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Analysis and Model of Consumption Patterns and Solar Energy Potentials for Residential Area Smart Grid Cells

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MASTER THESIS
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Project description

The system envisioned to create smarter power grids will enable means for better monitoring and control of electricity demand. This thesis will explore autonomy in Smart Grid cells (microgrids) taking part in the future power distribution grid, using a graph-based data model. By modelling electricity consumption, generation and storage, instantiated from different sources, the intention is to investigate measures for autonomously avoiding usage peaks and power outages in microgrids.

a) Do a literature study on consumption patterns in households, and the potentials of generation and storage of solar energy. Furthermore, find measures for reducing consumption and more efficient use of household energy in microgrids.

b) Study the dynamics of household consumption based on data gathered from the Demo Steinkjer project[1], and examine whether usage patterns are consistent with the previous investigations (studied in a)).

c) Study the dynamics of solar energy generation based on data gathered from elia[2] and uncover the potentials of solar energy as a local power source in microgrids aimed at avoiding usage peaks and power outages.

d) Model autonomy in a microgrid scenario using the acquired energy consumption and generation dynamics (from b) and c)) with purpose of:

- shaving usage peaks in high demand periods by utilizing local energy generation and storage.
- examining how long a microgrid can stay operational using stored energy reserves and local generation in the event that external energy supply is disrupted, i.e. with purpose of avoiding power outages.

[1]http://www.demosteinkjer.no
[2]http://www.elia.be

Preface

This master thesis was carried out at the Department of Engineering Cybernetics at the Norwegian University of Science and Technology (NTNU), with Associate Professor Sverre Hendseth as supervisor.

The author wishes to extend his gratitude to supervisor Sverre Hendseth and co-advisor Roberto Rigolin Ferreira Lopes for their support and guidance throughout the study.

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Erik Vattekar

Abbreviations

ICT - Information and Communications Technology
AMI - Advanced Metering Infrastructure
DSM - Demand Side Management
NVE - Norwegian Water Resources and Energy Directorate
ES - Energy Storage
BES - Battery Energy Storage
UPS - Uninterruptable Power Supply
DOD - Depth of Discharge
AMS - Advanced Metering System
GSM - Global System for Mobile Communications
GPRS - General Packet Radio Service
PV - Photovoltaic
CSP - Concentrated Solar Power

Abstract

Meanwhile environmental concerns and global energy consumption continue to increase, the current ageing power distribution grid is becoming increasingly inefficient and unreliable. The vision of Smart Grid is to create a widely distributed energy supply infrastructure by means of information and communications technology (ICT). By incorporating ICT in all aspects of electricity delivery, generation and consumption the intention is to ensure a better match between supply and demand, while also easing the transition to increased use of renewable energy sources. This study explores the dynamics of electricity consumption in households and the potentials of photovoltaic energy generation in residential Smart Grid cells (microgrids). That is, by analysing actual consumption patterns and solar generation data, the aim is to investigate the potential benefits of distributed energy generation and storage in futuristic microgrids. Furthermore, by using the acquired dynamics of energy generation and consumption it is attempted to model autonomy in microgrids with purpose of shaving usage peaks and avoiding power outages by use of local generation and storage.

Index Terms - microgrids, household consumption, photovoltaic energy generation, usage peak shaving, complex network theory

Sammendrag

Hvert år øker verdens befolkning med 80 millioner mennesker som følgelig fører til en konstant årlig økning i det globale energiforbruket. Samtidig med dette blir de nåværende, aldrende kraftdistibusjonsnettene i verden stadig mer upålitelig og ineffektive. Hensikten med Smart Grid er å skape et distribuert kraftsystem ved hjelp av informasjons- og kommunikasjonsteknologi (IKT). Ved å ta i bruk IKT i alle aspekter av energiforbruk, produksjon og leveranse er intensjonen å oppnå en mer effektiv utnyttelse av den produserte energien, samt å forenkle overgangen til fornybare energikilder. Hensikten med dette studiet er å utforske energiforbruk i husholdninger og energipotensialene til solcellepaneler. Ved å analysere faktiske forbruksmønstre og energiproduksjon fra solcellepaneler er målet å kartlegge potensialene for distribuert energiproduksjon i Smart Grid celler (dvs. "microgrids"). I tillegg er det forsøkt å modellere autonomi i microgrid-celler med den hensikt å redusere forbrukstopper og unngå strømbrudd ved hjelp av lokal energilagring og produksjon.

