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The environmental impact of smart grids communication systems: a case-study approach

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Abbreviations

ADC Analog to digital converter

AMI Advanced metering infrastructure

BAU Business as usual

BES Battery energy storage

CAC Central air conditioning

CAES Compressed air energy storage

CPP Critical peak pricing

DLR Dynamic line rating

DSL Digital subscriber line

DSM Demand side management

FACTS Flexible AC transmission systems

GHG Greenhouse gas

GWP Global warming potential

HAN Home area network

HEMS Home energy management system

HVDC High voltage direct current

ICT Information and communication technologies

LAN Local area network

LCA Life cycle assessment

LTE Long term evolution

MCU Microcontroller unit

MTU Maximum transmission unit

NAN Neighborhood area network

PEF Primary energy factor

PHS Pumped hydro storage

PLC Power line carrier

PMU Phasor measurement unit

PSB Polysulfide bromide battery

PTR Peak time rebates

RES Renewable energy source

RTP Real time pricing

SLP Synthetic load profile

STATCOM Static synchronous compensator

SVC Static VAR compensator

THD Total harmonic distortion

TOU Time of use

UNB Ultra-narrow band network

VRB Vanadium redox battery

WAMC Wide area monitoring and control

WAN Wide area network

WLAN Wireless local area network

3G Third generation

4G Fourth generation

Introduction

Interest in smart grids is growing rapidly in every part of the world. Projects and studies are rising to address new power system challenges such as the management of intermittent and decentralized energy sources or the introduction of new and resource demanding loads on the power grid. Various solutions are considered to deal with those new challenges; among them, demand side management, smart storage systems, wide area monitoring, etc. Most of those solutions involve extensive communication infrastructures deployment which environmental impact is not well known.

The environmental impact of smart grids implementation is a vast subject and can not be comprehensively treated in a single work. The objective of this work is therefore to give an insight into the environmental impact, and more specifically the carbon footprint, of definite smart grid infrastructures. We particularly focus on demand side management (DSM) infrastructures from Chapter 2. This work is divided into four chapters which are described here after.

The first chapter is a state of the art divided in two parts. The first part of this chapter gives an overview of technologies involved in smart grid deployment and briefly describes some typical smart grid applications and examples of real projects. This section of the work was important in the process of defining the practical cases we study in the following chapters. The second part of this chapter is a survey of the environmental impacts of smart grid information and communication infrastructures (ICT). This gives a first insight into smart grid environmental impact.

The second chapter introduces impact models for the different parts of a DSM infrastructure: the terminals, i.e. smart plugs and smart meters, the communication infrastructure and the processing units. We also take an interest in the quantification of data communication volume.

The third chapter investigates the *in-home monitoring system* impact with the help of the model developed in Chapter 2. Four types of in-home monitoring systems are studied: a global monitoring system which gives global consumption informations to the consumer; a device-specific monitoring system which provides detailed consumption informations about specific loads along with the global consumption information; and two static pricing monitoring systems which give additional prices informations.

Finally, the fourth chapter studies the environmental impact of a particular load shifting algorithm. The chapter begins with the description of consumption and production models used in the shifting algorithm. It then describes the algorithm and examines the emissions and saving potentials of its implementation. It also presents the savings and emissions variations with different parameters.

This work ends with a conclusion which briefly summarizes the main ideas and gives suggestions for further studies in the area.

Chapter 1

State of the art

Today's grid has limited communication needs, but there is now a growing interest in developing its communication infrastructure to implement new functionalities. This chapter is divided in two sections; the first one presents the current evolutions of the grid and some smart grid applications. The second part addresses the issue of the environmental impact of communication networks and the way to assess it. We then finish this chapter by a short explanation about the units and conversion factors used in the rest of this work and a conclusion.

1.1 Smart grids: an overview

The electrical grid is in constant evolution. Nowadays, various evolution trends on the grid are making it necessary to further develop efficient grids controls [1]:

- the increase of the electricity share around the world: since 2000, the world electricity consumption has increased by 20% and the european electricity consumption by 11% [2].
- The diversification of electrical loads: the typical example of a new developing load is the electric vehicle market. As explained in [3], such loads can potentially degrade the power quality on the network and therefore bring new challenges to load-control strategies.
- The transition to intermittent energy sources due to environmental and energetic sovereignty issues: sources like solar, wind or geothermic are renewable and free, but they are also much more difficult to handle than standard sources like coal, gas or nuclear due to their high intermittency. The demand-supply balancing method becomes therefore much more complicated and needs to be redesigned. Storage systems and demand side management are nowadays seen as attractive solution to tackle this intermittency problem.
- The shift of production: the multiplication of low-power production plants in residential neighborhood implies bidirectional flows on the network which was initially made for unidirectional flows (in terms of switching and protections devices especially) [4].
- The growing interconnection: contrary to decentralization, some projects study the possibilities to a more interconnected european grid with huge centralized renewable power plants where the resources are available [5, 6]. For such projects, low-losses High voltage direct current (HVDC) transmission lines, wide area control strategies and reactive-power compensation must be further developed.

In order to counterbalance this growing complexity, intelligent grids controls are currently developed. The objective of this chapter is to give an overview of smart grids goals and technologies.

1.1.1 Definition

The term *smart grid* gathers together all technologies allowing a better and optimized control of the electrical grids from production to distribution and consumption. Smart grids applications are numerous: power quality control, demand-supply matching, better grid automation, network planning, etc. The National Institute of Standards and Technology gives the following definition [7]: *A modernized grid that enables bidirectional flows of energy and uses two-way communication and control capabilities that will lead to an array of new functionalities and applications.*

1.1.2 Objectives

Smart grid is a way to give to the electrical network the capacity to adapt to the evolving needs of human societies. As electricity is a liberalized market, the economical aspect of smart grid is to keep in mind. Affordable and efficient technologies must therefore be deployed to pursue various objectives such as [8]:

- managing peak load capacity: Generation capacity and distribution system represent most of the grid costs. Both generation and distribution must be sized to handle peak load, which results in higher costs and environmental impacts; additional infrastructures must be built, and peak load generation plants are usually characterized by a lower conversion efficiency (to minimize costs). Peak load limitation is therefore considered a key factor for the future emissions and costs mitigation. Distributed storage, demand side management and intelligent distribution management can all serve this goal.

- Enhancing reliability: a smart grid can enhance reliability in different ways; it can help prevent overload and blackouts by providing efficient wide-area control and monitoring tools. In the case of unpredictable outages (caused by vehicle accidents, wind and ice storms, or animals shorting out transformers, for example), smart grid can help by rapidly isolating faults and reorganizing distribution.

- Reducing costs: this includes peak load management to minimize production needs when marginal costs are high and to avoid congestion costs in the transmission network. Reliability enhancement also plays a role in costs reduction by preventing outages and avoiding equipment from overloading and therefore from accelerated aging. A 2011 study from the Electric Power Research Institute, in the US, estimated the benefits-to-costs ratio of the smart grid deployment to be between 2.8 and 6, [9].

- Providing ancillary services: many additional services must be provided by power plants to ensure a good power quality on the grid: reactive power control, demand-supply regulation, primary and secondary reserves, etc. An efficient grid automation could benefits to those services and make the power quality management easier.

1.1.3 Overview of smart grids technologies

The objective of this section is to give an overview of smart grids infrastructure and technologies based on Figure 1.1. This overview is divided into two main parts:

- the electrical network, which includes all the devices exchanging electrical flows with the network. The goal of this part is to understand the stakes and issues linked with power systems.

- The data network, which covers all the technologies exchanging, processing and reacting to information from the electrical network.

Each element of this figure is commented hereafter.

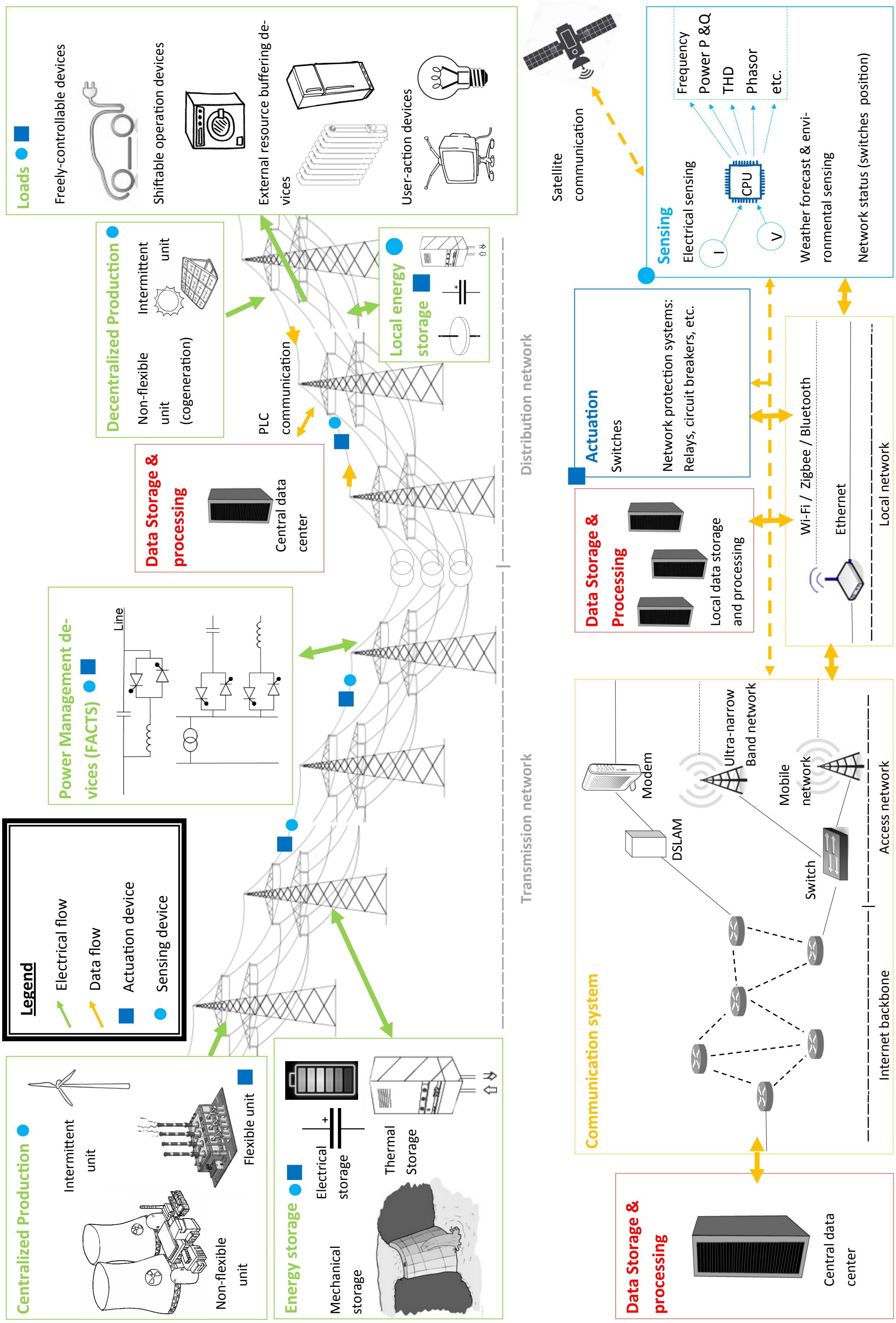


Figure 1.1: Smart grids - Overview.

Electric network

Environmental stakes are numerous in power systems: the transition to renewable energies, the consumption mitigation and the transmissions losses reduction are all considered solution for carbon footprint mitigation involving production, consumption, storage system and FACTS.

Electricity production : In classical grids, the production consists of centralized programmable plants. In Belgium, the base-load production is made of nuclear plants which produce constant output power. Coal-based production is adjusted on a daily-base and gas and hydraulic turbines, which are much more flexible, provide most of the remaining energy needs. Intermittent and decentralized energy sources such as wind turbines or solar panels are still in minority. Figure 1.2 shows a typical winter week production profile in Belgium.

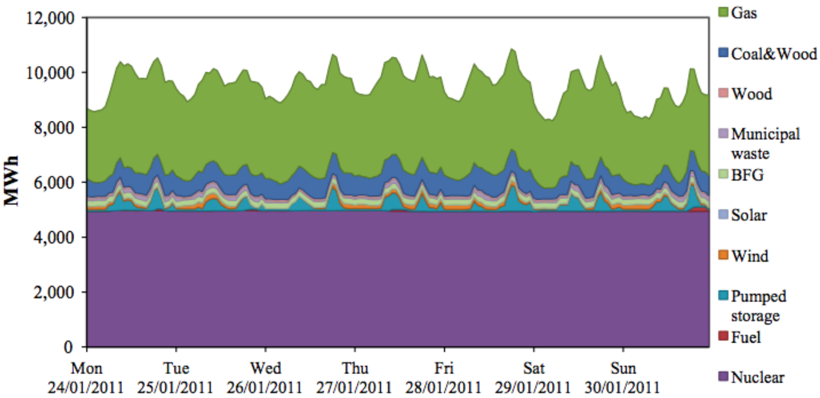


Figure 1.2: Typical winter production profile in Belgium [10]. Nuclear provides around 59% of Belgian energy while coal and gas produce respectively 5 and 28% of Belgian energy.

However, to reach 20-20-20[1] european objective, renewable intermittent sources have to be further developed in Belgium, introducing at same time a whole new set of challenges: production forecasting, supply-demand matching, bidirectional flows due to decentralized (residential) production, etc. In their paper, Messagie et al.,[10], present the CO2 emissions due to the different electricity production sources in Belgium (see Figure 1.3). This figure gives an idea of the quantity of CO2 that could be saved by switching from gas or coal-based production to renewable sources.

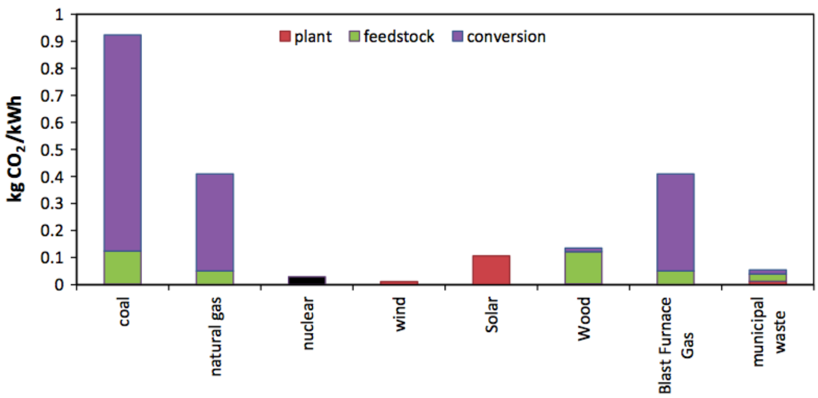


Figure 1.3: CO2e emissions due to different electricity production sources in Belgium [10]. While nuclear is the main source of electricity in Belgium, it only represents around 9% of the electricity carbon emissions. The remaining emissions are mainly due to coal(23%) and gas (61%).

[1] reduce CO2 emissions by 20% and increase renewable production and energy efficiency by 20% by 2020

Electrical loads : The total load can be divided into different groups including industrial machines, residential appliances, etc. Each category has its own specificity to be taken into account, some of them being critical for e.g. power quality. Figure 1.4 shows a belgian weekly load profile (data from Elia [11] , May 2015).

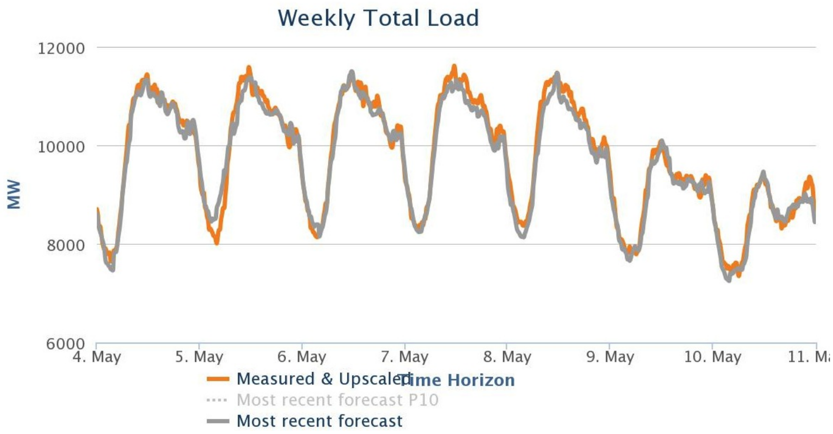


Figure 1.4: Electrical load in Belgium - May, [11]. Critical load takes place during weekdays because of the industrial activity.

With the development of intermittent energy sources, the idea of controlling loads in order to follow the production is attracting a lot of attention. In this perspective, electrical loads can be classified into four types, depending on their controllability [12]:

- Freely-controllable devices: *devices that are controllable within certain limits* [12]. Electric car batteries, for example, can either play the role of load or of energy storage to compensate short-term unbalance, if required by the grid. However, the batteries must be charged within a certain period of time and a minimum level of charge should be guaranteed.

- Shiftable operation devices: *batch-type devices whose operation is shiftable within certain limits, like (domestic) washing and drying processes. Processes that need to run for a certain amount of time regardless of the exact moment, like swimming pool pumps, assimilation lights in greenhouses and ventilation systems in utility buildings. The total demand or supply is fixed over time*, [12].

- External resource buffering devices: *devices that produce a resource, other than electricity, that is subject to some kind of buffering. Examples of these devices are heating or cooling processes, which operation objective is to keep a certain temperature within two limits. Devices in this category can both be electricity consumers (electrical heating, heat pump devices) and producers (combined generation of heat and power). Appliance of additional heat buffering devices can increase the operation flexibility of this type of devices substantially*, [12].

- User-action devices: *devices whose operation is a direct result of a user action. Domestic examples are: audio, video, lighting and computers*, [12].

Energy storage : it has been estimated that no more than 20% of local energy could be produced from renewable without storage system, [13]. Storage can thus enable more renewable energy integration by supporting local balancing of supply and demand, but at the price of more losses. Various storage technologies are available, each one with its own characteristics in capacity and power; hydropower, batteries, compressed air energy storage, flywheels, super capacitors, and superconducting magnetic energy storage,[14]. Depending on their energy to power ratio (see Figure 1.5), storage technologies have different time-scale applications (Bulk energy storage or power quality regulation). Decentralized storage can be used to reduce transmission losses.

Denholm and Kulcinski carried out a life cycle assessment (LCA) on three storage technologies in the USA, [13]: pumped hydro storage (PHS), compressed air energy storage (CAES) and advanced battery energy storage (BES) using vanadium (VRB) and sodium polysulphide electrolytes (PSB). The results are summarized in Table 1.1. Figure 1.6 shows the evolution of CO2e emissions due to storage technologies depending on the generation source.

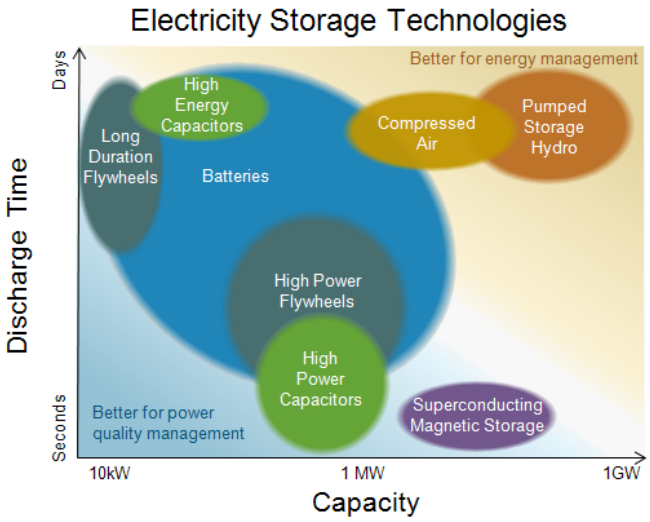


Figure 1.5: Power-Discharging time graph for some storage technologies, [15]. With its high capacity and discharge time, pumped storage is a good long-term management technology. Capacitors, on the other hand, are usually used for short-term power quality management.

Technology	Fixed energy use due to construction [GJ/MWh storage capacity]	Variable energy use due to operation and maintenance [GJ/GWh]	Efficiency [%]
PHS	373	25.8	74
CAES	266	5210	71
BES PSB	1755	54	65
BES VRB	2253	45	75

Table 1.1: Energy loss and emissions due to different storage systems [13]. CAES variable energy use is much higher than the other because the compressed air must be heated with fossil fuel before expanding through a turbine; it can therefore furnish more energy than it stores.

Oliveria et al. [16], from the VUB also made a LCA analysis of various energy storage systems in Belgium, which could interestingly complete the results presented here. Unfortunately, their article *Life Cycle Assessment of Energy Storage Systems to Balance Intermittent Renewable Energy Sources* is not available yet.

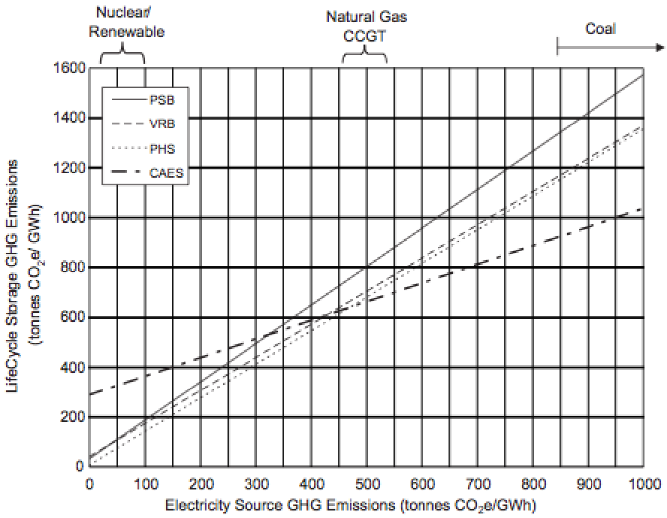


Figure 1.6: Emissions due to storage technologies depending on the generation source [13]. Depending on the energetic mix, the storage emissions vary.

Power management devices: Flexible AC transmission systems (FACTS) is defined by IEEE as, [17]: *a power electronic based system and other static equipment that provide control of one or more AC transmission system parameters to enhance controllability and increase power transfer capability.* FACTS are usually made of power electronic controlled impedances and are able to inject or absorb reactive energy (and sometimes active energy as well) at a given point of the grid, they are therefore a key technology to insure the quality of service in the future grid. They are remotely controllable and for that reason can be easily integrated to smart grid. The downside of such devices is their price, a paper from Kuek et al. estimates the price between 40 and 70 US$ per kVar provided on the grid bySVC or STATCOM [18]. Figures 1.7 show two types of FACTS: a SVC and a STATCOM.

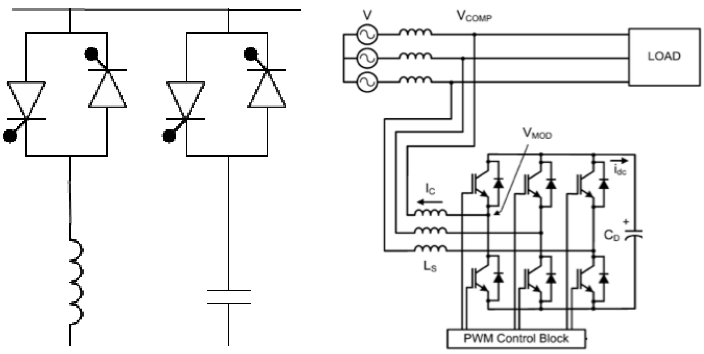


Figure 1.7: SVC (left) and STATCOM (right) help regulating power quality,[17, 19]. Those types of devices can be remotely controlled and could help intermittent energy integration by enabling efficient voltage control.

Data network

The data network is developed in parallel with the electric network and constitutes the brain of the grid. Data is generated by sensors located at several points of the electric networks, transported through various communication systems to processing units that handle it and send the decision back to actuators on the electric network. It allows the grid to be more intelligent, efficient and automatic. The current grid already possesses sensors and control centers, but with the advent of smart grids, the data network will considerably develop. The architecture of the decision making system can take different forms:

- a fully centralized system gathers together all the informations needed at one unique decision making unit. This unit is then able to compute the optimal response given all the information. This process has the advantage of taking decision from a very good knowledge of what is going on in the grid.

- A fully distributed system, on the other hand, consists in many decision making units that decide the best response given the local information to which it has access. This architecture has the advantage of requiring very little communication and being very fast as the decisions are made locally. Distributed algorithms are also more robust to local disturbances which only affect part of the distributed decision making units, the others being able to keep working as usual.

A real system can stand anywhere in between those two solutions. In [20], Wei and Wang studied the delay of both centralized and decentralized infrastructures for a fault detection and handling scenario in a microgrid. This paper concludes that for computationally intensive applications, centralized systems outperform decentralized systems due to the better performances of central processing units. The higher transmission delay is counterbalanced by the lower processing delay.
In the following paragraphs, we describe different technologies that may be used in smart grids; depending on the chosen architecture of a particular application, some technologies may be more or less relevant. Data network consumption is further studied in the following chapters.

Sensing: Sensors generate data to be sent and processed. Smart grids applications may use very different data types depending on specific system requirements:

- **electrical data**: this type of data is required to monitor the state of the grid, the power quality and the real-time supply-demand matching. Depending on the application, the information needed may differ: voltage and current amplitudes, phase, frequency, harmonic content, active and reactive power, etc. This information may usually be deduced from current and tension measurements, in amplitude and phase. Power meters, for example, may provide information about power and energy consumption, frequency, total harmonic distortion (THD) and power disturbances, depending on the sampling rate of their voltage and current sensors [21]. Phasor measurement units (PMU) can also provide precise phase measurement thanks to a GPS synchronization, [22].

- **Weather forecast data**: weather forecasts are especially useful to predict consumption and renewable production. This is necessary to anticipate a lack or excess of production and set up solution in advance in order to better match supply to demand. Weather data may also be useful for other purposes. Dynamic Line Rating (see section 1.1.4), for example, requires temperature, wind and solar radiation data, [23].

- **Other data**: other surrounding information may be necessary for other types of applications; speed, acceleration or position sensors, photodetectors, presence or motion sensors or all types of other sensors may help to handle electricity consumption in smart homes or buildings for example.

The deployment price of such a huge network of sensors is still an issue. Optimal placement for cost reduction is therefore the object of multiples studies, such as [24] about PMU optimal placement.

Communication systems: Possible communication technologies for smart grids are numerous. Depending on the application, priority requirements for the communication systems change: real-time, reliability, scalability, low cost, low latency, large bandwidth, etc. Communication technologies can be classified into three types [25]:

- **central network** (internet backbone): *it links the different access networks together. Mainly built from switches and routers connected by optical fibers, it uses fast technologies and a wide bandwidth over large distances* [25].
- **access network**: *access networks are organized as tree structures; users are all connected to a central node* [25] communicating with other nodes through a central network. The mobile network (3G, 4G), the DSL or the ultra-narrow band network are example of such access networks. PLC communication may also be used as an access network as long as it stays on low or medium voltage lines.
- **local network**: local networks are either connected to the central network via an access network or self-sufficient if data's are processed locally. Ethernet, wifi, zigbee, bluetooth or PLC communication are examples among others for local networks.

As some applications of smart grids need precise time synchronization, satellite communications are sometimes needed. Communication technologies and their characteristics and consumption are further described in Appendix A.

Data storage and processing: As explained earlier, data storage and processing units may be centralized or distributed. Technologies and processing capabilities requirements in both case are different. The final choice is a trade-off between rapidity, quality of decision, quantity of communication, and a lot of other factors.

Actuation: depending on the application, different types of actions may be required, [26]:

- action on the electric flow: breaker, switch, dimmer, etc.
- action on working conditions (of a motor, for example): valve, brake, etc.
- user interface action: light, speaker, display, etc.

1.1.4 Typical smart grid applications

The previous sections gave an overview of the smart grid infrastructure. Depending on the application developed, some elements are more important than others. A few of those applications are briefly described hereafter: wide area monitoring for enhancing reliability and observability on the grid, dynamic line rating for managing peak load capacity and reducing costs and demand side management for demand-supply matching and a better integration of renewable production.

Wide area monitoring and control

It is very difficult to monitor and prevent problems on the grid; wide area monitoring offers a solution to that problem by collecting data and providing information over the state of the grid. In [27], Zima et al. give a good overview of WAMC objectives and issues, [27]:

> *Power systems are today operated closer to their stability limits than at any time before, which makes them very sensitive to disturbances, and the monitoring and control issues have shifted from the preventive to the emergency ones. The dynamics and nonlinearities play a significant role in the critical power system operation. To properly observe the system dynamics, the needed measurements should possess the following characteristics: they must be taken from different network locations, with high sampling rate and at the same time instant (using global positioning system (GPS) time synchronization signal). PMU have all those characteristics. The core idea of the WAMC systems is the centralized processing of the data collected from various locations of a power system, aiming at the evaluation of the actual power system operation conditions with respect to its stability limits.*

WAMC applications are various and can be classified in two categories:

- *algorithms requiring a full observability of the network: frequency instability assessment and voltage instability assessment of meshed networks for example*, [27]. Those algorithms require a huge amount of communication as all the data must be gathered together at one central processing unit.

- *Algorithms not requiring an entire network observation: oscillation detection, line temperature monitoring, etc*, [27]. In this case, data may be processed locally, resulting in less communication and faster decisions.

In [28], Kuzlu et al. studied the communication requirements for wide area monitoring, their results for WAMC are presented in Table 1.2.

Application	Typical data size (bytes)	Typical data sampling requirement	Latency	Reliability (%)	Communication technologies
Wide-area protection					
Adaptive islanding	4–157	Once every 0.1 s	<0.1 s	>99.9	Wired:
Predictive under frequency load shedding		Once every 0.1 s	<0.1 s	>99.9	– Fiber optic
Wide-area control					
Wide-area voltage stability control	4–157	Once every 0.5–5 s	<5 s	>99.9	Wireless:
FACTS and HVDC control		Once every 30 s–2 min	<2 min	>99.9	– WiMAX
Cascading failure control		Once every 0.5–5 s	<5 s	>99.9	– Cellular
Precalculation transient stability control		Once every 30 s–2 min	<2 min	>99.9	
Closed-loop transient stability control		Once every 0.02–0.1 s	<0.1 s	>99.9	
Wide-area power oscillation damping control		Once every 0.1 s	<0.1 s	>99.9	
Wide-area monitoring					
Local power oscillation monitoring	>52	Once every 0.1 s	<30 s	>99.9	
Wide-area power oscillation monitoring		Once every 0.1 s	<0.1 s	>99.9	
Local voltage stability monitoring		Once every 0.5–5 s	<30 s	>99.9	
Wide-area voltage stability monitoring		Once every 0.5–5 s	<5 s	>99.9	
PMU-based state estimation		Once every 0.1 s	<0.1 s	>99.9	
Dynamic state estimation		Once every 0.02–0.1 s	<0.1 s	>99.9	
PMU-assisted state estimation		Once every 30 s–2 min	<2 min	>99.9	

Table 1.2: WAMC communication requirements estimation [28].

From Table 1.2, we can estimate that data transmission rate for WAM is around 14.7kbits/s/PMU (including 132 bytes header, see section 2.6), or 1.2 Gbits/day, without taking into account the necessary satellite communication. In [29], Marin et al. estimated that state evaluation of an entire grid would require PMU installation on around 20 to 25% of its busses.

Dynamic Line Rating

Electricity transmission is mainly limited by the thermal capacity of conductors which is usually defined as a static limit computed from worst case conditions, [23]. Dynamic line rating (DLR) consists in dynamically computing the operation limits of the equipments depending on weather and use conditions. The goal is to use the equipment at the maximum of its capacity in order to avoid additional infrastructure costs. In Belgium, for example, demand is higher during winter which also corresponds to a higher capacity of conductors due to lower temperatures. Thanks to DLR, this higher capacity could actually be used to avoid aditional infrastructures. The transmission capacity computation methods can be broken down in two main categories [23]:

- weather based (indirect methods), [23]: *The line rating is determined by measurement of ambient climatic conditions, and by means of the heat balance equation, to obtain the instantaneous conductor temperature rise available, and hence, the allowable current that can be transferred.*

- Sag based (direct methods), [23]: *The line rating is determined by direct measurement of the conductor state. The actual conductor temperature can be calculated using the relationship between conductor position/tension and temperature. The heat balance equation* *is used to determine the additional current that can be transferred before the conductor maximum operating temperature is achieved. It has the added benefit of providing a direct alarm should the conductor sag exceed or tension fall below a predetermined point that represents a violation of the required statutory ground clearance.*

Dynamic line rating requires the installation of a large number of sensors and data processing units along the grid, and is therefore expensive. In [30], Philips mentions the possibility of using weather data from online weather services; he concludes, however, that more precise local wind predictions are required which justifies the installation of local weather stations along the network. The operation limits can be computed locally, but DLR also requires centralization of the data in order to reorganize the transmission taking those limits into account.

Demand side management

The goal of demand side management is to control, to a certain extent, the electricity demand to pursue a fixed objective, [31]:

- energy efficiency: the goal here is to reduce absolute consumption by making the consumer more aware of his consumption. This new awareness may traduce in a better use of existing devices or in the acquisition of more efficient devices.

- Demand response: this consists in shifting demand in response to an external signal. This external signal itself is computed to reach a given goal; service reliability (e.g. peak shaving[2], spinning reserves) or costs reduction (e.g. peak shaving, intermittent production following).

Different methods have been implemented to pursue those goals; either by making the consumer more aware of his consumption through consumption display and dynamic pricing or by automating the load control.Demand side management is the main topic of the following chapters.

1.1.5 Existing smart grids projects

Smart grid projects are emerging in lots of countries and regions of the world. The goal of this section, is to present a non-exhaustive list of projects of various sizes along with their goals.

Microgrids

A microgrid provides electricity to a small group of consumers. Microgrids are usually made of local production and storage units along with smart demand side management technologies. They may vary in size and in goals; typical examples of microgrid objectives include: energetic sovereignty (islands), better stability, more energy savings (eco-neighborhoods) or the ability to disconnect from the main grid when there is a problem (hospitals, prisons, etc.).

<u>Islands:</u> Islands are very favorable environments for the development of smart grids. Small islands are very specific environments in terms of energy; they are isolated and therefore must acquire energetic independence. This is the reason why many islands are currently developing their renewable energy capacity faster than the rest of the world. Moreover, their lack of interconnection possibilities makes their grid management very challenging regarding their stability. Smart grid technologies seem very promising to help dealing with such problems.
As an example, El Hierro is an island located in the Atlantic ocean near the Moroccan coast, inhabited by 11 000 people, [32]. It is a volcanic island just like the rest of the archipelago (Canary islands). Since 2014, El Hierro is considered to be the first island of this size totally

[2]peak shaving consists in reducing peak demand, by time-of-use (TOU) pricing, for example. The goal is to avoid overload of the infrastructure and to limit as much as possible the use of peak production units, usually more costly and more polluting than base-load production units.

independent from the electrical point of view. This system consists of a 11,5MW wind farm, some photovoltaic and thermal solar panels, a 11MW pumped-storage hydraulic central and a back-up fuel oil central. This installation (Figure 1.8 provides enough electricity for the inhabitants and desalination factory on the island which corresponds to a yearly electricity demand around 40GWh with a peak demand around 8.15 MW, [33].

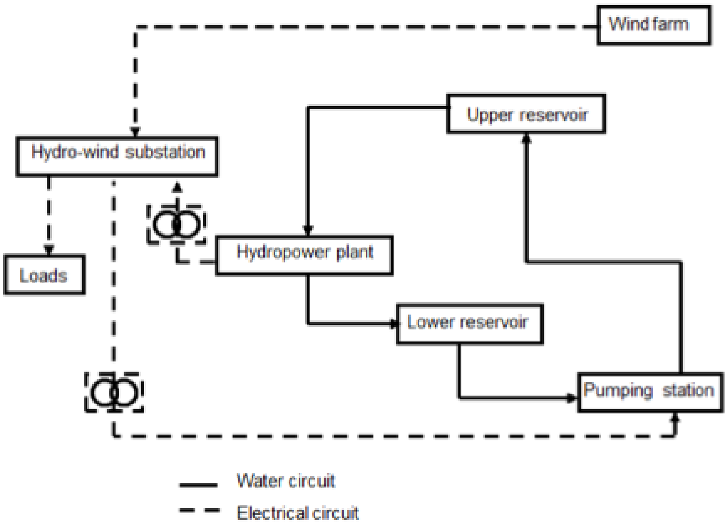


Figure 1.8: Generation system - El Hierro [33]. In addition to the represented system, the grid also has some solar generation and a back-up diesel central.

Information about the communication infrastructure of this project is unfortunately not available. Other similar projects are developed in islands all around the world: e.g. Graciosa island (Azores), Samso and Bornholm (Denmark), Malta, etc, [34].

Industrial microgrids: blackouts and disturbances may be very costly and difficult to handle for many industrial sectors. Moreover, some industries, like mining, need to establish in remote locations, making it difficult to connect to the grid. Those are two reasons for industries to develop their own microgrids. Again, those microgrids usually mix local production along with storage and demand side management solutions.
ABB [35] offers expert assessment for microgrids stability and control issues. The company worked on various projects, including El Toqui, a Chilean mine which goal was to increase the share of wind generation on its local network. The combination of storage systems and hydro plants with the wind turbines was found to be the optimal solution to avoid stability issues.

Other microgrids: Lots of microgrid projects are emerging around the world. SPIDERS (Smart Power Infrastructure Demonstration for Energy Reliability and Security) is an american military project which goal is to sustain critical operations during prolonged power outages. The system integrates diesel generators, solar PV and batteries along with demand side management strategies in case of outage. Technical data is not available.
i-BATs [34] is a Swiss microgrid project. It is set up in the technopole of Sierre (administrative district of Valais, Switzerland) with 50 companies and around 450 employees. Its goal is to match local consumption with local photovoltaic production. The demand side management is based on demand and production predictions based on machine learning models. Data is collected by multiple smart meters and sent every second to a central system. The prediction is then sent back to the consumer who can therefore make informed decisions about its consumption.
Another interesting example of microgrid is the Belgian antarctic Princess Elisabeth Station [36]. The station is equipped with 9 wind turbines, around $400m^2$ of solar panels, both photovoltaic and thermals, backup diesel generators and batteries and consumes around 54MWh/year. A demand management system is used to decide where to deliver energy depending on each task

priority level and on the available energy.

Super grids

The concept of super grid is, in a way, the opposite of microgrids. The idea is to favor renewable energy integration and to increase stability by increasing the interconnection between grids. Projects of super grids are flourishing all over European countries. The idea is to connect large scale renewable plants where renewable resources are available. By increasing the interconnection, we increase the demand time diversity and therefore increase the chances of using renewable energies when it is produced, avoiding this way a costly and inefficient storage. Interconnection also increases the time diversity of production, reducing at the same time the uncertainty of intermittent production forecast.
Medgrid is a project to install 20GW of renewable energy (mainly solar) by 2020 in the South and East mediterranean countries and interconnect those plants with the european grid.
TWENTIES is another european project coordinated by the spanish company Red Electrica de Espana [37]. It studies the feasibility of more wind and other renewable energy integration on the european grid (in the stability point of view). The scope of this study is large, but the main conclusions are that multiple applications are needed to efficiently integrate large amount of wind energy on the network:

- Coordination of wind turbines is needed in order to provide system services such as voltage and secondary frequency control.
- Demand side management can also provide ancillary services like voltage control
- Dynamic line rating can significantly increase transmission capacity (10-15%) and therefore increase the intermittent energy integration on the network.
- Efficient wide area monitoring is needed, to control flows and avoid local congestion in case of high wind production.

This study confirms the importance of communication systems for the future of the grid.

1.2 ICT impact assessments

As explained in the previous section, the smart grids information and communication infrastructures could widely develop in the next decades. In this second section, we review different studies of environmental impact assessment of such infrastructures.

