2015), an additional check is performed and actions are taken if the temperature deviates more than 5°C from the set-point. When a storage tank is used, a temperature range can also be applied to it, for instance when using DHW water storage that needs to be kept above 55°C to avoid Legionnaire's disease (Lee, Joo and Baek, 2015). (Dar *et al.*, 2014) transforms the requirement of a temperature constraint into a state of charge parameter of the buffer storage tank.

It should be noted that in MPC, the temperature constraints can be formulated as hard constraints (with fixed boundaries), or as soft constraints, integrating slack variables in the objective function, and penalizing the violation of these constraints with a high cost (see also section on the control objectives). Another remark raised by (Ma, Qin and Salsbury, 2014) concerns the use of unconstrained temperature range in real building applications: it might cause problems because the actuators (room thermostats) might have a specific acceptable range of temperature set-points.

3.5.3 Control inputs

The control strategies act upon certain parameters, which are called control inputs (or manipulated variables). No major difference was found for the control inputs between RBC and optimised control. In the reviewed papers, the following control inputs have been identified:

- **Temperature set-points**: several control strategies modulate the temperature set-points, whether in the room thermostats, the supply of the systems, or in a water storage tank.
- **On/Off control**: other control strategies directly force the systems to switch on or off, depending on the control algorithm decisions. The manipulated variable is therefore binary.
- **Thermal power**: when the power of the mechanical systems can be modulated (electric heating, inverter-controlled heat pump…), the controller can decide to adjust it in time. This control input is mostly used in simulations, in practice the modulation of the thermal power can also be obtained through changes in the set-points.

3.5.4 Control disturbances

Unknown disturbances always affect the behaviour of a controlled system. In general, RBC strategies take into account very few of them. On the other hand, MPC strategies need to forecast some of them, in order to predict the future response of the model to these disturbances, and not only to the control inputs.

The most common disturbance taken into account by MPC is the **outside weather conditions**, since they will affect the heating or cooling needs of the building the most. The external temperature is considered in the model in almost all of the reviewed papers. A notable exception is the paper of (Ma, Qin and Salsbury, 2014), where the authors found out that the outside temperature did not have as much influence on the output as the set-points or the heating power, and therefore neglected it. (Oldewurtel *et al.*, 2013; Sturzenegger *et al.*, 2013; Sichilalu and Xia, 2015; De Coninck and Helsen, 2016) only consider the external temperature when accounting for weather conditions. Several papers additionally consider the solar irradiation: (Halvgaard *et al.*, 2012; Váňa *et al.*, 2014; Bianchini *et al.*, 2016; Dahl Knudsen and Petersen, 2016). Besides the external temperature and the solar irradiation, (Santos *et al.*, 2016) and (Masy *et al.*, 2015) also take into account the effects of wind speed. In many cases, it is assumed that the forecast of these disturbances is perfect. When the MPC is implemented in a real building, weather forecast is retrieved from external services or derived from a local measurement.

Another major source of disturbance is the **internal gains**. They group the heat gains from occupants, appliances and equipment. Most commonly, a deterministic approach is applied, with a fixed schedule for these internal gains (Váňa *et al.*, 2014; Masy *et al.*, 2015; Bianchini *et al.*, 2016). Additionally, MPC may employ measurements such as occupancy sensors (Sichilalu and Xia, 2015), or plugs and lighting electricity circuits (De Coninck and Helsen, 2016).

3.5.5 Control signals

Several external parameters can be monitored to support the decisions made by the controller.

For simplification, it can be considered that each RBC only monitors one specific control signal, and reacts upon it. Usually, a threshold is present on this parameter, and when the threshold is passed, an action is triggered on the system. MPC strategies can monitor several signals and penalize excursions from a given reference profile.

For instance, the strategies aiming at peak shaving monitor the **net power exchange** between the building and the grid, and take actions when this exchange reaches too high values (De Coninck *et al.*, 2010, 2014; Dar *et al.*, 2014).

The strategies that aim at reducing the energy cost (notably EMPC) monitor the **electricity price**, and decide to use energy or not based on how expensive the current price is considered, always taking into account the thermal comfort requirements (Schibuola, Scarpa and Tambani, 2015; Le Dréau and Heiselberg, 2016). Time-of-use electricity tariffs are applied most often, with different values for peak periods and off-peak periods, and sometimes with an additional medium price in-between. In other papers, hourly tariffs are applied, reflecting day-ahead prices on the spot market.

The strategies which tend to increase the consumption of renewables can use different parameters in this objective. A measurement of the **electricity production of a local generation**

unit can be used, be it a PV system like in (Dar *et al.*, 2014; Schibuola, Scarpa and Tambani, 2015) or a wind turbine like in (Hong *et al.*, 2012). In (De Coninck *et al.*, 2014), a **voltage measurement** is used, because it is assumed that a under- or overproduction of electricity in the grid will result in voltage fluctuations at the feeder level. Finally, the **residual load** at local or national level can be monitored like in (Reynders, Nuytten and Saelens, 2013; Miara *et al.*, 2014).

At the level of the local controller, weather compensation is often implemented, through the use of heating curves. They consist in adapting the supply temperature of the heating/cooling systems, according to the ambient temperature, in order to save energy. They rely therefore on an **outside temperature** measurements.

3.6 Models supporting model-based control

Modelling and simulations allow engineers to investigate and analyse physical systems so that design flaws or failures can be avoided before being deployed in practice. In the domain of building engineering, models are created for different reasons. Here, the discussion is focused on models for control purpose.

Modelling of building systems can be generally divided into two parts: modelling of the building itself and modelling of mechanical and thermal systems supplying service to buildings, such as HVAC, domestic hot water system, solar thermal collectors, PVs etc. Here mainly modelling approaches for buildings and thermal energy storage (TES) systems are discussed, given that these two components contribute directly to the energy flexibility of buildings.