Contents

Chapter 1

Introduction

Each year the world population increases with 80 million, causing the need for energy to increase accordingly. In fact, estimates show that global annual energy consumption will more than double from its current level by 2050. Furthermore, the environmental impact caused by fossil-based energy systems continue to cause headaches, as we are concerned about the burden we put on coming generations regarding global warming. Further use of fossil fuels for energy generation will produce unacceptable levels of carbon dioxide which may have disastrous effects in the future, e.g. with regards to food production [1], [9].

Smart Grid represents the future in power distribution by means of information and communications technology (ICT). It is a collection of next generation power delivery concepts that includes new power delivery components, improved control and monitoring throughout the grid, and more informed customer options. By using two-way flows of both information and energy between suppliers and consumers the aim of Smart Grid is to manage electricity demand in a more sustainable, reliable and economic manner [10].

The transition to a smarter energy delivery network will also include support for more decentralized production and storage of energy. ICT technology is intended to be incorporated in all aspects of electricity generation, delivery and consumption, thereby increasing the potential for distributed generation and storage. This in turn will contribute to more efficient energy usage and a better balancing of supply and demand, while also easing the transition to increased use of renewable energy sources [19], [10].

Traditionally, the cost of large-scale collection, conversion and storage of renewable energy has not been feasible compared to conventional energy generation. However, the need for reducing the environmental impact of fossil-based energy systems has triggered increased research and development on renewable energy technologies in recent years, which consequently has reduced the costs and made them more competitive. In the dictionary[1] renewable energy is defined as *"any naturally occurring, theoretically inexhaustible source of energy"*, and examples of such sources include sunlight, wind, biomass and hydroelectric power. However, leading scientists have promoted *solar* driven production of environmentally clean electricity, hydrogen and other fuels as the only sustainable long-term solution for global energy needs [7].

Furthermore, the implementation of a smarter distribution grid will also enable means for more efficient energy usage in households, by use of advanced consumption metering and management-and-control systems [10]. In [3] it is stated that:

> *"Knowledge of household energy consumption is important for understanding future energy consumption trends and for making sound decisions on measures directed at households. (...) In order to secure sufficient electricity on demand for all consumers, there must be an equilibrium between production and demand, and adequate transmission capacity must be in place."*

Smart Grid is currently in a development stage whereas different architectural designs are being examined and tested. Thus, exploring household consumption patterns and the potentials of solar energy generation with respect to energy efficiency measures is of great importance at this stage.

The aim of this study is to explore autonomy in Smart Grid cells (microgrids) taking part in the future power distribution grid, using a graph-based data model. First, the consumption patterns of households will be analysed by examining data from Demo Steinkjer participant. After which, the energy generation potential of photovoltaic solar cells is investigated using data from

[1] http://dictionary.reference.com/browse/renewable+energy

elia. Finally, the obtained consumption and generation patterns will be utilized to model autonomy in a microgrid scenario. This model will investigate peak shaving in high demand periods (as described in section 2.5.4) and the ability of a microgrid to manage the entire energy demand of its participants temporarily in the event that external energy supply is disrupted, i.e. in *island mode* as described in section 2.1.2.

1.1 Structure of document

The thesis is structured as follows:

Chapter 2 addresses the theoretical background needed for performing this study. Chapter 3 describes two analyses performed on energy consumption patterns and solar generation potentials, while chapter 4 describes the microgrid autonomy model, and the results from obtained from simulations. In chapter 5 important issues arisen during the study is discussed, while chapter 6 concludes the thesis by summarizing its main findings.

Appendix A describes a tutorial on how to setup the database containing consumption and generation data, in addition to how one can extract data using python scripts. Appendix B, C and D contains code examples on how to reproduce the results in the analyses of energy consumption and generation in chapter 3. Appendix E presents the user interface and some code extracts from the autonomy model described in chapter 4. Appendix F contains the Demo Steinkjer IDs of the households used in both the analysis on consumption patterns in chapter 3 and the autonomy model in chapter 4.