1.2.1 General methodology

Every specific smart solution may or may not be sustainable, depending on the size of its own environmental footprint and on the actual reduction of environmental impact it brings about by improving other processes (Hilty et al. [38]).
In their paper, Hilty and al. address the methodology and difficulties of assessing a smart solution environmental impact.
They classify the impacts of ICT in two categories:

- direct impacts: those include negative impacts from the production, use and waste of the hardware.
- Indirect impacts: those are hypothetical impacts including emissions reduction or improved energy efficiency due to smart solution for example. Evaluating those impact is a challenge. It consists in defining a baseline (how much will electricity production pollute in the future years?), defining the actual impact of the solution (*to what extent will smart meters with the potential to support energy saving in private households actually change*

consumer behavior?,[38]) and anticipating systemic effect (*to what extent will smarter traffic management, if successful in avoiding congestion, attract more commuters to use private transportation, leading to additional emissions and new congestion?*,[38]).

In [39], Wiedmann and Minx compare two ways to assess environmental impacts:

- the bottom-up approach: the bottom-up method focus on individual assessment of subsystems. The global impact assessment of a sector is the sum of the impacts of each of its subsystems. As an example, let's imagine that we want to asses the impact of smart grid. We would begin by assessing each individual part of the smart grid: e.g. demand side management systems, wide area monitoring, etc. We would then compute the global smart grid impact as the sum of each of its parts.
  A bottom-up approach as the advantage of giving detailed information over each individual process and it is therefore easier to determine critical steps along the life cycle of a system. However, this method has the inconvenient of being time intensive and very sensitive to various parameters such as the system boundaries and to the chosen technology.
  Life cycle assessment (LCA) is a typical bottom-up approach for impact assessment. It consists in defining the system boundaries (to what extent will the system be studied?), collecting data's, judging its quality and dealing with allocation issues (how much of a technology emissions is due to one specific use?). Performing a LCA usually leads to a wide uncertainty range. Appendix B gives a more complete explanation of LCA methodology.

- The top-down approach: top-down assessment consists in analyzing the evolutions and trends in a whole sector, and breaking it into finer details. Again, let's imagine that we want to assess the future impact of smart grid communication technologies. The first step could be to observe ICT impact evolution over the last years and extrapolate this trend to future years. After that, we could estimate the share of smart grid communication in the global communication, again by observing last years and current trends to extrapolate it, for example.
  A top-down analysis can take into account some systemic effects such as technologies efficiency evolution, political trends, changes in social behaviors, etc. Unfortunately, this comes at the expense of details which make it much more difficult to identify the critical processes.

Those two methods can also be mixed, as proposed in [39] to get a global view of the problem as well as detailed results of some interesting subsystems. Challenges are numerous during the assessment process and many assumptions must be made. In the following section, we review different approaches to do so, using both top-down and bottom-up approaches. The first three papers review smart grid impacts as a whole, using top-down approach to evaluate direct impacts and bottom-up method to evaluate indirect impacts. The three next papers focus on a bottom-up LCA analysis of smart metering infrastructures.

1.2.2 Literature review

***How green is the smart grid?* [40]**

In [40], Hledik evaluates the impacts of the smart grid development in the USA in two different scenarios:

- the conservative scenario: *It considers the impacts of an upgrade to technologies that are commercially available today.* It considers a nationwide deployment of AMI, dynamic pricing and in-home information display.

- The expanded scenario: *It takes an expanded view of the smart grid to include the possible impacts of future technologies that could become available in the long-term.* It is assumed that the amount of generation from renewable sources will be doubled by 2030 which leads to a 19% renewable energy electric system. This new distributed system is also considered to generate less losses during transmission.

The study uses the Regional Capacity Planning (RECAP) modeling system to estimate the reduction of CO2 emissions depending on the means of production in the different regions of USA. This study seems to only take into account indirect impacts and does not mention any direct impact assessment. The results of those two scenarios are summarized in Table 1.3. Both scenarios are found to produce significant reduction of carbon emissions.

Smart Grid Technology	Impact Description	Impact Level	Applicable Scenario	Modeling Adjustment
Dynamic pricing with enabling technology	Peak reduction	11.5% reduction	Conservative and Expanded	Load forecast is adjusted with shifting of load during top peak hours to off-peak hours
	Overall conservation	2.6% reduction	Conservative and Expanded	Load forecast is adjusted by reducing demand by 2.6% in every hour
In-home displays	Overall conservation	1.4% reduction	Conservative and Expanded	Load forecast is adjusted by reducing demand by 1.4% in every hour
Distributed and expanded energy resources	Cleaner generation mix	Doubling of RPS	Expanded	RPS constraint is doubled for each model region
	Reduced distribution losses	10% reduction	Expanded	Distribution loss factor is reduced from 7% to 6.3%

Table 1.3: Summary of RECAP Modeling Adjustments [40]. It appears that dynamic pricing leads to both peak reduction (11.5%) and absolute reduction (2.6%).

The two scenarios described here above are compared with a business as usual (BAU) 2030 forecast based on US Energy Information Administration assumptions in its yearly energy outlook. The results were obtained by putting together and comparing results from previous studies. The assumptions seem to be reasonable and documented. However, this study does not take into account any negative impact from the smart grid installation and use, and therefore it most certainly overestimates the benefits.

The relevance of information and communication technologies for environmental sustainability - A prospective simulation study [41]

In [41], Hilty et al. present some results of ICT environmental impacts by 2020 in European Union. This study reviews impacts of ICT in different sectors such as transport, industry, agriculture, and energy sectors. The direct and indirect impacts of those scenarios were first assessed from extensive data collection about applications, penetration and environmental effects of ICT. Three scenarios were then developped based on ICT expert interviews (see Table 1.4), taking into account the uncertainty of future. Models were then built from the dataset and scenarios and validated during a model validation workshop with 10 international ICT experts. In order to account for uncertainty, worst-cases and best-cases were also tested.

Main characteristics of the three scenarios (Erdmann et al., 2005)

Uncertain Factor	'Technocracy' Scenario (A)	'Government first' Scenario (B)	'Stakeholder democracy' Scenario (C)
Technology Regulation	Incentives for innovation	Government intervention	Stakeholder approach
Attitudes to ICT	Moderate, conservative	Open and accepting	Highly accepting
ICT in business	High level of cooperation	High level of competition	Between A and B
Attitudes to the environment	Moderate/controversial	High awareness and interest	High awareness and interest

Table 1.4: Summary of scenarios from [41]. Scenario B leads to the greatest reductions in energy consumption and emissions and scenario C leads to the smallest reductions.

The total energy consumption is assumed to increase by 37% under worst case scenario and decrease by 17% under best case scenario by 2020. Without the projected ICT development,

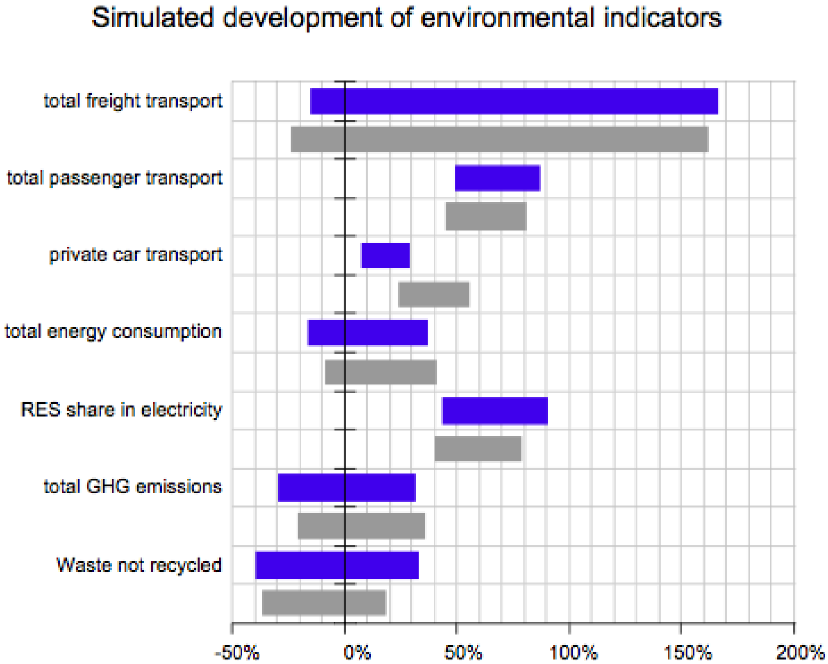


Table 1.5: *Simulated development of environmental indicators by 2020 in % increase or decrease of their values in the base year 2000. The length of the bars indicates the uncertainty of the results that is caused both by future scenario variation and data uncertainty. There are two bars per indicator, the upper (dark) bar showing the results for the projected ICT development, the lower (light) bar showing the results for the so-called "ICT freeze" simulations (i.e. ICT applications remain at the level of 2000). RES: Renewable Energy Sources, GHG: GreenHouse Gas,* [41].

both worst and best case scenarios would lead to more energy consumption. ICT development is most likely to have a decreasing effect on energy consumption.
ICT also enables a better integration of decentralized and intermittent energy production and combined heat and power generation. The estimated increase in renewable energy share ranges from 2% to 7% depending on the scenario.

This study was built very carefully in order to take uncertainty over future scenarios, data collection and models into account. This results in a very large range of evolution possibilities. The collected data and base assumptions (such as penetration, communication technologies, etc.) for each sector are unfortunately not mentioned in the paper which makes it difficult to compare with other studies. Even if quantitative results seem to be very uncertain, the qualitative results seem clear: ICT solutions in the energy sector seem to have the ability to reduce both consumption and emissions.

Smart 2020 [42] **and** ***Smarter 2020*** [43]

In its 2008 study, the climate group examines the global direct impact of ICT over the world (see Figure 1.9) and identifies the indirect impacts due to different uses of ICT such as smart logistics, smart buildings, smart grids, etc (see Figure C.1). According to GeSI, the global footprint of ICT in 2007 (including communications networks and devices, data centers, PC and other personal devices) was $830MtCO_2e$, about 2% of the total emission of humanity. The emissions from fabrication represent around one quarter of total ICT emissions, the rest being produced by its use. The BAU scenario predicts a 6% growth in emissions each year until 2020. Most of this growth is expected to come from the increasing number of customers in countries such as China or India.
The smart 2020 study considers that ICT could help reduce global emissions by $7,8GtCO_2e$

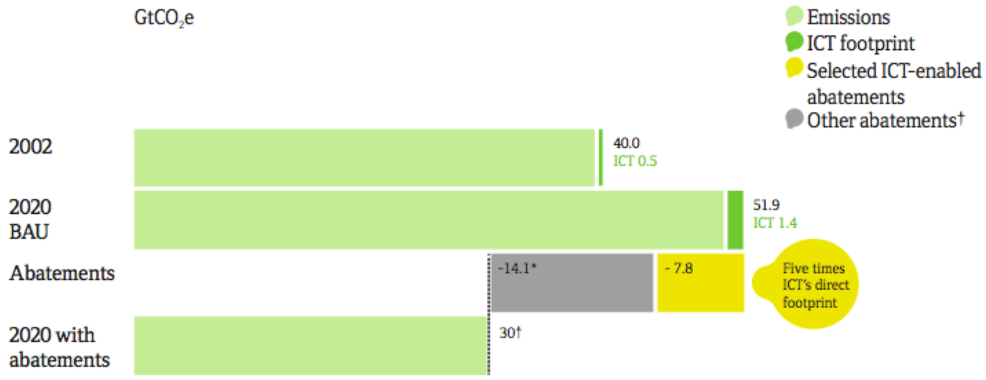


Figure 1.9: Global footprint (including ICT) and enabling effect [42]. The expected emissions by 2020 under BAU assumption are 51.9GtCO2e. When taking into account the potential abatements, the total emissions falls to 30GtCO2e. Abatements due to ICT development are about 5 times higher than its footprint. Other abatements include avoided deforestation and renewable energy integration.

by 2020, that is to say around five times it own emissions. This takes into account five major sectors for emission reduction: dematerialization, smart motor systems, smart logistics, smart buildings and smart grids. The expected abatements are estimated in a bottom-up approach; results for each subsystems are collected from previous studies. The mains results are shown in the Figure C.1. Appendix C shows the detailed assumptions considered for power system abatements.
This study gives a notion of ICT global footprint and potential to reduce emissions. However, its model seems somewhat simplistic. The footprint in 2020 is computed from a BAU assumption that doesn't take into account new smart technologies penetration, such as smart grids, logistics or buildings. Yet, those new technologies are considered in the enabling effect computation. Moreover, the rebound effect of such technologies has not been analyzed. ICT has the potential to improve efficiency, but the availability of some new technologies could still increase the overall consumption.

Finally, in its newer study (2012), the climate group presents even more optimistic figures (see Figure 1.11). The ICT footprint in 2011 was overestimated by the Smart 2020 study, and was corrected in this new study. Moreover, the ICT emission growth is expected to stay at 3.8% between 2011 and 2020 due to economic recession. This results in fewer emissions due to ICT technologies. On the other hand, ICT seems to play a more significant role in emission reduction than expected. The expected abatement in the power sector is presented in Figure 1.12 as it is relevant in this work.
The criticisms about Smarter 2020 study are the same as for Smart 2020: rebound effect and smart technologies consumption are not analyzed which most likely results in an overestimation of ICT positive impacts.

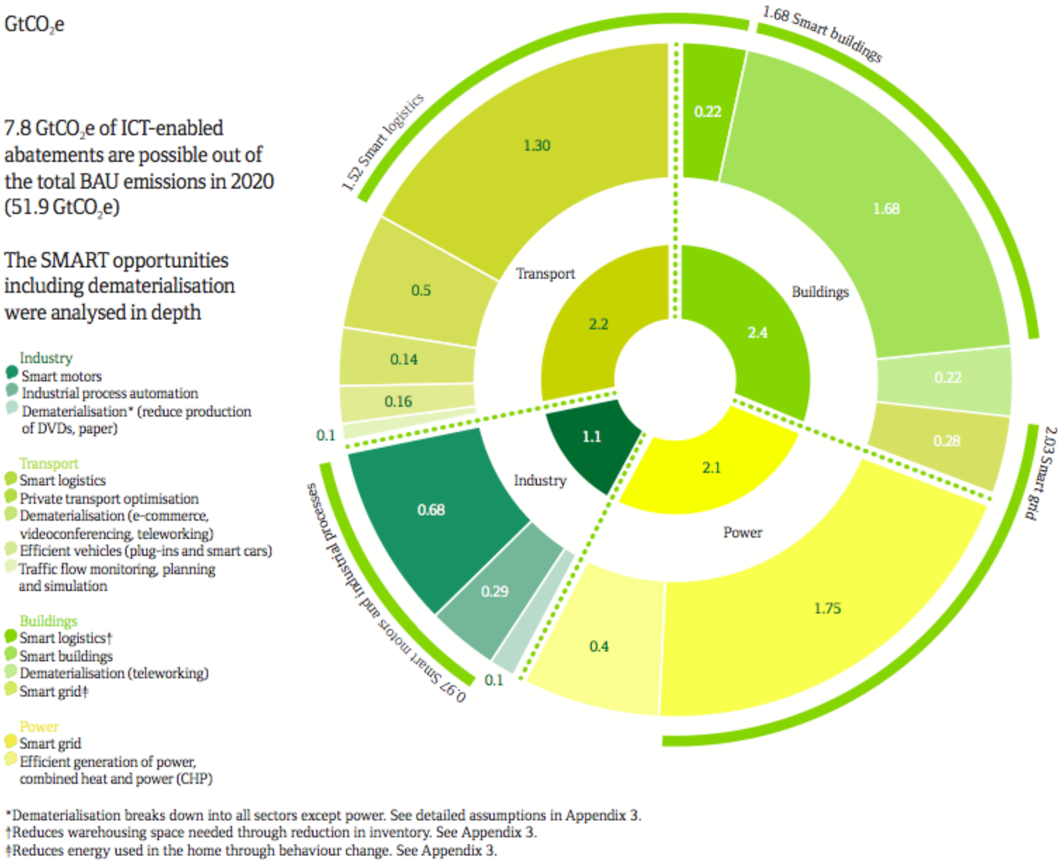


Figure 1.10: ICT enabling effect [42]. Smart grid is expected to generate 2.03GtCO2e reduction through reduced transmission losses, better renewable integration, better consumer information and DSM. An additional 0.4GtCO2e abatement is expected to come from higher efficiency in the generation of electricity.

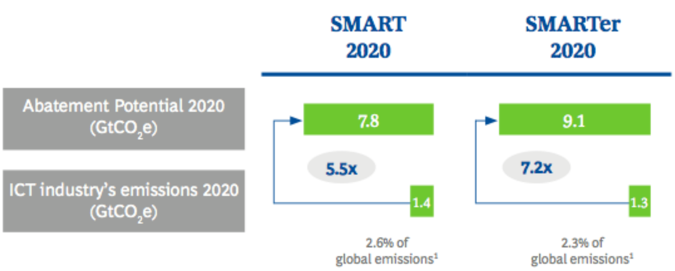


Figure 1.11: Smart 2020 vs Smarter 2020 [43]. Smarter 2010 predicts a more optimistic outcome by 2020 with 9.1GtCO2e abatements.

Sublever	Abatement potential ($GtCO_2e$)
Demand management	0.01
Time-of-day pricing	0.21
Power-load balancing	0.38
Power grid optimization	0.33
Integration of renewables in power generation	0.85
Virtual power plant	0.04
Integration of off-grid renewables and storage	0.20
Total	2.02

Figure 1.12: Power sector abatements [43]. The biggest abatement is expected to come from a better renewable energy integration with around 0.85GtCO2e reduction.

Assessing the Environmental Costs and Benefits of Households Electricity Consumption Management [44]

In her 2011 master thesis [44], Segtnan studied the costs and benefits of smart metering infrastructure installation in Norway. In order to do so, Segtnan applies the ReCiPe[3] method for Life Cycle Assessment (LCA) to assess the environmental costs of such an infrastructure. SimaPro and ecoinvent databases were used to establish the inventory.
The in-home system is composed of one controllable switch and a central smart meter able to communicate both with the switch and a central system. The smart meter data is transferred to a data concentrator via Power Line Carrier (PLC) communication. The data concentrator gathers together datas from a group of homes and send them to the central system through GSM network.

Type of device	Number per household	Power per house [W]
Smart Plug	1	0.2
Smart Meter	1	2.25
Communication module	1	0.5-4
Data concentrator	0.065	0.39-0.52
Central system	1e-4	0.0505
Life expectancy of the whole system: 20 years		

Table 1.6: System description

The rest of this LCA is based on the assumption of a 10000 houses network. The results are presented in terms of environmental impacts (such as climate change, ozone depletion, etc.). It is interesting to see that the major impact comes from the system components production, and especially from in-house components (smart meters and switches), followed by the use-phase (see Figure 1.13).
The second step of this work consists in evaluating the benefits of such an installation. In order to do that, the production of central Norway regions is analyzed. The electricity production in this region mainly consists in hydropower generation. However, the region also has two back-up 150MW gas power plants in case of shortage. The potential benefits of smart metering is then the possibility to avoid the use of those power plants by shifting the loads to off-peak periods. It is assumed that 50% of the households in the region are controlled, and each of them can provide a 1KWh/h reduction. This results in a reduction of 0,69 kgCO2e/$kWh_{shifted}$. The environmental impacts per kWh consumed for the two scenarios (without DSM in red and with DSM in blue) are presented in Figure 1.14. 12 out of 18 environmental impacts are higher in the scenario without DSM. With the DSM infrastructre, demand is flatenned in order to avoid peak-load production. Base-load production plants must therefore produce more energy which leads to those higher impacts. The 6 impacts that are higher in the DSM scenario are: human toxicity, agricultural land occupation and terrestrial ecotoxicity mainly due to wood-based generation, ionising radiation due to additional import of nuclear-based electricity, water depletion due to hydro power, natural gas and nuclear-based generation and metal depletion caused by hydro and wind power.
This master thesis presents a very complete LCA of a DSM infrastructure. Every step was analyzed based on databases and informations from suppliers. The second part of this study, however, seems rather simplistic and incomplete. The assumptions didn't take into account the different types of loads (shiftable or not) and the 1KWh/h per household reduction assumption seems arbitrary. Moreover, the case of Norway is very special and unique as more than 94% of its production is renewable. The results of this study can therefore not be generalized.

[3]ReCiPe is a definite weighting method for determining final indicators (see Appendix B)

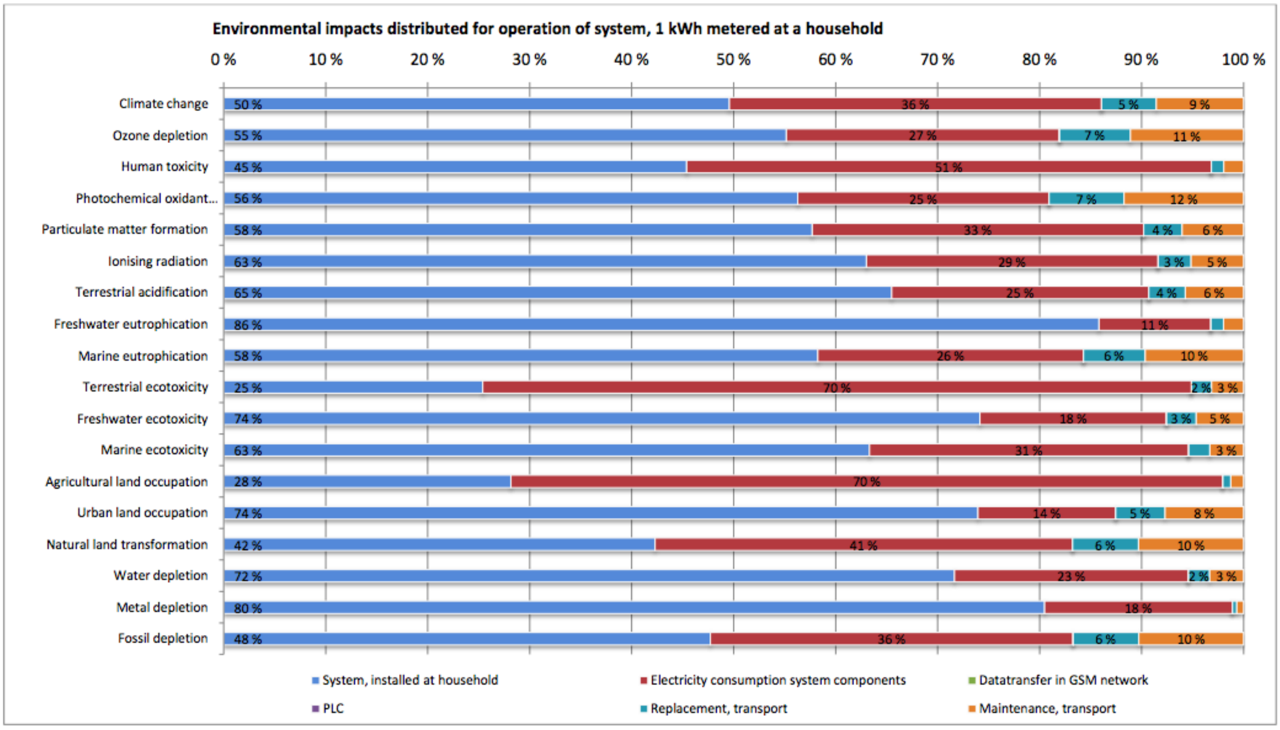


Figure 1.13: LCA results for 1kWh metered [44]. Most of environmental impacts are due to the system production, use-phase is the second cause of environmental impacts and communication seems to be negligible.

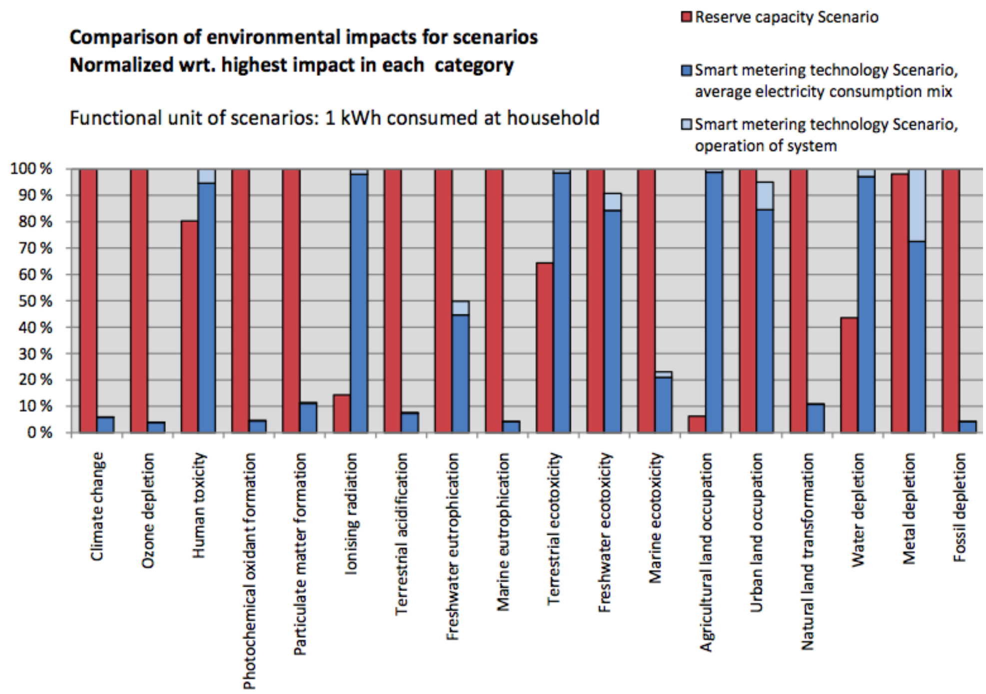


Figure 1.14: Comparison of environmental impacts for the two scenarios - Functional unit of scenarios: 1 kWh consumed at household [44]. Most of the presented environmental impacts are smaller with the DSM infrastructure. The 6 impacts that are higher in the DSM case are due to additional production requirements of base-load plants such as nuclear, wood and hydro power.

Environmental Impacts and Benefits of Smart Home Automation: Life Cycle Assessment of Home Energy Management System **[45]**

In this paper, Louis and al. [45] present the LCA analysis of a home energy management system (HEMS). This system is composed of different types of devices (see Figure 1.15): the smart meter which measure and display the home consumption, the field devices which are either smart plugs (remote controlled) or temperature sensors, management devices which include display devices and processing and memory devices, and at last communication devices to permit communication between smart meters and smart plugs as well as between smart meters and centralized aggregators.

Type of device	Number per household	Power per house [W]
Smart Plug (with com. module)	21	84
Smart Meter (without com. module)	1	20
Communication module	1	4.2
Life expectancy of the whole system: 5 years		

Table 1.7: System description

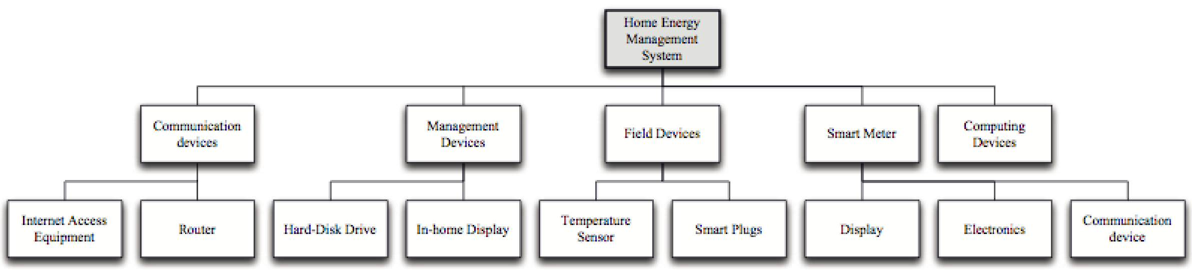


Figure 1.15: Definition of HEM system, [45].

This paper consider a scenario with 1 smart meter and 21 smart plugs in each home. The system is considered to have a 5-years life expectancy. The inventory is based on EcoInvent 3.01 database. The end-of-life management scenario is based on the European Waste Electrical and Electronic Equipment Directive which defines the requirement to comply with mandatory collection and recycling objectives. Finally, a smart plug is considered to have a constant 4W consumption and a smart meter to have a constant 20W consumption.
The results of this paper show that 84% of the emissions are due to the use-phase. The climate change impact over 5 years represents 2076 kgCO2e. The other impacts can be observed in Figure 1.16. A previous paper of those authors had showed that on a 1-year base, the home-automation system had the potential to reduce a Finnish 4-persons house emissions from 543 kgCO2/y to 473 kgCO2/y (reduction of 70 kgCO2/y). In terms of CO2 reduction, the system does not seem to pay itself back.

Smart Energy Management for Households **[46]**

In the first 7 chapters of her thesis, van Dam [46] studies the long-term behavioral response of consumers to home energy management systems (HEMS). Depending on the type of meter and of consumer interface, the effectiveness of HEMS is variable. Through 3 case-studies, during which actual datas where collected in consumer's houses equipped with different HEMS, the author identifies different types of users and studies the effectiveness of HEMS accordingly. The main conclusion of this first part is that, whatever the type of user or the type of HEMS installed, its impact on consumption behaviors tends to decrease over time. Figure 1.17 shows the results of the first case-study analyzed in this work, which consists in a single electricity meter monitoring the whole house consumption and a display unit. The initial consumption of

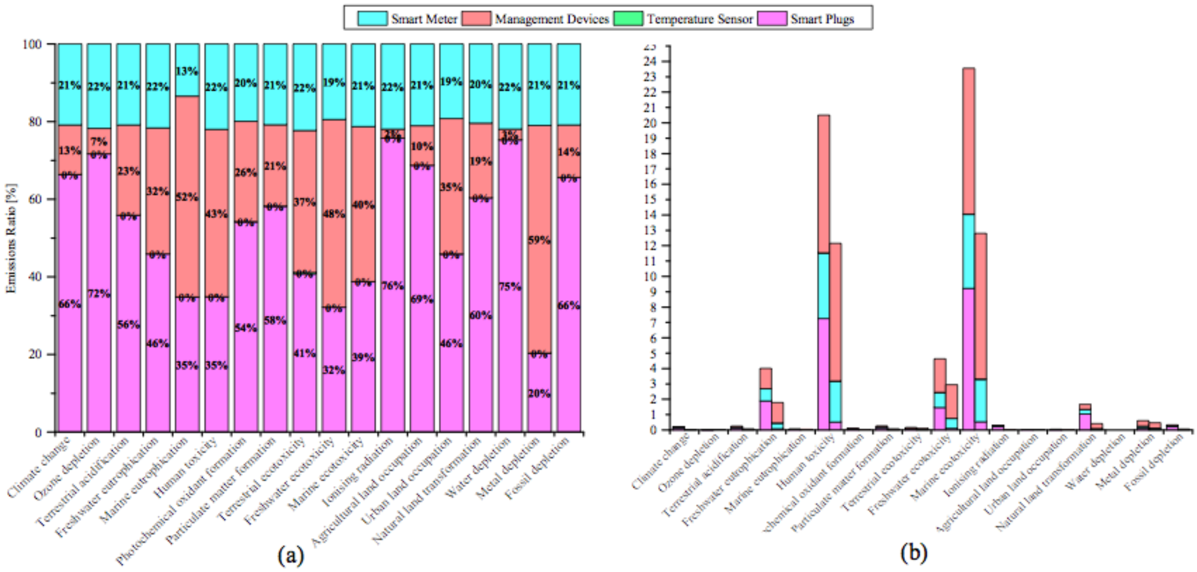


Figure 1.16: Environmental indicators, [45]. (a) Relative emissions showing the impact of each components relatively to each other, (b) absolute emissions illustrating the relevant impact when considering the use-phase (left bar), and without the use phase (right bar)

monitored houses was measured and formed the baseline scenario. This baseline scenario was corrected to take seasonal and annual consumption variation into account. The savings where monitored in the first 4 months and followed up 11 month later. The three groups represented on the graph correspond to consumers that kept the HEMS installed and continued to use it every day, consumers that kept the HEMS but didn't watch it regularly and consumers that uninstalled the HEMS after 4 months. The savings go from 4-17% savings after 4 months to -1-8% savings 11 months later.

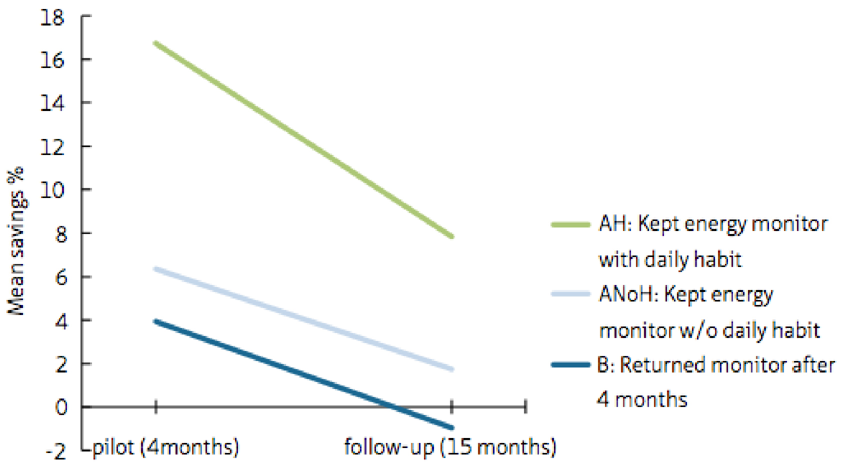


Figure 1.17: Case-study 1: Savings due to HEMS over time, [46]. We observe a fall-back in the measured net savings after 15 months.

The 8th chapter consists in the overall lifecycle impact assessment of three types of HEMS :

- The energy monitor which consist in a sensor, a transmitting unit and a display unit. This system gives a real- time feedback on overall electricity consumption within the home.
- The multifunctional HEMS gives historical, and in certain configurations real-time, feedback on overall gas and electricity consumption. It consists in two sensors for gas and electricity respectively, transmitting units, display and and adapter.

- The energy management device gives real-time and historical feedback on the electricity consumption of individual appliances. It consists in 9 smart plugs communicating with a USB flash-drive that can be connected to a computer in order to see the real-time consumption.

Different saving scenarios were developed: *constant saving scenarios* that considered the savings to be constant over the life-time of the system (between 2 and 10%), and a *fall-back scenario* that considered the savings to decrease over time from 8% at year 0 to 4% at year 1 and 0% after. On the other hand, the electricity consumption is supposed to increase by 1,5% each year. The cumulative energy demand over a 5-year period for each HEMS type is presented in Figure 1.18. The Figure 1.19 shows the pay-off time for each type of HEMS and each scenario.

	Energy monitor	Multif. HEMS (old)	Multif. HEMS (new)	Energy management device
CED prod+disp	231 MJ	1535 MJ	1176 MJ	1285 MJ
CED use phase	534 MJ	5493 MJ	2676 MJ	2639 MJ
Total CED	765 MJ	7028 MJ	3852 MJ	3924 MJ

Figure 1.18: CED Hems (production + installation & use phase), [46].

	'fall-back'	2%	4%	6%	8%	10%	'fall-back'	2%	4%	6%	8%	10%	'fall-back'	2%	4%	6%	8%	10%	'fall-back'	2%	4%	6%	8%	10%
0y	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
½y	+	+	+	+	+	+	+	-	+	+	+	+	+	-	+	+	+	+	+	-	-	-	+	+
1y	+	+	+	+	+	+	+	-	+	+	+	+	+	+	+	+	+	+	+	-	-	+	+	+
1½y	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+
2y	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
2½y	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
3y	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
3½y	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
4y	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
4½y	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
5y	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
	Energy monitor						Multifunctional HEMS (old)						Multifunctional HEMS (new)						Energy management device					

Figure 1.19: Pay-off time, [46]. Every scenario generate net savings after 1 year and a half maximum.

All three types of HEMS seem to be paid-off before its 5-year lifetime. However, the LCA does not take into account the data processing and storage units nor the router, necessary for communication. Note that those saving scenarios are again very uncertain and would require further studies.

Conclusion

The three first references of this review took an interest in the global CO2e emissions reduction potential of smart grids and other smart solutions. Figure 1.20 from [47] gives an overview of smart grid CO2e emissions reduction potential according to different sources, including [40, 42, 43].
The conclusion of those various researches is that smart grids should enable CO2e emissions reduction. However, the negative impacts of the installation and use of smart grids were not or

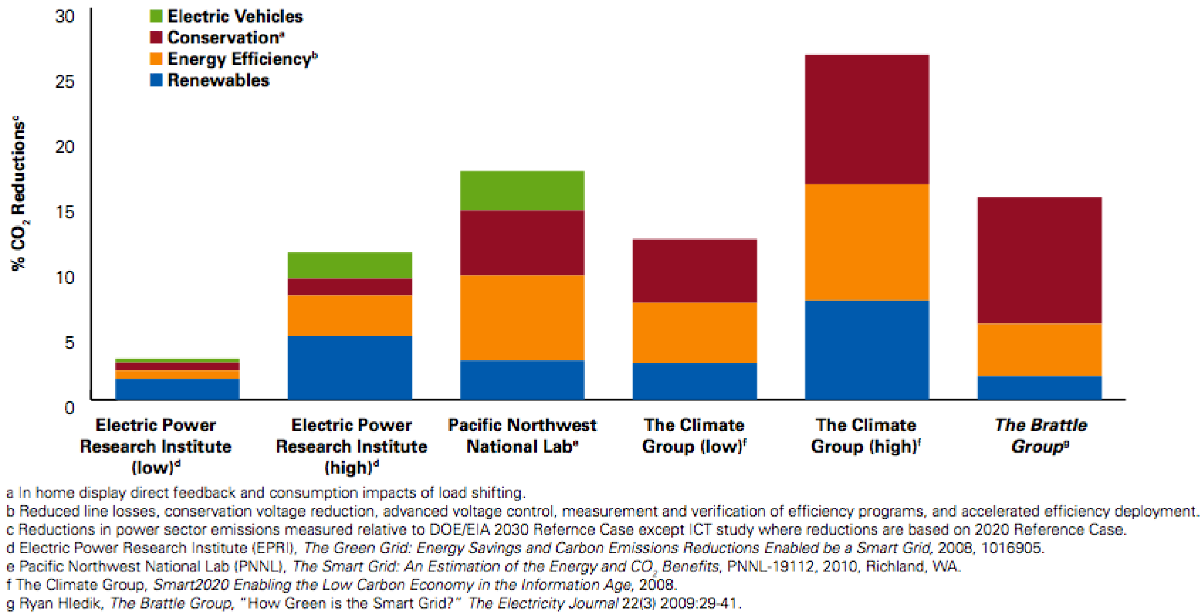


Figure 1.20: Potential Carbon Dioxide (CO2) Emissions Reductions from the Smart Grid: A Comparison of Estimates from Four Sources [47]. This graph only takes into account potential savings of smart grid implementation, and does not include the emissions due to its deployment.

only partially included in those results.

The three last references of this review studied the more specific scenario of demand side management. Negative effect of DSM infrastructure deployment were assessed using LCA. Positive effects were approximated using references and diminution scenarios under various assumptions. Figure 1.21 shows the LCA results comparison. As they were expressed in MJ, the results from [46] where converted to CO2e using the converting value of 565gCO2e/kWh, [25].
The EMH1 scenario has lower emissions due to its simplicity. It is a display-only scenario without possible load management. The high variability of the yearly consumption (use-phase) is due to the very different base assumption made in each scenarios.
The conclusion of [44, 46] established that DSM has a positive effect on emissions whereas [45] obtained more pessimistic results, concluding that DSM emissions were higher than its emissions reduction.