3.6.1 Modelling of buildings

From the degree how detailed a model represents a building, a building model in the literature can be roughly categorized into three groups: white-box, grey-box and black-box models.

White-box models

The white-box model, often referred to a physical model, describes a building in details based on first principles of building physics. Building performance simulation (BPS) programs commonly used by building modellers all adopt this approach, for instance, EnergyPlus, TRNSYS, ESP-r etc. Based on physical parameters and thermodynamic laws familiar to building engineers, the white-box model is a very intuitive representation of buildings, for example, information about geometry and materials of building construction are required for this type of model. Thus it allows building engineers to easily use, understand, analyse or even re-develop these parameters. However, because of the large amount of information input, it suffers from the complexity of model construction. (Privara *et al.*, 2013) advocated that modelling was the most expensive part of the predictive control. In addition, it causes difficulty in real-time control application due to its high computation power demand.

Several studies however explored the "offline" control application based on the white-box model. (Coffey *et al.*, 2010) proposed a model predictive control strategy using a detailed TRNSYS building model in the controller for the purpose of peak shaving. A software framework was outlined where the optimization work was done externally by GenOpt with genetic algorithm. The optimal decision was handled in another organization layer with outputs to the building energy management system. (Zhang *et al.*, 2014) took a similar approach with TRNSYS building model coupled with GenOpt optimisation. The TRNSYS building model was acted as the "real house", as well as the model in the controller, which facilitated the study without concerning model mismatch, an issue commonly existing in model-based control studies. (May-Ostendorp *et al.*, 2012) developed a model of a small office building in EnergyPlus, which was used for extraction of supervisory building control rules.

Besides offline control application, the white-box model is more often used to generate a synthetic database which is further utilized for system identification and validation of simplified models. Several of its typical applications will be covered in the section below after introduction of the grey-box and black-box models.

Grey-box models

The grey-box model uses simplified physical representations, for instance, using a network of resistors and capacitors based on electric analogy of building Resistance and Capacitance (RC) to describe a building. In the RC network model, a node of the network represents a space or a layer of wall/floor with a homogenous temperature; the thermal mass of the space or construction is represented by a capacitor. Figure 9 shows examples of RC network representation of a wall (left), a house with radiators (middle) and with a floor heating system (right).

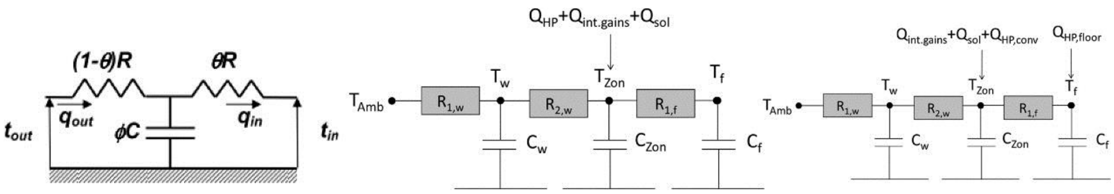

Figure 9. RC network representation of a building wall as 2R-1C (left), as grey-box model for a house with radiators only (middle) and as with a floor heating system additionally (right) (Masy *et al.*, 2015).

As in the electric RC network, the number of capacitors decides the order of the dynamic system; and similarly, the research findings of RC networks as well as linear systems can therefore be transplanted in the building system for analysis and controller design. This type of model appears to be the most widely applied in the literature.

The RC network model is included in the category of the grey-box model because the system parameters can be physically interpreted, for instance, time constant, resistance and capacitance of the system may be analysed and paralleled in the building system. Therefore observations and findings can still be physically sought. (Candanedo, Dehkordi and Lopez, 2013) analysed the capacitance ratio of the central zone and perimeter zone of an office after identifying these parameters. They claimed that the bigger capacitance of the central zone showed a slower change than the perimeter zone. According to (Madsen and Holst, 1995), a RC model may or may not describe the long-term dynamics of a building, depending on the number of time constants of the corresponding RC network. They suggested using at least two time constants for a single-story building. This recommendation is not difficult to understand since the physical building system is nonlinear, while the RC network approximate it using the linear system. To what extent a RC network represents a building system well enough was further investigated by (Bacher and Madsen, 2011) with the software CTSM. Different model structures describing either envelope, heater and sensor and their combinations were examined in a forward selection manner, where the model complexity is increased by one order at each step and using likelihood ratio tests to assess the relevance of the extension.

Comparing with the white-box model, the grey-box model is much simpler. It requires much less computation power and can be easily implemented in the real-time control application. However, some researchers are concerned about the accuracy of the grey-box model and proposed some in-between models. In the study of (Wang and Xu, 2006), a model was created by combining functions based on thermodynamics law with the grey-box model. Then parameter identification technique was applied with operation data to obtain the model. Besides dynamics of different thermal zones, the model also took into account the dynamics of internal mass and multilayer external walls and roof.

Black-box models

Unlike the grey-box model, the black-box model cannot necessarily be understood from a physical point of view. Black-box models are often pure mathematical models, deriving from data based on different machine learning algorithms, such as polynomial models (e.g. auto-regressive moving average (ARMA) models), artificial neural network (ANN) and so on.