Appendix G consists of the preliminary version of a paper called *"Towards a user-centric mechanism to compile the microgrid status collaboratively"*, written by the co-advisor on this thesis. Some of the results from the analyses of consumption patterns and energy generation potentials of solar cells (chapter 3) have been contributed to this paper. However, the paper is currently incomplete and thus has not been published yet.

Finally, appendix H (the attached CD-ROM) contains the datasets and python scripts used in the analyses in chapter 3, and the autonomy model described in chapter 4.

Chapter 2

Background

This chapter addresses the theoretical background needed for performing this study. First off, the concept of Smart Grid is described, revealing some of the benefits and challenges related to the transition into a smarter energy supply infrastructure. Secondly, the consumption patterns of Norwegian households are researched based on previous investigations, in addition to several methods for reduced and more efficient household consumption. After which, solar energy harnessing is described, in addition to the potentials of battery energy storage systems. Finally, complex network theory is described with emphasis on how it can be used to analyse and understand real world networks, such as e.g. electrical power grids.

2.1 Smart Grid

Historically, power distribution constitute a centralized unidirectional power delivery system that supplies energy to end users over large areas, using high voltage power lines. However, the growing demand associated with increased worldwide energy dependency has led to a need for a smarter and more distributed infrastructure in order to keep up with the increasing global energy requirements [10].

The vision of Smart Grid is to create a widely distributed energy supply infrastructure using two-way flows of both information and energy. It can be regarded as a system incorporated in all aspects of energy generation, delivery and consumption to ensure a more reliable, efficient and sustainable power distribution. By utilizing advanced consumption metering and monitoring, and intelligent management-and-control systems, the intention is to achieve a better match between demand and production, while also encouraging renewable energy to amount to a greater share of the total energy supply [10].

In [12] they list some of the key aspects that the implementation of Smart Grid is intended to include, i.e.

- Ability for the grid to self heal following a disturbance
- Power supply free from sags, swells, outages, and other power quality/reliability issues
- Support for renewable energy sources
- Better asset utilization via monitoring
- Increased monitoring through low cost sensors

To achieve a smarter power distribution, the overall macrogrid will be divided into a several autonomous cells, called microgrids, each with local energy generation and storage capabilities. The intention is that these microgrids can control their own generation and storage in response to e.g. variable supply conditions and demand in an autonomous fashion. Furthermore, the increased information flow to end users may also provide means for better user-centric control of energy consumption, and thereby allow end users to take a more active role in their electricity management [10].

2.1.1 The microgrid concept

In [19] they emphasise how the best way of realizing the emerging potential of distributed generation is to take a system approach which views generation and associated loads as a subsystem or *microgrid*. As mentioned, microgrids are cells where power is produced, transmitted, consumed, monitored and managed locally, while still being integrated in a larger central grid. In response to varying demand it will be able to autonomously control its own generation and storage to e.g. prevent usage peaks. Also, during disturbances in the central grid, the generation and corresponding loads of a microgrid can be isolated from the disturbance without harming the transmission grid's integrity, i.e. by *islanding* the microgrid from the central grid temporarily [19]. Below, in figure 2.1, the basic concept of a microgrid is illustrated [23].

Figure 2.1: The basic concept of a microgrid [23]

The potential benefits of such an approach are many. Most importantly, it provides opportunities for better matching energy production with demand, as it will enable means for e.g. evening out usage peaks in the central grid and enabling better user-centric control of energy usage. Furthermore, as the local generation sources are intended to be renewable it will also contribute to renewable energy amounting to a greater share of the total energy supply [19].

2.1.2 Microgrid operation and structure

The structure of microgrids is an important design decision which will vary depending on several factors such as e.g. geographical location, and supply and weather conditions. Furthermore, the intended controller capabilities and operational features, accompanied by distributed energy generation and storage, will also require a conceptually different structural approach than that of conventional power systems [15]. Some of the main reasons for this are listed in [15], i.e.

- Steady-state and dynamic characteristics of distributed generation and storage units, particularly electronically coupled ones, are different than those of the conventional large turbine-generator units.
- A microgrid is inherently subject to a significant degree of imbalance due to the presence of single-phase loads and/or distributed generation and storage units.
- A noticeable portion of supply within a microgrid can be from "non-controllable" sources, such as solar- or wind-based units.
- Short- and long-term energy storage units will play a major role in control and operation of a microgrid.
- A microgrid must readily accommodate connection and disconnection of distributed generation and storage units while maintaining its operation.
- A microgrid may be required to provide prespecified power quality levels or preferential services to some loads.