1.3 Environmental impact assessment in this work

As explained in Appendix B and in the previous section, environmental impacts can cover a wide range of different impacts including resources depletion, terrestrial or marine toxicity, human health, etc. In this work, we focus on the global warming potential expressed in kgCO2e. In the next chapters, we equally use the words impact and emissions to refer to global warming potential.
Production and end-of-life results are usually directly expressed in carbon dioxide equivalent units. When collected data is expressed in electric or in primary energy, we use the conversion factors given in Appendix D to convert it into carbon emissions. Without any additional information on the production phase, we use the world average factors.
Use-phase is usually presented with both its electricity consumption and carbon dioxide equivalent emissions. Appendix D shows how to convert electricity consumption to kgCO2e emissions depending on the region of the world. In this work, we use the Belgian conversion factor which is $0.22kgCO2e/kWh_{elelc}$.

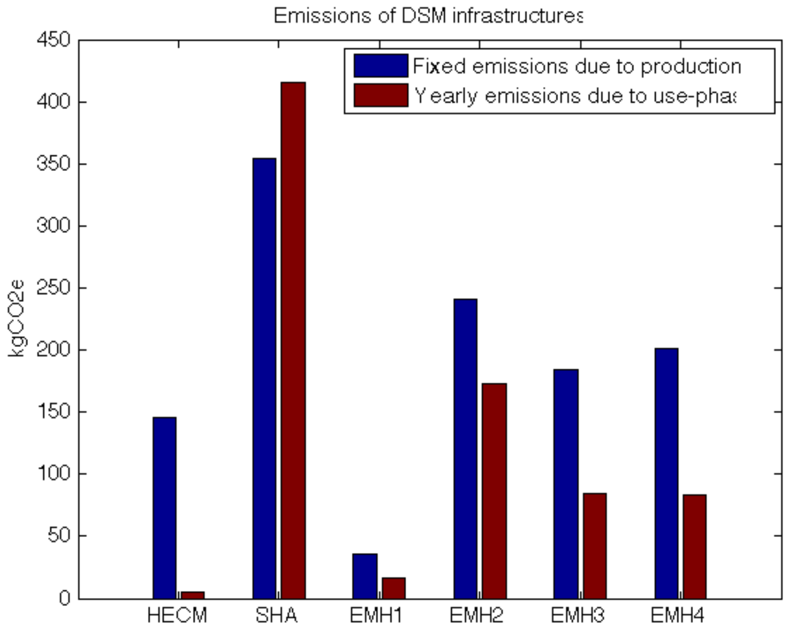


Figure 1.21: CO2e emissions due to production and use-phase of DSM infrastructure for [44] (HECM), [45] (SHA) and [46] (EMH).

In Chapter 3 and Chapter 4, we use the terms *savings* to refer to indirect impacts and *absolute savings* to refer to the difference between indirect impact and direct impact.
In the rest of this work, we often refer to use-phase consumption and system emissions. Appendix E gives typical values of home-appliances consumption and of some activities emissions as references values to compare with our results.

1.4 Conclusion

The smart grid is a vast subject, involving lots of different technology types; from energy production and storage, to communication systems and data processing, and including complex mathematical problems (optimal sensor placement, centralized vs distributed algorithms, etc.). Its development is just beginning and its applications could multiply in the future. Moreover, it seems to have a real potential of emissions reduction through a better renewable energy integration, losses reductions and DSM. However, the implementation of such solutions also has an environmental cost which must be taken into account. The next chapters further study the impacts of DSM infrastructures.

Chapter 2

Model of demand side management

In this chapter, we analyze the direct impacts due to production, use-phase and end-of-life of a demand side management network(DSM). First, we present the chosen DSM infrastructure model. Then, we introduce the consumption and production models for each part of the infrastructure: smart meters and smart plugs along with their communication modules, the communication network and the processing units. We briefly address emissions allocation subject. And finally, we focus on the required data rate, present the results and conclude this chapter.

2.1 Network model and description

The chosen DSM infrastructure is presented in Figure 2.1. It consists in a Home Area Network (HAN) made up of smart plugs and smart meters and a Wide Area Network (WAN) linking the central server with the smart meters and with other devices such as weather station, storage system or other parts of the electrical grid. The HAN is considered to work with Zigbee communication. The smart meter then communicates with the server via a Wi-Fi access to the internet backbone network. Communication between the server and other systems (weather station, storage, etc.) are considered to pass through the mobile access network.
We study the use-phase impacts which depends on the operation intensity and the production and end-of life impacts, which are constant for each device and must be scaled considering the lifetime of the device. For devices such as smart meters, smart plugs, server and Zigbee HAN gateway, we consider that the impacts are entirely due to DSM. However, only part of the access networks and internet backbone impacts must be dedicated to DSM as it is also used for other purposes. For those parts of the infrastructure, we use a "per bit" impact quantification, making the hypothesis that DSM does not significantly change the information quantity circulating through those networks.

2.1.1 Smart plug

The main objective of smart plugs is the remote control, through an actuator, which allows to delay some loads within a given period of time in order to reach an objective (i.e. peak shaving). It is therefore equipped with a communication module, usually Zigbee or PLC. A smart plug is also able to measure active power [48, 49, 50, 51, 52] and sometimes offers other options such as reactive power measurement [49, 51, 52]. Through the communication module, those consumption informations can be sent to smart meters and other devices.

2.1.2 Smart meter

The smart meter measures the global consumption of the house, and is usually able to perform quality analysis as well [53, 54]. It communicates through the HAN with smart plugs or display units. It is also able to communicate with a central server through a WAN. It usually gives real-time consumption informations through a display unit, and is often used by electricity providers to implement remote billing [55, 53, 54]. Its processing capacity is limited, and more detailed

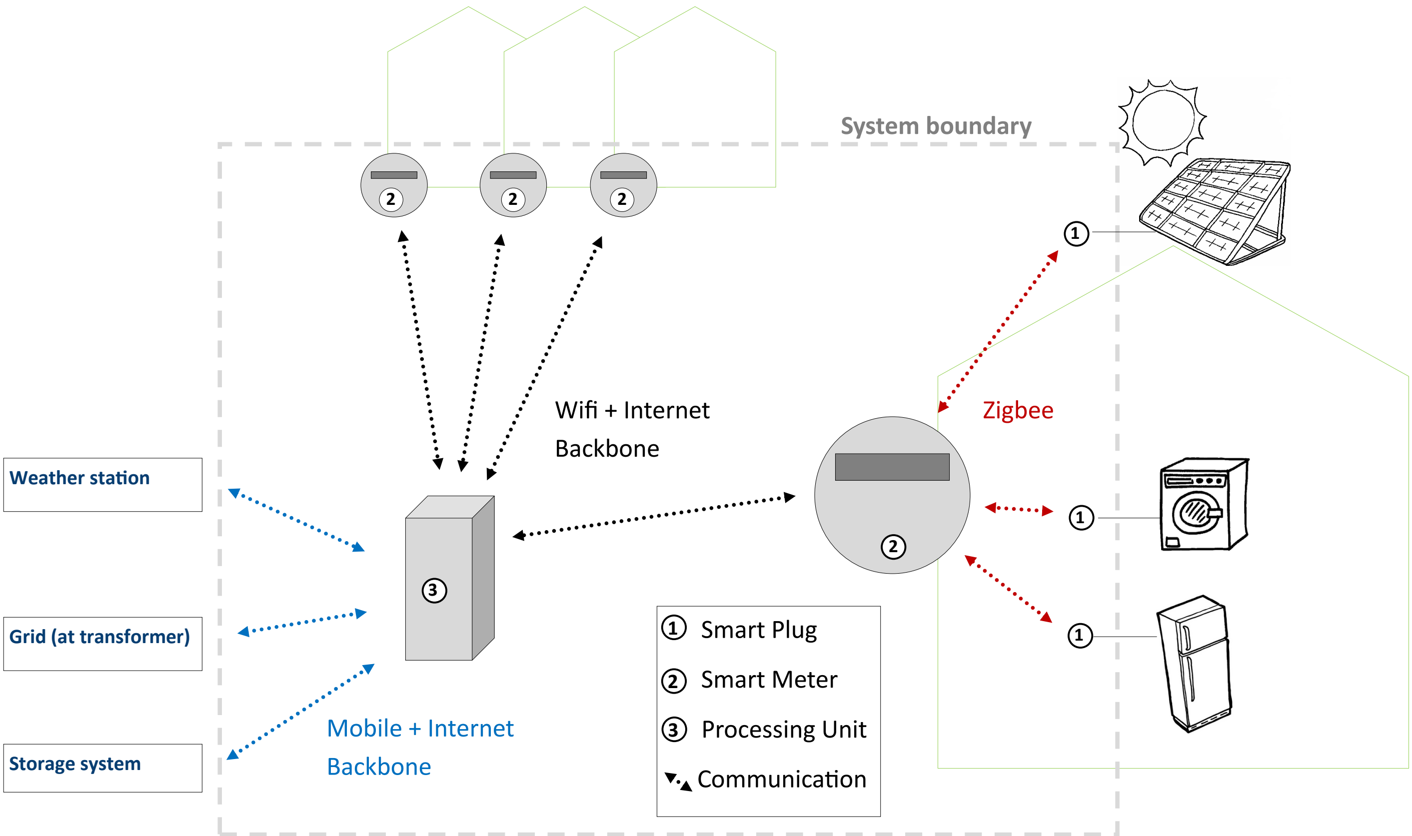


Figure 2.1: Demand Side Management (DSM) network.

consumption analysis is often computed by an external computer communicating with the smart meter [54].

2.1.3 External devices

Other informations may be required by the central server to perform its decision algorithm. For example, local production prediction and weather previsions, state of a storage system or state of the network at the transformer may be used to ensure a good power quality for example. This work only takes into account the communication with those external devices.

2.2 Terminals

The terminals studied here are of two types: the smart meters and the smart plugs. Both types are made of the same basic blocks (see Figure 2.2, [56]): the voltage and current sensors are followed by a signal amplifier and a analog to digital converter (ADC).

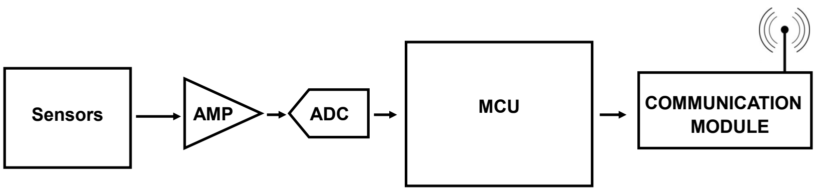


Figure 2.2: Terminals schematic, [56]. Terminals are made of a sensing part, sending data to a microcontroller (MCU) that processes and stores it, the communication module is the able to send it to other entities.

Those information is then processed and stored in a microcontroller unit (MCU) in order to get

active power, reactive power, energy consumption, power factor and other values depending on the terminal usage. Part of the information can be stored locally, and relevant information can be sent through the communication module. The communication module is also able to receive information, which is then processed and stored, resent on the network or used to activate an actuator (in the case of the smart plug for example).
The consumption model of those devices is presented hereafter.

2.2.1 Use-Phase

We consider three main contributions in the terminal consumption: a constant consumption due to measurements [1], its processing and display (see smart plug and smart meter subsections), a variable contribution due to communication (see communication module subsection) and a variable part due to other sources of processing such as decision algorithms (this is presented in the next section, along with the central processing units). This last contribution is only taken into account for some (partially) decentralized decision algorithms. As smart meters and smart plugs only have limited processing capacity, we consider adding a microprocessor and some flash memory when needed by the algorithm.

Smart plug

Table 2.1 shows the consumption and characteristics of different smart plugs currently on the market. As those values take into account an average consumption for communications, we have

Brand	Model	Power consumption [W]	Sensing characteristics	Communication module
Ecowizz [48]		0.9 (average)	Active power, 15 minutes data update, 3% precision	Zigbee+5dBm
D-Link [57]	DSP-W215	5 (max)	No information	Wifi
Pikkertion [49]	ZBS-110V2	0.5 (average)	Active & reactive power, 14kHz	Zigbee
Trendnet [50]	THA-101	6 (max)	Active power, energy	Wifi
Billion [51] & [52]	SG3010 (T1-T4)	0.7 (average)	Active & reactive power, energy (total & per interval) 2% precision	Zigbee
	SG3015 (T1-T2)	1.4 (average)	Active & reactive power, energy (total & per interval) 1% precision	Zigbee

Table 2.1: Smart plugs consumption.

[1] In reality, measurement consumption depends on various parameters such as the sampling rate, the type of sensor, the type of data processing, etc. But as those parameters are not accessible by the customer, and as it is difficult to separate those different contribution without further information, we consider here that measurement has constant consumption.

to subtract this contribution to get the consumption due to sensing and processing. Making the assumption that the communication modules are mainly in receiving modes (smart plugs usually send data every 15 minutes, the assumption is therefore reasonable), we may assume that the constant consumption of smart plugs due to measurement and its processing is somewhere between 0.4 and 1.3 (making the assumption of a 100mW receiving mode Zigbee module). We exclude here the two extreme values of 5 and 6W.

Smart meter

Table 2.2 presents the consumption and characteristics of various smart meters. Some of them already include a communication module, others offer the possibility to add such modules. Note that the power of the communication module is not taken into account in the power consumption presented.

Brand	Model	Power	Sensing characteristics	Communication module
Sensus [55]	iConA Gen 4	0.8W	Active & reactive energy	Zigbee (optional)
General Electric [58] & [59]	SGM3000	1.2W	Active & reactive energy	Zigbee (optional) +3G,4G,DSL (optional)
	SGM1100	1.52W	Active & reactive energy	PLC (optional)
Landys + Gyr [60] & [61]	E130 FOCUS	1.8W	Active energy	/
	E330 FOCUS	1.9W	Active & reactive energy	/
Echelon [53]	MTR500	2W	Active & reactive energy quality monitoring, 1kHz (sampling)	PLC
Schneider Electric [54]	Serie PM800	10 W with display options	Active & reactive power & energy, THD, 6.4kHz, 1sec data update	/
	Serie PM700	3 W	Active & reactive power & energy, THD, 1.6kHz, 1sec data update	/
	ION8800	10 W (max) 8 W (typ)	Active & reactive power & energy, quality monitoring, 51.2kHz, 0.5 or 1sec data update	/

Table 2.2: Residential power meters consumption. The power does not take into account the communication modules.

Most of those smart meters are able to display time-of-use pricing or critical peak pricing as incentives for load shifting. They also allow remote billing and load scheduling. The three Schneider Electric meters also support a more complete load management through communication with an external computer. The PowerLogic ION 6.0 is a power management software allowing the consumer to observe his real-time consumption on is laptop, to add controllable devices (with smart plugs) to his network and to remotely control them either manualy or by

adding automatic *event watcher* able to turn on or off devices based on predetermined conditions (e.g.prices, hour, etc).
The consumption of smart meters highly depends on its characteristics: the type of display, the sampling rate, the type of data it provides, etc. In our model, we consider a constant consumption between 1 and 10W.

Communication module

We consider a Zigbee communication between smart plugs and smart meters. The smart meter then transfers the data to the access network through the Wi-Fi access network. The consumption of Zigbee and Wifi modules in transmitting (Tx), receiving (Rx) and sleep (sleep) modes are presented in the Tables 2.3 and 2.4.

Brand	Model	Max data rate	P_{sleep} [mW]	P_{Rx} [mW]	P_{Tx} [mW]	Tx Power Max (dBm)
ModFlex	ProFLEX01[62]	250 kbps	0.0264	115	577.5	+10
TI	CC2420 [63]	250kbps	0.0033	62.04	57.42	+10
	CC2520 [64]	250kbps	0.0033	61.05	110.88	+5
Telegesis	ETRX3 [65]	250kbps	0.02	103.95	462	+20
Digi	Xbee Znet 2.5 [66]	250kbps	0.0033	132	148.5	+3

Table 2.3: Communication modules - Zigbee - Supply: 3.3V.

Brand	Model	Max data rate	P_{sleep} [mW]	P_{Rx} [mW]	P_{Tx} [mW]	Tx Power Max (dBm)
Microchip	RN171 [67]	11 Mbps	0.0132	132	396	+12
	MRF24WG0MA [68]	11 Mbps	13.2	514.8	792	+18
	MRF24WB0MA [69]	2 Mbps	0.825	280.5	508.2	+10
Murata	SN8200 11b [70]	11 Mbps	10.39	363	1221	+18
	SN8200 11g [70]	54 Mbps	10.39	363	957	+14.5

Table 2.4: Communication modules - Wifi - Supply: 3.3V.

The energy used by such communication modules may be expressed as follow:

$$E_{com} = P_{Tx}T_{Tx} + P_{Rx}T_{Rx} + P_{sleep}T_{sleep}$$

with $T_{Tx} = \frac{1}{Max\ data\ rate}$, the time required to transmit one bit, P_{Tx}, the transmitting mode power, P_{Rx}, the receiving mode power, T_{Rx}, the time spent in receiving mode, P_{sleep}, the sleep mode power and T_{sleep}, the time spent in sleep mode. The non-transmitting time is shared between receiving and sleep modes. Various wireless standard protocols are used. Wifi modules are typically always in receiving mode when waiting for an information; they can switch to sleep mode when no information is expected to arrive in a certain period of time. Zigbee modules, however, are designed to be more energy efficient. In addition to a smaller receiving mode consumption, they also use duty cycling to further diminish their consumption, [71]. Duty cycling consists staying most of the time insleep mode and turning to receiving mode periodically to check for messages. To ensure that a message has been transmitted, the transmitter has to repeat the message untill receiving a reception acknowledgment from the receiver. The typical duty cycle (portion of time in receiving mode) is around 1%. Duty cycling causes a higher retransmission rate and latency and is therefore not suited to high transmission rate applications. In [72], Chintalapudi and Venkatraman estimate that the number of retransmissions due to duty cycling could vary between 3 and 8. In this work, however, we make a the conservative assumption that neither Wifi nor Zigbee use duty cycling and that they both stay in receiving mode when expecting a message.

2.2.2 Production phase

The review in Chapter 1 presented some DSM life cycle assessment results. Those results are detailed by device in Table 2.5. The smart plugs are considered to always have a communication module included. The smart meters, however, may need 0, 1 or 2 communication devices, depending on it purpose.

Terminal	Source [44]	Source [45]	Source [46]	Life time
Smart meter	42.9	74.34 (with 1 communication module)	/ / /	5 years
Smart plug	24.2	11.13	22.4	5 years
Communication module	37.4	/	/	5 years
Management device	/	46.02	/	/

Table 2.5: Emissions due to production and end-of-life [kgCO2e/unit].

The communication module considered in Table 2.5 is a PLC module. As we consider Zigbee communication, the value of 37.4 [kgCO2e/unit] seems exaggerated, given the emissions of smart plugs already oncluding such modules. In the next chapters, we consider WAN communication modules to produce around 37 kgCO2e during the production phase, but LAN modules to produce between 5 and 10kgCO2e during production, which seems more reasonnable given the total emissions of smart plugs. The meters used in those papers do not allow to run local decision algorithm. To be able to locally take decision, we need to add a microprocessor and some memory. Those elements are further considered in the processing unit section.

2.2.3 Results

Figures 2.3 show the yearly consumption of Zigbee and Wifi modules depending on the data sending rate, without taking into account any sleep time. The Zigbee consumption varies between 0.5 and 5 kWh a year. The red line, representing the average consumption goes from 0.8 to 2.4 kWh a year. The Wifi module consumption is higher and varies between 1.15 and 13.4 kWh a year. The average consumption (red line) goes from 2.9 to 6.8 kWh a year. This high variability confirms the interest of studying more precise scenarios, taking into account the communication requirements.

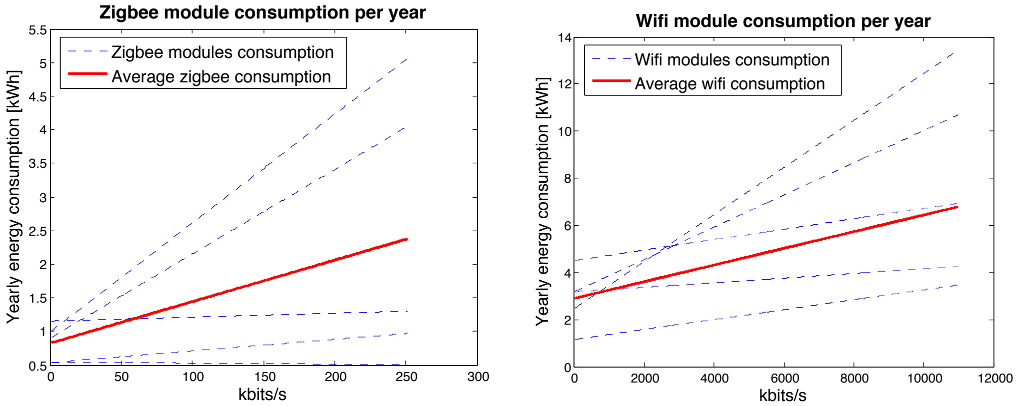


Figure 2.3: Zigbee (left) and Wifi (right) modules consumption. This graph only takes into account the use-phase consumption.

From now on, we use the average modules (red lines) in the models (Table 2.6).

Characteristics	Zigbee average module	Wifi average module
P_{Rx} [W]	0.095	0.33
P_{Tx} [W]	0.27	0.774
Data rate [kbps]	250	11e3

Table 2.6: Average communication modules.

Figures 2.4 show the yearly consumption of smart plugs and smart meters depending on the data sending rate. Smart plugs consumption varies between 3.45 and 15.5 kWh a year. Smart meters consumption varies from 12.48 to 95.2 kWh a year. If we take into account the production, a single smart plug emits between 3.14kgCO2e and 8.25kgCO2e each year. To produce absolute savings, it must therefore be installed to a load which saving potential is higher than those values; Appendix F further develop this subject.

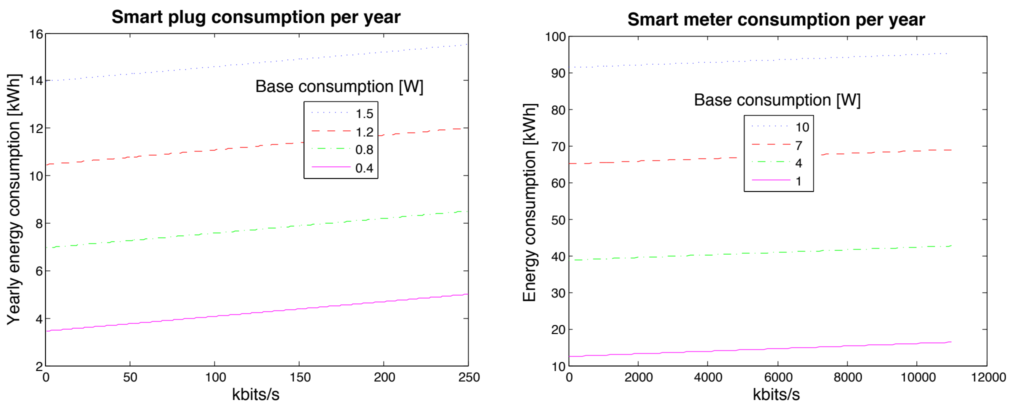


Figure 2.4: Smart plug (left) and smart plug (right) consumption with average communication modules. This graph only takes into account the use-phase consumption.

Finally, Figure 2.5 gives and idea of the consumption variation with and without duty cycling. With a duty cycle of 1% and a number of retransmission of 1, 4 and 8, we observe that duty cycling performs better below 64.4kbps, 20kbps and 10.4kbps respectively. For higher data rates, the retransmission consumption is higher than the duty cycling savings. The communication requirements of smart plugs is most likely lower than 10.4kbps, and duty cycling is therefore interesting in this context.

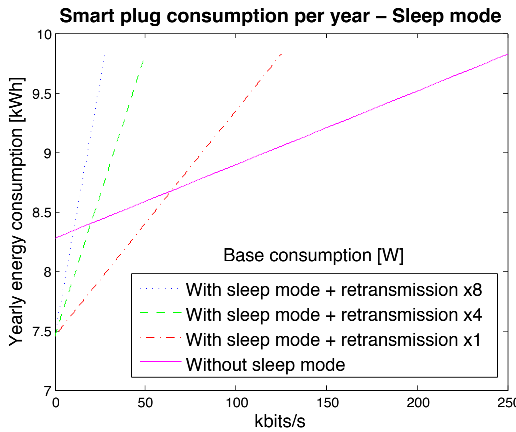


Figure 2.5: Smart plug consumption with and without duty cycling. The smart plug constant consumption is 0.85[W]. The duty cycle used in this graph is 1%, and the breaking points for 1, 4 and 8 retransmissions are 64.4, 20 and 10.4 kb/s respectively. This graph only takes into account the use-phase consumption.

2.3 Communication network

2.3.1 Use-Phase and production phase

As explained earlier, we consider that information is transmitted to the central server through the internet network. This section is based on Baudoin's work [25]. The internet model used in this work is represented in Figure 2.6.

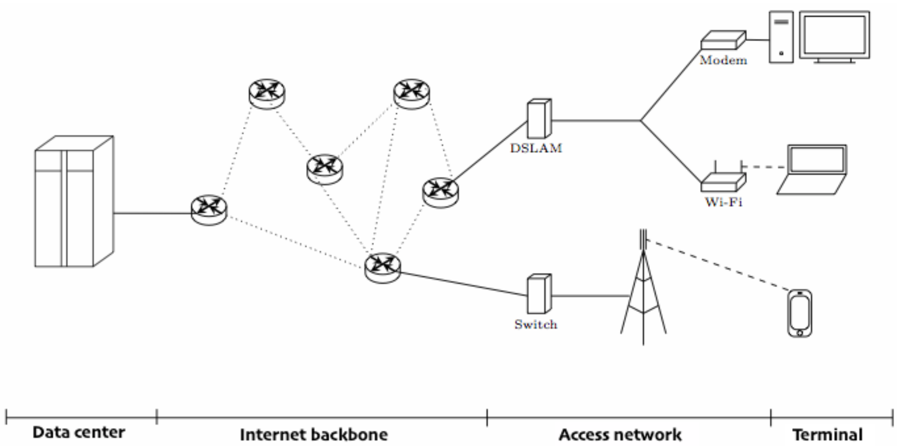


Figure 2.6: Simplified Internet model [25].

Table 2.7 gives a summary of Internet ICT consumption. The second column gives the average consumption of each technology during its use-phase in *electrical Joules* by Mb. It has to be multiplied by the primary energy factor (PEF) [2] in order to get it in *primary Joules*. The third column gives the consumption during the production-phase, as a percentage of its use-phase consumption.

[2]The PEF mainly depends on the energy source, extraction method, transformation and transport. On average, it is equal to 2.6 in Europe and 3.3 in the US [25].

[3]In [25], it is considered that 1000 users are connected to a DSLAM, and that each user has an average download rate of 1Mb/s, two hours a day. This is translated here by a 7.2Gb/day/userdata rate.

[4]The Wifi consumption presented in this work was 83.4 J/Mb. But, it does not take into account the modem

Section	Consumption [J/Mb]	Production & End of life	Hypothesis	Life time
Data centers	126.1	11%	/	4 years
Internet backbone	4.6	5%	/	5 years
DSL access	80.4	7%	7.2Gb/day/user[3]	/
Wifi access	146.4[4]	7%	7.2Gb/day/user	3 years
Mobile network	358	11%	1065Mb/day/station	10 years

Table 2.7: Internet network consumption, [25]. Depending on the task and the distance, the consumption of ICT varies; this work gives consumption values under precise conditions, described in the fourth and fifth columns.

As mentionned earlier, this table gives the average consumption of each technology. It is important to realize that depending on the task and the distance, the consumption of ICT varies; this work gives consumption values under precise conditions, described in the fourth and fifth columns. The data's and models used to compute those numbers are further explained in [25].

2.3.2 Results

Figure 2.7 shows the consumption of the access and backbone networks, depending on the data rate. Note that the x-axis is now expressed in Mbits/s. As soon as we run models with multiple smart plugs and smart meters, the communication network often plays a minor role in the total consumption of DSM network.

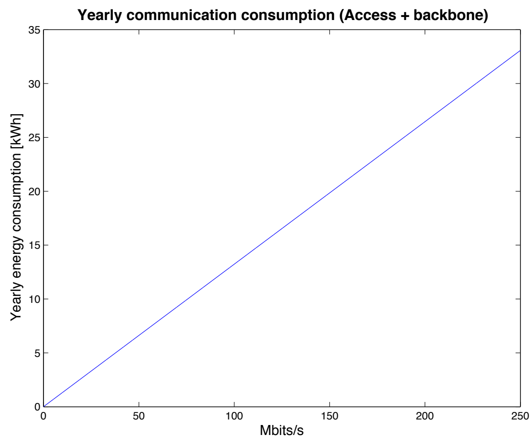


Figure 2.7: Communication network consumption.

2.4 Processing units

In this section, we study the consumption and production-phase impacts of two types of processing units: servers, which are able to centralized large amounts of data and process them, and microprocessors, which may be integrated into smart meters and smart plugs in order to take local decisions.

consumption. We corrected this number by adding the modem consumption into this model:

$$E_{wifi} = \frac{24(P_{modem} + P_{router} + P_{DSLAM/user})}{n_{hours}T_{avg}}$$

with $P_{modem} = 5W$, the average power consumption of a modem, $P_{router} = 5.5W$, the average consumption of a router, $P_{DSLAM/user} = 1.7W$ the average power consumption of a DSLAM for each user, $n_{hours} = 2h$, the number of hours of Wifi connection utilization and $T_{avg} = 1Mb/s$, the average data flow during utilization.

2.4.1 Use-Phase

In [73], Bol et al. present the LCA of five microprocessors, which are *representative of five typical application categories.* The selected application categories characteristics are presented in Table 2.8.

Typical applications	High-end servers/workstations	Mainstream laptops	Set-top boxes and digital TVs	Smart phones, netbooks and tablet PCs	Active RFIDs, eHealth and wireless sensors
Logic circuit	Six-core CPU	Dual-core CPU	Multimedia processor	Application processor	Ultra-low-power MCU
CMOS process	32 nm HP	32 nm HP	45/40 nm LP	45/40 nm LP	130 nm LP + Flash
Die area	$240 mm^2$ ±30%	$80 mm^2$ ±30%	$70 mm^2$ ±30%	$50 mm^2$ ±30%	$10 mm^2$ ±30%
Lifespan	2 years ±30%	3 years ±30%	4 years ±30%	2 years ±30%	7 years ±30%

Table 2.8: *Selected application categories of microprocessors with corresponding CMOS chips* [73].

The use-phase power consumption model proposed in [73] is the following:

$$E_{tot} = E_{act} + E_{stb}$$

$$E_{tot} = P_{act}T_{act} + P_{stb}T_{stb} = P_{act}T_{act} + P_{stb}(T_{on} - T_{act})$$

$$P_{act} = P_{idle} + (P_{max} - P_{idle})\alpha_F^{1.5}$$

$$P_{idle} = P_{max}/\beta_{idle}$$

$$P_{stb} = P_{max}/\beta_{stb}$$

with E_{tot}, the total energy consumption of the processing unit, E_{act}, the energy consumption in active mode, E_{stb}, the energy consumption in standby mode, P_{act}, the power in active mode, T_{act}, the fraction of time spent in active mode, P_{stb}, the power in stanby mode, T_{stb}, the fraction of time spent in standby mode, $T_{on} = T_{act} + T_{stb}$, the fraction of time the circuit is turned on, P_{idle}, the idle power in active mode, when $\alpha_F = 0\%$, P_{max}, the maximum power at full processing, when $\alpha_F = 100\%$, β_{idle}, the idle power reduction factor and β_{stb}, the standby power reduction factor. The values used for these parameters are presented in Table 2.9.

Typical applications	High-end servers	Mainstream laptops	Set-top boxes and digital TVs	Smart phones and ultra-mobile PCs	RFIDs, eHealth and industrial sensors
Logic circuit	Six-core CPU	Dual-core CPU	Multimedia processor	Application processor	Ultra-low-power MCU
P_{max}	95W ±30%	35W ±30%	3W ±30%	1W ±30%	10mW ±30%
β_{idle}	5|3|2	5|3|2	5|3|2	5|3|2	5|3|2
β_{stb}	20|10|5	20|10|5	20|10|5	10000|100|20	10000|1000|100
α_F [%]	10|30|50	5|20|50	33|66|99	10|30|50	10|33|100
T_{on} [%]	90|95|99	10|23|99	90|95|99	11|71|99	0.03|7|99
T_{act} [%]	90|95|99	5|16|23	6|10|20	6|8|17	0.03|0.07|1

The three values represent best, typical and worst cases regarding life-cycle energy demand, respectively.

Table 2.9: Parameters values used in [73]

To have an idea of the server CPU consumption for a given algorithm, we need to evaluate the active time, T_{act}, and load factor, α_F, of the CPU for that algorithm. To assess those values, we run the algorithms (which is described in the next chapter) on a test processor, observe the time and load factor values and extrapolate those values for another chosen processor.

Evaluating T_{act}

The active time needed by a CPU to run a given algorithm depends on various factors, [76]: the word size (8, 16, 32 or 64 bits), the instruction set, the clock rate, the number of cores, the cache size, the other processes running at the same time on the processor, the system scheduling algorithm, etc. It is then extremely difficult to assess the relative performances of two different processors. We use a simplified model whichl only takes into account the clock rate and number

Test processor characteristics [74]	Server processor characteristics [75]
Intel Core 2 Duo 2.3 GHz RAM: DDR3, 4GB	Intel Xeon X5650 6-cores, 2.66GHz RAM: DDR3, 288GB

Table 2.10: Processors characteristics.

of cores.

Clock rate: the clock speed determines the number of instructions the CPU is able to perform in one second. All the other characteristics unchanged, we consider that an increase in clock speed leads to a proportional decrease in execution time.

Number of cores: increasing the number of cores in a processor does not necessarily lead to a proportional decrease in execution time; it depends on the level of parallelism of the performed algorithm and on the system scheduling algorithm. Amdahl's law gives an upper bound of multi-core reduction time, R_t, [77]:

$$R_t \leq (1 - P) + P/n$$

$$S = \frac{1}{(1 - P) + P/n + H(n)}$$

with P, the parallel portion of the algorithm, n, the number of processors, S, the real speedup and $H(n)$, the overhead including inter-thread activities such as communication and synchronization. In reality, the situation is worst than Amdahl's law predictions due to load balancing, scheduling (shared processors or memory) and communication between processors, [78]. In practice, we consider that the considered algorithms work on a single CPU, as long as it is manageable; the number of cores is therefore not taken into account unless explicitly mentioned.

We only consider 32-bit CPUs, so that the word size does not influence the performances.

Evaluating α_F

The load factor of a CPU diminishes as the number of cores increases. However, doubling the number of cores does not decrease α_F by two, as the management system needs more resources to split up the work. As we already take the number of cores into account in T_{act}, we simply consider that α_F remains the same as in the test processor.

From CPU consumption to total consumption

In [25], Baudoin studies the consumption of data centers. This consumption is mainly due to electronic devices, cooling devices and power supply systems. We know, from [25], that the CPU represents 33% of IT consumption, on average, and that the IT itself represents between 30 and 68% of the total consumption of a datacenter. It seems reasonable to assume that cooling and power supply system consumption is proportional to IT consumption. To evaluate the total consumption du to the DSM server, we therefore multiply the CPU consumption by a fixed number taking into account all those factors. This factor varies between 4.5 and 10.

In the case of microprocessors, we do not have to take all those factors into account. The only additional factor we introduce is the flash memory consumption. In [73], memory is already taken into account in ultra-low power MCU, but not in the other processors. In [79], Boyd estimates the consumption of flash memory between 0.3MJ/GB and 5MJ/GB.

2.4.2 Production phase

The following table presents the production-phase emissions for complete rack servers, micro-processors and memory.

Type	Model	Production phase Emissions / Energy	End-of-life (recycling) Emissions / Energy	Source
Rack server	Dell PowerEdge 11G	509 kgCO2e	-85 kgCO2e	[80]
	Dell Power Edge 12G	561 kgCO2e	-61 kgCO2e	[80]
Microprocessors	6-core CPU	4.4 kgCO2e [5]	/	[73]
	2-core CPU	1.2 kgCO2e [6]	/	[73]
	Application processor	0.6kgCO2e [7]	/	[73]
	ULP MCU	0.06 kgCO2e [8]	/	[73]
Flash Memory	/	0.3 - 5 kgCO2e/GB	/	[79]

Table 2.11: Processing units - Production and end-of-life emissions.

2.4.3 Results

The consumption of the processing units depends on the algorithm implemented, on its execution time and on the frequency at which it has to be run. We present here (see Figure 2.8) the results for hypothetical algorithms having execution times varying between a few seconds to 20 minutes (on a single core) and a load factor of 0.9. We observe the impact on the yearly server CPU consumption depending on the number of times we run it per year (from once a month to tenth a day)).

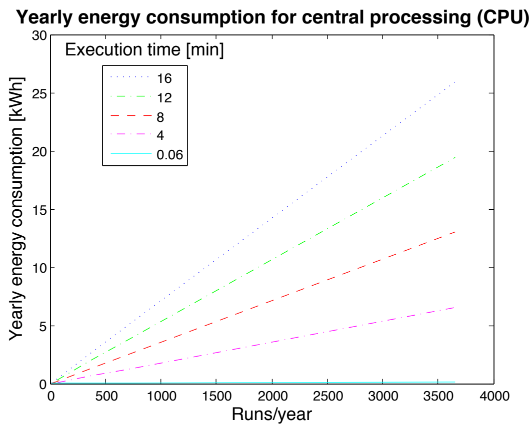


Figure 2.8: Server CPU consumption due to the execution of an algorithm.

Figure 2.8 presents the CPU consumption of a server. As said earlier, this consumption must be multiplied by a factor between 4.5 and 10 to take the other IT and cooling consumption into

[5] $84 MJ_{prim}$/die converted into kgCO2e using the converting value of $3MJ_{prim}/MJ_{elec}$ and 565gCO2/kWh=0.157kgCO2e/MJ.

[6] $23 MJ_{prim}$/die converted into kgCO2e using the converting value of $3MJ_{prim}/MJ_{elec}$ and 565gCO2/kWh=0.157kgCO2e/MJ.

[7] $12 MJ_{prim}$/die converted into kgCO2e using the converting value of $3MJ_{prim}/MJ_{elec}$ and 565gCO2/kWh=0.157kgCO2e/MJ.

[8] $1.21 MJ_{prim}$/die converted into kgCO2e using the converting value of $3MJ_{prim}/MJ_{elec}$ and 565gCO2/kWh=0.157kgCO2e/MJ.

account. We observe here that the consumption of a CPU varies greatly with the execution time of the algorithm it has to run and with the number of time it has to run this algorithm. It is therefore interesting to study DSM algorithm consumption on a case by case basis.

2.5 Emissions allocation

As previously explained in Chapter 1, allocating emissions to a given application is not easy. Indeed, some devices can be used by different applications, and deciding which part of the emissions to allocate to which application is difficult. In this work, we face the problem for smart plugs, smart meters and server emissions.

Smart plugs emissions are considered to be entirely due to studied DSM infrastructures. Smart meters emissions is allocated in two different way. In the consumption monitoring chapter, emissions are entirely allocated to the monitoring infrastructure. In the load shifting algorithm chapter, on the other hand, we also consider the case with pre-installed smart meters. In this case, the only additional emissions due to the algorithm are due to additional communication requirements.

Finally, server emissions are not considered to be entirely due to DSM infrastructures. Execution times are indeed short and we therefore consider that DSM algorithm can be execute on hosting servers. The emissions allocated to DSM infrastructure include the execution time of the DSM algorithm on the server and part of the standby and production emissions. In [81], Wu and Buyya estimate that the traditional utilization rate of hosting servers is between 10 and 35%. We therefore allocate a fraction of server's production and standby mode emissions corresponding to:

$$f = \frac{T_e}{T_a} = \frac{T_e}{6 \cdot 0.225 \cdot 365 \cdot 24 \cdot 3600}$$

with T_e the yearly execution time of the DSM algorithm in seconds, T_a the total active time of the hosting server corresponding to 22.5% of the total time (which is the mean value between 10 and 35%). We add a factor 6 because we consider that the DSM algorithm is executed on a single core while the server we consider has 6 cores.