(Jiménez, Madsen and Andersen, 2008) presented a detailed guidance on how to identify an ARMA with exogenous terms (ARMAX) model for the building using the Matlab system identification toolbox IDENT. The relationship between the RC network and the polynomial models (or parametric models) were also explored. (Huang, Chen and Hu, 2014) developed an ANN model based on the model structure of nonlinear autoregressive with exogenous terms (ARX). A three-layer Multilayer Perceptions (MLP) was chosen and the Levenberg-Marquardt algorithm was used as the training algorithm to minimize the mean square errors between the predicted and measured data. In this study, a RC-network model was also created and results showed that the ANN model gave slightly better predictions than the ARX model. Research from (Ruano *et al.*, 2006) showed that the ANN model could perform even better than the white-box model. However, choosing the correct order number for the ANN model is challenging and its model structure is complicated, which could result in a non-convex optimization problem that is difficult to solve. (Dong and Lam, 2014) examined the feasibility and applicability of the support vector machine (SVM) algorithm in building load forecasting. In this case, coefficients of variance and the percentage errors of all prediction results were within 5%.

Comparison of model types

The advantage of black-box models is their flexibility of model structure, compared to grey-box models. (Jiménez, Madsen and Andersen, 2008) have shown that the RC network model is just one special type of the polynomial models. However, since the polynomial model is more flexible in its parameters and structure, the original physical meaning of the RC network model cannot be retained in the expansion of parameters and structure. As to other machine learning algorithms, the choices can be abundant, but each has its own limitations too.

Nonetheless, the black-box and grey-box models have lower complexity than the white-box one, so they are more widely applied in real-time control practice. However, the former two types rely heavily on measurement data, which can remain an obstacle in reality. In the literature, one common approach is using the white-box model built in BPS programs to generate synthetic database, as mentioned previously, for system or parameter identification for the simplified models. This approach diminishes the potential problems existing in system identification using real measurements, such as sampling rates selection, satisfaction of excitation condition and data duration requirement etc. Moreover, the simplified models can also be validated with the white-box model (Ma *et al.*, 2012; Ma, Qin and Salsbury, 2014; Masy *et al.*, 2015).

In a study from (Ma *et al.*, 2012) the Building Control Virtual Test Bed (BCVTB) environment was utilized to integrate EnergyPlus and Matlab. The input-output information of the EnergyPlus model was used to identify the ARX model in Matlab. This simplified model was used in the MPC to provide optimal cooling set points for a five-zone building (see Figure 10).

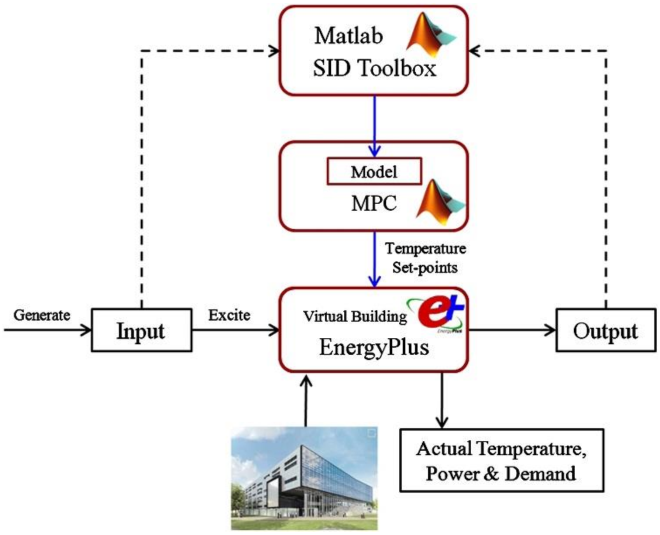

Figure 10. A system framework in BCVTB (Ma *et al.*, 2012).

The study from (Garnier *et al.*, 2015) created a complex building model in EnergyPlus, and an ANN model was then identified based on the input-output data generated by EnergyPlus. The optimal network topology was identified with 18-24 hidden neurons using a dataset of 2 months.

Although different types of models exist, each of them has its own advantages and disadvantages, as well as its application field as discussed above. Selecting the most appropriate model and tool to solve a problem is a critical step for reasonable building simulation. Most models are highly dependent on the specific case.

3.6.2 Modelling of TES systems

Like the building thermal mass within the building itself, controlling the charging and discharging of a TES system can contribute to the energy flexibility of buildings, such as reducing peak power demands.

Common TES systems found in the buildings are hot water tanks for service water and ice storage tanks for cooling often installed in commercial buildings. Currently, only simplified TES models and low-order RC-networks have been applied for the model-based control. (Salpakari and Lund, 2016) integrate a one-node model for a water tank into an MPC. (Berkenkamp and Gwerder, 2014) developed a linearized model of a stratified water tank for an optimal control problem. Figure 11 shows the different layers or nodes of the tank model.

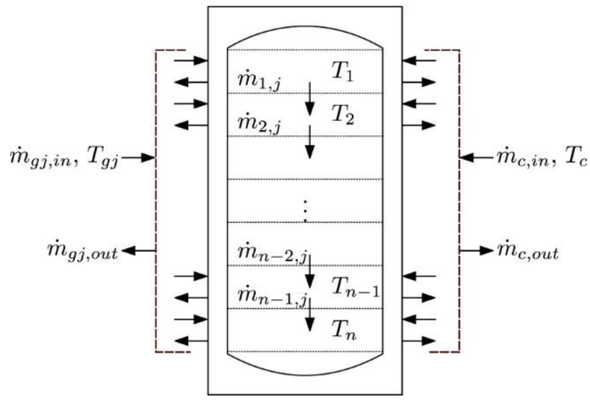

Figure 11. Stratified hot water tank (Berkenkamp and Gwerder, 2014).

(Beghi *et al.*, 2014) assumed a lumped-capacitance model for ice storage that considered both sensible and latent heat transfer. The model regarded the average temperature of water/ice (storage medium), heat exchange efficiency and heat loss as the function of insulation (self-discharge).

Those simplified TES models integrated into MPC and optimal control sometimes are not capable to capture the dynamics in the complex process of heat and mass transfer. For this reason, researchers have introduced model-free reinforcement learning and model-based solutions, such as ANN models (Rosiek and Batlles, 2011). The reinforcement learning and ANN models can solve nonlinear problems with fast computation. However, the computation time extends substantially as the number of states increase in the optimization and state-space model.