Also, a microgrid is intended to provide sufficient generation capacity, controls, and operational strategies to supply at least a portion of the load after being disconnected from the distribution system, i.e. remain operational as an *islanded* entity. Thus, considering this there must exist provisions for both islanded and grid-connected modes of operations, and a smooth transition between the two in order to ensure the best utilization of microgrid resources [15].

In [22] an example regarding a power system capable of temporarily *islanding* parts of a power grid is described, located on the Danish island of Bornholm. The Bornholm distribution system supplies 28,000 customers, and had a peak load in 2007 of 56 MW. The local generation capacity primarily consist of wind turbines and diesel generators, and using this capacity the system can be operating isolated from the external distribution grid in islanded mode. Therefore, given this ability, the Bornholm power system has become a unique facility for experiments with new Smart Grid technologies [22], [17].

Moreover, in the paper in appendix G it is proposed a microgrid approach using a preferential attachment structure (as described in section 2.8), aimed at end users with both generation and storage capabilities. Here the idea is that the microgrid participants are rearranged following the energy availability as illustrated in figure 2.2 below.

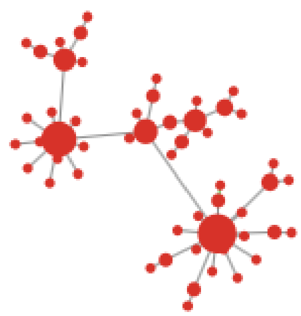


Figure 2.2: Preferential attachment structure (as described in the paper in appendix G)

The diameter of each node (or household) indicates its generation and storage capacity which is determined according to its degree (i.e. number of connections to other nodes), as described in section 2.8. This structural approach is attempted in the *distributed generation mode* of the autonomy model described in chapter 4.

2.1.3 Smart Metering

The concept of Smart Grid will depend on an efficient system capable of handling a tremendous amount of data from different sources in very short periods of time. The primary goal of *Smart Metering* is to gather data from remote consumption meters and transfer this information to power utilities, where in turn the data can be processed. The proposed implementation of this concept is referred to as the Advanced Metering Infrastructure (AMI).

Either on request or on a schedule, AMI systems will be able to measure, collect and analyse the energy usage in households, and communicate the results to utility companies [12], [26].

The author of [12] lists some of the key attributes that deployment of AMI is intended to provide, i.e.

- Two-way communication to the electric meter to enable time stamping of meter data, outage reporting, communication into the customer premise, remote service connect/disconnect, on-request reads, and other functions
- Ability of the AMI network to self register meter points
- Ability of the AMI network to reconfigure due to a failure in communications
- AMI system interconnection to utility billing, outage management systems, and other applications

Furthermore, the integration of a smart metering solution will also provide means for improvements in terms of Demand Side Management (DSM). That is, in addition to reducing the expenses related to system maintenance (by e.g. enhanced fault location, faster system restoration after outages etc.) accompanied by the other benefits obtained from an improved information flow to utility companies, the AMI is also intended to provide means for better user-centric monitoring and control of energy consumption. That is, through providing end users real-time and predictive updates regarding e.g. consumption and electricity prices, the end users are allowed to take a more active role in their electricity management [26].

2.2 Household energy consumption in Norway

In 2013, the Norwegian Water Resources and Energy Directorate (NVE) published a report on energy consumption in Norwegian households. This report assessed the historical growth in energy consumption and also derived an average consumption breakdown of households divided among space heating, water heating, and electrical appliances and lighting. In addition, they investigated how weather conditions affect the annual amount of energy consumed by households, and what energy sources are most contributing to household consumption [3].

Their findings yield that consumption growth has flattened out the last 15 years and that use of electricity and fuelwood as energy sources increases, while oil consumption decreases. Since 1995 the annual consumption in households has varied between 44 TWh and 46 TWh, with the exception 2010, which was a particularly cold year. This is illustrated in figure 2.3 below, where we can observe how the annual consumption has varied from 1976 until 2010. We can also observe the distribution of energy supply among the different energy sources, revealing electricity as the most substantial source [3].