2.6 Estimation of volume of data transfer

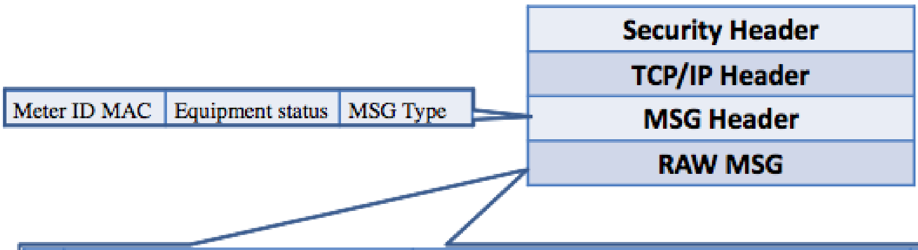
Figure 2.9, from [82], shows a possible packet structure for DSM communication. This structure contains three headers: the security header necessary for the encryption and security of the information, the protocol (here TCP/IP) header and the message header for the application operation. "The message header contains meter ID MAC address, equipment status, and the Type of Message". The raw message may vary in type and size.

In [82], Fouda et al. considered a message header of 50 bytes. Appendix G presents the principal protocols headers, and maximum transmission units (MTU) along with three security headers. The table hereafter presents the header parameters we select.

Header	Length (bytes)
Security	12
TCP/IP	40
WLAN	30
Message	50

Table 2.12: Header length.

Each message has to be sent with those headers. If the maximum transmission unit is exceeded, the raw message has to be separated in several packets, each of them containing all the headers.



	Type of Message (ToM)	Description	Size
1	Command / Request	To update meter, to control load, to change tariff, etc.	25 Bytes
2	Meter Periodic Data read	Real Power (kW) Reactive Power (kVAr) Micro-generation (kW) Voltage Power Factor	32 Bytes
3	Confirmation / Notification message	Failure notifications, messages, etc.	25 Bytes
4	Meter sends Error Report	This report is automatically produced when failure occurs within the system	18 Bytes
5	Meter sends Performance Report	This report is produced on occurrence of the failure or as scheduled to determine meter performance	150 Bytes
6	Meter sends Outage Report	Outage report is sent after the supply has been restored	14 Bytes
7	Weekly read submission	Output data after one week	28 Bytes
8	One month of data	Meter sends one month of data	40320 Bytes
9	Last day import data	Summary of usage on the last day	192 Bytes

Figure 2.9: Packet structure for DSM communication [82]. The header contains informations such as encryption codes, adresses of emitter and destination, type of message, etc. Different types of raw messages are then possibles, varying in size depending on the quantity of information it has to carry.

We consider a MTU of 1280 bytes. The raw message length depends on the information it has to carry and is computed by:

$$n_b = \text{ceil}(log_2(n_{message}))$$

with $n_{message}$ the number of different messages that can be carried. As an example, sending a measure, possibly varying between 0 and 10000 with a 1% precision requires $n_{message} = 10000 \times 100 + 1$. The message length is therefore 20 bits.

2.7 Summary

Table 2.13 presents a summary of this chapter results. The range of values is very wide and should be reduced by studying specific scenarios as we do in the following chapters. Those first results only give an insight of what might be the consumption of a demand side management system.

Figure 2.10 shows the repartition of emissions, considering use-phase and production, for a single house with 1 smart meter sending 1kbps over the internet network, 5 smart plugs, each of them sending 1kbps over the HAN, and 1min/day of server use.

The smart meter and smart plugs emissions represent 49% and 42% of the total emissions. Smart meter and smart plugs communications are responsible for 1% and 6% of the total emissions, mainly due to receiving modes, and server and communication network emissions represents 2% of the emissions together.

[9]Considering $T_{act} = 5\%, T_{stb} = 15\%$ and $T_{act} = 20\%, T_{stb} = 80\%$ as presented in [73].

[10]Considering $T_{act} = 0\%, T_{stb} = 5\%$ and $T_{act} = 2\%, T_{stb} = 97\%$ as presented in [73].

[11]The expected lifetime is 10000 write/read cycles. But we consider that memory lifetime is the same as smart plugs and smart meters, as it is most likely that memory is going to be changed at the same time than those devices.

Element	Use-phase consumption [kWh_{elec}/year]	Production phase emissions [kgCO2e]	Life time [year]
Smart plug	3.5 to 15.5	11 to 25	5
Smart meter	12.5 to 95.2	75 to 80	5
Communication network	0 to 35	7-11% of use [kWh]	3 to 10
Server	0 to 259	0 to 246.9	2
Optional elements			
Microprocessor	0.26 to 1.07 [9]	0.6	2
LP microcontroller	0 to 0.002 [10]	0.06	7
Extra memory	0.09 to 1.9/GB	0.3 to 5	5 [11]

Table 2.13: Summary.

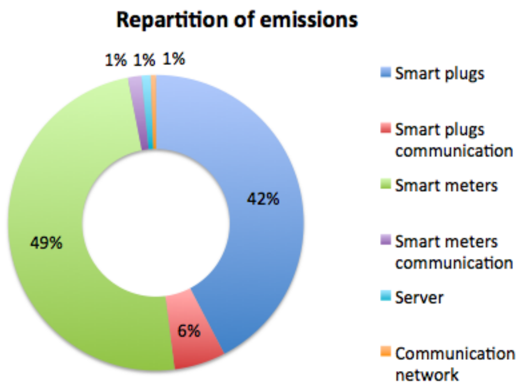


Figure 2.10: Repartition of emissions for a single house with 1 smart meter sending 1kbps over the internet network, 5 smart plugs, each of them sending 1kbps over the HAN, and 1min/day of server use.

2.8 Conclusion

This chapter presented the models for the different parts of the infrastructure. This allows us to perform a case by case study in the next chapter. From the first results we observed, we may already guess that the central communication network (access and backbone) plays a minor role in the DSM consumption, and that the smart meters and smart plugs consumption largely pass the central server consumption. The variability of all those results justify the case by case study of the next chapter.

Chapter 3

Case-study 1: Consumption monitoring

In this chapter, we compare direct and indirect impacts of smart energy management systems based on results reviewed in Chapter 1 among other [46, 83, 84, 85]. The main characteristic of the systems studied in this chapter is the type of feedback they provide to the consumer. The feedback is the way of presenting consumption information to the consumer in order to motivate a reaction: consumption reduction or shifting. As pointed out in [46] and in [83], different types of feedback may be implemented with different features:

- frequency and duration: feedback is more effective when given directly after an action. *Quick feedback would improve the link between action and effect, and therefore, increase consciousness about the action's consequences*, [83].
- Content : *Feedback may be given on electricity consumption alone (e.g. kWh), on cost, or on environmental impacts of consumption. These different contents frame the problem in different terms and thus activate different motives and personal and social norms. It remains an open question which motives and norms would be strongest in which target groups* [83].
- Breakdown: *Providing a breakdown, e.g., for specific rooms, appliances, or times of the day, is almost the only way of providing a direct link between action and result and thus, establishing consciousness of the relevance of individual actions* [83].
- Comparisons: *There are two basic types of comparisons: historic comparison relates actual to prior consumption. Normative comparison compares consumption to that of other households. Comparisons may stimulate specific motives for energy conservation, for example, a sense of competition and ambition* [83].

In this chapter, we study the impacts of different types of feedback: a simple global feedback, a device-specific feedback and two static pricing feedbacks. The saving scenarios are based on experimental results. For each case, we present different saving scenarios, the possible range of emissions and give results for the best case, the worst case and some average cases.The best case is the case with the maximum savings and the minimum emisisons; the worst case is the case with minimum savings and maximum emissions; and the average cases parameters are given in the system parameters tables.

3.1 Global consumption monitoring

In this first case, we observe the impact of a single smart meter per house, without any other device or communication. The system parameters are given in Table 3.1. In this case, van Dam [46] observed a fall-back in the energy savings of consumers, from 8% to 1.9% in 11 months. From those observations, we build two fall-back scenarios: in the first scenario, the savings keep decreasing after the 11 months until reaching 0; in the second scenario, the savings stay constant after the 11 months. Figure 3.1 shows four initial saving scenarios for each fall-back scenario, and the smart meter emission range. The 8% and 17% initial saving scenarios were observed in [46], the 5% and 12% initial saving scenarios are mentioned in [83] as typical scenarios observed in various studies. Some other studies, however, observe smaller savings or no saving at all [83].

System description			
Household consumption	4800 kWh/year	Smart meter consumption	1-10 W
		average: 5.5 W	
Initial savings	5%, 8%, 12% and 17 %	Production emissions	40 - 45 kgCO2e
		average: 42.5 kgCO2e	
Remaining savings	0 and 23% of initial savings	Life expectancy	5 years
kgCO2e/kWh_{elec}	0.22 (Belgium)	Fall-back rate	83 %/year

Table 3.1: Global monitoring - System parameters.

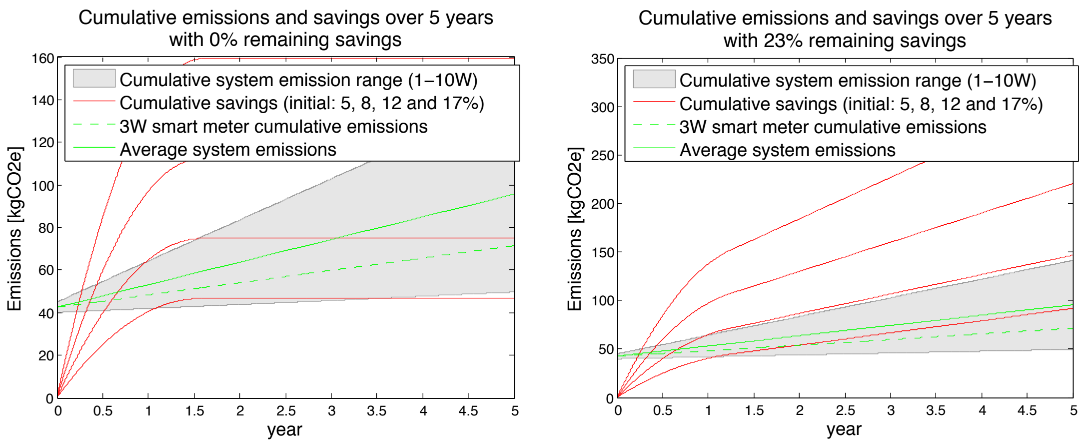


Figure 3.1: Case-study 1: smart meter emissions and savings. In the full fall-back scenario (left), savings are temporary as the system emissions counterbalance most of it after 5 years. In the remaining savings scenario (right), the saving potential is much higher.

From Figure 3.1 we see that even for a simple single-element system, the range of uncertainty is wide for both savings and emissions. We may draw some conclusions from those first results:

- it is crucial to choose the right type of smart meter, in order to limit its consumption to the minimum required.
- It is important to target consumers with enough reduction potential (e.g. motivation and appliance types).
- It is important to limit the fall-back effect so that savings keep increasing over time.

We also observe that for low-power smart meter, production is the main source of CO2 emissions; for high-power smart meter, however, use-phase takes over.
Table 3.2 summarizes the results obtained for the global monitoring system. In this table, we express the results with and additional factors; the $kgCO2e_{saved}/kgCO2e_{emitted}$ (also called saving factor in thes rest of this work) is region-specific as it already takes into account the local GWP. If it is bigger than 1, the system saves more emissions than it produces. The average system's results are obtained using the two intermediate saving scenarios; 8 and 12%. The saving factor is also presented in Figure 3.2 for different scenarios.

Results (over 5 years)			
Total consumption [kWh] (only use-phase)	43.8 to 438	Savings [kWh]	212.7 to 1417.34
Total emissions [kgCO2e]	49.6 to 141.4	Savings [kgCO2e]	46.8 to 311.8
$kgCO2e_{saved}/kgCO2e_{emitted}$: 0.33 to 6.28			

Table 3.2: Global monitoring system - results. If $kgCO2e_{saved}/kgCO2e_{emitted} > 1$, the system generates more savings than emissions.

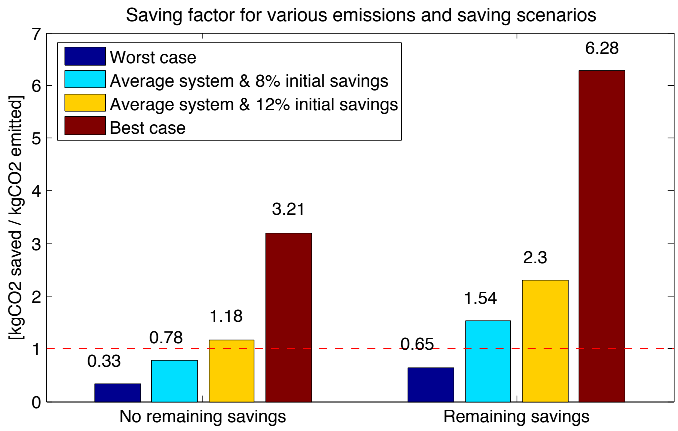


Figure 3.2: Case-study 1: saving factors for various emissions and saving cases. If $kgCO2e_{saved}/kgCO2e_{emitted} > 1$, the system generates more savings than emissions.

3.2 Device-specific consumption monitoring

In this section, we analyze a more complete system with smart plugs monitoring specific devices consumption and a smart meter monitoring the global consumption. Both types of devices send information to a computer which analyses and shows consumption results to consumers. We do not take into account the software execution consumption, but we consider one additional Zigbee module in receiving mode for the communication with the computer. For this scenario, we consider initial savings of 9%, 13.7% and 18%, as presented in [84]. The system parameters are summarized in Table 3.3. Table 3.4 presents the parameters used to estimate the communication requirements.

System description			
Household consumption	4800 kWh/year	Smart meter consumption	1-10 W
kgCO2e/kWh_{elec}	0.22 (Belgium)	Smart plug consumption	0.4-1.3 W
		average: 0.85 W	
Initial savings	9%, 13.7% and 18 %	Number of smart plugs	1 to 20
		average: 10	
Remaining savings	0 and 23%	Extra communication module	1
Life expectancy	5 years	Smart meter production	40-45 kgCO2e
		Smart plug production	11 to 25 kgCO2e

Table 3.3: Device-specific monitoring - system description.

In Figure 3.3 we compare the emissions of a device-specific monitoring with the savings it generates. The expected savings are low, between 78.8kgCO2e and 323.9kgCO2e in 5 years, in comparison to the possible system emissions which range from 72.2kgCO2e to 911.1kgCO2e in 5 years. The additional smart plugs compared to the global consumption monitoring system

Communication requirements			
Range of measures	0W to 10000 W	Communication rate	1s to 15min
		average: 1min	
Precision of measures	1%	Message length	20 bits
Number of bits	0.86 to 756 bps/device	Header length	736 bits

Table 3.4: Device-specific monitoring - Communication scenarios.

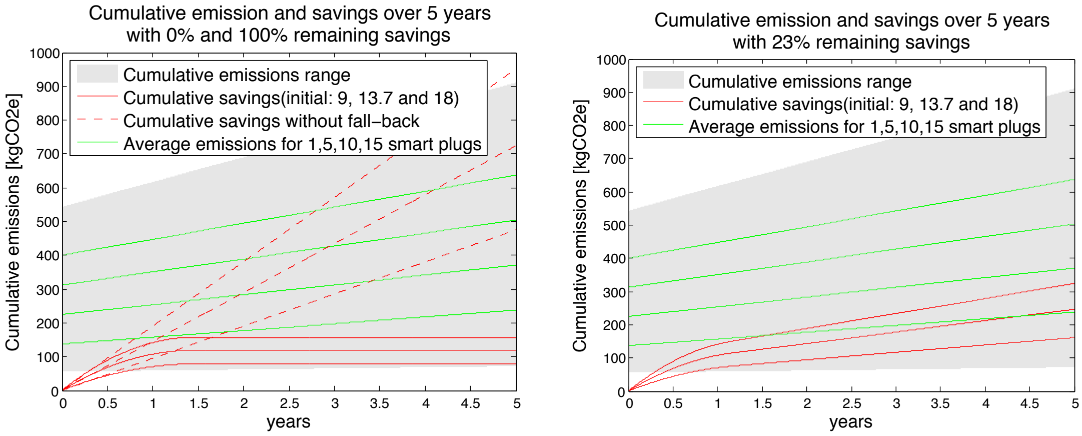


Figure 3.3: Device-specific monitoring emissions and savings. The system emission range is wide due to the number of parameters taken into account. Expected savings are small compared to the possible system emissions.

seem to have a negative effect on the absolute savings of the system.
Figure 3.4 shows the repartition of emissions due to use-phase and production phase. We observe that the critical phase is the production phase. Base-consumption of smart meter and smart plugs prevails over communication during the use-phase. Given the low transmission rate, 0.86 bps to 756 bps per device, the communication consumption of a single module does not vary significantly; from 4.15 kWh to 4.17 kWh in 5 years. This means that the receiving mode is predominant in terms of consumption. The increase in communication consumption between best and worst case is mainly due to the increasing number of communication modules (from 1 to 20 smart plugs per house).

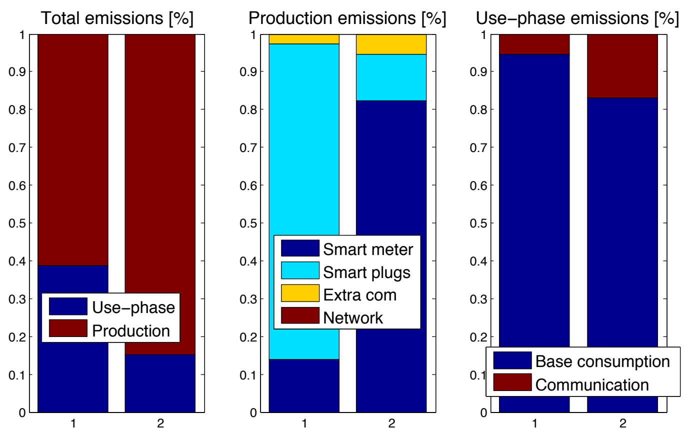


Figure 3.4: Repartition of emissions. 1: Worst case (maximum emissions) 2: Best case (minimum emissions). Production generate 59.7 to 77.5% of the total emissions of the system.

Table 3.5 shows the resulting emissions and savings over 5 years. It does not consider the

System emissions and savings (over 5 years)			
Consumption [kWh] (only use-phase)	73.79 to 1668.6	Savings [kWh]	358.3 to 1472.4
Emissions [kgCO2e]	72.2 to 911.1	Savings [kgCO2e]	78.8 to 323.9
$kgCO2e_{saved}/kgCO2e_{emitted}$: 0.09 to 4.5			

Table 3.5: Device specific monitoring - Results.

scenario without fall-back in the saving rate which is not realistic. Figure 3.5 shows the saving factors for various scenarios. We observe that most of the factors are below 1, which means that the system is most likely to generate more emissions than savings.

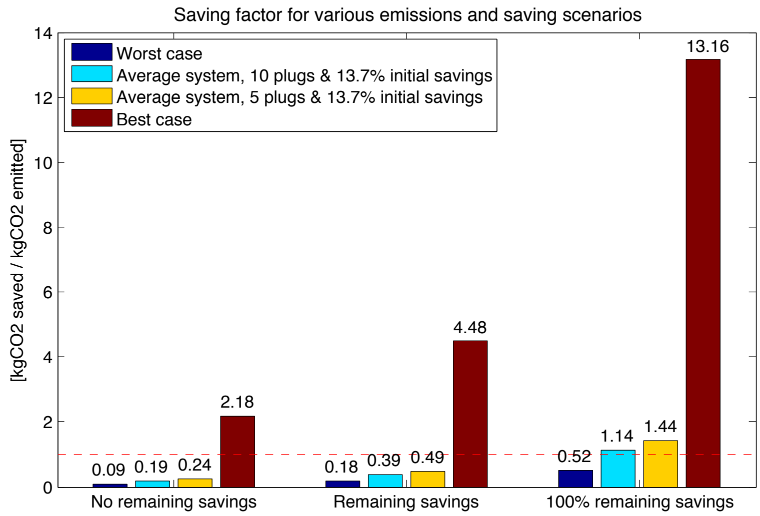


Figure 3.5: Saving factors for different scenarios. The system is most likely to generate more emissions than savings in the two first scenarios. In the *100% remaining savings* scenario, however, the average systems generate savings.

3.3 Time varying pricing

Time varying pricing consists in changing the price of electricity with the time of use, and works as an incentive for users to shift part of their consumption when demand is lower. Various pricing strategies exist:

- time of use (TOU): it refers to prices set in advance but varying throughout the day, every day.
- Critical peak pricing (CPP): the consumer faces higher rates during critical peak periods.Those periods may vary from a few hours to an entire day and are decided in advance by the energy supplier. The client is forewarned when it is a CPP day. Observed peak reduction is higher than in TOU, but it concerns only a few critical days during the year.
- Peak time rebates (PTR): consumers can earn a rebate if they decrease their consumption during critical peak periods. As for the CPP, this period may be an entire day but is only applied a few days every year.
- Real-time pricing (RTP): prices vary in real-time according to the demand-supply balance. This type of pricing strategy is interesting for automated load control systems.

In the following sections, we compare the emissions and savings due to static pricing (TOU, CPP and PTR) systems implementation. We do not address the real-time pricing subject because of the lack of data for the saving scenarios.

3.3.1 Static pricing

Static pricing consists in fixing prices in advance considering consumption (and eventually intermittent production) forecasts; it means that prices are not refreshed in real-time. In [85], Faruqui and Sergici present a survey of 15 recent time varying pricing studies. Their conclusions are presented in the table hereafter (see Table 3.6). Those results represent the percentage of consumption reduction during peak hours and CPP days (around 10 per year). More detailed results are presented in Appendix H.

Rate Design	Number of Observations	Mean	95% Lower Bound	95% Upper Bound	Min	Max
TOU	5	4%	3%	6%	2%	6%
TOU w/ Technology	4	26%	21%	30%	21%	32%
PTR	3	13%	8%	18%	9%	18%
CPP	8	17%	13%	20%	12%	25%
CPP w/ Technology	8	36%	27%	44%	16%	51%

Table 3.6: Reduction in peak load for 5 static time varying pricing strategies [85]. The TOU and CPP w/ Technology refer to static princing systems with smart plugs enabling to remotely control loads.

This table presents impacts with and without enabling technologies. In the paper, those enabling technologies are described as: *two-way programmable communicating thermostats and always-on gateway systems that allow multiple end-uses to be controlled remotely.* Most of the reviewed studies in this paper were conducted in the USA; only one was conducted in France, and we have no information about those particular results. However, a recent experiment in Germany [86] found out that TOU pricing in the residential sector could lead to a 4.5 to 5.5% peak-load reduction, which is close to the results presented in Table 3.6.

As this table does not present absolute reduction but peak load reduction, mainly resulting from load shifting, translating those results into emission savings is not as straightforward as in the previous cases; it depends on the electricity production mix during the shifting period. In [10], the belgian electricity production global warming potential (GWP) is evaluated depending on the season. We see in this paper that the GWP varies between 0.18 and 0.25 kgCO2e/kWh during a typical winter day and between 0.12 and 0.22 kgCO2e/kWh during a typical summer day. Typical savings for load shifting are then 0.07 kgCO2e/$kWh_{shifted}$ in winter and 0.1 kgCO2e/$kWh_{shifted}$ in summer.
According to Elia's website, peak hours in Belgium take place during weekdays between 8am and 22pm. From the belgian synthetic load profiles (SLP) curves, we found out that 49.7% of the residential demand is during those peak hours. We therefore consider that TOU applies to those 49.7%. That is to say, TOU results in $0.497 * 0.04 * 4800 = 95.5kWh_{shifted}$. CPP and PTR are considered to represent 10 days a year (as tested in the studies reviewed in [85]).

Without enabling technologies

This system is made of a single smart meter per house receiving price informations through the internet network from a central server. The system description is presented in Table 3.7. The emissions due to the central server are neglected. The communication consumption of such methods varies with the frequency of price refreshing (from once a day for CPP and PTR to once a month or once a week for TOU), the number of different pricing period per day and the range of prices (see Table 3.8).

System description			
Household consumption	4800 kWh/year	Smart meter consumption	1-10 W
kgCO2e/kWh_{elec}	0.22 (Belgium)	Smart meter production	75 to 80 kgCO2e
Extra savings	4%, 13% and 17% during peak hours	Initial savings	5%, 8%, 12% and 17%
Life expectancy	5 years	kgCO2e/$kWh_{shifted}$	0.07

Table 3.7: Static pricing without enabling technologies - System parameters for different scenarios.

Communication requirements			
Number of refreshing	1/day to 1/month	Number of period per day	4 to 48
Range of prices	0 to 2 €/kWh	precision	0.1 %
Number of bits per period	11 bits	Message length	44 to 528 bits
Header length	640 bits		

Table 3.8: Static pricing without enabling technologies - Communications requirements for different scenarios.

Once more, the communication consumption does not vary significantly in those scenarios. The difference between worst case (1 refreshing per day and 48 periods per day) and best case (1 refreshing per month and 4 periods a day) is 0.04kWh in 5 years. Communication consumes around 2.9 kWh/year, most of which is due to the smart meter receiving mode. We may consider that the receiving time is approximatively known by the smart meter, in that case, it could stay in sleeping mode most of the time. We consider that the receiving period may take place during one given hour each day, the rest of the time, the smart meter is in sleep mode. In this case, the yearly consumption of communications drops to 0.18kWh.

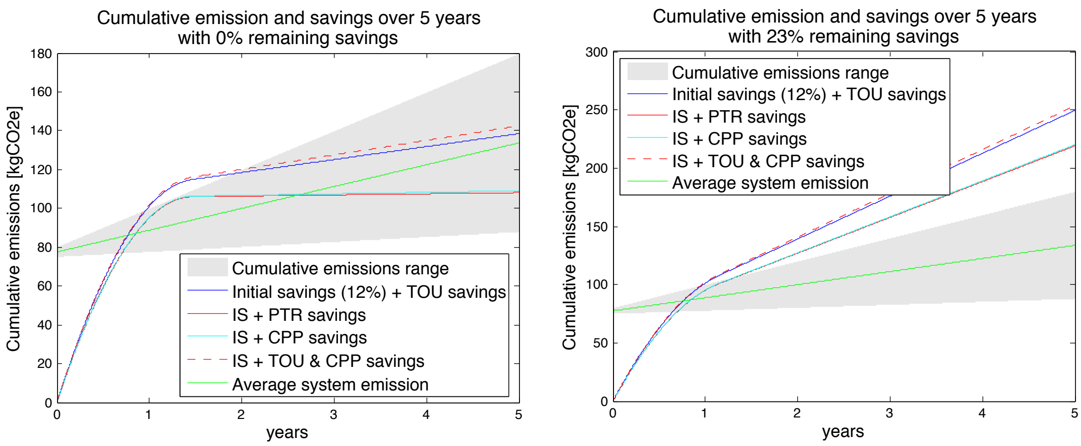


Figure 3.6: Cumulative emissions for static pricing - initial savings = 12%. Full fall-back scenario (left) does not generate savings at the end of the 5 years (or very little). The remaining savings scenario (right), on the other hand, is expected to generate savings.

In Figure 3.6, we observe that emissions due to the device production and use increase compared to the global consumption monitoring scenario because of the extra communication module needed with the smart meter. Savings also increase compared to the simple global consumption case. For a 12% initial saving, the total emissions of the system and the expected savings over 5 years are very close. In order to avoid overloading this section, the 5% and 17% initial savings curves are presented in Appendix I. Table 3.9 presents the emissions and savings of the system, and the saving factor is presented in Figure 3.7. The average system results are obtained by using the TOU and CPP savings.

Emissions and savings (over 5 years)			
Total consumption [kWh] (only use-phase)	58.3 to 452.5	Shifted kWh's Savings [kWh]	42.5 to 477.0 212.7 to 1417.3
Total emissions [kgCO2e]	87.8 to 179.5	Savings [kgCO2e]	46.8 to 343.3
$kgCO2e_{saved}/kgCO2e_{emitted}$: 0.26 to 3.91			

Table 3.9: Static pricing without enabling technologies - Results.

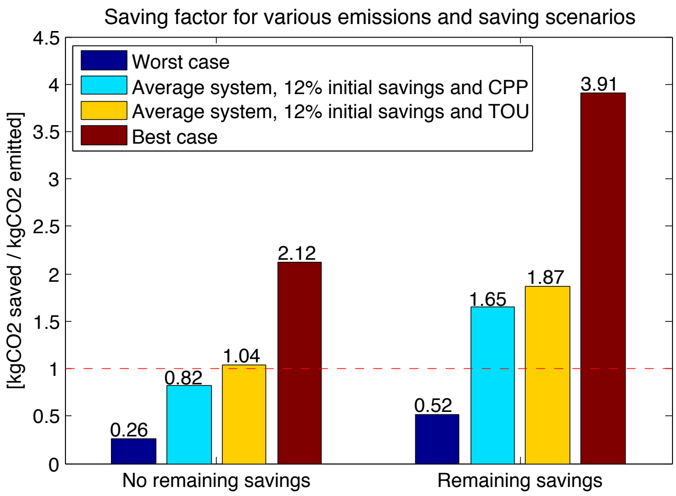


Figure 3.7: Static pricing without enabling technologies - Saving factor.

With enabling technologies

This system includes a smart meter able to communicate both with smart plugs and with the customer's mobile through the internet network. Just as in the previous case, the time of use price data goes through the internet backbone and to the smart meter via Wifi. Mobile communication is also added to allow consumers to have access to their consumption informations and to remotely control their smart plugs. The system parameters are shown in Table 3.10, and the additional communication requirements are presented in Table 3.11.

System description			
Household consumption	4800 kWh/year	Smart meter consumption	1-10 W
kgCO2e/kWh_{elec}	0.22 (Belgium)	Smart plug consumption	0.4-1.3 W
Initial savings	9, 13.7 and 18%	Number of smart plugs	1 to 20
Extra saving	26 and 36%/year during peak hours	Extra communication module	1
		Smart meter production	75-80 kgCO2e
Life expectancy	5 years	Smart plug production	11 to 25 kgCO2e

Table 3.10: Static pricing with enabling technologies - System parameters.

Extra mobile communication			
Range of measures	0 to 10000 W	Communication rate	1sec to 15min
Precision of measures	1%	Message length	20 bits/smart device
Header length	1056 bits		+ 11 bit of pricing data

Table 3.11: Static pricing with enabling technologies - Communications requirements.

In this scenario, the communication consumption varies from 22.8 to 125.8 kWh in 5 years. As usual, it is mainly due to receiving modes as transmitting rate is low. However, in the worst case scenario, the mobile consumption also plays a significant role in the communication consumption (around 13% of the communication consumption which itself represents 0.9% of the total consumption).

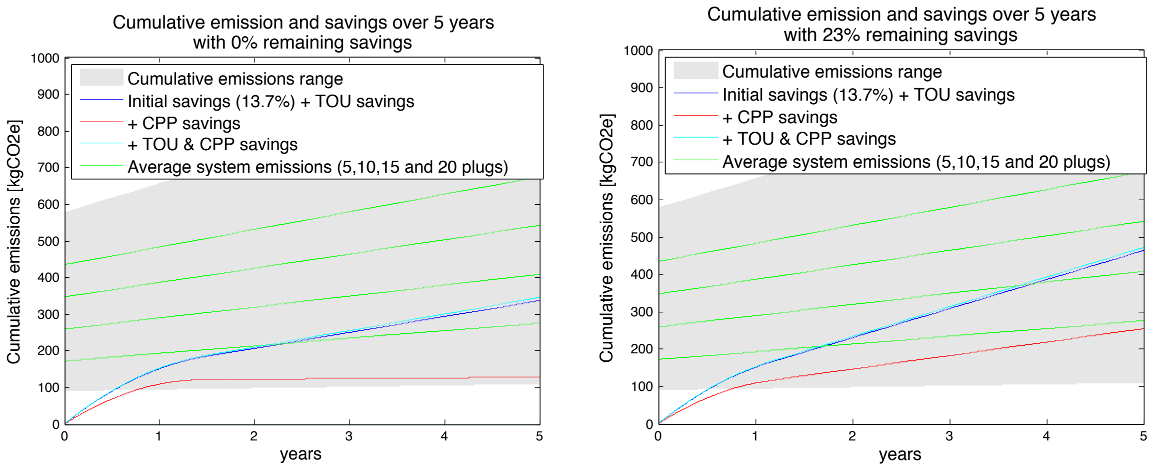


Figure 3.8: Cumulative emissions for static pricing - initial savings = 13.7%. Neither the full fall-back scenario (left) nor the remaining savings scenario (right) generate enough savings to compensate for sure the expected emissions of the system. For 5 smart plugs or less, however, savings can be expected for an average system.

Figure 3.8 shows us that the average saving scenario does not generate enough savings to counterbalance the average system emissions. From Figure 3.9, we see that those emissions are mainly due to the smart meters and smart plugs production. The use-phase impact is dominated by the constant consumption of smart plugs and smart meters and by the receiving modes of communication modules. Sleeping modes are, however, not allowed here, as the consumer must be able to remotely control his appliances.

Emissions and savings (over 5 years)			
Total consumption [kWh]	83.9 to 1777.5	Shifted kWh's	117.6 to 3218.3
(only use-phase)		Savings [kWh]	358.3 to 1472.4
Total emissions [kgCO2e]	109.5 to 970.1	Savings [kgCO2e]	87.2 to 549.4
$kgCO2e_{saved}/kgCO2e_{emitted}$: 0.09 to 5.02			

Table 3.12: Static pricing with enabling technologies - Results.

Table 3.12 shows the emissions and savings of the static pricing with enabling technologies system. The wide range of both savings and emissions leads to a wide range of $kgCO2e_{saved}/kgCO2e_{emitted}$ factors. When installing few smart meter to well-chosen appliances, the absolute savings can be positive. CPP strategy alone, does not generate lots of savings. The TOU pricing strategy is more efficient as it takes place every day. Figure 3.10 shows the saving factor for different saving

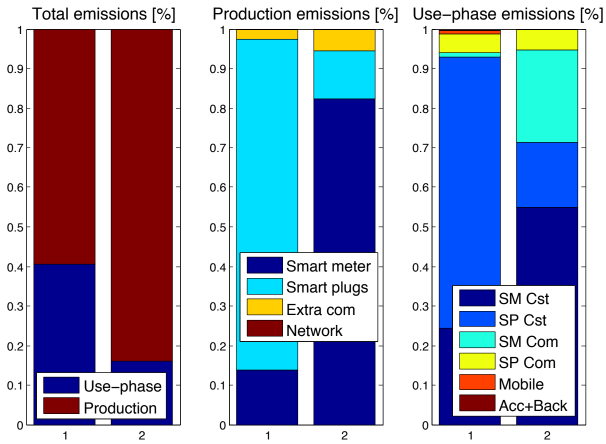


Figure 3.9: Repartition of emissions. 1: Worst case (maximum emissions) 2: Best case (minimum emissions).

and emissions scenarios. The average scenarios are computed with the TOU saving strategy.

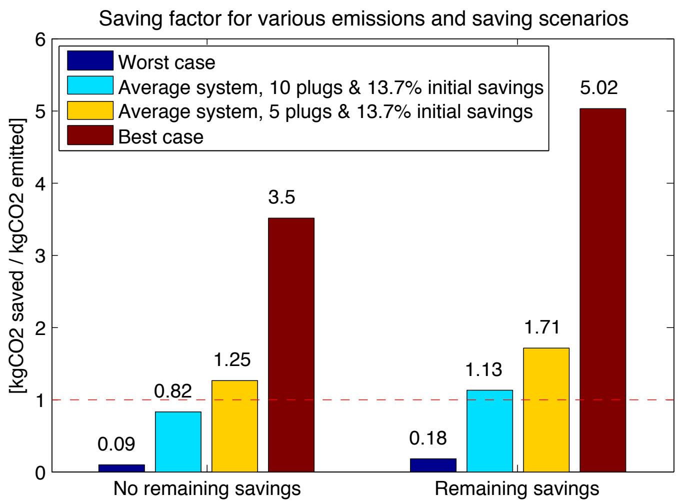


Figure 3.10: Saving factor for fall-back and remaining savings scenarios.

3.4 Summary

The results from the four cases studied in this chapter are summarized in Table 3.13. The first scenario might generate savings when chosen properly and with a good will consumer. The second case, however, seems to generate too much additional emissions to be compensated. As for the first case, the third case might generate absolute savings if the system parameters are favorable. Nevertheless, the expected savings are lower for case 3 than for case 2, which means that adding static pricing to the first system has an absolute negative effect on the whole system savings. The static pricing with enabling technologies system is also able to generate savings if the parameters (number of smart plugs, consumption, etc) are chosen wisely. In that case, it seems positive to add communication to the device-specific monitoring system, because it leads to increased savings in average.
Table 3.14 focuses on the communication results of the four systems. For each system, the total communication consumption is given and expressed as a percentage of the global consumption of the system. The receiving and transmitting modes consumption is then expressed as percentages of the communication consumption.

Emissions and saving potential for a single house over 5 years			
Scenario	Results	Best and Worst case	Average
1) Global consumption monitoring	Absolute savings [kgCO2e] $kgCO2e_{saved}/kgCO2e_{emitted}$	-94.6 to 262.2 0.33 to 6.26	-20.6 to 124.6 0.78 to 2.3
2) Device-specific monitoring	Absolute savings [kgCO2e] $kgCO2e_{saved}/kgCO2e_{emitted}$	-832.3 to 251.7 0.09 to 4.5	-516.9 to -257.3 0.19 to 0.49
3) Static pricing without enabling technology	Absolute savings [kgCO2e] $kgCO2e_{saved}/kgCO2e_{emitted}$	-132.7 to 255.5 0.26 to 3.91	-24.6 to 115.7 0.82 to 1.87
4) Static pricing with enabling technology	Absolute savings [kgCO2e] $kgCO2e_{saved}/kgCO2e_{emitted}$	-882.9 to 439.9 0.09 to 5.2	-72 to 196 0.82 to 1.71

Table 3.13: Summary. The simple global consumption system can be expected to generate savings. Adding communication to this system, for static pricing strategy, lower its saving potential due to the additional communication module needed and the low additional savings expected. The device-specific monitoring system, on the other hand, is not expected to generate savigs on its own, but can benefit from the addition of static pricing, as case 4 has better results.

This table shows the part of communication in the total consumption of each system. We clearly see in this table that transmission only represents a very small part of this communication consumption due to the low transmission rates needed in such systems. Sleep mode could be used to reduce communication consumption, but it is not always possible. If remote control of appliances is needed, the sleep mode can not be used.

3.5 Conclusion

Throughout this chapter, we observed the savings and emissions of four in-home monitoring systems: the global consumption monitoring which only displays the global consumption of the house, the device-specific monitoring which displays the global consumption along with the consumption of specific devices, and two static pricing systems (global and device-specific). We observed that potential savings are usually of the same order of magnitude than predicted emissions due to the systems production and use. It is therefore difficult to predict whether or not a system is going to generate absolute savings. The production phase of each system is critical in terms of emissions and requires special attention. The constant consumption of smart plugs and smart meters is also a great source of emissions. As for the communication, it seems to play a minor role in emissions, but low power receiving modes and intelligent sleep mode management could further reduce its impact. The next chapter studies an automatic load management system with its saving potential and its emissions.