3.6.3 Advanced mathematical techniques for flexibility control

As discussed earlier, most business cases for energy flexible buildings depend on time varying energy pricing. Predictable time of use pricing alters tariffs at known times of day, while a dynamic market offers real-time pricing. Real-time electricity pricing that reflects intermittent renewables is analysed as a stochastic process (Kitapbayev, Moriarty and Mancarella, 2015).

Mathematical finance techniques take stochastic input data to quantify the flexibility of a possible investment; in this case a district energy system. One technique, "real options", assists business decision making. Applied to a district energy system equipped with CHP, the high level control decision is to operate the local CHP power plant in favour of dynamically priced utility energy.

(Kitapbayev, Moriarty and Mancarella, 2015) find that the real options technique surpasses discounted cash flow analysis of investments, by modelling uncertainty and operational flexibility. In summary they prove by simulation that "short term flexibility can change the long term business case". Research of large energy systems with flexible operation and pricing will drive advanced mathematical modelling and simulation. Reviews of simulation software and their solvers can be found in Appendix B.

4. Discussion

KPIs indicate overall performance of a building and are a function of measured data or parameters. A KPI is intended to concisely communicate performance, and allow comparison. Therefore their calculation relies on building performance data as positioned in Figure 12 and defined in Table 4.

4.1 KPIs and control strategies for energy flexible buildings

An effective KPI provides an accurate measure of overall system status, supports decision making and resource allocation. A building KPI applies throughout its operational lifespan; across all seasons and occupancy levels. KPIs differentiate themselves from performance metrics and short term monitoring data by being both "predictive" and "persistent", (Deru and Torcellini, 2005; Mauboussin, 2012) define an indicator as "a high-level performance metric that is used to simplify complex information and point to the general state or trends of a phenomenon". Due to their high-level characteristic, KPIs are positioned at the apex of the performance evaluation triangle in Figure 12. Raw monitoring data is gathered and processed into higher level metrics and finally KPIs.

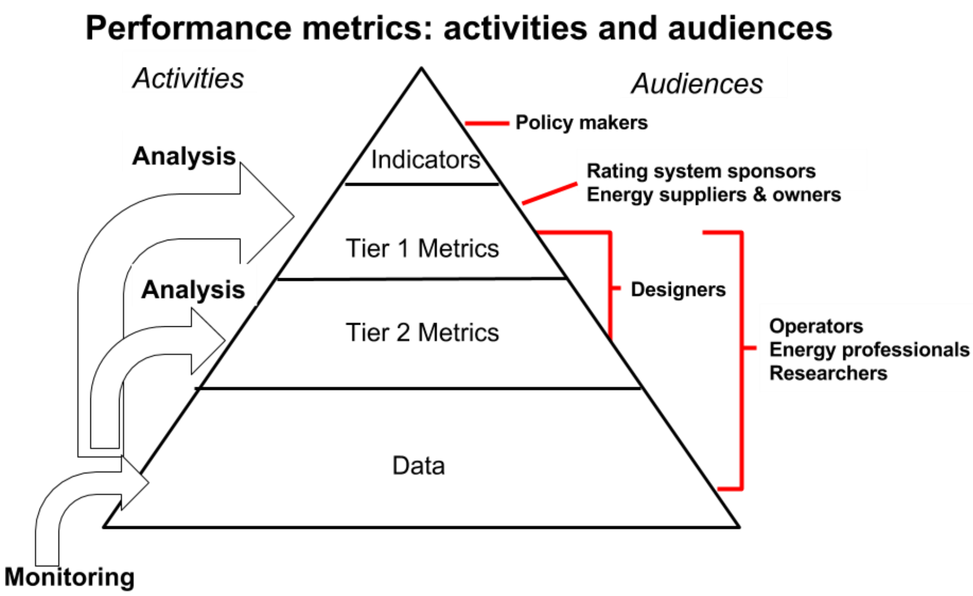

Figure 12. Building performance evaluation – different metric types and audiences (Deru and Torcellini, 2005).

The audiences for monitoring data, metrics and indicators appear on the right hand side of the triangle. Generally, longer term metrics match more strategic audiences. Consideration of audiences is not new, but liable to be overlooked. During the transition from research to the field or common practice, one must remember the audience needs:

- Indicator (KPI): Policy makers
- Tier 2 metrics: Designers, suppliers & building owners
- Tier 1 metrics: Designers, operators & researchers
- Monitor data: Operators & researchers

A conference paper resulting from IEA Annex 67 (Clauß *et al.*, 2017), splits control strategies of energy flexible buildings into two groups. First, maximum use of on-site generation, or "self-consumption", and second energy load shaping. The latter constitutes a form of demand side management. Renewable energy (RE) integration with heat pumps has two similar results: first, maximisation of self-consumption; second, load shaping such as load smoothing and peak reduction (Fischer and Madani, 2017). In their review of heat pump (HP) applications with smart grids, (Fischer and Madani, 2017) identify three application types: the renewable energy integration, grid services and pricing. Potential grid services from flexible HP operation are: voltage control, congestion management and operating reserve. Drawbacks are the seasonality of peak reduction and reserve capacity remains at development and demonstration stage.

It should be noted that large scale heat pump integration requires dedicated control to avoid grid voltage problems. To minimise cost, HPs can perform load shifting to reduce overall electrical purchase costs, at the expense of HP energy efficiency.

A KPI of RE self-consumption is generally fulfilled by a rule based control, which is a subset of non-predictive control, Figure 13. The fast response to theoretically support grid frequency or voltage regulation, also necessitates rule based control according to review by (Fischer and Madani, 2017). While energy flexible buildings may reduce demand peaks, their unsuitability to provide grid ancillary services is discussed in the subsection 4.3.