Communication consumption over 5 years			
Scenario	Results	Best and Worst case	Average
1) Global consumption monitoring	Total consumption [kWh]	0	0
	Total consumption [%]	0	0
	Rx consumption [kWh]	0	0
	Tx consumption [kWh]	0	0
2) Device-specific monitoring	Total consumption [kWh]	12.5 to 91.8	29.1
	Total consumption [%]	5.5 to 17	6.9
	Rx consumption [%]	99.6 to 100	99.996
	Tx consumption [%]	0 to 0.4	0.004
3)Static pricing without enabling technology	Total consumption [kWh]	14.48 to 14.52	14.49
	Total consumption [%]	3.2 to 24.8	5.7
	Rx consumption [%]	99.77 to 100	99.98
	Tx consumption [%]	0 to 0.23	0.02
4) Static pricing with enabling technology	Total consumption [kWh]	22.8 to 125.8	60.3
	Total consumption [%]	7 to 28.6	8.9
	Rx consumption [%]	81 to 99.93	99.8
	Tx consumption [%]	0.07 to 19	0.2

Table 3.14: Communication consumption - Summary. The consumption of communications represents between 3.2% and 28.6% of the total consumption of the system; which itself is 15% to 40% of the total emissions. The receiving mode (Rx) consumption is predominant compared to transmitting (Tx) consumption.

Chapter 4

Case-study 2: Load shifting algorithm

In this chapter, we study the emissions and savings due to a specific algorithm developed by Latiers [87]. Most of this chapter is based on Latiers and Saussez master thesis, and on Léonard and Rochet master thesis, [88, 89, 90].
In this chapter we first present the consumption an production curves models which are useful for the next part. We then explain the shifting algorithm and estimate its emissions and savings potential. We finally observe the variation of both emissions and savings with some parameters and conclude this chapter.

4.1 Residential consumption curve

In [89], Léonard and Rochet built a model of Belgian residential consumption. This model is based on different elements:

- The consumption curves of various appliances in different modes: Léonard and Rochet produced physical models of those various appliances and compared it to measurements from Latiers and Saussez master thesis measurement campaign.
- The consumption statistics: three sets of statistics were needed to build this model: 1) the possession statistics used to determine how many appliances were likely to be found in a typical neighborhood, 2) the use statistics to determine how many times each appliance is likely to be used each day, and 3) the time of use statistics to determine when it is more likely for each appliance to be started. Those statistics were taken from Crioc and Remodece reports.

From those data, Léonard and Rochet were able to build a residential consumption model generating random standard houses and neighborhoods. Figure 4.1 shows the average consumption of a household generated by this model.

4.1.1 Variation of the consumption curve throughout the year

Figure 4.1 shows an average consumption curve based on yearly statistics and on a measurement campaign conducted in March 2010. Yet, residential consumption varies with various parameters: season, weather, type of day (weekday, weekend, holidays, etc.). The goal of this section is to model those variations.

Seasonal variations

In [89], Léonard and Rochet explained a method to take into account monthly variations of the consumption curves. Those seasonal variations have to be modeled differently for the different types of loads:

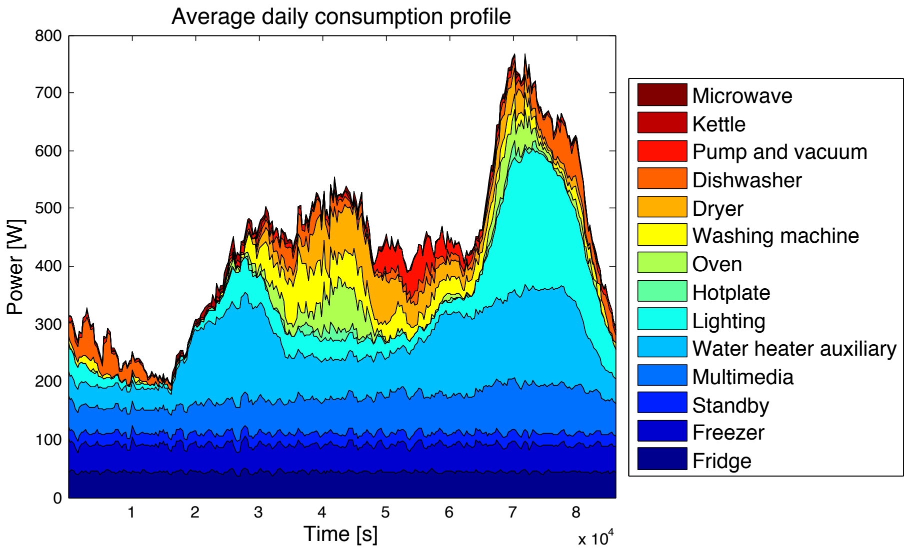


Figure 4.1: Residential consumption curve [89].

- Cooling loads: the consumption of cooling loads should increase with temperature. The influence of the temperature is already taken into account in the physical model of those loads. The ambient temperature is considered to be a ponderation of outside temperature and 22 degrees (1:3).

- Boiling loads: boiling loads consumption, on the other hands, should decrease when temperature increases. We assume that water temperature is a waited average between temperature of the previous month, the current month and 15 degrees (1:1:2). Léonard and Rochet observed that boiling loads consumption decreases by 10% on average between winter and summer. Based on this observation and knowing that the measurement were taken in March, when average water temperature is around 11.6 degrees, we deduced an empirical multiplication factor: $f = -0.0136T_{water} + 1.1584$.

- Water boiler auxiliaries: they are considered to be directly proportional to monthly degree-day. A degree-day is the difference between outside temperature and inside temperature. This is a unit used to quantify heating or cooling.

- Lighting: lighting decreases with the lengthening of days. We used available monthly datas from Remodece studies to take that phenomenon into account.

- Cooking loads: It has been observed that cooking loads were used less often during summer. The monthly average consumption of such loads is given by: $C_{month-av} = 1 - 0.55\frac{T_{month}}{T_{year}}C_{year}$; with T_{month}, the monthly average temperature, T_{year}, the yearly average temperature, C_{year}, the yearly average consumption.

Figure 4.2 shows the comparison between the seasonal variation model and the SLP curves.

Weekly variations

The consumption also varies with the type of day; weekdays, saturdays or sundays are the three main types of day we can observe in the SLP curves. To model those types of day, we need to change both the daily usage statistics and the time of use statistics used in the model. We choose to multiply the daily usage statistics by factors selected to match the SLP curves at best; $f_{weekday} = 0.88$, $f_{saturday} = 1.2$, $f_{sunday} = 1.3$, we also multiplied the light and heater auxiliary consumption by those factors. For each day type, and for each period of the day we also computed a correction factor for the time of use statistic curves. Those correction factor

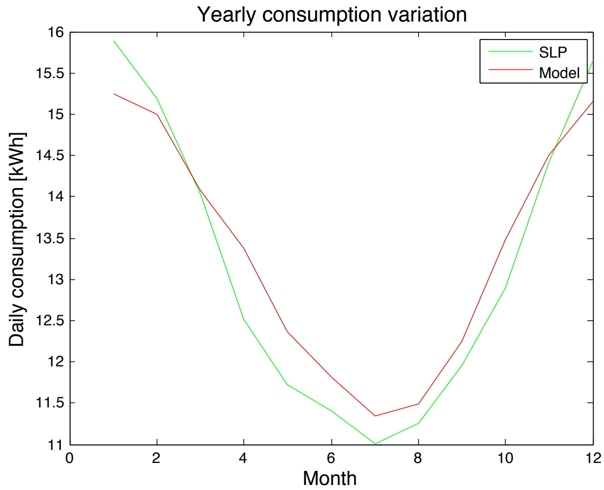


Figure 4.2: Seasonal variations of consumption.

were computed as follow:

$$f(t) = \frac{C_{day}(t)/C_{day_{total}}}{C_{av}(t)/C_{av_{total}}}$$

with $C_{day}(t)$, the consumption at time t of a particular day-type, $C_{day_{total}}$, the total daily consumption of this day-type, $C_{av}(t)$, the consumption at time t of an average day, and $C_{av_{total}}$, the total daily consumption of an average day. Figure 4.3 shows the three SLP curves for the three considered day types along with the correction factor for each day type. Once multiplied by those factors, the time of use statistic curves are slightly modified to better match each day-type consumption. Figure 4.4 shows the model and SLP curves for each day type.

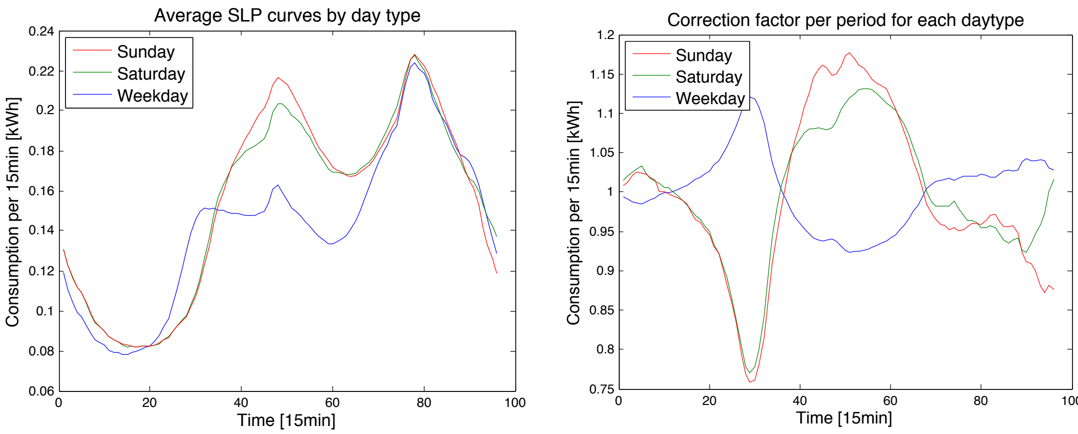


Figure 4.3: Weekly variations of consumption - SLP curves and Correction factor curves.

4.2 Production curve

During their measurement campaign, in March 2010, Latiers and Saussez [88] measured the production of a $200W_p$ Mithras photovoltaic panel and of a 5.8kW Fortis Montana wind turbine. We therefore have 31 production profiles available for both wind and solar production. As for the consumption, we generated yearly production variations to take into account the changing weather during the year. In this work, we focus on solar production, as residential wind production is not very developed yet.

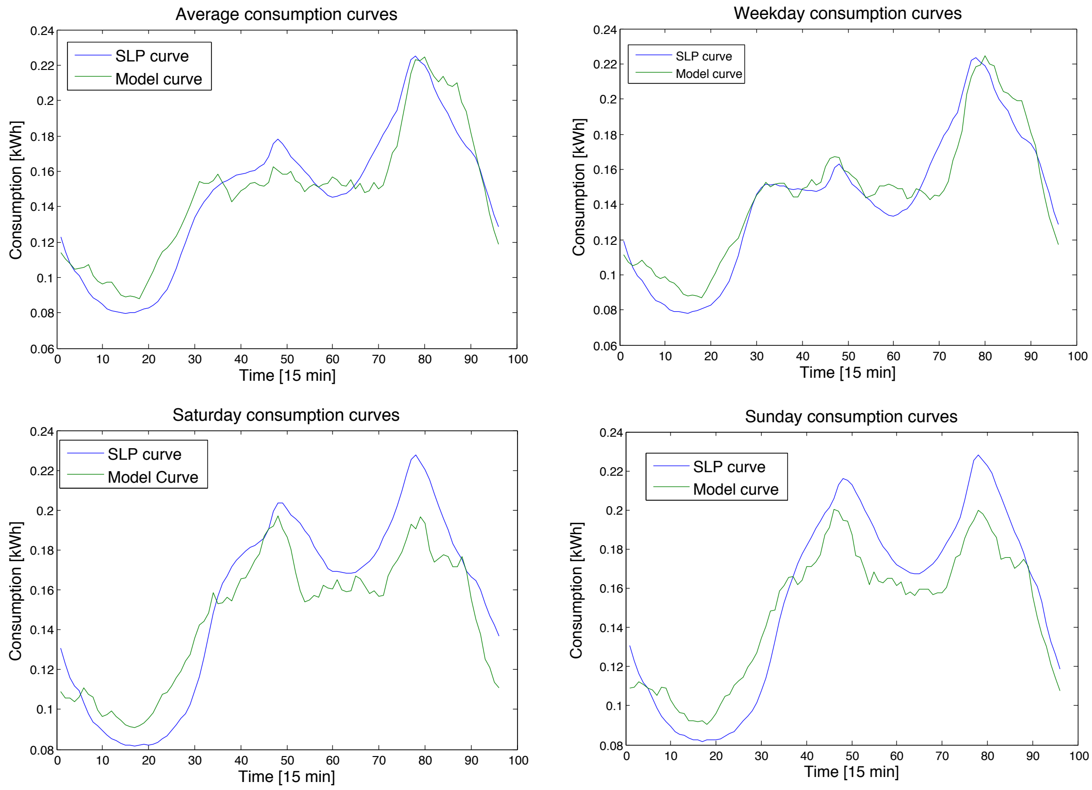


Figure 4.4: Weekly variations of consumption - Day-type from upper left to lower right: yearly average day, weekday, saturday and sunday (all three from March). We observe a peak of consumption around 20pm fore each day type. The peak of consumption around 11.30am is also present for all types of day, but changes in magnitude.

4.2.1 Variation throughout the year

From the measurements, taken in March 2010, and from the sunset time, sunrise time and average irradiance for each month,[91, 92], we developed a simple model to generate plausible production curves for every other month: we shifted the start and end time of solar production according to the sunset and sunrise data we have, and interpolated the midday gap when necessary. Then, we scaled the total daily production according to the monthly average irradiance. Figure 4.5 shows two generated photovoltaic production profiles, for December and June and some curves from Elia's website.
The comparison of those two graphs shows that the order of magnitude of the production model for each month seems good.

4.3 Load shifting algorithm

The load shifting algorithm presented in this section was developed by Latiers as part of his thesis [87]. It is an algorithm based on a production prediction curve, on consumption statistics and on average consumption curves of the different types of loads. The algorithm starts with a day-ahead optimization whose goal is to determine optimal delay statistics for each type of shiftable load depending on its launching period and on its maximum delay. The results of this optimization is then a 4-D matrix containing delay probabilities at each time step for each type of load, requested starting time and maximum acceptable delay. Objective functions to reach this goal are discussed later. The second part of this algorithm generates a real neighborhood consumption curve and randomly applies delays to each shiftable load with the probabilities previously computed by the optimization. Figure 4.6 shows an example of shifted consumption

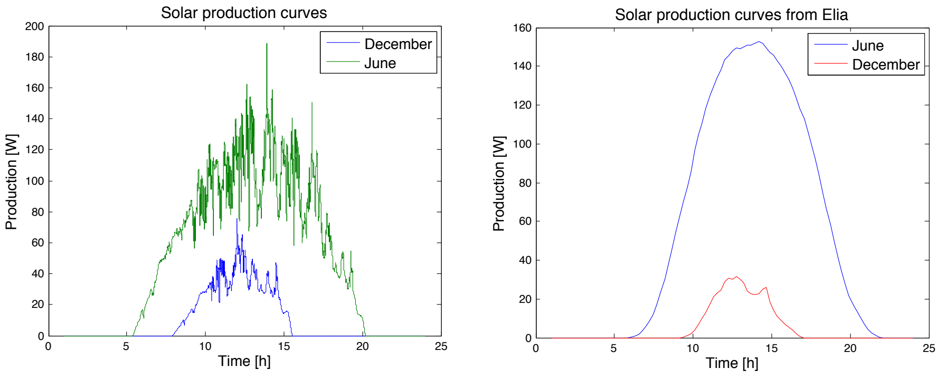


Figure 4.5: Photovoltaic production profiles from model and from Elia's website (11 June 2015 and 16 december 2014).

curve produced by the described algorithm.

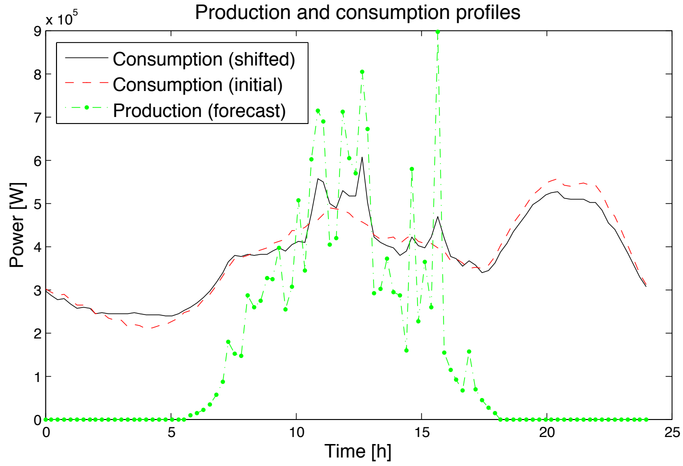


Figure 4.6: Example of shifted consumption curve.

The main parameters of this algorithm are the following:

- The type of day: we observe the results for four types of days: weekdays, saturdays, sundays and the average day.
- The month: production and consumption vary with the time of the year, we observe the impact of this variation on the savings of the algorithm.
- The number of houses: an increased number of houses leads to an increased number of shiftable loads and solar panels. We expect the savings to increase linearly with the number of houses.
- the time step: a load requesting to start at time t can be shifted to time $t + nT$, with n, a natural number and T the time step. Reducing the time step therefore leads to a more precise load shifting, but it is also more computationally intensive as the dimension of the data and the number of points increase.
- The number of solar panels per house: when the number of solar panels per house is very small, the whole production is naturally consumed by the neighborhood, and the algorithm does not generate more savings. On the other hand, when the number of solar panels is very high, the algorithm is not able to generate more savings because of the limited number of shiftable loads it disposes of.

- The objective function: as explained in the next subsection, we try different objective functions, and observe their impact on the algorithm results.
- The production forecast: we observe the impact of two production forecast parameters: its granularity and its accuracy. We run the optimization with varying granularity and accuracy and observe the savings when applying the resulting statistics the the real neighborhood with the real production curve.
- The consumption statistics accuracy: we observe the impact of the use of inaccurate consumption statistics. This means that we use two set of statistics; an inaccurate set in the optimization problem, and the real set when simulating the real neighborhood
- The portion of shiftable loads: we consider three types of shiftable loads: the dishwasher, the washing machine and the dryer. The portion of those loads being actually shiftable depends on the consumer's choices. The saving potential should increase with the portion of shiftable loads amongst those.

4.3.1 Optimisation problem formulation

The optimization problem may be formulated as follow:

$$\min_{X_a} F(C_{non-flex}[t] + C_{flex}[t] - P[t]) \tag{4.1}$$

with $C_{non-flex}$, the non-flexible consumption, C_{flex}, the flexible consumption (shiftable loads), which is the variable of this equation, and P, the local production. The objective F may be expressed in different ways which are described hereafter. Constraints of this problem are expressed as:

$$C_{flex}[t] = \sum_{a=1}^{n_{app}} St_a \Bigg(\underbrace{(1 - fs_a)(P_a[t] \otimes St_a[t])}_{Non-shiftable} + \underbrace{\sum_{d=0}^{n_{period}} fs_a(P_a[t] \otimes S_a[t] X_a[d,t])}_{Shiftable} \Bigg) \quad , \qquad \forall t \tag{4.2}$$

$$\sum_{d=0}^{n_{period}} X_a[d,t] = 1 \quad , \qquad \forall t, a \tag{4.3}$$

$$\sum_{d=0}^{n} X_a[d,t] \geq \sum_{d=0}^{n} L_a[d] \quad , \qquad \forall t, n, a \tag{4.4}$$

with S_a, the daily number of starts for appliances of type a, fs_a, the portions of actually flexible loads among potential flexible loads (depending on the consumer choices), $P_a[t]$, the average consumption profile of appliance of type a, St_a, the starting time probability of appliances of type a, $X_a[d,t]$, the optimal delay statistics, computed by the algorithm, d, the delay and $L_a[d]$, the maximum delay probability. The variable of this problem is $X_a[d,t]$.
Equations (4.2), (4.3) and (4.4) can be explained as follow:

- The total consumption is the sum of every load consumption profile convoluted with the number of start at each time step (Equation (4.2)).
- Each load has to be started before its maximum delay (Equations (4.2) and (4.3)).

Objective functions

Our goal is to shift loads in order to use as much local solar production as possible. We present different objective functions to reach this goal. The linear or quadratic objectives functions are solved with Cplex, while non-linear objectives functions are solved with the Minos solver[93]. Note that the constraints of the problem are linear, and that all the objectives described below are convex. There is therefore no problem of resolution here. The following subsections present those functions.

Sum of squares: This is a classical objective which gives priority to minimizing the maximum flow. This is interesting because it allows to use smaller transformers between the grid and the neighborhood.

$$F = \sum_{t=1}^{n_{period}} \Big(C_{non-flex}[t] + C_{flex}[t] - P[t]\Big)^2 \tag{4.5}$$

Sum of absolute values: This objective minimizes the total daily energy flow between the neighborhood and the grid.

$$F = \sum_{t=1}^{n_{period}} \Big|C_{non-flex}[t] + C_{flex}[t] - P[t]\Big| \tag{4.6}$$

Reduced interval: The two first objectives are applied equally at every time of the day. This is not a problem for the sum of absolute values objective as it tends to shift load from the period with no production to the period with more production than consumption. This can however be a problem for the sum of squares objective as it does not necessarily shift loads to the production period; it tends to shift loads from peak consumption to low consumption which is not necessarily taking place during the production period (see Figure 4.6; loads are shifted from peak hour at 8pm to the night low consumption period around 4am). With those new objective functions, we try to minimize flows only during the solar production period to avoid that problem.

$$F = \sum_{t=t_{startProd}}^{t_{endProd}} \Big(C_{non-flex}[t] + C_{flex}[t] - P[t]\Big)^2 \tag{4.7}$$

Maximum: This objective focus on the minimization of the area between the two curves when production is higher than consumption. That is to say, it minimizes the non-used solar production, which is exactly what we want.

$$F = \sum_{t=1}^{n_{period}} \max\Big(\Big(C_{non-flex}[t] + C_{flex}[t] - P[t]\Big), 0\Big) \tag{4.8}$$

Maximum squared: This objective gives priority to minimizing the maximum flow during the production period.

$$F = \sum_{t=1}^{n_{period}} \max\Big(\Big(C_{non-flex}[t] + C_{flex}[t] - P[t]\Big)^2, 0\Big) \tag{4.9}$$

4.4 System impact evaluation

In this section, we study two different scenarios of emissions for the physical implementation of the previously presented algorithm in a 800 houses neighborhood: in the first scenario, the delay statistics are sent to every shiftable load which is therefore able to take its own decision based on those statistics. In the second scenario, the delay statistics are stored at the central server; each shiftable load send starting request to the central server which takes a decision and send the corresponding delay to each load.

As a comparison, the total impact of an average Belgian household is 4800 [kWh/year] · 0.22 [kgCO2e/kWh]=1056 [kgCO2e/year]. The average system parameters are given in Table 4.1.

System parameters			
Number of smart meters	1/house	Number of smart plugs	3/house
Smart meter consumption	5.5W		$+4/house_{monitored}$
Smart meter production	77.5 kgCO2e	Smart plug consumption	0.85W
System lifetime	5 years	Smart plug production	18 kgCO2e

Table 4.1: Reference system parameters.

We study the effect of the variation of those parameters in Section 4.6.

4.4.1 Scenario 1: delay statistics communication

In this scenario, we consider that the optimization algorithm is run on a central server and that its results are communicated to each shiftable load which is therefore able to take its own decisions based on the statistics it locally stores. The total consumption is the sum of the central server consumption, the communication consumption, and the smart meters and smart plugs consumption.

Central server

As the algorithm we consider is not very computational intensive, we consider that other applications can be run on the same server. Only part of the production and the standby consumption are therefore allocated to the DSM infrastructures as explained in Section 2.5. Table 4.2 presents the parameters and resulting emissions of the algorithm execution on the Intel Xeon X5650 processor whose specifications are given in Section 2.4.1. The factor used to get the total server consumption (with cooling, power supply, etc) is 7.25 (see Section 2.4.1).

	Parameters	Consumption [kWh/year]	Production [kgCO2e]	Total emissions [kgCO2e/year]
Central server	Execution time: 93.4 s Number of executions: 1/day Load factor: 0.16 Consumption factor: 7.25 Lifetime: 2 years	43.93	2.78	11.05

Table 4.2: Central server emissions due to use-phase and production phase.

Communication

The communication is divided into three part: the production forecast communication to the server, the consumption statistics communication to the server and the resulting statistic communication from the server to the smart plugs. Only the transmission consumption is presented here, the receiving mode consumption is included into the smart meter and smart plugs consumption. All communications are included in this section: mobile, access and backbone network along with the local communication of smart plugs and smart meters.

<u>Production forecast:</u> The shifting algorithm uses a production forecast curve to determine the shifting statistics. Depending on the precision of this curve, the communication consumption varies. We consider that each production data varies from 0W to 200W with a precision of 1%. In that case, each point of the curve is coded on 15 bits. The granularity of the prediction

also plays a role in the communication requirements. For day-ahead predictions, a one hour granularity is standard, [94]. Just like in the previous chapter, we also take the header of 132 bytes into account. This results in a daily communication of 1416 bits, which translates into a yearly consumption of 5.2^{-5}kWh and production emissions of 1.23^{-6} kgCO2e if we consider that those communication go through the mobile network and the internet backbone. This is further reduced if the communication is sent through a Wifi or DSL access. Compared to the previously presented server consumption, the impact of this communication is negligible.

Consumption statistics: As previously explained, the algorithm is based on the consumption statistics. To get those statistics we consider that a representative portion of the neighborhood sends its statistics to the server. This portion of the neighborhood needs to install more smart plugs, to monitor the consumption of every significant load. Lets assume that those statistics are send daily over a wifi access network and the internet backbone network. We consider that 10% of the households send daily data including date (7bytes), number of use of monitored devices (number of loads x 5bits), start times (number of use x 11 bits), maximum delay (number of uses x 11bits), consumption curves (number of loads x 96 x 17bits). The number of uses information concerns user-action devices and shiftable devices including microwave, kettle, dishwasher, dryer, washing machine, oven and hotplate. Four more smart plugs are then necessary for the statistics monitoring. The average number of start of all those devices together is considered to be 5/day. The base consumption and fridge, freezer, lighting, water heater auxiliary and pump and vacuum consumption are monitored by the smart meter and assembled in one unique consumption curve. Table 4.3 summarizes the communication requirements, and Table 4.4 shows the resulting consumption. This consumption only takes into account the data transmission. The emissions due to production and base consumption of additional smart plugs is given in the Subsection *smart plugs and smart meters*.

Case 1: Communication requirement			
Number of use	5 start/house	Header length	132 bytes
Message length	14.9kbits/device	MTU	1280 bytes
Total message length (per house): 17kbits/day			

Table 4.3: Consumption statistics communication requirements.

	Parameters	Consumption [kWh/year]	Production [kgCO2e]	Total emissions [kgCO2e/year]
Consumption statistics communication	Monitored houses: 10% Additional smart plugs: 4 /house Com: 17kbits/house/day	0.023	0.0003	0.0052

Table 4.4: Consumption statistics communication requirements.

Delay statistics: In this scenario, the delay statistics resulting from the optimization are sent to every shiftable load (3/house). Each shiftable load has to receive a P(P+1)(P+1) matrix [95] with the delay probability by time step, for each starting time and each maximum delay. Table 4.5 details the communication requirement. Table 4.6 shows the resulting consumption and emissions due to the delay statistics communication. As for the consumption statistics, those results only take into account the data transmission consumption.

Case 1: Communication requirement			
Amount of data	$P(P+1)(P+1)$	Header length	132 bytes
Data range	0-1	Number of time periods	96
Data precision	0.01%	Data coding	15bit/data
Message length	13.6Mbits/device	MTU	1280 bytes
Total message length (per shiftable device): 15.1Mbits/day			

Table 4.5: Delay statistics communication requirement.

	Parameters	Consumption [kWh/year]	Production [kgCO2e]	Total emissions [kgCO2e/year]
Delay statistics communication	Com: 15.1Mbits/device/day Devices: 3/houses	208.1	2.82	46.4

Table 4.6: Delay statistics communication consumption.

Smart plugs and smart meters

The additional consumption due to smart plus and smart meters includes the consumption of sensing and processing systems considered to be constant as explained in Section 2.2, the receiving consumption of communication modules and the consumption of additional local memory.

	Parameters	Consumption [kWh/year]	Production [kgCO2e]	Total emissions [kgCO2e/year]
Delay statistics communication	Smart meters: 1/house	41525.7	62000	21535.6
	Smart plugs: 3/house	19863.6	43200	13010
	+ $4/house_{monitored}$	2648.5	5760	1734.7
	Additional memory	5.8	96.0	20.5

Table 4.7: Smart plugs and smart meters production and consumption.

4.4.2 Scenario 2: bidirectional communication

In this scenario, we consider that the optimization algorithm is run on a central server and that its results are stored on the same central server. Each load communicates its type, starting time and maximum delay, and receives a delay command from the central server. The central server consumption stays the same, but no additional local memory is needed, and the communication is reduced.

Communication

The production forecast and consumption statistics communication requirements stay the same as in the previous scenario. The communication with the devices, however, is smaller. Each shiftable device sends its starting time (11bits) and maximum delay (11bits), and the central server responds with the delay the shiftable load has to apply (15bits). Table 4.8 details de communication requirements for this scenario, and Table 4.9 shows the resulting consumption and emissions.

Case 1: Communication requirement			
Message length	22bits/shiftable device	Header length	132 bytes
Response length	15bits/shiftable device	Number of messages	1.4/house/day
Total number of bits (per house): 3kbits/day			

Table 4.8: Delay statistics communication requirement - Scenario 2.

	Parameters	Consumption [kWh/year]	Production [kgCO2e]	Total emissions [kgCO2e/year]
Delay communication	Com: 3kbits/house/day	0.041	0.00056	0.0092

Table 4.9: Delay statistics communication consumption - Scenario 2.

4.4.3 Scenarios comparison

Table 4.10 shows the results for the two scenarios. We see that the difference between those two scenarios is small, and that most of the emissions are due to smart meter and smart plugs constant consumption and their production. Due to the low data rate, the receiving mode of smart plugs and smart meters are responsible for most of the communication consumption. This consumption can be reduced by using duty cycling. Table 4.11 shows the new results while considering a duty cycle of 5% and an average number of resent of 5. We can also consider that smart meters are already deploying for remote billing and other applications. Therefore, smart meter production and constant consumption can be removed from the assessment. The additional communication is still taken into account.

Scenarios 1 and 2 without duty cycling				
	Scenario 1		Scenario 2	
	Consumption [kWh/year]	Total emissions [kgCO2e/year]	Consumption [kWh/year]	Total emissions [kgCO2e/year]
Central server	43.93	11.05	43.93	11.05
Communication				
Tx	208.123	46.4	0.064	0.0144
Smart plug Rx	4650.9	1023.2	4650.9	1023.2
Smart meter Rx	2981.7	656.0	2981.7	656.0
Constant and production				
Smart plug	17858.9	13010	17858.9	13010
Smart meter	38544	20879	38544	20879
Additional memory	5.82	20.48	0	0
Total	64295.7	36360.5	64081.8	36291.4
Total per house	80.37	45.45	80.10	45.36
Tota w\o smart meter	22770	14824.8	22556.1	14755.7
Total per house	28.46	18.53	28.19	18.45

Table 4.10: Consumption of scenario 1 and 2 without duty cycling. Smart meters are responsible for more than half of the emissions. If they are already installed for another application, it can be considered that the only additional consumption due to the shifting algorithm is the communication consumption.

Figure 4.7, shows the repartition of emissions due to production and consumption.

Scenarios 1 and 2 with duty cycling				
	Scenario 1		Scenario 2	
	Consumption [kWh/year]	Total emissions [kgCO2e/year]	Consumption [kWh/year]	Total emissions [kgCO2e/year]
Central server	43.93	11.05	43.93	11.05
Communication				
Tx	214.14	47.7	0.067	0.0147
Smart plug Rx	265.8	58.5	265.8	58.5
Smart meter Rx	2350.5	517.1	2350.5	517.1
Constant and production				
Smart plug	20133.8	14221.4	20133.8	14221.4
Smart meter	38544	20879	38544	20879
Additional memory	5.82	20.48	0	0
Total	61527.2	35751.4	61304.9	35680.5
Total per house	76.9	44.68	76.63	44.63
Tota w\o smart meter	20632.6	14354.6	20410.3	14283.7
Total per house	25.79	17.94	25.51	17.85

Table 4.11: Consumption of scenario 1 and 2 with duty cycling. The consumption is reduced by 9% in the case without smart meters, and by 4% when taking the smart meter into account.

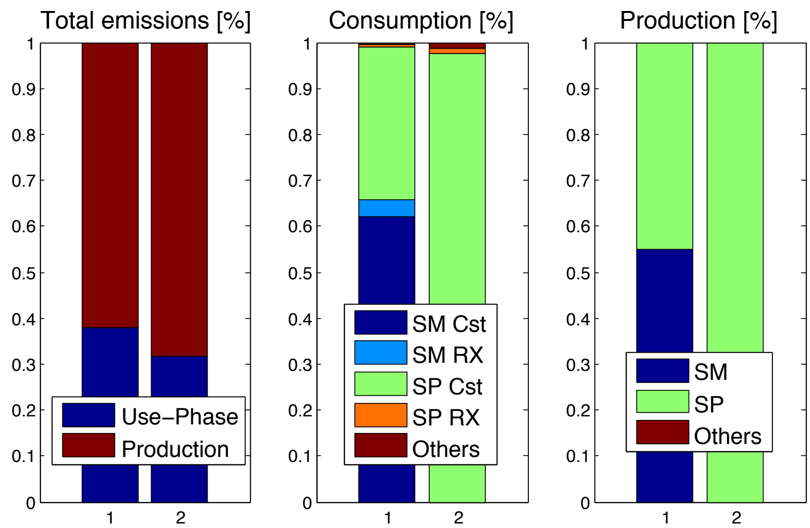


Figure 4.7: Repartition of emissions for first scenarios with (1) and without (2) smart meter. The category Others includes the transmitting consumption, the server and the additional memory. The smart plug constant consumption represents between 33 and 97% of the total consumption, while the *others* represent between 0.5 and 1.3%. The smart plug also generates between 45 and 99.8% of the production emissions.

4.5 System savings evaluation

In this section, we study the saving potential of the previously described algorithm. We define the savings as the additional renewable energy consumed locally instead of taking it from the grid. We therefore compute the difference between the local renewable energy consumed without the load shifting infrastructure and the local renewable energy consumed with it. We translate those results into kgCO2e savings using results from Figure 1.3; solar energy produces around 0.1 kgCO2e/kWh while the Belgian average GWP is 0.22kgCO2e/kWh. Every additional kWh consumed from local solar production therefore generates 0.22-0.1=0.12kgCO2e savings.
Every simulation is run over 31 days and the resulting means and standard deviations are presented. The standard parameters used during the simulations are given in Table 4.12, unless expressly stated otherwise.

Standard simulation parameters			
Time step	15 min	Number of houses	800
Number of solar panels	10/house	Number of wind turbines	0
Type of day	Yearly average	Month	March
Objective function	Sum of squares	Forecast granularity	15min
Consumption statistic error	0%	Production forecast error	0 %
Portion of shiftable	30%, 30%, 60% [1]		

Table 4.12: Standard simulation parameters used in this chapter.

In the system impact evaluation, we considered 3 smart plugs installed per house. However, we consider here that only part of the potentially shiftable loads (dryers, washing machines and dish washer) are actually shiftable. From the use statistics of [89] and the portion of shiftable loads considered in Table 4.12, we estimate that only 1 smart plug is needed per house. We observe the impact of the number of smart plugs installed in Section 4.6
Due to the use of a statistical model to generate consumption curves, the results can vary between two simulations with the same parameters. We run the algorithm 10 times with the same production profile and the parameters given here above. We observe savings varying between 7.8 and 10.3 with a mean of 8.6 and a standard deviation of 0.7.

4.5.1 Seasonal variations

As both production and consumption profiles vary with the season, we expect that the saving potential of the algorithm also varies along the year. Table 4.13 gives the mean and standard deviation of four simulated months: March, June, October and December. Figure 4.8 shows the 4 observations along with the interpolation of the mean and standard deviation evolution. We observe that savings are higher during summer than during winter. This can easily be explained: as shown in Figure 4.9, production is lower and consumption is higher during winter, resulting in less opportunities for savings.
Considering the interpolated function, the average saving is around 7.67kgCO2e/day with a standard deviation of 3.35kgCO2e/day. In the following sections, we do not observe results for every season, we take March as the reference month and we apply a correction factor of 0.956, based on the previous results, to estimate the yearly average savings.

[1] 30% of dryers, 30% of washing machines and 60% of dish washers.

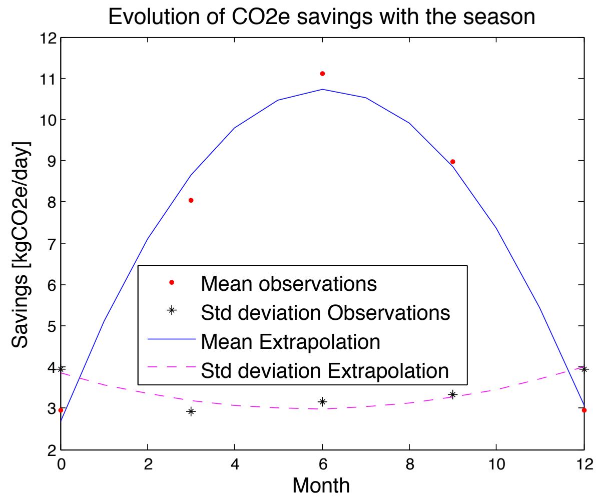


Figure 4.8: CO2e savings variation with the season. The interpolation functions equations for mean and standard deviation are respectively: $y = 2.68 + 2.64x - 0.22x^2$ and $3.84 - 0.30x + 0.026x^2$.

Month	kgCO2e savings		kWh savings	
	μ	σ	μ	σ
March	8.02	3.95	66.87	24.23
June	11.11	2.91	92.57	26.27
October	8.97	3.15	74.76	27.71
December	2.93	3.95	24.48	32.95

Table 4.13: Season - Results.

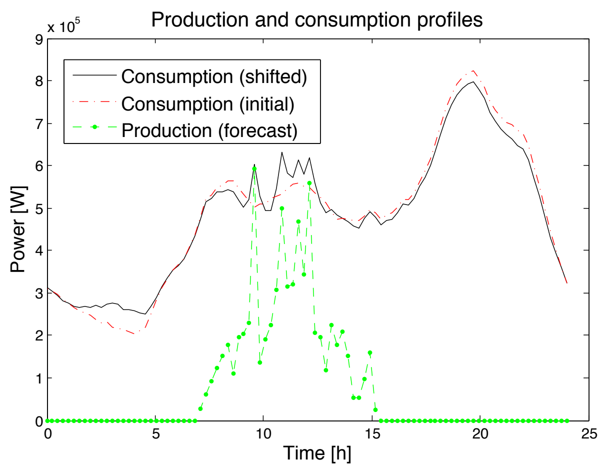


Figure 4.9: Winter consumption and production curves. As the production is most of the time lower than the consumption, the shifting algorithm does not produce a lot of additional savings.

4.5.2 Weekly variations

As explained in Section 4.1, the consumption curve varies with the type of day. We observe here the impact it has on the savings. This simulation was run with 500 houses. Table 4.14 presents the simulation results with 500 houses and the scaled results for 800 houses.

Day type	kgCO2e savings 500 houses		kgCO2e savings 800 houses		kWh savings 500 houses	
	μ	σ	μ	σ	μ	σ
Weekday	4.66	1.83	7.46	2.93	38.83	15.27
Saturday	6.44	2.75	10.30	4.40	53.67	22.91
Sunday	7.49	3.09	11.98	4.94	62.43	25.76
Mean	5.24	2.17	8.38	3.47	43.73	18.12

Table 4.14: Type of day - Daily savings.

As the number of start of shiftable loads is higher during weekends, the savings are also higher. Indeed, the algorithm is able to shift more loads, resulting in higher savings. We observe that the mean day we use in our simulations is representative of the weekly savings: $\mu_{mean} = (5 \cdot 4.66 + 6.44 + 7.49)/7 = 5.32$, $\sigma_{mean} = (5 \cdot 1.83 + 2.75 + 3.09)/7 = 2.14$; the weekly average saving is very similar to the mean day type saving.
We also observe the difference in savings for each type of day if we use the mean statistics rather than specific day type statistics. Table 4.15 presents the resulting savings.

Day type	kgCO2e savings 500 houses		kgCO2e savings 800 houses		Difference 800 houses
	μ	σ	μ	σ	μ
Weekday	4.90	1.85	7.84	2.96	+0.38
Saturday	5.90	2.78	9.44	4.44	-0.86
Sunday	6.41	2.45	10.26	3.92	-1.72

Table 4.15: Type of day - Savings generated for each type of day when using mean day statistics.

The better results for weekdays is probably due to the variability of the results as explained earlier. The use of average statistics does not impact significantly the weekday savings. It does however impact the weekend savings, resulting in a decrease of 8 to 15% of weekend savings which represents around 144kgCO2e savings per year (around 5% of the estimated yearly savings). This means that while mean day is representative of the weekly average savings, it is still important to use proper day type consumption statistics in a real-system, to maximize savings.

4.5.3 Variation of the number of houses

Figure 4.10 shows the evolution of the savings with the number of houses, and Table 4.16 gives the mean and standard deviation for each observation. The savings increase linearly with the number of houses. The intercept of the estimated mean line is non-null which is only due to the statistical variation of the results, but it should be null.

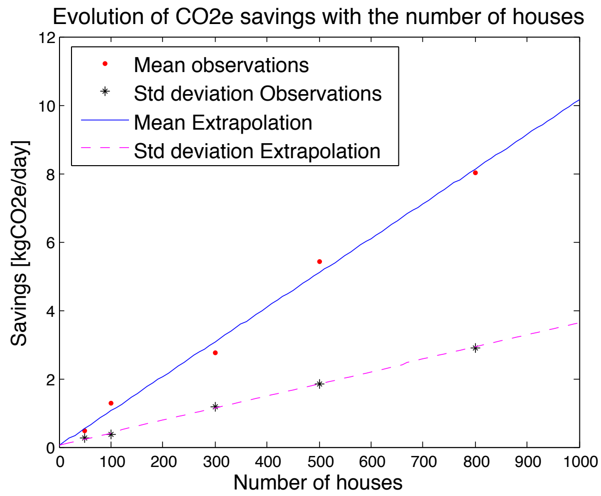


Figure 4.10: CO2e savings variation with the number of houses. The savings increase linearly with the number of houses. The equations of mean and standard deviation evolution are respectively: $y = 0.0466 + 0.0101x$ and $y = 0.0629 + 0.0036x$.

Number of houses	kgCO2e savings		kWh savings	
	μ	σ	μ	σ
50	0.47	0.26	3.94	2.16
100	1.30	0.37	10.81	3.05
300	2.74	1.18	22.81	9.86
500	5.42	1.85	45.15	15.41
800	8.2	2.91	66.87	24.23

Table 4.16: Number of houses - Results.

4.5.4 Estimated yearly savings

From the previous results, we can estimate the yearly saving to $7.67 \cdot 365 = 2799.55[kgCO2e]$ or 3.50[kgCO2e/house]. This is a lot smaller than the estimated emissions of the system even in the more optimistic scenario of 17.85[kgCO2e/house] emissions, which is more than 5 times bigger than the expected yearly savings. In the next section, we study the variation of both savings and emissions with different parameters.

4.6 Parameters sensitivity analysis for emissions and savings

In this section, we study the impact of parameters variation on both savings and emissions. The goal is to determine whether there are some conditions more favorable which would induce more savings than emissions. Appendix J presents additional results for the system emissions variations.

4.6.1 Effect of system parameters

In this section, we observe the effect of two parameters on the system emissions: the portion of monitored houses and the GWP of the electricity production. Figure 4.11 shows the evolution of emissions with those two parameters. We also present the variation of savings with the GWP. The precision of consumption statistical data used in the algorithm should increase with the number of monitored houses. But without additional data, we can not evaluate the evolution of savings with the portion of monitored houses. We briefly address the effect of error in consumption data on the savings in Sections 4.6.8 and 4.6.9.

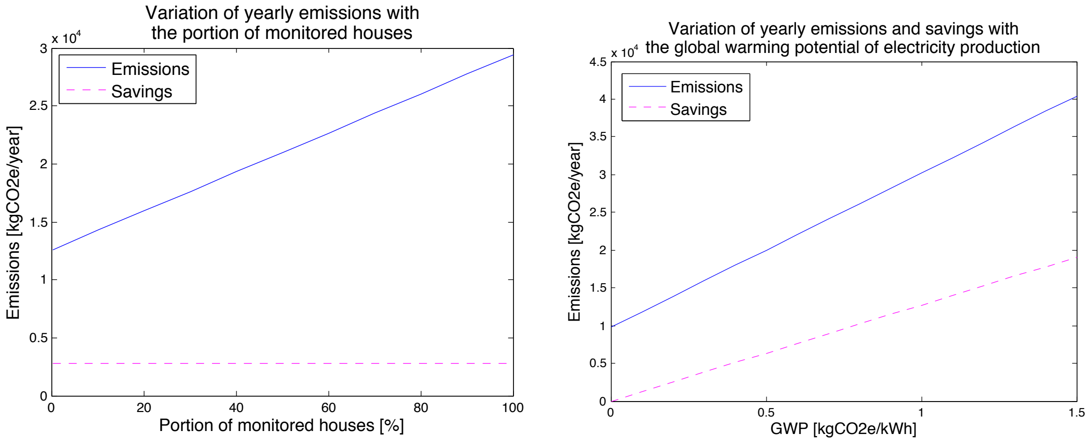


Figure 4.11: Variation of emissions with the portion of monitored houses and with the local GWP. It is considered here that the GWP of solar production stays the same: 0.1kgCO2e/kWh Without additional information, we can not evaluate the variation of the savings with the portion of monitored houses.

The emissions increase more rapidly with the GWP than the savings of the system. Depending on the number of smart plugs per houses, the slope of the emissions variation with the GWP varies. Appendix J presents interesting results for systems with 1 and 2 plugs per house. Due to the additional smart plugs needed in monitored houses, the portion of monitored house also has a big impact on the emissions of the system.

4.6.2 Effect of the smart plugs parameters

Figure 4.12 shows the evolution of the emissions with the number of smart plugs installed per house. 1 smart plug per house corresponds to the case in which only the shiftable loads are equipped with a smart plug. Figure 4.13 shows the effect of four other parameters on the system emissions: the lifetime of smart plugs, the number of additional smart plugs in monitored houses, the smart plug production emission and the smart plug consumption.

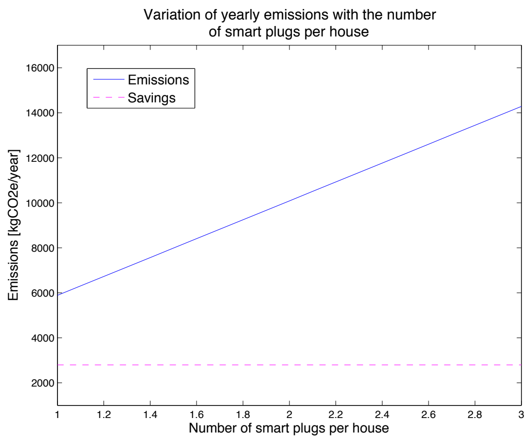


Figure 4.12: Emissions variation with the number of smart plugs per house. 1 smart plug per house corresponds to the case in which only the portion of shiftable loads is equipped with smart plugs. 3 smart plugs per houses is the other extreme case in which every house installs 3 smart plugs even if the consumer decides to not allow shifting delays.

In every case of Figues 4.12 and 4.13, the emissions are higher than the expected savings. Figure 4.14 shows various emissions curves with different association of parameters. We observe

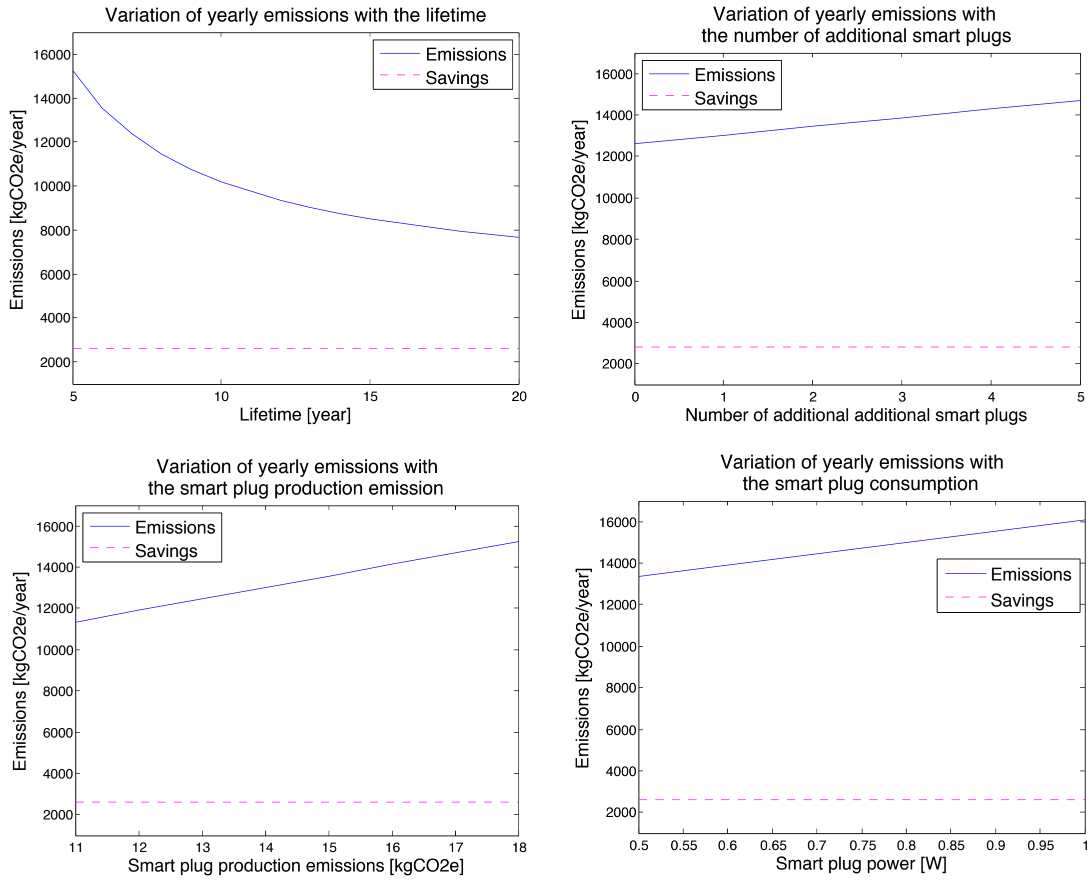


Figure 4.13: System emissions variation with 4 parameters (from upper left to lower right): the lifetime of the smart plugs and additional memory, the number of additional smart plugs in monitored houses, the smart plugs production emissions and the smart plug consumption.

that for short lifetime, the production emission is predominant as the red curve with higher emissions but smaller consumption present higher impact. But when the lifetime is longer, the consumption becomes more important than the production emissions. For a lifetime of around 10 years, the light blue curve with higher consumption and smaller production emissions becomes higher.

Different observations can be pointed out from Figure 4.14. It is important to install the right number of smart plugs. Installing smart plugs to every appliances, even when the consumer does not accept to shift it, leads to emissions which are much higher than the expected savings. The lifetime of the system also has a significant impact on the total emissions of the system. The additional smart plugs needed to monitor every appliance in 10% of the houses also generate significant emissions. Monitoring the house consumption globally instead of using device specific smart plugs would significantly reduce emissions. With the right set of parameters, the load shifting algorithm seems to be able to generate significant savings. More combinations of parameters are presented in Appendix J. The following sections observe the effect of different parameters on the expected savings of the system.

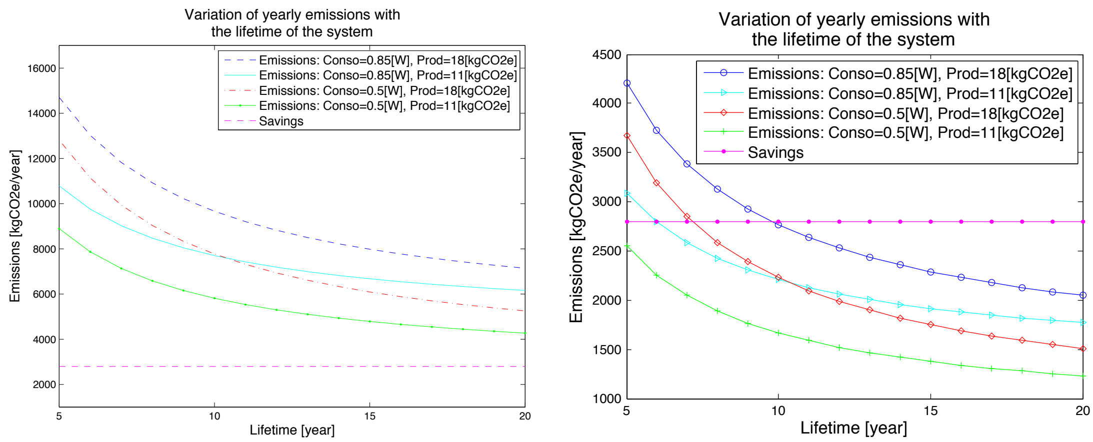


Figure 4.14: System emissions variation. Left: 3 smart plugs per houses and 4 additional smart plugs per monitored house. Right: 1 smart plug per house and no additional plug in monitored houses. The lifetime of the system plays a significant role in yearly emissions. If the number of smart plugs is limited to the bare minimum, savings can be expected from the system.

4.6.3 Effect of the objective function

The objective functions tested in this section have been explained in Section 4.3.1. Figure 4.15 shows the results for four objective functions: the least squares, the sum of absolute values, the maximum and the maximum squared. The results are then presented in Table 4.17 with two additional objectives: the least squares and sum of absolute values applied during the solar production period.

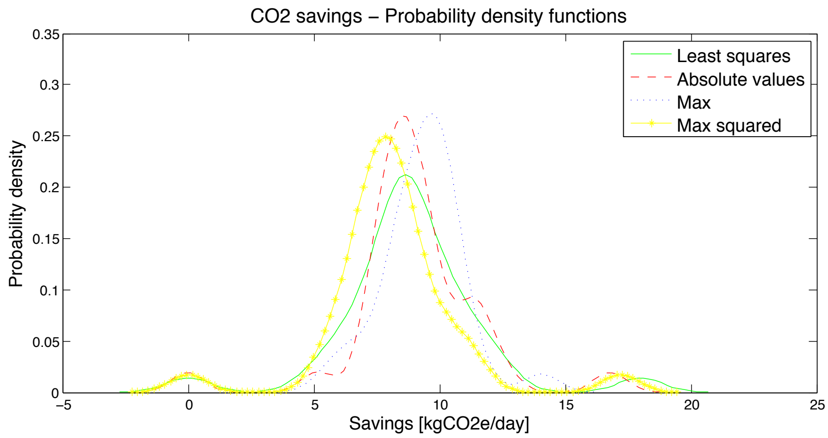


Figure 4.15: CO2e savings for various objective functions. The max and absolute value objectives seem to generate higher savings than the other objectives.

In terms of savings, the max objective is the best one with the sum of absolute values, but both objectives are very close to the least square objective. We expected a bigger difference between the least square objective and the two other: absolute value and max. Those results are due to the maximum delays imposed to shiftable load. This prevent the Max and absolute value objectives to shift evening load to the next day production period. The average maximum flow reduction, however, is much higher for the least square objective and the max squared objective. We also observe in Figure 4.15 that the savings probability density functions are not normally distributed; they are therefore not completely characterized by their mean and standard deviation. However, we consider that those two values are still useful and can give a good idea of the quality of the results. Table 4.17 also shows the execution time for each objective. The 34.5 additional seconds needed for the Max objective compared with the least

Objective	kgCO2e savings (daily)		kWh shifted (daily)		Maximum flow reduction (%)		Execution time
	μ	σ	μ	σ	μ	σ	[sec]
Least squares	8.81	2.86	73.43	23.86	5.31	0.98	103.23
Absolute values	8.99	2.65	74.90	22.10	1.91	0.55	125.92
Least squares 2	7.37	2.59	61.46	21.63	-1.25	1.96	92.23
Absolute values 2	7.38	3.38	61.48	28.16	-3.24	5.13	123.48
Max	9.04	2.29	75.33	19.12	2.03	0.71	137.7
Max squared	8.20	2.63	67.76	21.95	5.41	0.87	140.17

Table 4.17: Objective functions - Results.

square objective leads to 0.0055 extra kgCO2e/day. As the additional savings are higher than this value, the increasing time is worth it.

4.6.4 Effect of the time step

Figure 4.16 shows the evolution of the daily savings with the time step. Table 4.18 shows the results for each simulated time step along with the execution time. Both savings and execution time increase rapidly when the timestep decreases.

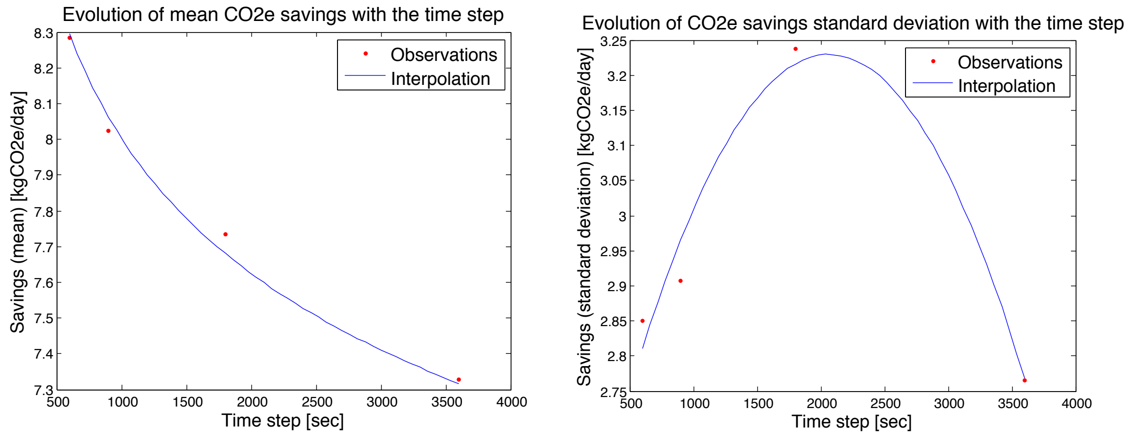


Figure 4.16: 1) Mean CO2e savings variation with the time step (right). The interpolation equation is : $y = 12.98x^{-0.07}$. 2) CO2e savings standard deviation variation with the time step (left). The interpolation equation is : $y = 2.40 + 0.0008x - 2 \cdot 10^{-7}x^2$.

Timestep (sec)	kgCO2e savings (daily)		kWh shifted (daily)		Execution time
	μ	σ	μ	σ	[sec]
600	8.28	2.84	69.03	23.75	338.9
900	8.02	2.90	66.87	24.23	103.5
1800	7.74	3.23	64.46	26.98	12.7
3600	7.33	2.76	61.06	23.05	1.5

Table 4.18: Timesteps - Results

The system consumption should also increase when reducing the time step for two reasons: the processing time increases and the size of the message to send to smart plugs increases as well (scenario 1). Figure 4.17 shows the evolution of additional emissions and savings with the time step, compared to the reference case of 900sec. We observe that in the scenario 1, emissions increase much faster than the savings. The time step which maximize the difference between savings and emissions in thise scenario is 13min30. In the second scenario, the communication does not increase with the diminution od the time step. Emissions of the system do not increase as fast as in the first scenario. In thise case, the best time step is found to be 2min30.

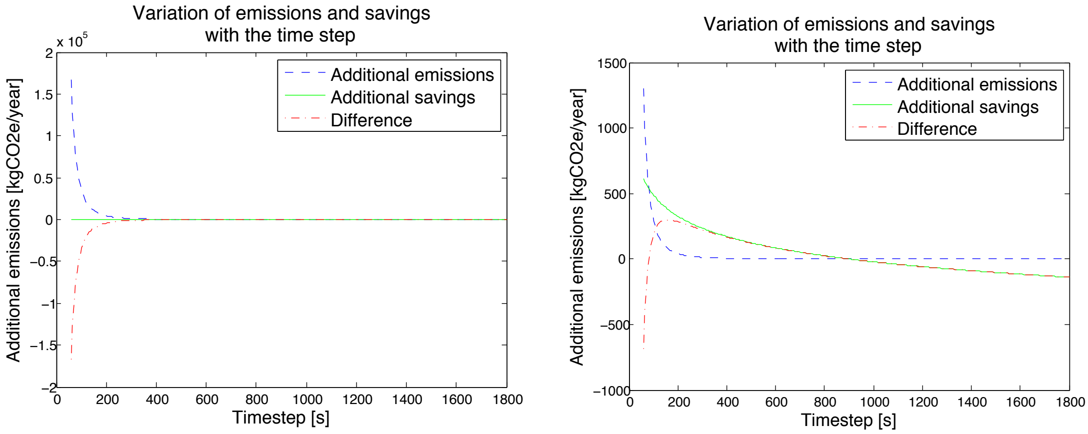


Figure 4.17: Additional emissions and savings compared to the 15minutes time step. 1) Scenario 1: the additional emissions overstep by far the additional savings due to a shorter time step. The time step generating the smaller losses is at 13min30. 2) Scenario 2: the additional emissions are only caused by the execution time of the algorithm. The optimal time step is at 2min30.

4.6.5 Effect of the number of solar panels per houses

Figure 4.18 shows the savings variation with the number of solar panels per house. We observe that savings increase with the number of solar panels per houses. The low savings for a small number of solar panels is due to low production which is therefore already consumed and does not give lots of opportunities for additional savings with a DSM infrastructure. This is the same effect as for the winter low savings, see Figure 4.9. For higher numbers of solar panels, the savings reach a limit due to the limited number of shiftable loads. Table 4.19 gives the mean and standard deviation for every observation.

Number of solar panels	kgCO2e savings		kWh savings	
	μ	σ	μ	σ
5	4.77	3.68	39.75	30.71
10	8.02	2.91	66.87	24.23
15	9.48	2.62	78.98	21.80
20	9.59	2.24	79.88	18.65
25	10.54	1.98	84.84	16.49

Table 4.19: Number of solar panels per houses - Results.

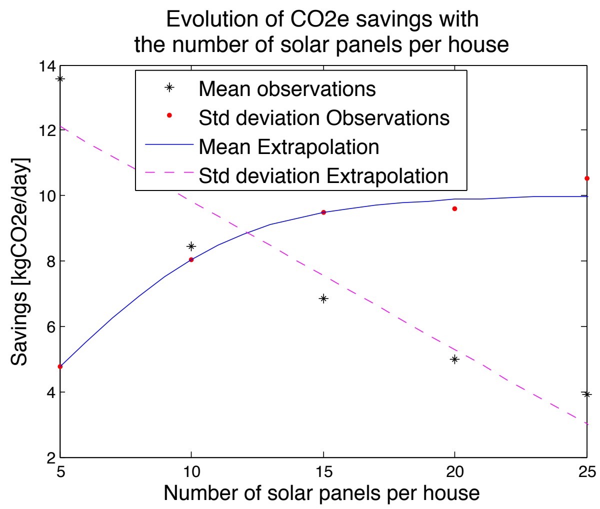
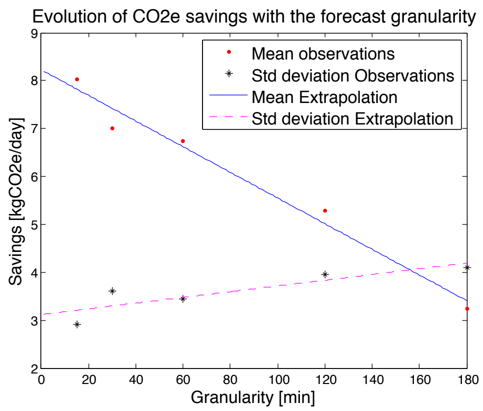


Figure 4.18: CO2e savings variation with the number of solar panels per house. The equations for mean savings and standard deviation are: $y = \frac{10}{1+exp(-0.3(x-5.3))}$ and $y = 14.4 - 0.46x$.

4.6.6 Effect of production forecast granularity

Figure 4.19 shows the savings variation with the granularity of production forecast. As explained in Section 4.4.1, for day-ahead predictions, a one hour granularity is standard, [94]. This leads to a reduction of expected savings from around 8 kgCO2e/day to around 6.7 kgCO2e/day. This represents a reduction of more than 16%, and leads to a reduction of around 452kgCO2e/year. The savings are here bounded by technical limits which does not, for now, allow to have day-ahead precise forecasts with low granularity (minute or second). Table 4.20 shows the mean and standard deviation of simulation results.



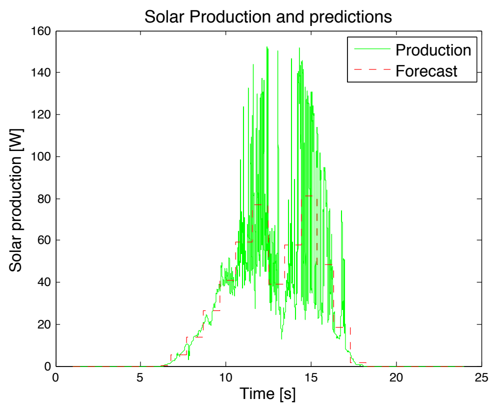


Figure 4.19: Right: CO2 savings variation with the production forecast granularity. The mean savings decrease with the time step as: y= 8.23-0.03x. The standard deviation, on the other hand, increases with the time step as y=3.12+0.006x. Left: example of prediction curve with a granularity of 60 minutes.

Granularity $[min]$	kgCO2e savings		kWh savings	
	μ	σ	μ	σ
15	8.02	2.91	66.87	24.23
30	7.01	3.60	58.38	30.02
60	6.73	3.44	56.10	28.68
120	5.28	3.96	44.03	32.97
180	3.24	4.10	27.02	34.13

Table 4.20: Granularity of production forecast - Results.

4.6.7 Effect of production forecast error

For this parameter, we present the savings for both the *least squares objective* and the *max objective*. Figure 4.20 shows the variation of savings with the production forecast error. The incorrect production curve is produced by applying an error to the each point of the curve. The applied error is the same for all points, the form of the incorrect production curve stays therefore similar to the real form, changing only in magnitude. We observe that the least square objective is not very sensitive to forecast errors in magnitude. Indeed, because of the square, the least square tends to favor the solution where the difference between production and consumption curves is as constant as possible. Least square objective is therefore more sensitive to production form error than to magnitude error. This can be observed in Figure 4.21, which shows that even if the production is underestimated, the loads are still shifted during production period. The least square mean savings extrapolation is a 3rd degree function which predicts better results with errors between 40 and 50 % than without error. This is of course not true, in reality we observe very similar savings between 0 and 50% error. As for the max objective, it is much more sensitive to the magnitude of the production forecast curve. This is an interesting results, as it shows that even if the max objective seems to have better results in Section 4.6.3, this higher sensitivity to production forecast error can lead to smaller savings in real conditions.

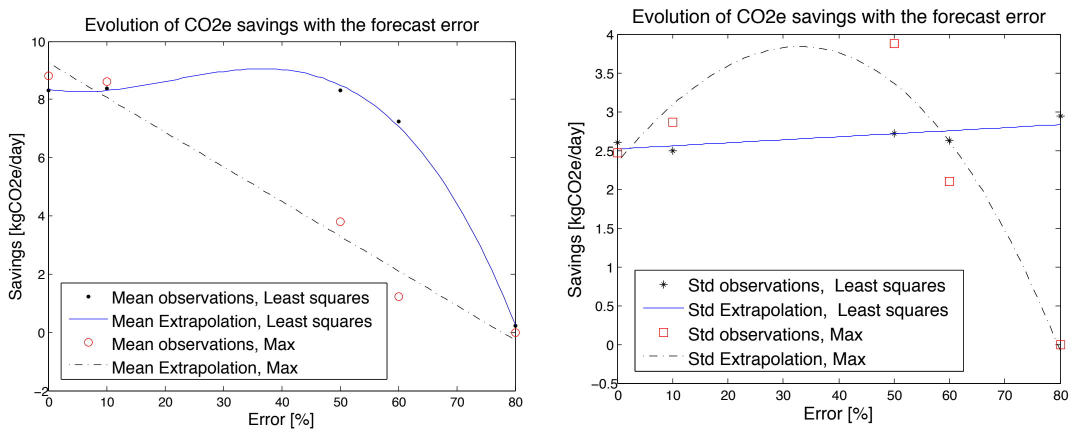


Figure 4.20: CO2 savings variation with the production forecast error. The max objective savings is more sensitive to production magnitude error than the least square objective. The least square mean interpolated equation is $y = 8.35 - 0.032x + 0.0033x^2 - 0.0001x^3$ and the max mean interpolates equation is $y = 9.25 - 0.12x$.

Table 4.21 gives the results for every simulation represented in Figure 4.20. The forecast error described here is not representative of every types of error that can be observed in day-ahead forecast. To have more representative results, we should test the model with real prediction and production curves. This is not done in this work.

	Objective: least squares				Objective: Max			
Forecast Error [%]	kgCO2e savings		kWh savings		kgCO2e savings		kWh savings	
	μ	σ	μ	σ	μ	σ	μ	σ
0	8.31	2.60	69.22	21.69	8.82	2.47	73.48	20.57
10	8.38	2.49	69.88	20.79	8.60	2.86	71.69	23.87
50	8.32	2.72	69.32	22.63	3.80	3.87	31.70	32.29
60	7.24	2.62	60.32	21.87	1.23	2.10	10.24	17.50
80	0.21	2.93	17.62	24.45	0	0	0	0

Table 4.21: Production forecast error - Results. The Max objective is much more sensitive to production forecast error than the least square.

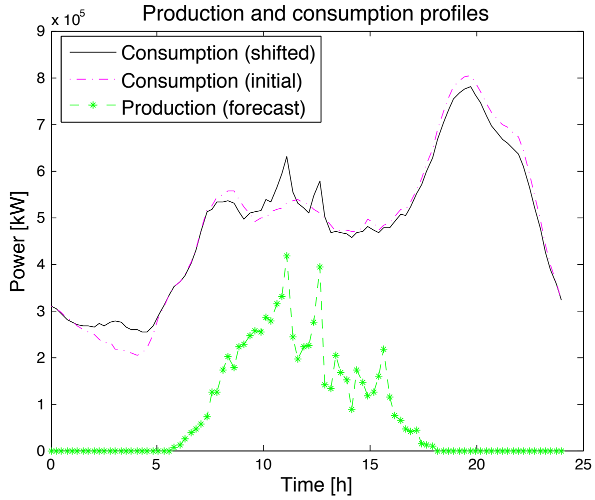


Figure 4.21: Production and consumption curves. This figure shows that even when the production curve is underestimated, it still causes load to be shifted at the right moment. This means that if the production is higher than expected, savings will be observed thanks to the shifting.

4.6.8 Effect of the number of starts error

As for the production forecast error, the least square objective is not very sensitive to the number of load starts error as long as the starting times are correct. Figure 4.22 shows the evolution of the savings with the error on the number of starts. Table 4.22 shows the results for each executed simulation.

Error [%]	kgCO2e savings		kWh savings	
	μ	σ	μ	σ
0	8.31	2.60	69.22	21.69
10	8.32	2.99	69.30	24.89
20	8.13	3.24	67.75	27.03
40	7.80	2.92	64.50	24.37
60	7.74	2.89	64.47	24.05

Table 4.22: Consumption statistics error - Results.

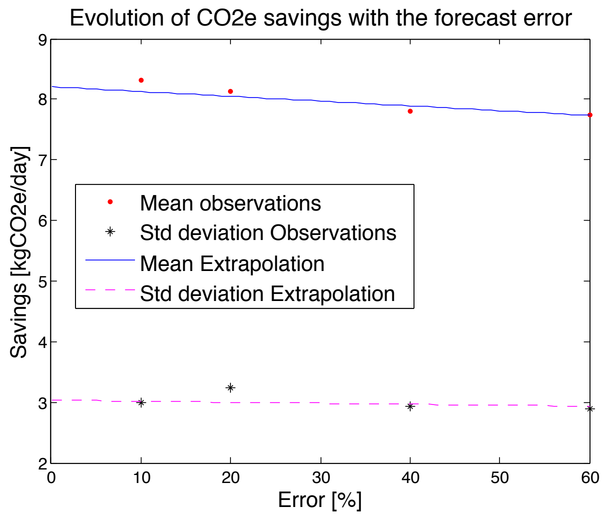


Figure 4.22: Variation of savings with the number of load starts prediction error. The objective is not very sensitive to that parameter. The mean savings interpolated function is given by y=8.21-0.0079x, and the standard deviation equation is given by y=3.03-0.0016x.

4.6.9 Effect of the load starting time error

We observe here the effect of an error in the starting time statistics for the different types of loads. The wrong starting time statistics are obtained by shifting the real starting time curves. The effect is similar for both least squares and max objectives, although a bit less severe in the max case. Figure 4.23 shows the evolution of the savings for both objectives, and Table 4.23 shows the results for executed simulations.

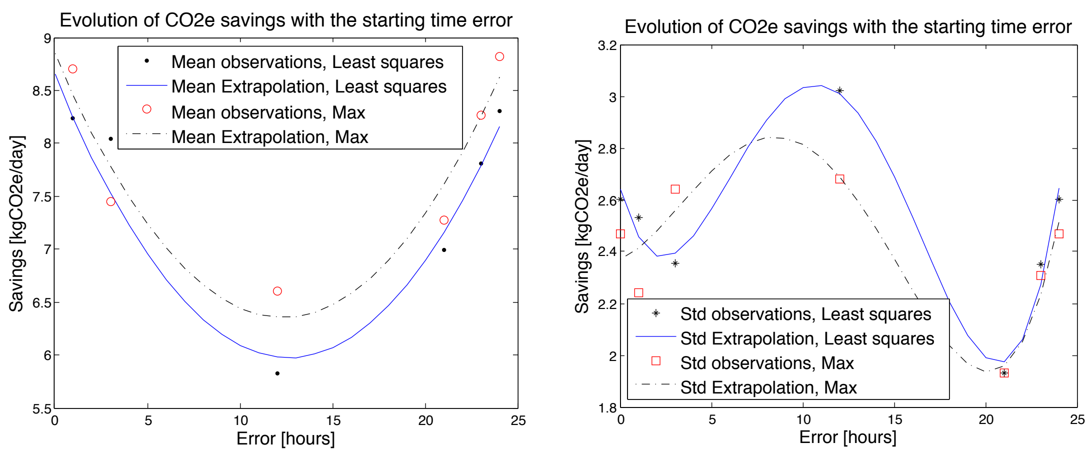


Figure 4.23: Variation of savings with the error in time of consumption forecast. Left: mean values. Right: standard deviation values. The effect is a bit less sever for Max objective. Equation of interpolated mean savings are: $y = 8.65 - 0.43x^2 + 0.017x^3$ for the least square and $y = 8.85 - 0.41x^2 + 0.0165x^3$ for the max objective.

The effect of the starting time error is bigger than the effect of the number of starts error for the least square objective. This is due to the same reason as for the production forecast error; this objective is more sensitive to the form of both production and consumption curves than to their magnitude.

Forecast Error [%]	Objective: least squares kgCO2e savings		kWh savings		Objective: Max kgCO2e savings		kWh savings	
	μ	σ	μ	σ	μ	σ	μ	σ
0	8.31	2.60	73.48	20.57	8.82	2.47	73.48	20.57
1	8.24	2.53	72.54	18.66	8.71	2.24	72.54	18.66
3	8.05	2.35	62.11	22.01	7.45	2.64	62.11	22.01
12	5.82	3.02	55.06	22.34	6.6	2.68	55.06	22.34
21	7.00	2.35	60.59	16.09	7.3	1.93	60.59	16.09
23	8.31	2.60	68.89	19.25	8.27	2.31	68.90	19.24

Table 4.23: Consumption starting time error - Results.

4.6.10 Effect of the portion of shiftable

Finally, the portion of shiftable loads depends on the consumers choices. We observe here the increase in savings due to the increase of portion of shiftable loads. When 100% of dish washers, washings machines and dryers are controllable, the savings go up to 18.4kgCO2e/day in March which traduces into 6447kgCO2e/year. This could lead to absolute savings if the system is chosen wisely. Figure 4.24 shows the evolution of savings with the portion of shiftable load, and Table 4.24 gives the results for each observation point.

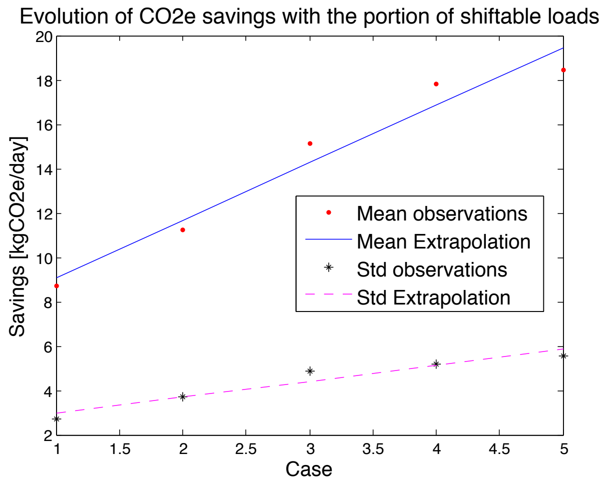


Figure 4.24: Savings variation with the portion of shiftable loads.

Case	Portion of shiftable loads [%]			kgCO2e savings		kWh savings	
	Dryer	Washing machine	Dish washer	μ	σ	μ	σ
1	30	30	60	8.72	2.72	72.63	22.64
2	50	50	70	11.24	3.7	93.67	30.84
3	70	70	90	15.15	4.87	126.28	40.54
4	90	90	100	17.82	5.18	148.53	43.16
5	100	100	100	18.43	5.58	153.55	46.9

Table 4.24: Portion of shiftable load - Results.

4.6.11 Test with wind production

We test here the shifting algorithm with the wind production curves from [88]. The GWP of wind production in Belgium is estimated to be 0.012kgCO2e/kWh [10]. Figure 4.25 shows the saving potential in the month of March depending on the number of wind turbines in the neighborhood. Table 4.25 gives the results for each simulated point. The maximum savings is higher than with the solar production. This is due to two factors: the GWP of wind production is lower than the GWP of solar production; and wind production can take place the whole day. This means that loads with a small maximum delay can still be shifted to renewable production period.

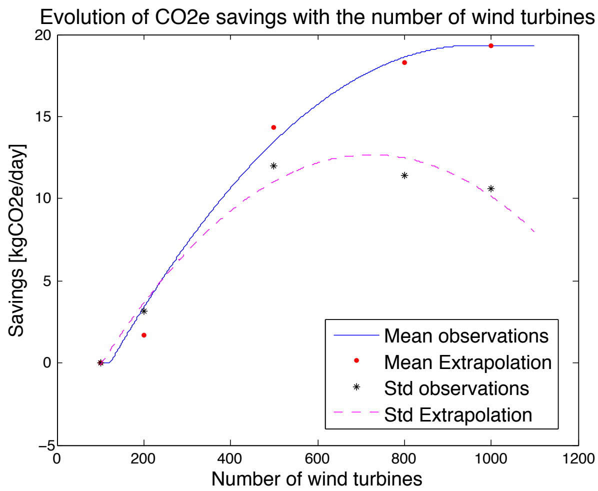


Figure 4.25: Savings variation with the number of wind turbines in the neighborhood. The expected savings are higher than for solar production due to the lower GWP of wind generation. The standard deviation is also higher than with the solar production.

number of wind turbines	kgCO2e savings		kWh savings	
	μ	σ	μ	σ
100	0.006	0.036	0.03	0.17
200	1.70	3.15	8.18	15.13
500	14.35	11.96	68.91	57.46
800	18.29	11.43	87.83	54.89
1000	19.33	10.61	92.83	50.95

Table 4.25: Number of wind turbines - Results.