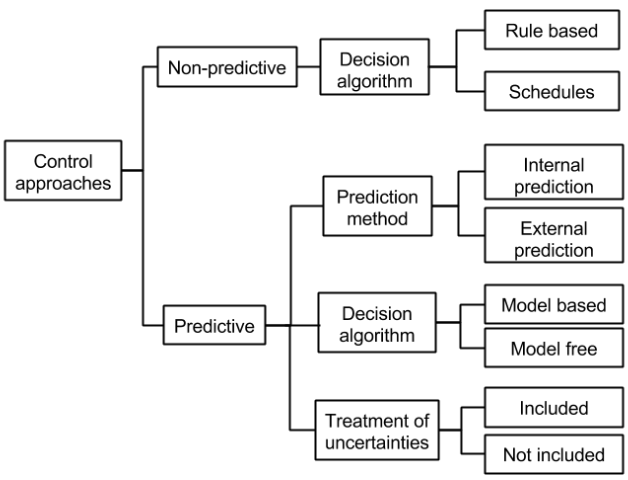

Figure 13. Applied control strategies for heat pumps in a smart grid context. Only passive intelligent systems are considered (Fischer and Madani, 2017).

Predictive control differentiates itself over rule based control during changeable conditions (see section 3). Pricing structure, demand pattern or comfort requirements are examples of volatile conditions identified by (Fischer and Madani, 2017). Prediction responds to cost-impacting external signals and internal signals that drive operation. The main challenge is predicting “the energy building heat demand for space heating and domestic heating”. The solution is to improve operational building data, which building controls can then fully exploit. ICT toolkits and semantic web technologies are proposed to exploit building information modelling (BIM) and building occupancy data (Steel, Drogemuller and Toth, 2012; Costa *et al.*, 2013).

Given building energy data, sophisticated model predictive control (MPC) employs energy flexibility such as load shifting, to achieve KPIs encoded in a “cost function”. This is one of the conclusions of an IBPSA 2017 conference paper emanating from IEA Annex 67 (Clauß *et al.*, 2017). (Dahl Knudsen and Petersen, 2016) exemplify a MPC controller shifting consumption in order to prioritise, or balance, KPIs of energy cost and CO2 emissions.

Recent literature recognises that building energy metrics must consider the connected energy system (Graabak, Bakken and Feilberg, 2014; Mathiesen *et al.*, 2016). The implied assumptions of a NZEB exporting without constraint to the grid, unravel where NZEBs cluster onto the same electrical feeder (Baetens *et al.*, 2012). This illustrates an isolated KPI of low annual net energy, becoming increasingly expensive to the energy system beyond threshold of buildings.

4.2 Metrics of energy flexible buildings

Key performance indicators evaluate overall building energy performance. They are higher level metrics computed from data such as building energy consumption, or load (l) and energy generation (g).

Self-consumption (SC) is an energy KPI directly influenced by the energy flexibility of a demand location, such as a building scaled up to a neighbourhood. Calculation of self-consumption is a function of energy export (ex) and import (im) data, gathered over time period (T). Import and export are expressed in terms of building load (l) and generation (g) in following equations, and described with other building performance data in Table 4.

$$g_{sc}(t) \;=\; \begin{matrix} g(t) \;\; if\; l(t) \geq g(t) \\ \\ l(t) \;\; if\; l(t) < \; g(t) \end{matrix}$$

$$g_{ex}(t) \;=\; \begin{matrix} 0 \;\; if\; l(t) \geq g(t) \\ \\ g(t) - \; l(t) \;\; if\; g(t) < l(t) \end{matrix}$$

Table 4. Common building energy performance metrics.

Symbol	Name	Unit
l	Final energy consumption (load)	kWh
l_{im}	Imported energy consumption	kWh
g	Local energy generation	kWh
g_{ex}	Local energy generation exported	kWh
g_{sc}	Local energy generation self-consumed	kWh
e	Exported local production	kWh
C_i	Cost of energy import	€/kWh
C_0	Reference cost	€/kWh
r_E	Revenue of energy export	€/kWh
η	Energy conversion efficiency	[-]
t	Time step	s, h or day
T	Period of time considered (e.g. year)	Aggregated timesteps e.g. year

4.2.1 Traditional metrics of building energy performance and comfort

KPIs for individual building energy efficiency are well covered in the literature. Many KPIs are normalised by floor area (m2) in an effort to allow comparison between buildings. Normalisation by another parameter, such as number of occupants or rooms is possible but out of report scope. A summary of traditional performance metrics appears in Table 5.

Table 5. Traditional building energy performance metrics, with-out normalisation.

KPI	Formula
Total final (secondary) energy use	FE = $\int_T \quad l(t)\, dt$
Total cost of final energy	CE = $\int_T \quad C_E(t) l(t)\, dt$
Total primary energy use	PE = $\int_T \quad \frac{1}{\eta(t)} \quad l(t)\, dt$
Total net energy use	NE = $\int_T \quad l_{im}(t) - g_{ex}(t)\, dt$

Occupant comfort does not measure building energy flexibility. Nevertheless, occupant comfort does constrain building energy flexibility. Chapter 1 of Carlucci's book (Carlucci, 2013) classifies thermal comfort metrics. A common metric type percentage time or hours outside of a defined comfort range. (Oldewurtel, 2011) measure thermal comfort by integration over time of room temperatures above or below a defined range. The computed violations in hours per annum, quantify thermal comfort alongside energy efficiency gains. Recent thermal comfort metrics account for discomfort magnitude by weighting the variations from the comfort range. Total weighted variation over a period, sum to the exceedance value (Carlucci, 2013).