From the discussion here above, it may seem that wind is the perfect solution to increase the savings of the load shifting algorithm. This is not necessarily true for one main reason: wind generation is more difficult to predict than solar production. This is a big issue for the described algorithm.

It would be interesting to test the saving potential with various generation mix of solar and wind in the neighborhood. This is not done in this work.

4.6.12 Summary

Many parameters have an influence on the system emissions and savings. Figures 4.26 and 4.27 shows savings and emissions for different set of parameters. More results are presented in Appendix J.

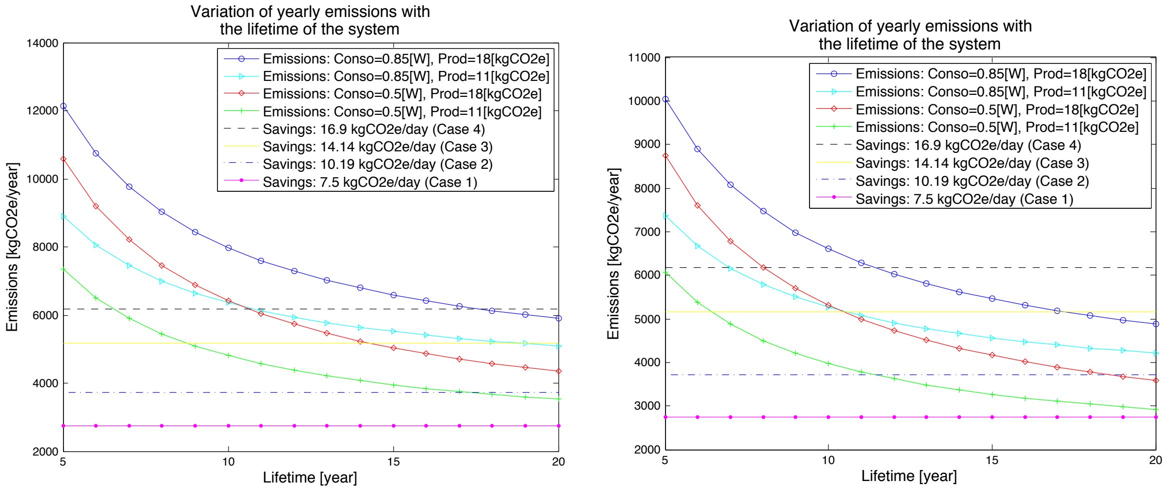


Figure 4.26: System emissions and savings variation with 2.39 plugs per house and with 4 (left) and 0 (right) additional plugs in monitored houses. The 4 saving scenarios are detailed in Table 4.26.

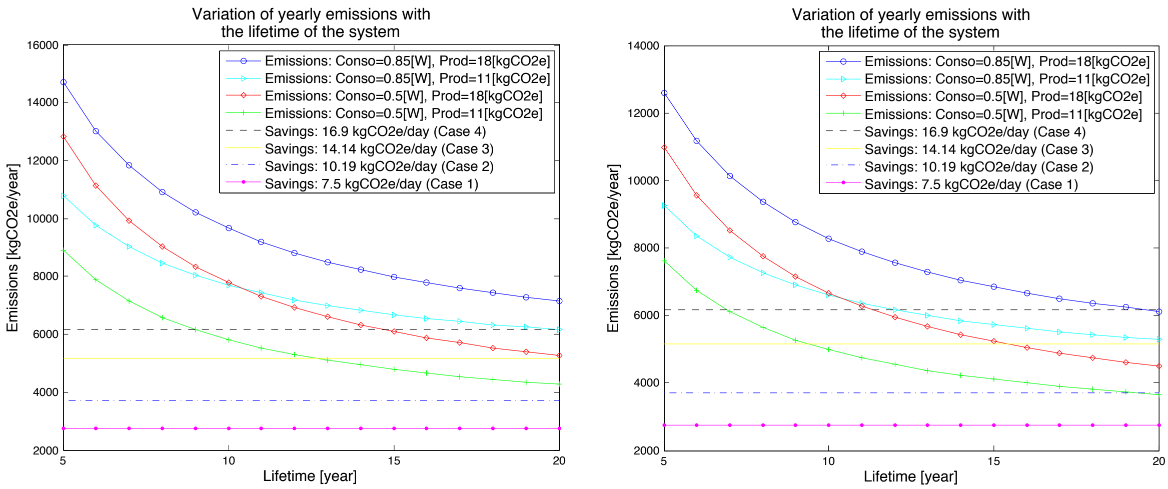


Figure 4.27: System emissions and savings variation with 3 plugs per house and with 4 (left) and 0 (right) additional plugs in monitored houses. The 4 saving scenarios are detailed in Table 4.26.

Table 4.26 gives the parameters of the 4 saving scenarios represented in Figures 4.26 and 4.27. From those figures, we can point out different observation:

- It is crucial to limit the number of smart plugs to the bare minimum. Only shiftable loads should be equipped with smart plugs.
- The lifetime of the equipment is important as it helps reducing the yearly emissions.

[2]The number of smart plug per house is calculated based on possession statistics and portion of shiftable loads. The total number of smart plugs in the neighborhood is an integer.

	Case 1	Case 2	Case 3	Case 4
Objective	Least squares			
Timestep [min]	30	30	15	15
Number of solar panels	20	20	20	20
Forecast granularity [min]	60	60	60	60
Forecast error [%]	15	15	15	15
Consumption statistic error [%]	20	20	20	20
Consumption time error [min]	15	15	15	15
Portion of shiftable [%]	30,30,60	50,50,70	70,70,90	100,100,100
Number of smart plugs per house [2]	1	1.385	1.864	2.39
Savings [kgCO2e/day]	7.5	10.19	14.14	16.9

Table 4.26: Saving scenarios.

- It is also important to pay attention to the consumption and production emissions of the smart plugs in order to minimize the emissions.

Table 4.27 shows yearly emissions and savings results along with the absolute savings and the $kgCO2e_{saved}/kgCO2e_{emitted}$ factor. Depending on the system parameters, the absolute savings can me positive or negative. Appendix J gives further details about the different sets of parameters.

Yearly emissions and savings			
Total emissions [kgCO2e/house]	1.54 to 15.18	Savings [kgCO2e/house]	3.42 to 7.71
Absolute savings [kgCO2e/house]	-7.46 to 4.06	$kgCO2e_{saved}/kgCO2e_{emitted}$	0.43 to 2.26

Table 4.27: Load shifting algorithm - Results.

Finally, Figure 4.28 show the saving factors for the 4 savings cases presented in Table 4.26. Three emissions scenarios are presented. The only scenario able to generate absolute savings is the scenario with the minimum number of smart plugs in all houses and no additional smart plugs in monitored houses.

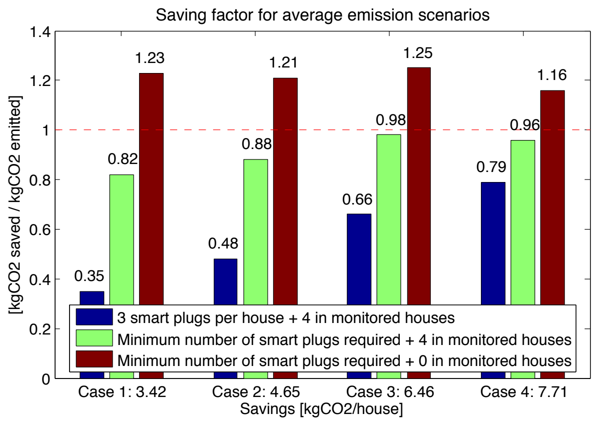


Figure 4.28: Saving factor for average system emissions. System parameters: 10 years lifetime, 0.5W power consumption and 18kgCO2e production emissions. This average system has a positive absolute savings when the minimum number of smart plugs are installed in houses and monitored houses.

4.7 Conclusion

In this chapter, we presented a load shifting algorithm along with the production and consumption curve models it uses. We estimated the savings and emissions with defined parameters and we observed the sensitivity of those results to different parameters. The savings are bounded by technical limitations: the granularity of the day-ahead production forecast, the production forecast error and the consumption statistics in number and time of use. Some other parameters are adjustable to maximize the savings: the time step, the number of solar panels per house, the production mix and the portion of shiftable load. The number of solar panels per house and the portion of shiftable load depends on the consumer decisions, but could be partially controllable with some incentives. The emissions of the system also depend on various parameters: the number of smart plugs, their consumption, their production emissions and their lifetime.

We conclude that it is very important to limit the number of smart plugs installed to the bare minimum. It is also important to give incentives to the consumers to maximize the portion of shiftable loads amongst the installed smart plugs. As for the previous chapter, the communication consumption is small compared to the constant consumption and to the production emissions of the system. However, we observed that for the emissions scenario 1, communication can become much higher if the time step is small.

To complete this study, other tests could be conducted. First, various renewable energy mixes could be tested to see of we can increase the savings. And secondly, it would be interesting to run the algorithm with real day-ahead prediction curves to see the impact of real production and consumption forecast errors.

Conclusion

This work was divided in 4 chapters. In Chapter 1, we gave an overview of technologies involved in smart grids deployment and briefly described some typical applications of smart grids. We also addressed the subject of ICT impact assessment and reviewed some papers on that subject.
Chapter 2 presented a model of DSM infrastructure impact assessment. Use-phase and production emissions were addressed for each part of the infrastructure: terminals, communication and processing units. We already observed in that chapter that smart plugs and smart meters constant consumption and their production emissions were likely to represent most of the system impacts. A more detailed analysis of the terminal's base consumption influencing factors would be very interesting to complete this chapter.
In Chapter 3, we used the model of Chapter 2 to analyze 4 consumption monitoring systems: the global consumption monitoring which only displays the global consumption of the house, the device-specific monitoring which displays the global consumption along with the consumption of specific devices, and two static pricing systems (global and device-specific). We observed that the emissions due to communication were small compared to the production and constant consumption of smart meters and smart plugs emissions. We also observed that depending on the system parameters and on the consumers behaviors, the monitoring systems could lead to absolute savings or not.
Finally, in Chapter 4, we studied the emissions and savings potential of a load shifting algorithm and performed a sensitivity analysis on different parameters. Again, we observed that depending on the consumer behavior and on the system parameters, the implementation of the load shifting algorithm could lead to absolute savings. To go deeper into the analyze of the saving potential of the load shifting algorithm, we could test it in real conditions, with real day-ahead production and consumption forecast curves. This would allow to have a better idea of the real performances of the algorithm.

From those results, we conclude that a DSM infrastructure needs various factors to successfully generate CO2e savings:

- consumers with high elasticity to outside signals, typically the consumption price.
- Loads with sufficient reduction potential or shifting potential. As smart plugs are a great source of emissions, they must be installed to loads which reduction potential is higher.
- The availability of reliable informations about the production impacts and the consumption of devices such as smart plugs and smart meters. This would allow to choose the best fitted device with the lowest emissions.

In this work, we focused on residential DSM. But from those conclusions, we believe that industrial DSM could have a higher emissions reduction potential.
This work is based on many assumptions and simplifications, resulting in a wide range of uncertainty for all the studied systems. To reduce this range of uncertainty, it would be interesting to study a real system whose consumption a mitigation impacts could be measured with more precision.
Smart grid impact assessment is a vast subject which still need to be analyzed in more details. This work only scratches the surface of the subject and many other studies could be conducted: the communication requirements for storage systems to anticipate the production and consumption variations; the power quality management communication requirement, micro grid infrastructure impacts, etc.

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Appendix A

Smart grid communications - Review

The objective of this appendix is to give a review of the communication systems available for the development of smart grids along with their main characteristics, advantages and consumption. The network structure needs depend on various criterions: latency, bandwidth, range, price, consumption, possible interferences, scalability, security, etc. The final choice will depend on the application type, needs and its possible future developments.

A.1 Local network

According to Saponara and Bacchillone in [96], HANs architecture consists in four main elements:

- *Smart endpoints, such as smart meters, displays, refrigerators, appliances, and thermostats.*
- *The access points or network nodes composing the HAN network.*
- *A network operating system and a network management software.*
- *A gateway that connects the HAN network to the outside information services, in the LAN or WAN network.*

Gateways are not always useful, some local networks are self-sufficient. Various standards have been developed for HANs. Some of them are presented in the table hereafter. Other standards are available such as: X10, 6LoWPAN, EnOcean, UWB, etc (see [97]).

Technology	Characteristics	Advantages	Disadvantages	Comments
Wi-Fi	11Mbps, 1-100m (range), 0.3usec (latency)	High transmission rate, secure	High consumption, sensitive to interferences	Source: [98]
Zigbee	250kbps, 10-100m (range), 30msec (latency)	Low consumption, secure, reliable, cost	Low transmission rate	Source: [98]
Bluetooth	1Mbps, 10m (range), 18-21usec (latency)	Low consumption	Short range	Source: [98]
Z-Wave	200kbps, 30-100m (range)	Low consumption, no interference with Wi-Fi networks	Low transmission rate	Source: [96] Zensys Corp

Wavenis	100kbps, 200-1000m (range)	Low consumption, no interference with Wi-Fi networks	Low transmission rate	Source: [96] Coronis System
HomePlug (PLC)	14Mbps, 1-3km (range)	Preexistent infrastructure, wide coverage	Losses, noise, interferences, etc.	Source: [98] Homeplug Alliance
Insteon (PLC)	38.4kbps, 45m (range)	Low consumption, Preexistent infrastructure	Low transmission rate, Losses, noise, etc.	Source: [96] SmartLab Inc

A.2 Access network

Access networks are long range wired or wireless networks. Access networks are usually connected to each other through a backbone network. However, the technologies presented hereafter can also be used as self-sufficient neighborhood area network (NAN), without transmitting to a backbone network.

Technology	Characteristics	Advantages	Disadvantages	Comments
3G	2Mbps, 1- 10km (range)	Bandwidth, security, reliability	High costs, High power consumption	Source: [99]
4G - LTE	75Mbps, 1.4-5-30km (range)	Speed, High data rate	Not widespread yet, power consumption, high cost	Source: [100]
WiMax	1-75Mbps, up to 1-5 km	Low latency, low costs	Not widespread yet, power consumption	Source: [99]
PLC	14Mbps, 1-3km (range)	Preexistent infrastructure	Losses, noise, interferences, etc.	Source: [98] G3-PLC Alliance
UNB	100bps, up to 15km (range)	Low consumption, wide coverage, low cost	Ultra-low data rate, mainly unidirectional communications	Sources: [101] & [102]
DSL	256kbps-100Mbps, 300m (range)	High bandwidth, security	Low range (from DSLAM)	Source [103]
Optical fiber	26Tbps, 50km (range)	High speed, large distances, broad bandwidth	High cost	Source: [104]

A.3 Backbone network

The objective of the backbone network is to route information from one point to another, possibly in different regions and connected to different access networks. The backbone network mainly consists in switches and routers communicating with each other through wired or wireless technologies. Optical fibers are usually used in backbone networks (internet backbone for example) due to their low losses over long distances, low interferences, and broad bandwidth. Various routing algorithms and backbone infrastructure are possible. This subjects will not be developed here.

A.4 Power consumption

The consumption of those communication technologies varies with the application. It is very difficult to precisely model the telecommunication consumption. This section will present results from various authors in order to get an insight of the subject.

A.4.1 Access networks

Figure A.1 shows the results of Vereecken et al. in [105]. Those results take into account the DSLAMs for wired transmission and base stations for wireless communication, but they do not include the home gateways (e.g. Modem). In this graph, core represents what we called earlier the backbone network, the HSPA is the 3G technology and GPON is an optical fiber network (point-to-multipoint). The consumption is expressed per subscriber (3Mb/s).

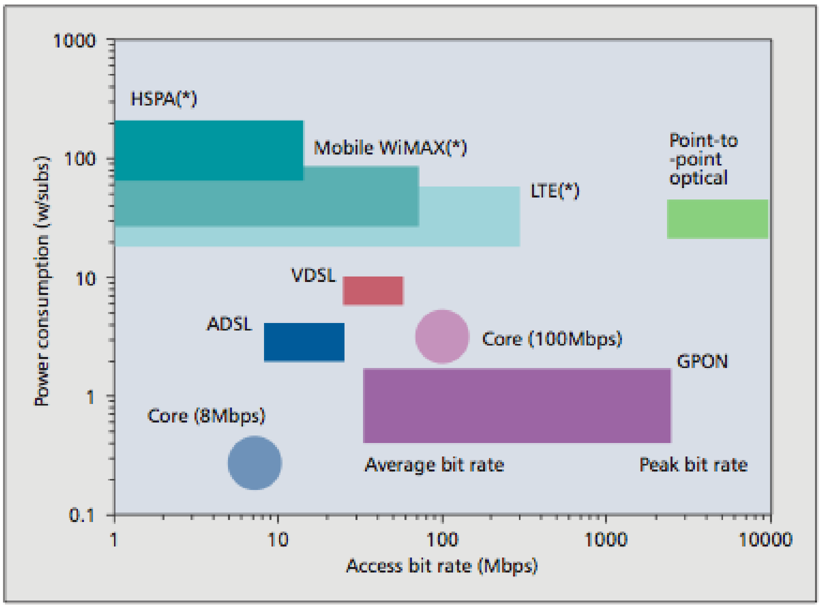

Figure A.1: Consumption of several access network technologies [105]

In [106], Baliga et al. develop a model of the power consumption per user in a telecommunication network:

$$P = \frac{2P_{TU}}{M_{TU}} + \frac{2P_{RN}}{M_{RN}} + P_{CPE}$$

where P_{CPE} is the power consumed by the customer equipment (i.e. modem), P_{RN} is the power consumption of the remote node (i.e. DSLAM), M_{RN} is the number of users sharing the remote node, P_{TU} is the power consumption of the terminal unit (i.e. provider central office) and M_{TU} is the number of users sharing the terminal unit. The factor 2 in the first and second terms is an overhead that takes into account additonal consumption such as cooling and power supply consumption, [106]. Their results are shown in figure A.2.

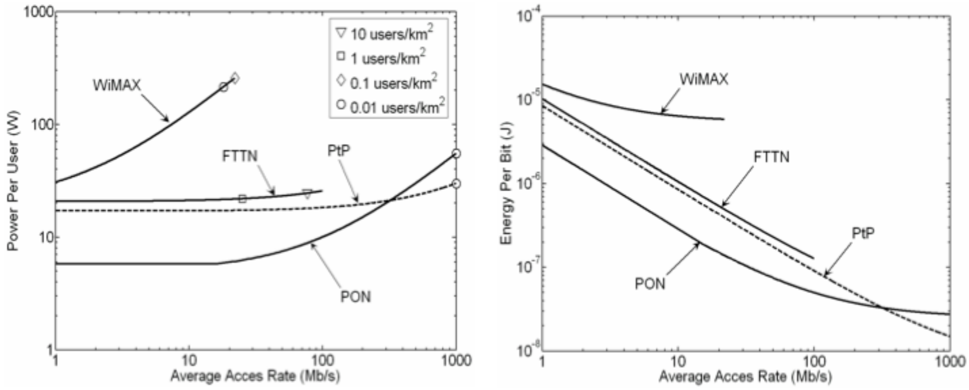

Figure A.2: Consumption of several access network [106] - PON: Passive Optical Network, FTTN: Fiber to the Node, PtP: Point-to-Point Optical Access Network

FFTN uses optical fibers to connect central office to the remote node which is then connected to customers by good-quality copper-pairs. PON is entirely made of optical fibers from the central office to the remote node and to the customer. Finally PtP is also entirely made of optical fibers, but directly connects the customer to the central office, allowing a higher data rate to the customer.

A.4.2 Local networks

The European code of conduct for broadband equipment [107] sets the power consumption targets for various communication technologies. Figure A.3 shows the power targets for home gateway central functions plus WAN interface and figure A.4 shows the targets for LAN interfaces.

Home gateway central functions plus WAN interface	**Tier 2011-2012:** 1.1.2011- 31.12.2012		**Tier 2013-2014:** 1.1.2013 - 31.12.2014	
	Idle-State (W)	***On-State (W)***	***Idle-State (W)***	***On-State (W)***
ADSL2plus	2,6	3,8	2,4	3,4
VDSL2 (8, 12a, 17a, but not 30a)	3,5	6,0	3,2	4,6
VDSL2 (30a)	4,2	6,7	4,7	5,3
Fast Ethernet WAN	2,5	3,3	2,0	3,0
Gigabit Ethernet WAN	3,2	6,2	2,5	5,0
FibrePtPFast Ethernet WAN	2,9	5,6	2,9	5,0
Fibre PtPGigabit Ethernet WAN	3,5	6,2	3,2	5,6
GPON	4,0	6,5	3,5	5,0
1G-EPON	3,7	5,5	3,5	4,7
10/1G-EPON	5,1	7,0	4,8	6,2
10/10G-EPON	5,6	8,8	5,3	7,7
XG-PON1	5,1	7,3	4,8	6,5
DOCSIS 2.0	3,7	4,6	3,7	4,6
DOCSIS 3.0 basic configuration	6,2	7,1	6,2	7,1
DOCSIS 3.0 additional power allowance for each additional 4 downstream channels	2,2	2,8	2,2	2,8
WiMAX	7,7	10,6	3,5	6,0
3G	4,0	7,0	3,5	6,0
LTE	4,0	7,0	3,5	6,0

Figure A.3: Power targets for home gateway central functions plus WAN interface [107]

Home gateway LAN interfaces and additional functionality	Tier 2011-2012: 1.1.2011- 31.12.2012 Idle-State (W)	Tier 2011-2012: 1.1.2011- 31.12.2012 On-State (W)	Tier 2013-2014: 1.1.2013 - 31.12.2014 Idle-State (W)	Tier 2013-2014: 1.1.2013 - 31.12.2014 On-State (W)
Powerline- High speed for broadband home networking (less than 30MHzbandwidth)	2,5	3,0	1,5	2,0
Powerline- High speed for broadband home networking (between 30 and 68 MHz bandwidth)	2,5	4,7	2,0	2,7
PowerLine - Low speed for smart metering and appliances control (Green Phy)	0,9	2,0	0,8	1,5
Bluetooth	0,2	0,3	0,1	0,3
ZigBee	0,15	0,15	0,1	0,1
Z-Wave	-	-	0,1	0,2
IEC 14543-310 ("EnOcean")	-	-	0,1	0,2
Femto cell (Home use, RF power ≤10mW)	7,0	8,0	6,0	7,0
Femto cell (Home use, RF power 10mW-50mW)	11,0	12,0	9,0	10,0

Figure A.4: Power targets for LAN interfaces [107]

A.4.3 Terminals

Terminals like phones, computers or sensor nodes must be equipped with a communication module in order to connect to a local or access network. Figure A.5 shows the consumption of such modules for various local network technologies.

Technology	Manufacturer	Part Number	Supply Voltage (V)	TX current (mA)	RX current (mA)	TX power (mW)	RX power (mW)
Zigbee	TI (Texas Instrument)	CC2420 Transceiver	3	17.4	18.8	52.2	56.4
Zigbee	TI	CC243x System on Chip (SoC)	3	25	27	75	81
Bluetooth	TI	CC2540 SoC	3	24	19.6	72	58.8
Bluetooth	Cambridge Silicon Radio	Bluecore2	1.8	57	47	102.6	84.6
Zwave	Zensys	ZW0201	3	36	23	108	69
UWB	Freescale	XS112	3.3	227	227	749.1	749.1
WiFi	Conexant	CX53112	3.3	219	215	722.7	709.5
EnOcean	EnOcean	Dolphin EO3000I	2.5	0	23	Not given	57.5
Wavenis	Coronis Systems	Wavenis SoC	3	Not given	17	Not given	51

Figure A.5: Consumption of various communication module types [97]

In [108], Huang et al. study the power consumption of 3G, 4G and Wifi in terminals. They propose the following model of consumption (see figure A.6 for quantitative datas):

$$P = \alpha_u n_{bu} + \alpha_d n_{nb} + \beta$$

with α_u, the upload power consumption depending on the data rate in mW/Mbps, n_{bu}, the upload rate in Mbps, α_d, the download power consumption depending on the data rate in mW/Mbps, n_{nb}, the download rate in Mbps and β in mW.

	α_u (mW/Mbps)	α_d (mW/Mbps)	β (mW)	α_u/α_d
LTE	438.39	51.97	1288.04	8.44
3G	868.98	122.12	817.88	7.12
WiFi	283.17	137.01	132.86	2.07

Figure A.6: Communication modules consumption for Wifi, 3G and 4G-LTE [108]

A.5 Smart grid communication requirements

The communication requirements may differ in latency, reliability and amount depending on the application. The table hereafter (figure A.7) summarizes the estimated communication requirements from the Department of energy (USA), [109]. *The DOE (Department of energy) has determined that there are six functional categories into which most, if not all, Smart Grid applications fall: advanced metering infrastructure, demand response, wide-area situational awareness, distributed energy resources and storage, electric transportation, and distribution grid management*,[109].

Application	**Network Requirements**				
	Bandwidth	**Latency**	**Reliability**	**Security**	**Backup Power**
AMI	10-100 kbps/node, 500 kbps for backhaul	2-15 sec	99-99.99%	High	Not necessary
Demand Response	14kbps- 100 kbps per node/device	500 ms- several minutes	99-99.99%	High	Not necessary
Wide Area Situational Awareness	600-1500 kbps	20 ms-200 ms	99.999-99.9999%	High	24 hour supply
Distribution Energy Resources and Storage	9.6-56 kbps	20 ms-15 sec	99-99.99%	High	1 hour
Electric Transportation	9.6-56 kbps, 100 kbps is a good target	2 sec-5 min	99-99.99%	Relatively high	Not necessary
Distribution Grid Management	9.6-100 kbps	100 ms-2 sec	99-99.999%	High	24-72 hours

Figure A.7: Communication requirements for smart grids [109]

The bandwidth requirements estimated in [109] (Figure A.7) seem high and is probably an upper bound of the real bandwidt required. In [28], Kuzlu et al. give more detailed communication reuirement estimations. Table A.3 summarizes some of their results.

Application	Typical data size (bytes)	Typical data sampling rate	Latency	Reliability
Home automation	10-100	Once every period of 1-15min	Seconds	>98%
Building automation	>100	Once every period of 1-15min	Seconds	>98%
Static pricing	100	1 per device per data 4 times a year	<1min	>98%
Demand response	100	Once per starting request	<1min	>99.5%
Distribution storage (charge/discharge command)	25	6-18 times per day	<5sec	>99.5%

Table A.3: Communication requirements for typical smart grid applications, [28].

Appendix B

Life-cycle assessment - Methodology

Life cycle assessment is a useful tool to assess environmental impacts due to the life cycle of a product. It can be used to compare the impacts of different products with the same functional unit, to assess the environmental friendliness of a given solution or to give an insight of the processes that could be improved in order to lower the environmental impact of a product, for example. It is a powerful tool if used and interpreted correctly. The goal of this appendix is to give an introduction to the LCA methodology and interpretation.

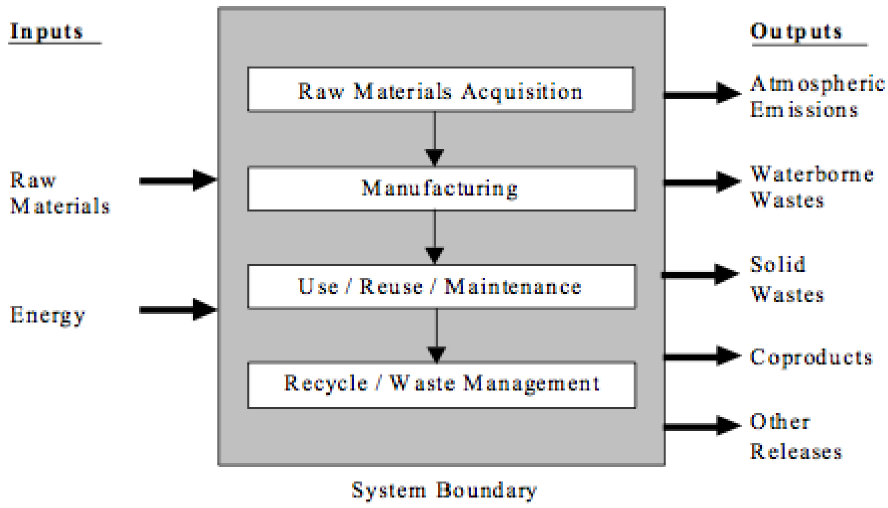

Figure B.1: Life cycle assessment - stages [110]

B.1 ISO1404 standard (2006)

The ISO1404 standards for Life Cycle Assessment describes the process of performing a LCA in 5 steps:

- the definition of the goal and scope of the LCA: during this step, the functional unit is defined in order to be able to compare the results with other LCAs of similar products. It consists in quantifying the function of the product in term of number of use or time for example. During this step, the limits of the scope are also defined. It consists in defining the steps and processes included in the different steps of the assessment: production (extraction of raw materials, transport, transformation, etc), use-phase (installation, energy consumption, maintenance, etc.) and end-of-life (recycling, incineration, wastes, etc.). Two LCAs are comparable if they have the same functional unit and scope.
- the life cycle inventory analysis (LCI) phase: it consists in defining the material and energy flows for each step of the life cycle. This step involves a huge data collection: material

composition of the devices, the exact processes during the production, the energy and material uses during each process, etc.

- the life cycle impact assessment (LCIA) phase: this steps consists in translating the inventory into different impacts such as climate change, ozone depletion, human toxicity, resource depletion, etc. The types of impacts are discussed later in this appendix.

- the interpretation phase: this step consists in interpreting the results of the previous step. As the impacts are numerous, it is not simple to decide which impacts are more important in order to compare the quality of different solutions. This is done by weighting the different impacts, to obtain a single final result. The weighting methods are discussed later in this appendix.

- the reporting and critical review of the LCA: finally, this step consists in detecting and understanding the sources of uncertainty due to hypothesis and lack or imprecision of datas. It is of great importance to realize the limits and uncertainty of the results in order to avoid hasty conclusions. Performing a sensitivity analysis of uncertain parameters may help drawing good conclusions.

In practice, various LCA tools (excel sheets or specific software) and databases are available on the internet (usually with a limited free version): ecoinvent, agri-footprint, ELCD, USLCI, GaBi,CIRAIG, SimaPro, openLCA, etc. Those tools significantly reduce the data collection effort as they include quantities of raw materials and processes datas. Some of those also offer a software or excel sheet that directly computes the impacts indicators from the described system.

B.2 Impact assessment and interpretation

The inventory results is a list of input and output flows of raw materials, emissions, energy, etc. This list is extremely difficult to interpret and understand. The idea of impact assessment is to regroup those flows into a limited number a indicators easier to understand. For the final interpretation those indicators are weighted and regrouped into fewer indicators (sometimes a unique final indicator). *It is obvious that the characterization models are a source of uncertainty: the relationships modeled reflect our incomplete and uncertain knowledge of the environmental mechanisms that are involved in climate change, acidification, etc*[111]. Figure B.2 summarizes the process of impact assessment and interpretation. Various indicators and final weighting methods are available. Figure B.3 presents commonly used impact categories and their descriptions. Some of the existing indicators are described in [112]: ReCiPe, CML-IA, Ecological scarcity 2013, EDIP 2003, IPCC 2013 etc. Some of them describe a complete set of indicators, others focus on one single effect such as cumulative energy demand, greenhouse gas emissions, ecosystem damage, etc.

B.3 Critical review of the LCA

The goal of life cycle assessment is to increase awareness of environmental impacts and to have all the information needed to take environmental friendly decisions. If the conclusions of a LCA are wrong, uncertain or not clear enough, this could lead to the opposite effect. Therefore, it is extremely important to detect, understand and clearly present the uncertainties and hypothesis of each LCA. One way to confirm, or disconfirm, a LCA result is to perform a sensitivity analysis on the most uncertain parameters. Those can be: the lifetime, energy use, production processes, etc, depending on the system analyzed. Determining break-events leading to different conclusions may help to assess the robustness of the initial conclusion. Testing different impact assessment may also be interesting. Another important thing to keep in mind is that the set of impact types is vast, and therefore one good result for a single impact doesn't mean that the solution is generally good. The priorities must be chosen depending on the context, the local

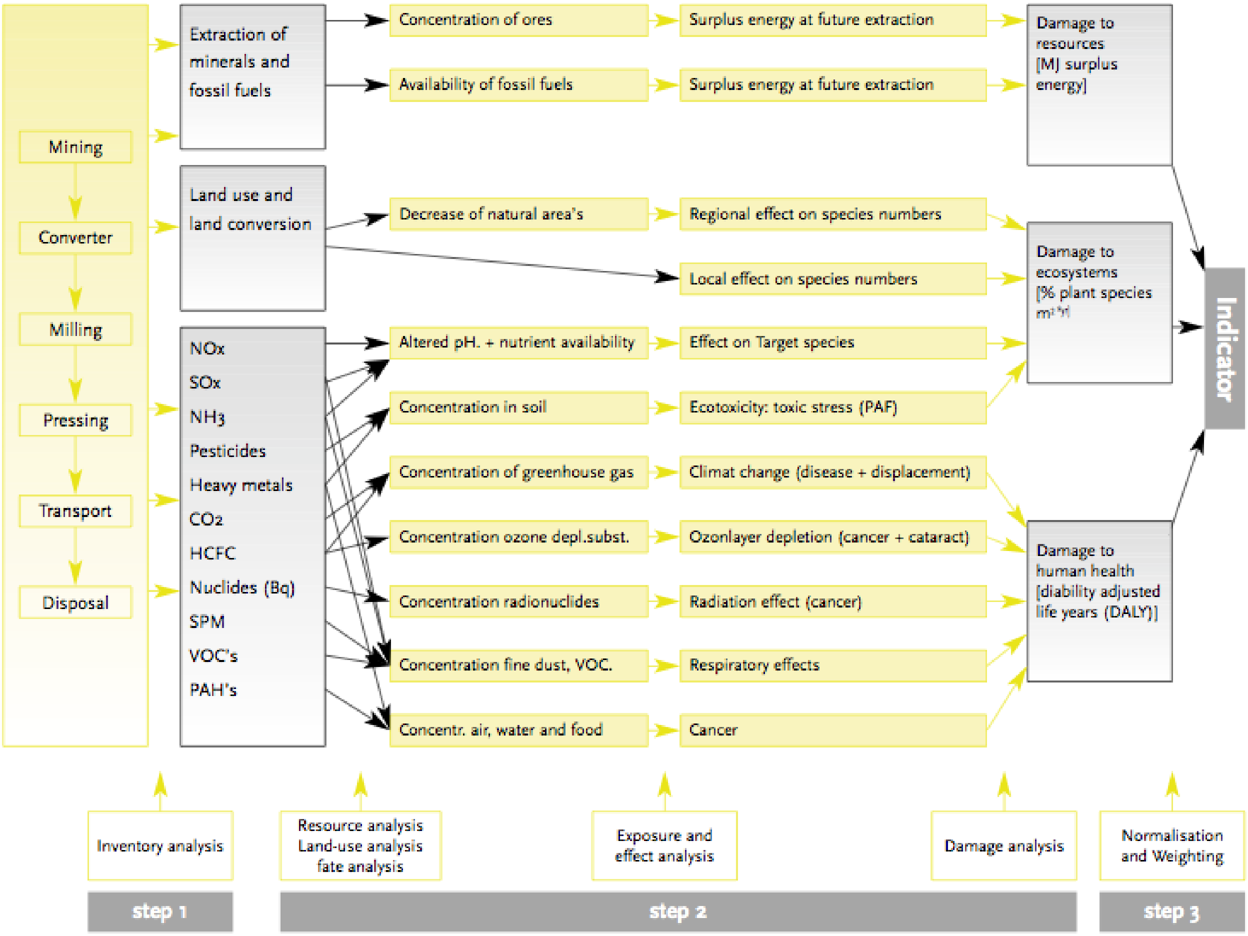

Figure B.2: Impact assessment - Eco-indicator 99 [113]

situation and other external factors. And more important, those priorities (or the method used) must be specified with the results.

Impact Category	Scale	Examples of LCI Data (i.e. classification)	Common Possible Characterization Factor	Description of Characterization Factor
Global Warming	Global	Carbon Dioxide (CO_2) Nitrogen Dioxide (NO_2) Methane (CH_4) Chlorofluorocarbons (CFCs) Hydrochlorofluorocarbons (HCFCs) Methyl Bromide (CH_3Br)	Global Warming Potential	Converts LCI data to carbon dioxide (CO_2) equivalents Note: global warming potentials can be 50, 100, or 500 year potentials.
Stratospheric Ozone Depletion	Global	Chlorofluorocarbons (CFCs) Hydrochlorofluorocarbons (HCFCs) Halons Methyl Bromide (CH_3Br)	Ozone Depleting Potential	Converts LCI data to trichlorofluoromethane (CFC-11) equivalents.
Acidification	Regional Local	Sulfur Oxides (SOx) Nitrogen Oxides (NOx) Hydrochloric Acid (HCL) Hydroflouric Acid (HF) Ammonia (NH_4)	Acidification Potential	Converts LCI data to hydrogen (H+) ion equivalents.
Eutrophication	Local	Phosphate (PO_4) Nitrogen Oxide (NO) Nitrogen Dioxide (NO_2) Nitrates Ammonia (NH_4)	Eutrophication Potential	Converts LCI data to phosphate (PO_4) equivalents.
Photochemical Smog	Local	Non-methane hydrocarbon (NMHC)	Photochemical Oxident Creation Potential	Converts LCI data to ethane (C_2H_6) equivalents.
Terrestrial Toxicity	Local	Toxic chemicals with a reported lethal concentration to rodents	LC_{50}	Converts LC_{50} data to equivalents; uses multi-media modeling, exposure pathways.
Aquatic Toxicity	Local	Toxic chemicals with a reported lethal concentration to fish	LC_{50}	Converts LC_{50} data to equivalents; uses multi-media modeling, exposure pathways.
Human Health	Global Regional Local	Total releases to air, water, and soil.	LC_{50}	Converts LC_{50} data to equivalents; uses multi-media modeling, exposure pathways.
Resource Depletion	Global Regional Local	Quantity of minerals used Quantity of fossil fuels used	Resource Depletion Potential	Converts LCI data to a ratio of quantity of resource used versus quantity of resource left in reserve.
Land Use	Global Regional Local	Quantity disposed of in a landfill or other land modifications	Land Availability	Converts mass of solid waste into volume using an estimated density.
Water Use	Regional Local	Water used or consumed	Water Shortage Potential	Converts LCI data to a ratio of quantity of water used versus quantity of resource left in reserve.

Figure B.3: Commonly used impact categories [110]

B.4 Limitations of LCA

LCA method has some limitations:

- The high uncertainty of the results, depending on the scope definition, models, weighting choices, precision of the collected data, etc.
- LCA is very time and data intensive.
- Data is not always available to conduct a proper LCA.
- LCA does not take into account rebound effect or any other social (or economic) effect due to the development of a new technology.
- LCA has *a low spatial and temporal resolution* [114] (it is linked to a given technology, and a given location).

Appendix C

Smart & Smarter 2020 - Power abatements

Figures C.1 and C.2 show the assumptions and abatement potential in the power system sector according to the smart and smarter 2020 reports [42, 43]. Both reports are based on previous studies.

SMART grids: Global impact

2.03 $GtCO_2e$ – Assumptions behind the numbers in Fig 13.1. Chapter 3

Lever	$GtCO_2e$	Assumptions
Reduce T&D losses	0.90	• 30% reduction (14% to 10%) of T&D losses for developed countries and 38% (24% to 15%) reduction for developing countries
Demand management	0.02	• 3% (10 days a year) reduction in spinning reserve
Reduce consumption through user information	0.28	• 5% reduction in energy consumption • Effective in 75% of residential new builds and 50% of residential retrofits • Effective in 60% of commercial new builds and 50% of commercial retrofits
Integration of renewables	0.83	• 10% reduction in the carbon intensity of generation of developed countries • 5% reduction in the carbon intensity of generation of developing countries
Intelligent load dispatch	No data available	

Figure C.1: Smart 2020 assumptions for smart grid abatements by 2020, [42]

The smart 2020 report evaluates the potential abatement due to smart grid to 2.03GtCO2e. The bigger abatements are expected to come from renewable energy integration and from reduced transmission losses.
The smarter 2020 report estimates the abatement potential to 2.02GtCO2e. The renewable energy integration is still considered to generate the biggest part of this abatement, reduced transmission losses and peak shaving are other significant sources of savings.

Power

Sublever	Abatement potential ($GtCO_2e$)	Addressable emissions ($GtCO_2e$)	Savings potential (%)	Sub-model details	Sources
Demand management	0.01	0.25	4.0%	Addressable emissions based on total power capacity (6.9TW, 0.55 kg CO_2/kWh emissions factor used) and average ratio of energy savings as a result of DR (65 Wh/W)1 Savings potential based on penetration from case studies.[1]	1. IEA & EPRI: "The Green Grid"
Time-of-day pricing	0.21	21.48	1.0%	Sublever addresses all emissions related to electricity generation1 with a conservative total savings potential taken from report on smart grid[2]	1. IEA 2. PNNL: "The Smart Grid: An Estimation of the Energy and CO_2 Benefits"
Power-load balancing	0.38	0.64	60.0%	Addressable emissions equals non-base electricity generation (those associated with oil)1 – saving potential based on penetration of storage[2]	1. IEA 2. BCG Perspectives: "Revisiting Energy Storage"
Power grid optimization	0.33	1.10	30.0%	Addressable emissions based on those associated with T&D losses (7% of all electricity)[1] - 30% savings estimation from previous SMART 2020 report	1. The Energy and Resources Institute "T&D Losses" & IEA
Integration of renewables in power generation	0.85	3.40	25.0%	Addressable emissions based on change of emissions due to greening of power grid based on IEA [2] degree scenario1 – savings potential based on prior SMART 2020 estimation, represents contribution of ICT technology	1. IEA ETP
Virtual power plant	0.04	0.14	26.0%	Total addressable emissions is based on future VPP capacity (30GW)[1] with an estimate that a typical VPP incorporates 25% renewables and reduces energy demand by 1%[2]	1. Pike Research: "Virtual Power Plants" 2. Expert interviews
Integration of storage into off-grid applications	0.20	600 GW	400 hr/yr	BCG estimates there are 600 GW of installed fleet of diesel generators running ~400 hr/yr for island or off-grid applications	1. BCG Perspectives: "Revisiting Energy Storage" & Power Systems Research

Figure C.2: Smarter 2020 assumptions for smart grid abatements by 2020, [43]

Appendix D

Conversion of impact units

In this work, we work with various units such as electric kWh, primary kWh or kgCO2e. The goal of this appendix is to explain the conversion factors between those units.

D.1 Primary energy

Primary energy is the energy embodied in natural resources prior to undergoing any human-made conversions or transformations [115]. *Primary energy is the relevant parameter that characterizes the environmental impact of a product during its use stage. Comparability across different fuels can only be achieved through comparing primary energy* [116]. The primary energy factor (PEF) takes the losses (extraction, transport...) and conversion efficiency into account. The PEF depends on the primary energy source, and the average PEF of a country or region depends therefore on the energetic mix of this region. The table hereafter gives the average PEF for various countries and regions.

Country/Region	PEF $[kWh_{prim}/kWh_{elec}]$	Source
France	2.58	[117]
Germany	2.6	[117]
Netherlands	2.56	[117]
Poland	3	[117]
Spain	2.6	[117]
Sweden	2	[117]
UK	2.92	[117]
Europe	2.46	[118]
USA	3.3	[25]

The PEF is also presented per primary energy source in Europe in [118], some of the results are given in the table hereafter.

Primary source	PEF $[kWh_{prim}/kWh_{elec}]$
Lignite	2.30 - 2.69
Coal	2.31 - 2.45
Gas	1.79 - 1.98
Oil	2.75 - 2.78
Nuclear	3.15 - 4.5
Solar	1.03 - 1.25
Wind	1.03

D.2 Carbon dioxide equivalent

The carbon dioxide equivalent is another way to characterize primary energy sources. For the same electric energy delivered to a customer, the carbon dioxide equivalent varies according to the type of primary energy used. The tables hereafter present the carbon dioxide equivalent factor for various regions.

Country/Region	CO2e [$kgCO2e/kWh_{elec}$]	Source
Asia	0.782	[119]
Belgium	0.220	[120]
Europe	0.436	[119]
Singapour	0.635	[119]
South Africa	1.101	[119]
UK	0.589	[119]
US - Canada	0.658	[119]
World	0.565	[25]

Appendix E

Examples of home appliances consumption and of activities emissions

In this work, we often refer to use-phase consumption and system emissions. This appendix gives references values of consumption and emissions to give the reader some benchmarks.

E.1 Home appliances consumption

Table E.1 gives some typical home appliances consumptions. The average consumption of a belgian household is 4800kWh/year.

Appliance	Typical consumption [kWh/year]	Source
Fridge	384	[89]
Freezer	543	[89]
Dish washer	234	[89]
Washing machine	184	[89]
Dryer	347	[89]
Kettle	70	[89]
Lighting	487	[89]

Table E.1: Typical home appliances consumption.

E.2 Carbon dioxide emissions of some activities

Table E.2 gives some typical activities carbon dioxide emissions.

Activity	Typical emissions [kgCO2e]	Source
Brussels - Paris by plane	58.5	[121]
Brussels - Paris by car	35	[121]
Brussels - Paris by train	6.8	[121]
Buying a new car	$6 \cdot 10^3$ to $35 \cdot 10^3$	[122]
Buying a newspaper	0.3 to 0.8	[122]
Eating beef	19.5/kg	[123]
Eating vegetables	0.7/kg	[123]

Table E.2: Daily activities emissions.

Appendix F

Smart plug saving potential

As explained in Chapter 2, smart plugs emit between 3.14kgCO2e and 8.25kgCO2e every year, considering production emission between 11.13kgCO2e and 22.4kgCO2e, a 5 years lifetime, yearly consumption of 3.45kWh to 15.5kWh and a GWP of 0.22kgCO2e/kWh_{elec}. To produce absolute savings, a smart plug must therefore be used with a load which potential savings is higher than those values. This appendix briefly studies the conditions in which this could be the case.

F.1 Shiftable loads

Shiftable load potential savings can be evaluated knowing two informations: the amount of energy than can be shifted, and the difference of GWP between the time it should have been started and the time it is shifted to.

$$S = E_{shifted}(GWP_{initial} - GWP_{new})$$

with S, the saving potential in kgCO2e, $E_{shifted}$ the energy shifted in kWh, $GWP_{initial}$, the GWP at the time the load requests to start in kgCO2e/kWh, and GWP_{new}, the GWP at the time the load is shifted.
Table F.1 gives different cases in which the smart plug could generate absolute savings. As a comparison, some typical yearly consumption of home appliances are given here after, [124]: dish washer, 200kWh to 340kWh; washing machine, 160kWh to 230kWh; dryer, around 215kWh.

	Annual load consumption [kWh]	Portion of time shiftable [%]	GWP_{diff} [kgCO2e/kWh]
Case 1	>138	>50	>0.12 [1]
Case 2	>69	100	>0.12
Case 3	>165	>50	>0.1 [2]
Case 4	>82.5	100	>0.1
Case 5	>235.7	>50	>0.07 [3]
Case 6	>118	100	>0.07

Table F.1: Smart plugs savings - Shiftable loads.

[1] A GWP_{diff} of 0.12 can for example be obtained when shifting load from the usual Belgian electricity mix with a GWP of 0.22 to a local solar production with a GWP of 0.1.

[2] This GWP_{diff} can for example be observed when shifting a load from peak hour to low consumption hour during summer in Beglium.

[3] This GWP_{diff} can for example be observed when shifting a load from peak hour to low consumption hour during winter in Beglium.

F.2 Loads with consumption reduction potential

Some loads can reduce their consumption when used with a smart plug to remotely disconnect them when in standby mode for example. Table F.2 shows some cases which could generate savings.

	Load power in standby [W]	Portion of time in standby [%]	GWP [kgCO2e/kWh]
Case 1	>5	>90	0.22
Case 2	>8.6	>50	0.22
Case 3	>43	>10	0.22

Table F.2: Smart plugs savings - Standby mode savings.

According to Mohanty in [125], appliances like television and Hi-fi stereo have an average standby power around 7.2W and the kitchen oven has an average power consumption of 14.5W in standby mode.

Appendix G

Communication protocols - Headers and MTU

In addition to the message itself, a significant amount of data is required by comunication protocols to carry additional information such as the source and destination of a message, the type of the message, its beggining and end, etc. Error control bits and retransmission are other sources of overhead among others. *The seven layer Open Systems Interconnection model (OSI model) for network architecture* (see Figure G.1) *provides a useful abstraction for network protocol design. As a user's data is passed down the communication protocol stack, each layer adds additional control and identification information to the user's data* [126].

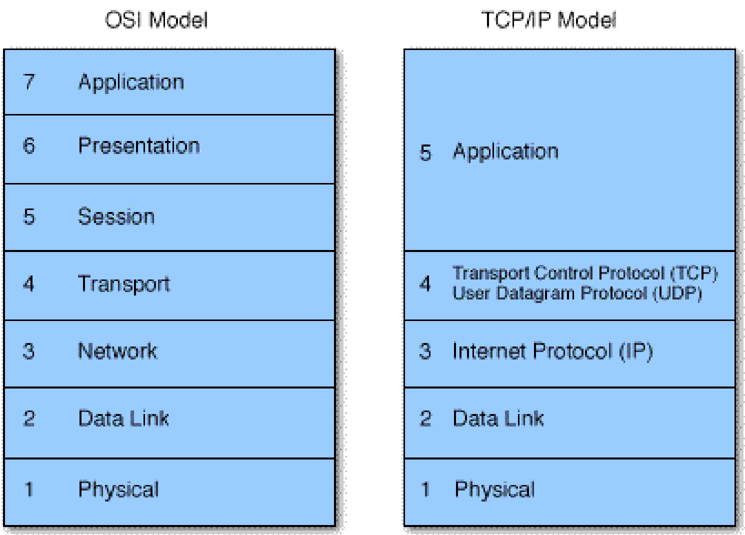

Figure G.1: OSI stack model (left) and TCP/IP model (right) [127]

The table hereafter shows the principal protocols for each layer of the TCP/IP model along with their header length, [128] [129], and their Maximum Transmission Unit (MTU), [130].

TCP/IP model stack	Protocols	Header (bytes)	Maximum Transmission Unit (bytes)
Physical & Data link	Ethernet	14	1500
	WLAN	30	7981
Network	TCP	20	1460
	UDP	8	1500
Transport	IPv4	20	68
	IPv6	40	1280

Retransmission losses must be taken into account. In [131], C.Chen et al. estimate that the TCP/IP retransmissions use around 3.5% of the total bandwidth.
One key issue of smart grid communication is the security of informations. In their paper, M.Kgwadi and T.Kunz copare three secure algorithms for WLAN: BiBa, HORSE and ECDSA [132]. The main results are summarized in the table hereafter.

Security Scheme	Overhead	Security level (probability of guessing a valid signature)	Computational effort (at receiver)
ECDSA	40 bytes	2^{-80}	High
HORSE	12 bytes	2^{-35}	Low
BiBa	9 bytes	2^{-35}	Low

Appendix H

Household response to dynamic pricing of electricity - A survey of the experimental evidence

This appendix further presents the results of Faruqui and Sergici in [85]. Figure H.2 shows the detailed results for each type of static pricing by experiment. Figure H.1 shows the kWh/hour saving potential depending on the peak price. This figure shows that consumers with central air conditioning systems (CAC) have more consumption reduction potential during critical days (CPP). This means that Belgian reduction potential is probably closer to the *No CAC* curve than to the average curve.

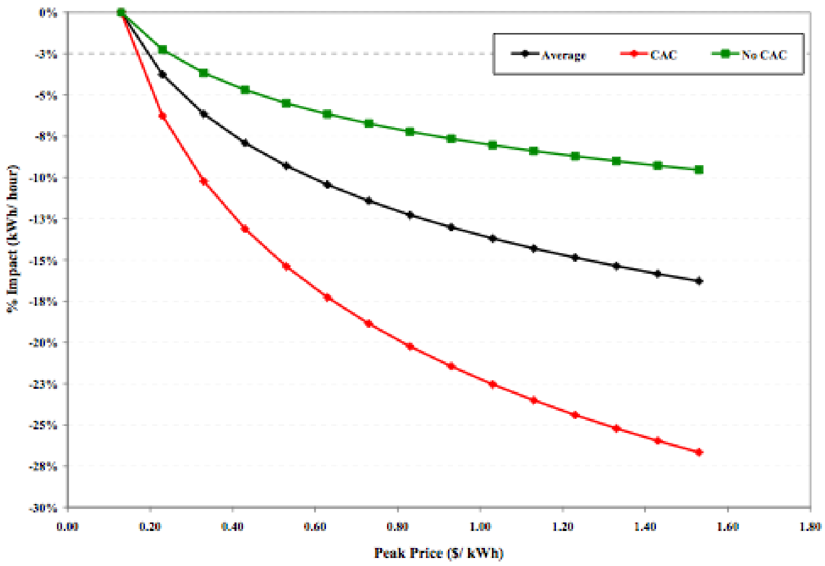

Table H.1: Residential demand response curves on critical days [85].

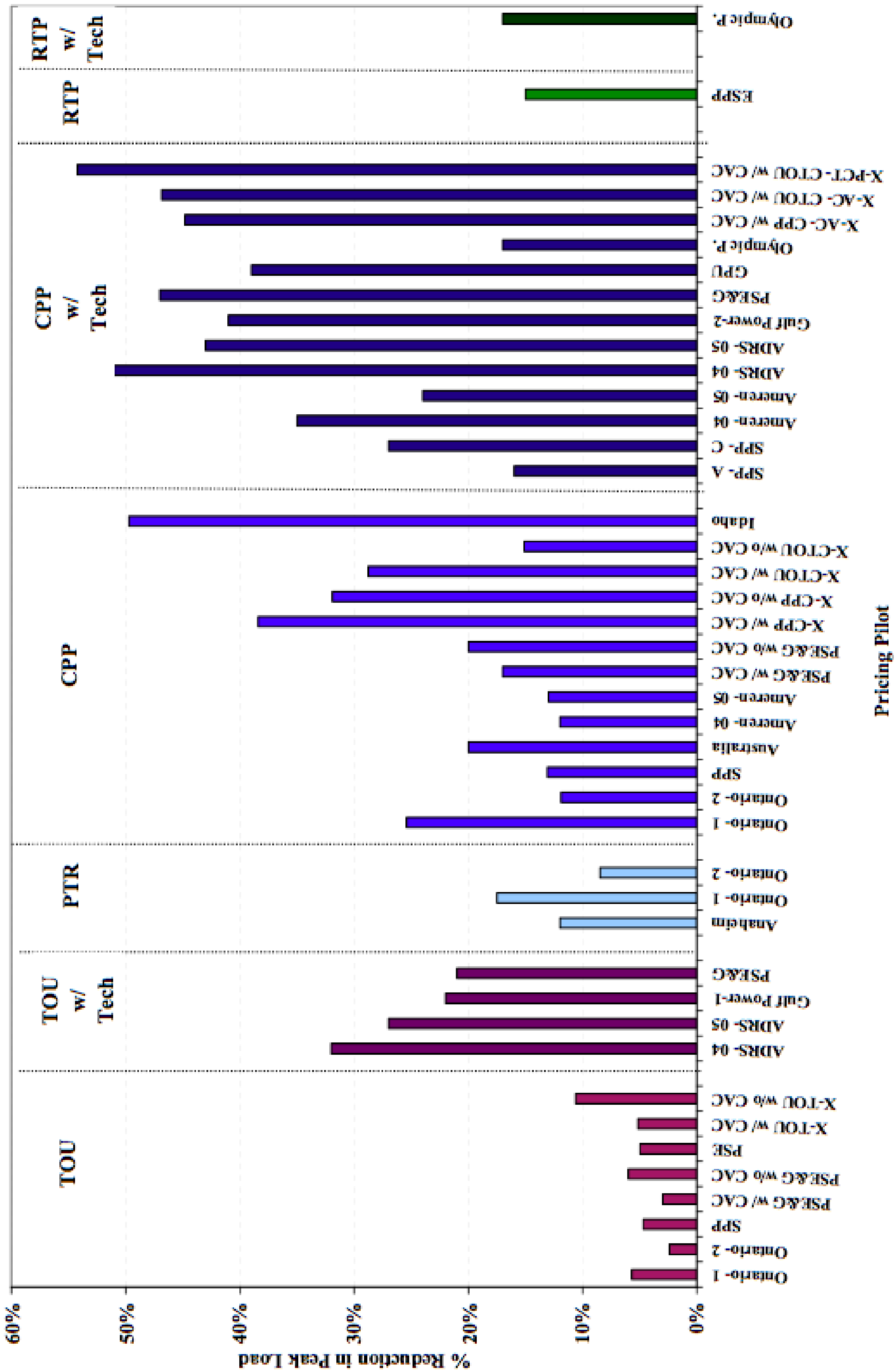

Table H.2: Review of 15 static pricing experiments [85].

Appendix I

Chapter 3 - Additional results

This appendix presents graphs that were not given in Chapter 3 to not overload the reader. The graphs of Section 3.3 shows the average system savings. In this appendix, the best and worst saving scenarios are also presented.

I.1 Static-pricing without enabling technologies

Figure I.1 shows that with the full fall-back scenario, savings are to expected. Indeed, the emissions due to use-phase increases faster than the savings. If the fall-back is limited, however, savings can be expected at the end of the 5 years.

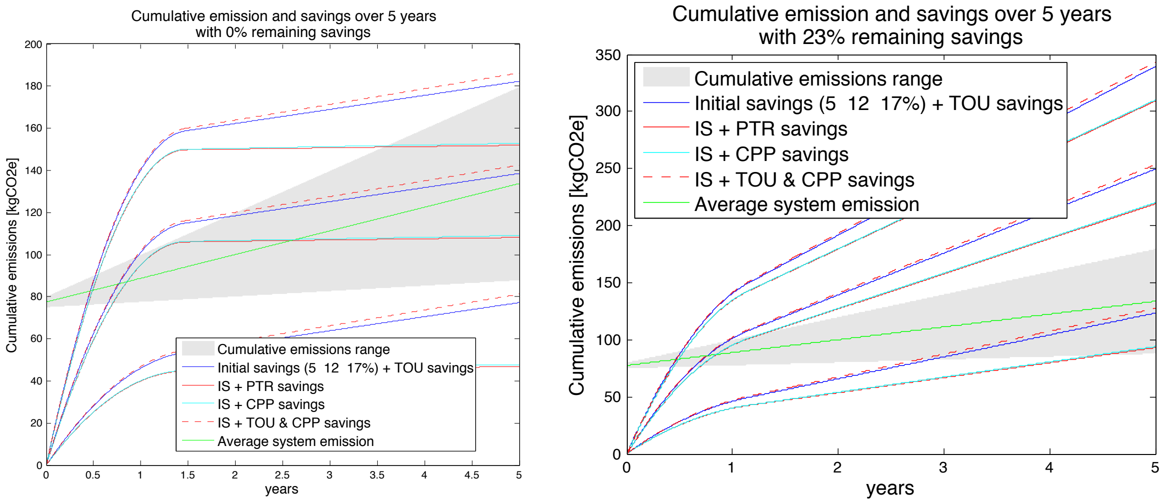

Figure I.1: Static pricing without enabling technologies. In the full fall-back scenario (left), no savings are expected. In the second scenario, however, savings are much higher.

I.2 Static-pricing with enabling technologies

Figure I.2 shows that the emissions are globally higher than the expected savings.

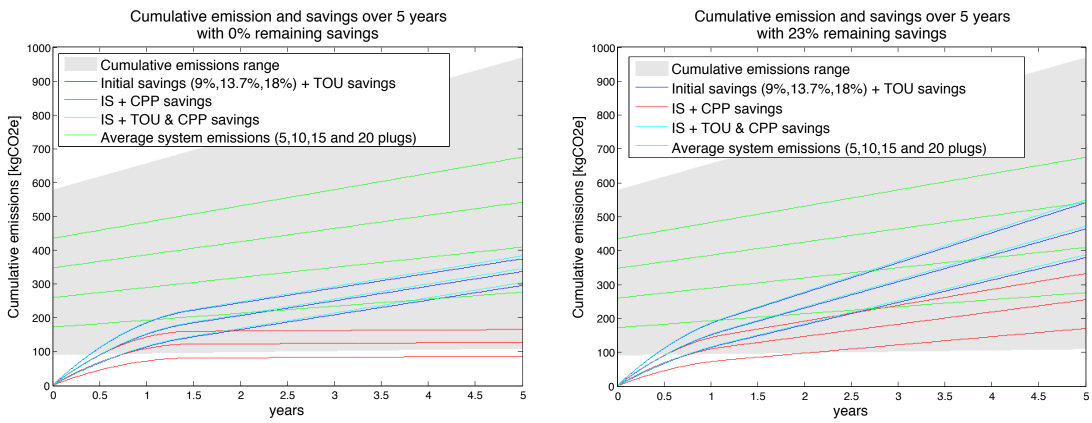

Figure I.2: Static pricing with enabling technologies. The emissions are higher than the expected savings.

Appendix J

Chapter 4 - Additional results

Given the number of parameters of the model presented in Chapter 4, all the results were not presented in the text. This appendix shows the results that were not given in Chapter 4. The parameters used in the simulations are the standard parameters defined in Chapter 4, unless specifically stated otherwise. In those standard parameters, only part of the loads is considered to be shiftable. This part corresponds to 1 load per house. 1 smart plug per house should therefore be sufficient. But we analyze the cases in which more plugs are installed.

J.1 Variation of system emissions and savings with the GWP

In Chapter 4, we presented the variation of emissions and savings with the GWP for a system with 3 smart plugs per house. Figure J.1 shows the same variation but for systems with 1 and 2 smart plugs per house.

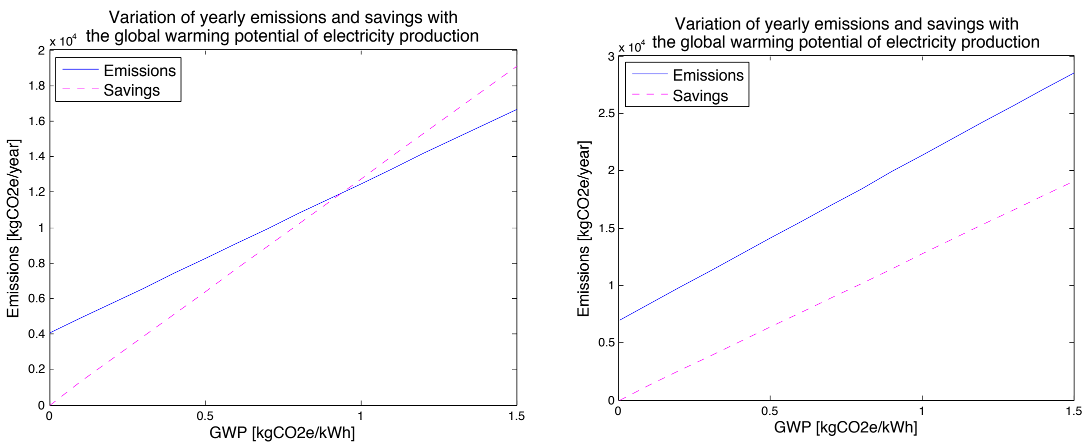

Figure J.1: Left: Evolution of emissions and savings for a system with 1 plug per house. Right: Evolution of emissions and savings for a system with 2 plugs per house.

For systems with 2 and 3 smart plugs per houses, the emissions increase faster than the savings. For a system with a single smart plug per house, the consumption of the system is lower and the emissions of the system therefore increase slower with the GWP than for the other systems. We observe that for a GWP of 0.9kgCO2e/kWh, the savings of the system become higher than the emissions.

J.2 Variation of system emissions with various combination of parameters

We present in the 2 next subsections the emissions due to different combinations of parameters.

J.2.1 System with 2 smart plugs per house

Figure J.2 presents the emissions for a system with 2 smart plugs per house. The only expected savings are for the system with 0.5W smart plugs with production emissions of 11kgCO2e and a lifetime of 15years.

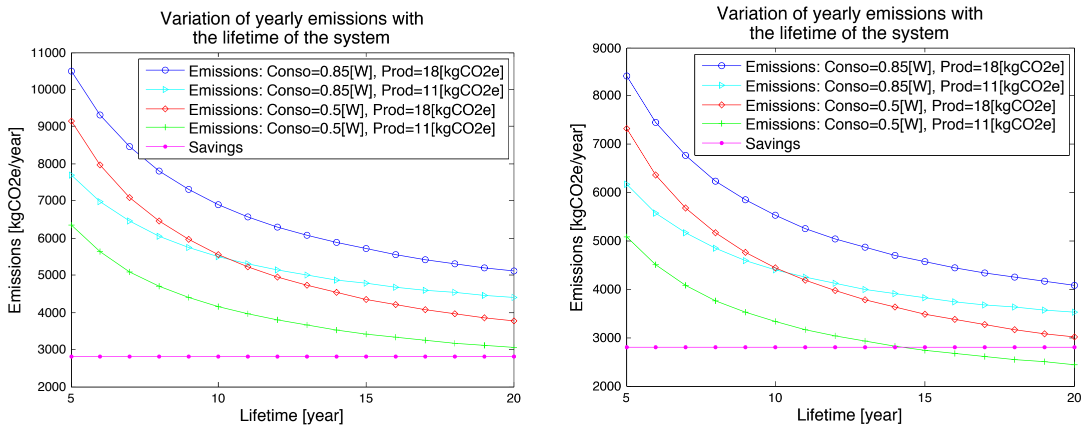

Figure J.2: Variation of emissions with the lifetime of the system and other parameters. Left: 2 plugs per house and 4 additional plugs for monitored house. Right: 2 plugs per house and no additional plugs for monitored houses.

J.2.2 System with 1 smart plug per house

Figure J.3 shows the emissions for a system with 1 plug per house. In this case, emissions can be expected for various combination of parameters. If not additional smart plug is used in monitored houses, the results are even more optimistic. For a lifetime of 10 years, every presented system has a positive absolute saving.

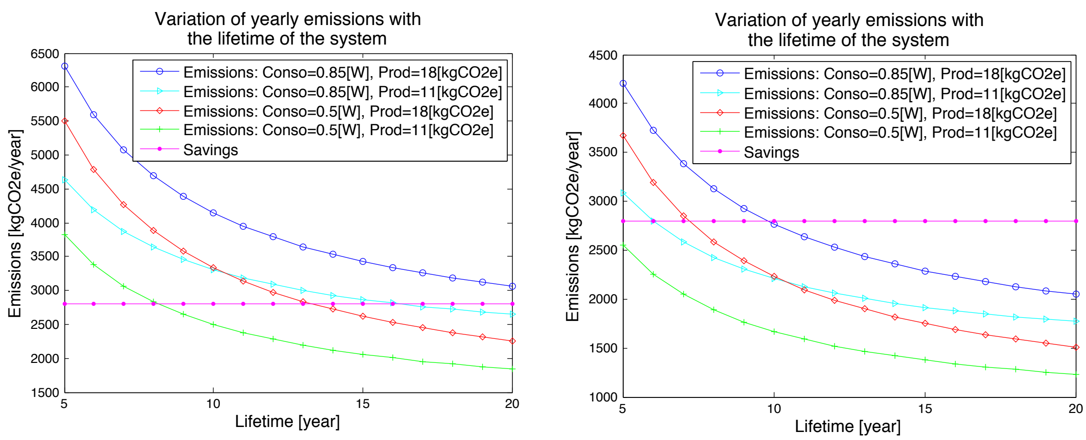

Figure J.3: Variation of emissions with the lifetime of the system and other parameters. Left: 1 plugs per house and 4 additional plugs for monitored house. Right: 1 plugs per house and no additional plugs for monitored houses.

J.3 System savings and emissions for different sets of parameters

In this section we observe both savings and emissions variation with different parameter. For each portion of shiftable loads tested in Chapter 4, we give more detailed results.

	Case 1	Case 2	Case 3	Case 4
Objective	Least squares			
Timestep [min]	30	30	15	15
Number of solar panels	20	20	20	20
Forecast granularity [min]	60	60	60	60
Forecast error [%]	15	15	15	15
Consumption statistic error [%]	20	20	20	20
Consumption time error [min]	15	15	15	15
Portion of shiftable [%]	30,30,60	50,50,70	70,70,90	100,100,100
Number of smart plugs per house [1]	1	1.385	1.864	2.39
Savings [kgCO2e/day]	7.5	10.19	14.14	16.9

Table J.1: Saving scenarios.

J.3.1 Case 1

Figure J.4 shows the emissions and savings for the case 1 described in Table J.1. Table J.2 summarizes the results of this case.

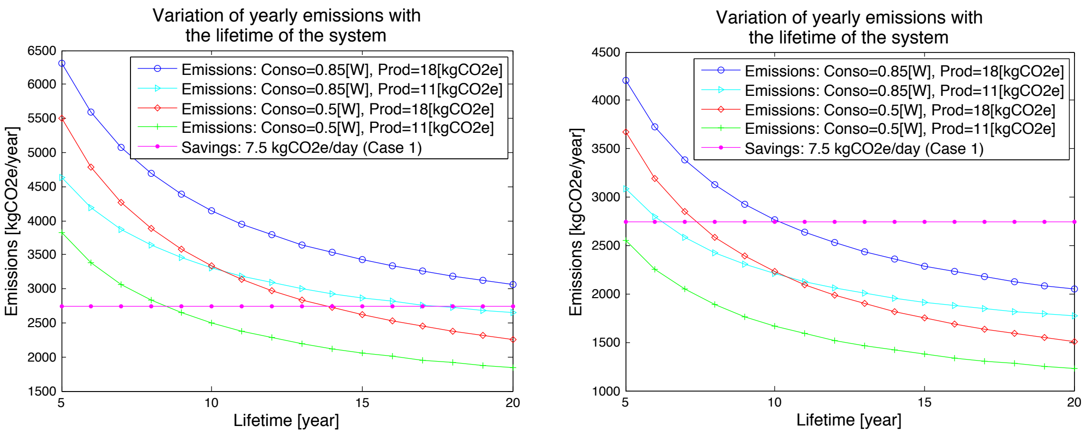

Figure J.4: Emissions and savings for the case 1 as described in Table J.1. Left: 4 additional smart plugs per monitored house. Right: No additional smart plug per monitored house.

Yearly emissions and savings			
Total emissions [kgCO2e/house]	1.54 to 7.88	Savings [kgCO2e/house]	3.42
Absolute savings [kgCO2e/house]	-4.46 to 1.89	$kgCO2e_{saved}/kgCO2e_{emitted}$	0.43 to 2.23

Table J.2: Load shifting algorithm - Case 1 Results.

J.3.2 Case 2

Figure J.5 shows the emissions and savings for the case 2 described in Table J.1. Table J.3 summarizes the results of this case.

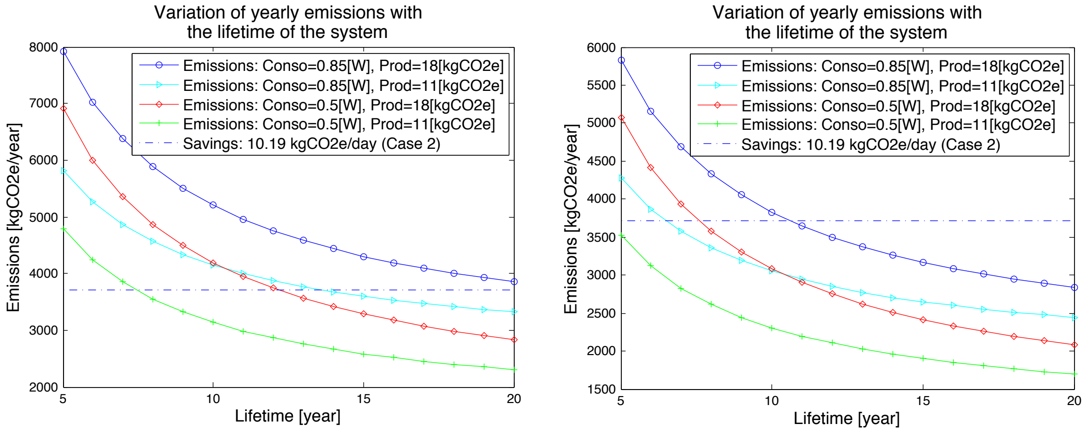

Figure J.5: Emissions and savings for the case 2 as described in Table J.1. Left: 4 additional smart plugs per monitored house. Right: No additional smart plug per monitored house.

Yearly emissions and savings			
Total emissions [kgCO2e/house]	2.12 to 9.90	Savings [kgCO2e/house]	4.65
Absolute savings [kgCO2e/house]	-5.26 to 2.52	$kgCO2e_{saved}/kgCO2e_{emitted}$	0.47 to 2.19

Table J.3: Load shifting algorithm - Case 2 Results.

J.3.3 Case 3

Figure J.6 shows the emissions and savings for the case 3 described in Table J.1. Table J.4 summarizes the results of this case.

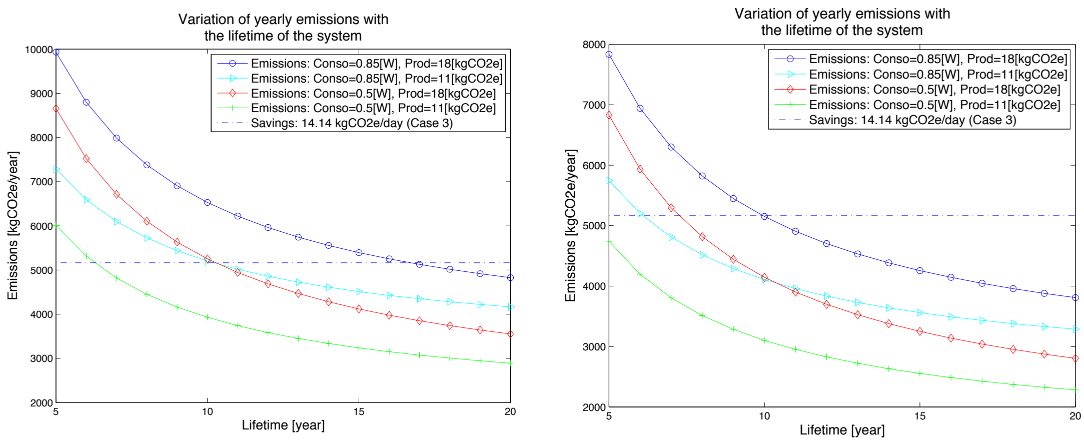

Figure J.6: Emissions and savings for the case 3 as described in Table J.1. Left: 4 additional smart plugs per monitored house. Right: No additional smart plug per monitored house.

Yearly emissions and savings			
Total emissions [kgCO2e/house]	2.85 to 12.42	Savings [kgCO2e/house]	6.46
Absolute savings [kgCO2e/house]	-5.96 to 3.60	$kgCO2e_{saved}/kgCO2e_{emitted}$	0.52 to 2.26

Table J.4: Load shifting algorithm - Case 3 Results.

J.3.4 Case 4

Figure J.7 shows the emissions and savings for the case 4 described in Table J.1. Table J.5 summarizes the results of this case.

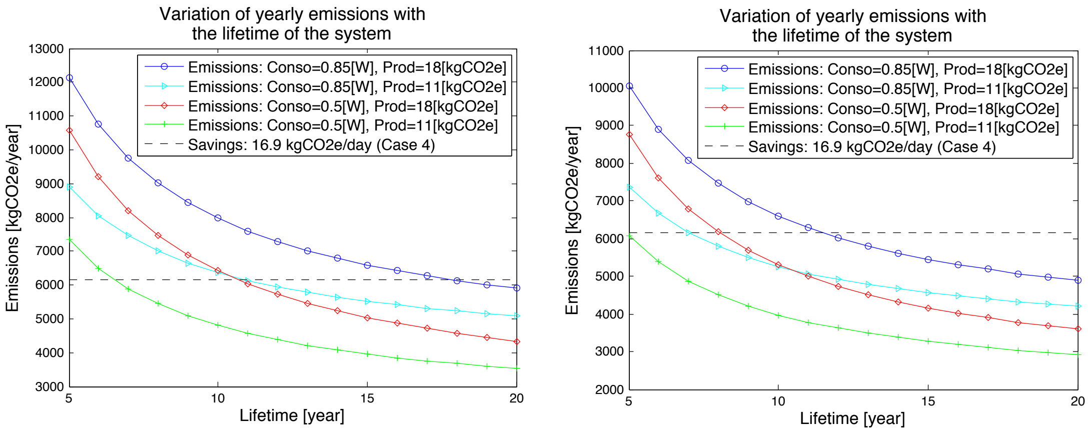

Figure J.7: Emissions and savings for the case 4 as described in Table J.1. Left: 4 additional smart plugs per monitored house. Right: No additional smart plug per monitored house.

Yearly emissions and savings			
Total emissions [kgCO2e/house]	3.65 to 15.18	Savings [kgCO2e/house]	7.71
Absolute savings [kgCO2e/house]	-7.46 to 4.06	$kgCO2e_{saved}/kgCO2e_{emitted}$	0.51 to 2.11

Table J.5: Load shifting algorithm - Case 4 Results.

Appendix K

Evaluation of the carbon footprint of this work

Figure K.1 summarizes the main activities of this work along with their carbon footprint.

Activity	Quantity	Carbon footprint per unit	Global carbon footprint [kgCO2e]	Source
Computer use (internet research + report writing)	400 hours	0.0036kCO2e/h [1]	1.43	[73, 120, 133]
Internet research	200 hours	0.00122kgCO2e/h [2]	0.306	[120, 25, 134]
Sources download	550.7Mo	0.017kgCO2e/Gb [3]	0.075	[120, 25]
Dropbox & Copy use	22.5Go	0.017kgCO2e/Gb	3.06	[25]
Simulation executions	500 hours	0.0185kgCO2e/h [4]	9.25	[73, 120, 133]
Work printing	500 pages	4.25kgCO2e/1000pages	2.125	[135]
Total : 16.246 kgCO2e [5]				

Table K.1: Carbon footprint assessment of this work. The main contribution comes from the computer consumption while running simulations.

The main sources of emissions are the the simulation executions, the use of Dropbox and Copy to save backup versions of the work, and the printing of the work.

[1] Considering a load factor of 20% based on observation, a idle power of 9W and a maximum power of 90W [133] and a GWP of 0.22kgCO2e/kWh [120].

[2] Considering and average download rate of 0.072Gb/hour, [134], a consumption of 0.077kWh/Gb [25] and a GWP of 0.22kgCO2e/kWh [120].

[3] Considering a consumption of 0.077kWh/Gb [25] and a GWP of 0.22kgCO2e/kWh [120].

[4] Considering a load factor of 95% based on observation, a idle power of 9W and a maximum power of 90W [133] and a GWP of 0.22kgCO2e/kWh [120].

[5] Without taking into account the rebound effect: Master thesis $\overset{?}{-}$> Diploma -> Working contract -> Company car -> etc.