Other measures of thermal comfort focus on human perceptions, as opposed to physically measured indoor temperatures. PMV (predicted mean vote) predicts the self-reported thermal perceptions by a large group of persons. PMV forms the basis of standard EN 15251 Indoor Environmental Criteria, reviewed by (Olesen, 2007). (Garnier *et al.*, 2015) constrain MPC by PMV score, not the traditional temperature range. (Cigler *et al.*, 2012) use MPC to optimise PMV, reporting a 10-15% energy saving compared with "typical" MPC.

4.2.2 Next generation metrics for energy flexible buildings

Recent research extends building energy metrics from performance and energy efficiency to energy flexibility. (Le Dréau and Heiselberg, 2016) introduce a flexibility factor (FF) to measure load shifting from high price periods. For a given cost reference C_o, FF ranges from -1 to 1. If all energy is consumed during low pricing, FF maximises at 1. The flexibility factor metric is adaptable to energy consumption, cost or GHG emissions that appear in a review by (Clauß *et al.*, 2017).

When focussing on building energy self-sufficiency, a self-consumption factor measures the proportion of energy consumption covered by local generation. Cover factors are applied to building simulations (Baetens *et al.*, 2012). A value of 0 represents no local generation consumed in the building, whereas 1 indicates that all energy consumption is covered by local generation.

(Reynders, Diriken and Saelens, 2015) measure the flexibility due to the thermal mass of buildings called structural thermal energy storage. Three equations in Table 6 use the ADR (active demand response) notation. C_{ADR} is the available storage and storage efficiency η_{ADR} varies with time depending on boundary conditions including climate, occupants and heating system. Both of these are building characteristics. The power shifting capacity l_{shift} is the difference in heating power during ADR (l_{ADR}), and the reference heating power during l_{ref} normal operation.

The review by (Stinner, Huchtemann and Müller, 2016) categorises operational flexibility as either temporal flexibility, power flexibility or energy flexibility. Energy flexibility is a combination of temporal and power flexibility, and a simplified equation appears in Table 6. They refer to forced and delayed flexibility discussed a few years prior by (Nuytten *et al.*, 2013). Delayed flexibility draws on stored energy to meet load. Its quantification in hours equals the time the heat generator can be kept idle based on an initially full storage. Forced flexibility is the duration that the heating source can be forced on, while storing excess energy. By both flexibility metrics, a central CHP equipped with a centralised energy storage exceeds that with distributed storage.

(Stinner, Huchtemann and Müller, 2016) aggregate their quantification of operational flexibility to districts. They add to the literature that scales up demand side analysis from stand-alone buildings to districts or neighbourhoods, (Koch, Girard and McKoen, 2012; Kitapbayev, Moriarty and Mancarella, 2015).

Table 6. Overview of KPIs related to demand side flexibility.

KPI	Equation	Reference
Flexibility factor (FF) (where C_o is reference price)	$FF = \frac{L_L - L_H}{L_L + L_H}$ $L_L = \int_0^T l(t)\,dt \quad where\ c_E(t) \leq C_0$ $L_H = \int_0^T l(t)\,dt \quad where\ c_E(t) > C_0$	(Le Dréau and Heiselberg, 2016)
Self-consumption factor (or supply cover factor)	$\gamma_s = \frac{\int_o^T min(g(t), l(t))\,dt}{\int_o^T g(t)\,dt} \quad losses + storage = 0$	(Dar *et al.*, 2014)
Self-generation factor (or load cover factor)	$\gamma_l = \frac{\int_o^T min(g(t), l(t))\,dt}{\int_o^T l(t)\,dt}\ losses + storage = 0$	(Dar *et al.*, 2014)
Available structural storage capacity	$C_{ADR} = \int_0^T (l_{ADR} - l_{ref})\ (t)\,dt$	(Reynders, Diriken and Saelens, 2015)
Storage efficiency	$\eta_{ADR} = 1 - \frac{\int_o^\infty (l_{ADR} - l_{ref})\,dt}{\int_o^T (l_{ADR} - l_{ref})\,dt}$	(Reynders, Diriken and Saelens, 2015)
Shifting efficiency	$\eta_{shift} = \frac{-\Delta\, l_{heat\ discharged}}{-\Delta\, l_{heat\ charged}}$	(Le Dréau and Heiselberg, 2016)
Power shifting efficiency	$l_{shift} = l_{ADR} - l_{ref}$	(Reynders, Diriken and Saelens, 2015)
Forced flexibility	$\epsilon_{forced} = \int_0^{T_{forced}} l_{flex,forced}\ (t)\,dt$	(Nuytten *et al.*, 2013; Stinner, Huchtemann and Müller, 2016)
Delayed flexibility	$\epsilon_{delayed} = \int_0^{T_{delayed}} l_{flex,delayed}\ (t)\,dt$	(Nuytten *et al.*, 2013; Stinner, Huchtemann and Müller, 2016)

KPIs vary by control strategy as (Salpakari and Lund, 2016) describe. Different metrics of self-consumption and grid feed-in apply to rule based control and cost-optimal control respectively. As expected self-consumption predominates where FITs (feed in tariffs) fall short of energy prices or are absent altogether.

FITs financially reward distributed generators, such as PV equipped nZEBs, for grid energy exports. Analysis of building energy flexibility has adapted to the energy market innovation. Energy metrics, such as grid feed-in, extend from a standalone building to the interaction of the building and connected grid. (Sartori *et al.*, 2010) specify "grid feed-in" in their definitions of nZEB as "the energy flowing from the buildings to the grids".

4.3 Buildings interaction with an energy system (grid)

Grid connected energy flexible buildings affect the demand from their grid as they vary energy load. In practice, management of large demands takes place infrequently as discussed later; and excludes residential buildings. Demand flexibility overlaps conceptually with demand side management (DSM), whose benefits and challenges are reviewed by (Strbac, 2008).

4.3.1 Flexible building energy demand and electrical battery storage

Energy flexibility of residential buildings promises to shave peak grid demand, especially of aggregated buildings. Aggregation at neighbourhood scale is proposed by (Koch, Girard and McKoen, 2012) and modelled successfully by (Corbin and Henze, 2016). Beyond peak shaving and occasional demand balancing, other grid support by energy flexible buildings appears unlikely. A role for battery storage in grid voltage control and generation reserves is dismissed by (Huntoon, 2016) due to: variable battery charge, lack of control and short battery life. (Lund, Marszal and Heiselberg, 2011) criticise building level batteries, recommending aggregation of building demand in order to level load mismatch. Small distributed batteries would increase losses by simultaneous charging and discharging. Investments to compensate for individual building mismatch are wasteful, because the grid serves aggregated not individual building load.

(Lund, Marszal and Heiselberg, 2011) propose a new metric, the mismatch compensation factor (f_{MMC}). It compares the local generation capacity necessary to balance energy imports and exports ($C_{ENERGY\text{-}BALANCE}$), against the generation capacity necessary to compensate for the mismatch ($C_{COST\text{-}BALANCE}$), see Table 4.4. An $f_{MMC} > 1$ indicates excess load mismatch, remediated by increasing the local generation capacity.

A comprehensive review of future utility networks by MIT (MITEI, 2016), propose capacity payments to "unlock" flexible demand. The authors view volumetric tariffs as "responsible" for inefficient investment and consumption. On the other hand, the review cautions that flexible demand "constitutes the economically efficient consumption of a service, not the provision of a service". Certain barriers listed by (Huntoon, 2016) such as, lifetime, ICT and lack of dynamic pricing, are framed as surmountable pre-requisites by MITEI. In terms of battery life, levelised cost of storage requires a ten year life. Aggregated battery storage by ICT across residential buildings, is already reported as successful in an industry pilot (Nikolaus, 2015).

4.3.2 Flexible building energy demand and grid operators perspective

Demand side management (DSM) is welcomed by grid operators to reduce peak demand, caused by the short-term weather events. In Ireland, "demand side units" combine on-site generation or plant shutdown in order to participate in DSM. (Eirgrid Group, 2016) describe DSU as *dispatchable*.

"*A Demand Side Unit (DSU) consists of one or more individual demand sites that we can dispatch as if it was a generator. An individual demand site is typically a medium to large industrial premises. A DSU Aggregator may contract with the individual demand sites and aggregate them together to operate as a single DSU*."

In order to contribute to grid capacity, energy flexible buildings must meet system adequacy criteria set by the national grid operator. For example (Eirgrid Group, 2016) who rely on two distinct metrics. Dispatchable grid capacity contributes to a grid security KPI of Loss of Load Expectation (LOLE), measured in hours/year. The Expected Unserved Energy (EUE) KPI measures the impact of grid shortage. EUE is often normalised by total net energy of the system, and measured in per million of energy load that is unserved.

Useful interaction of energy flexible buildings with the grid is likely to depend on the local electricity market. For example most scenarios of the Irish electricity market indicate capacity shortfall, which are unlikely to be remedied by current market revenues (Eirgrid Group, 2016). On the other hand, Denmark is less likely to risk capacity shortfalls according to (Danish Energy Agency, 2015) assuming operation of its multiple interconnectors.

A report by (Denholm *et al.*, 2016) quantifies the impact of grid flexibility options in three US case studies. In a PV example, demand response would provide significant value, if shiftable loads occurred in the spring and autumn. Flexibility was already provided by combined cycle generators, with further flexibility possible by increased transmission and grid storage. Few benefits are found from PV acting as reserves. More cooperation between system operators would increase variable generation and reduce system costs. In conclusion, grid operators have many options to increase energy flexibility before relying on energy flexible buildings. The exception remains peak demand reduction.

4.3.3 Next generation energy flexibility indicators of system interaction

When considering the interaction between a building and its connected energy system ("grid"), a variety of new generation metrics and KPIs emerge. The aforementioned grid feed-in is the simple sum of "the energy flowing from the buildings to the grids", (Sartori *et al.*, 2010). An example of its use by (Salpakari and Lund, 2016), finds significantly more flexibility in energy storage than shiftable appliances. Longer time periods reflect the intermittent nature of renewable energy generation. Metrics that incorporate time resolution over longer time periods are reviewed and appear in Table 7.

Loss of load probability (LOLP) is the percentage of time that local generation does not cover building load. In other words, the proportion of time that the building relies on energy from the grid. The load match index, as defined by (Voss *et al.*, 2011), incorporates the proportion of load met by local generation during the intervals of grid reliance. Load matching is sensitive to time resolution; especially sub-hourly (Koch, Girard and McKoen, 2012; Salom *et al.*, 2015) use the load match index to scale up ZEB behaviour from building level to neighbourhood scale.

The timing of energy imports and exports affect the GHG emissions of a building as the generation portfolio varies, (Graabak, Bakken and Feilberg, 2014). A metric of marginal conversion factor is GHG intensity of electricity not used as a result of interventions for demand reduction. Use of this metric allows optimal control of a ZEB in terms of GHG. The aforementioned metrics of flexibility factor (FF) and mismatch compensation factor (f_{MMC}) are adaptable to from economic to GHG inputs.

The grid interaction index prioritises the variability of load mismatch (Voss *et al.*, 2011; Salom *et al.*, 2014). Over an annual period, the grid interaction index is the standard deviation of all the per time-step values. By measuring grid interaction, the performance of the local grid is accounted for in building energy flexibility.

Table 7. Load matching and grid interaction.

KPI	Equation	Reference
Grid feed in (assuming no storage)	$GFI = \int_{t \in T} min(0, g(t) - l(t))$	(Sartori *et al.*, 2010)
Load match index (LMI)	$f_{load,T} = min\left[1, \frac{on\ side\ generation}{load}\right] \times 100\ [\%]$ $LMI = \frac{1}{T}\int_{t \in T} min(1, \frac{g(t)}{l(t)})$	(Voss *et al.*, 2011; Koch, Girard and McKoen, 2012)
Grid interaction index (f_{grid}) (Time interval (T) and year)	$f_{grid,T} = \frac{net\ grid}{max\ \lvert net\ grid \rvert} \times 100\ [\%]$ $f_{grid,year} = SD(f_{grid,T})\quad SD = std\ deviation$	(Voss *et al.*, 2011; Salpakari and Lund, 2016)
Loss of Load probability (LOLP)	Proportion of period (T) when exported energy < 0. $LOLP = \frac{\int_o^T f(t)\, dt}{T}\quad f(t) = 1, if\ e(t) < 0;\ f(t) = 0, if\ e(t) \geq 0$	(Salom *et al.*, 2014)
Mismatch compensation factor (economic)	$f_{MMC} = \frac{C_{COST-BALANCE}}{C_{ENERGY-BALANCE}}$	(Lund, Marszal and Heiselberg, 2011)

Appendix A – Literature classification

Parameters for literature classification:

- Information about the literature
  - Publication year
  - Authors
  - Publication title
  - Source
- General information about the study
  - Building type (residential, office)
  - Location
  - Study type (experimental, simulation, review)
  - Heating and cooling system (on-site renewable, main energy supply, distribution system)
- Information about the applied control technique and strategy
  - Control type (rule based, MPC, etc.)
  - Control objective and horizon
  - Control parameters (inputs, disturbances, and constraints)
  - Simulation models
- Key performance indicators (KPIs) and grid services
- Main results of the study

Appendix B – Optimisation testing by simulation: tools and solvers

Most energy management systems that exist in buildings rely on non-predictive types of control. Their design rules are relatively simple. The transfer of the new predictive control strategies to the field, however, persistently lags research efforts (Fischer and Madani, 2017). One proposal to implement new control strategies in the field is to co-design the HVAC control algorithm with its sensors (Haghighi, 2013).

Planning a path to embed predictive building control is out of the scope of this report. Nevertheless, modelling and simulation contribute to the de-risking of control upgrades and technical education in control strategies.

Software tools and solvers

Modelica is a modelling language enabling simulations of multidisciplinary problems. As an object-oriented and equation based language, Modelica enables reuse of model components and simpler, more efficient code. Object oriented code blocks inside a model, interlink across a causal interfaces representing different physical phenomena such as heat transfer. Compared to other simulation tools, Modelica components are easier to organise into complex systems and provide an engineering view. In the case of energy flexible buildings a view of the energy generation, distribution and consumption is visible from a single model.

Recent IEA Annex 60 Modelica libraries (Wetter *et al.*, 2015) offer building energy simulation based on low order, resistance-capacitance (RC) models (Lauster *et al.*, 2014). The equation based nature of Modelica is suited to solving Kirchhoff's laws circuit laws derived from the RC model (see section 3). The rationale for Modelica modelling of building energy performance is articulated by (Wetter, Bonvini and Nouidui, 2016). Best practice on building simulation, focussing on the Modelica language, can be found at Berkeley Lab website (Wetter *et al.*, 2014).

Simulation integration solvers and optimisation

A popular Modelica software package is Dymola that defaults to the DASSL integration algorithm. Introduced in 1982, DASSL is a differential / algebraic system solver, implemented with an adaptive time step. Its performance in Modelica is compared to other integrators: Radau, Lsodar, Dorpi45, Rkfix and Euler (Jorissen, Wetter and Helsen, 2015). The Euler integration performed well in terms of computational time, assuming accuracy was not essential.

MATLAB offers a range of optimisers listed below

- IPOPT (Interior Point Optimization), open source
- BARON (Branch and reduce optimisation navigator)
- Xpress
- Gurobi[2]
- MOSEK[3] (large scale sparse problems)

[2] http://www.gurobi.com/ (free for academic and research use)

- Optimisation toolbox
- YALMIP[4]

YALMIP is a comparatively recent addition to the MATLAB toolbox, attracting academic attention due to its simplicity of use (Löfberg, 2004; UCD IEEE PES, 2017). It relies on many external solvers, while YALMIP itself "concentrates on efficient modelling and high level algorithms".

Commercial solvers are exemplified by IBM CPLEX; implementing the simplex method in C language. Turning to the popular Python language, Pyomo is the associated open source optimiser. Additionally, the Deap Python library is a useful alternative because it enables black-box optimization via genetic algorithms.

GenOpt, short for Generic Optimization Program, is a program developed by (Wetter, 2001). It can be used with the common building performance simulation programs such as EnergyPlus, TRNSYS, Dymola (Modelica-based), DOE-2 and so on. The objective function may be written as free format in the building performance simulation (BPS) programs. GenOpt evaluates the objective function written in the output text files of the BPS programs. It suits optimisation problems where the gradient of the objective function is unavailable or non-existent. Its applications extend to parametric studies.

The embedded algorithms in GenOpt include Generalized Pattern Search, Particle Swarm, Discrete Armijo Gradient, Simplex Algorithm of Nelder and Mead, Interval Division and so on. However, new algorithms can be added to the algorithm library without knowing the details of the program structure.

GenOpt excels in simplicity and interaction with BPS programs, but lags in optimisation speed. Therefore, simple problems such as linear or quadratic programming are solved more efficiently by other software such as MATLAB.

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[3] https://mosek.com/ (free for academic and research use)
[4] https://yalmip.github.io/ (free toolbox for MATLAB)

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