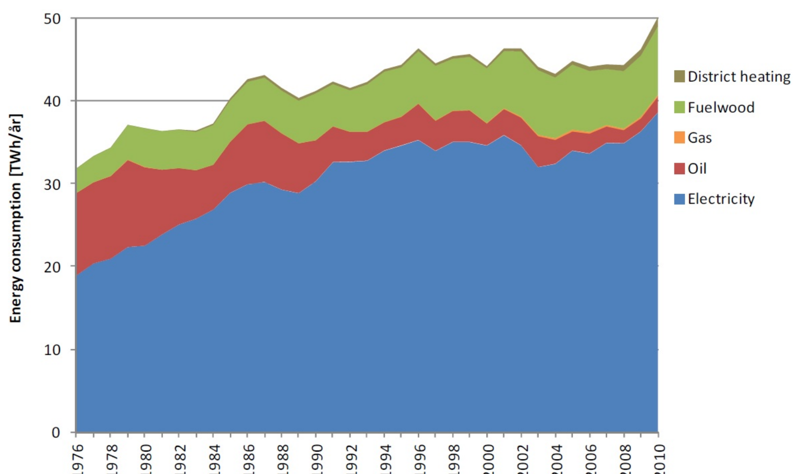


Figure 2.3: Household energy consumption in mainland Norway, 1976-2010 [3].

In [3] they argue that the flattening in energy consumption is due to several factors, most important of which are the implementation of energy efficiency measures, better heating systems, and higher outdoor temperatures as a result of climate change. However, their research also shows that annual consumption is considerably influenced by outdoor temperatures. In particular was the consumption in 2010, which had the coldest winter months in over two decades, as much as 5 TWh higher than the average in previous years. Provisional figures from 2011, on the other hand, indicate that annual energy consumption resumes the flattening trend described above [3].

Furthermore, the reduced growth in floor area per person in recent years has also impacted this flattening trend, as energy consumption is closely related to the floor area each consumer occupy. That is, less growth in floor area per person results in less growth in energy consumption [3].

Moreover, in figure 2.4 below, an average breakdown of household consumption in Norway is illustrated, unveiling the distribution of energy among the different usage areas for end users.

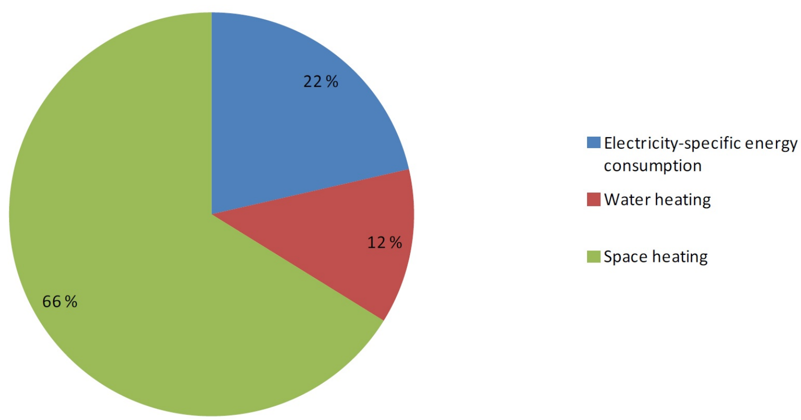


Figure 2.4: Breakdown of consumption in an average Norwegian household [3].

The research in [3] concludes that, as of 2011, 66 % of all household energy in Norway is used for space heating, 12 % is used for water heating, and 22 % on remaining appliances and lighting. The distribution is based on an average consumption of 21 kWh/year per household, and thus about 13.9 kWh of which is used for space heating. However, they emphasize that it is difficult to provide an exact conclusion on the breakdown of end-use consumption. That is, to determine, with a sufficient degree of certainty, the consumption patterns of end users in Norway requires comprehensive measurements, which currently is impossible to provide. Factors such as geographical location, size of household, behaviour of household occupants etc.

varies significantly, and thus the average distribution presented in figure 2.4 may not be representative for the variety of households in Norway. They also underline that end-use consumption is dynamic as building stock, technology, and usage patterns change over time [3].

Below, in figure 2.5, the daily consumption pattern of households and commercial buildings in Norway is illustrated [3].

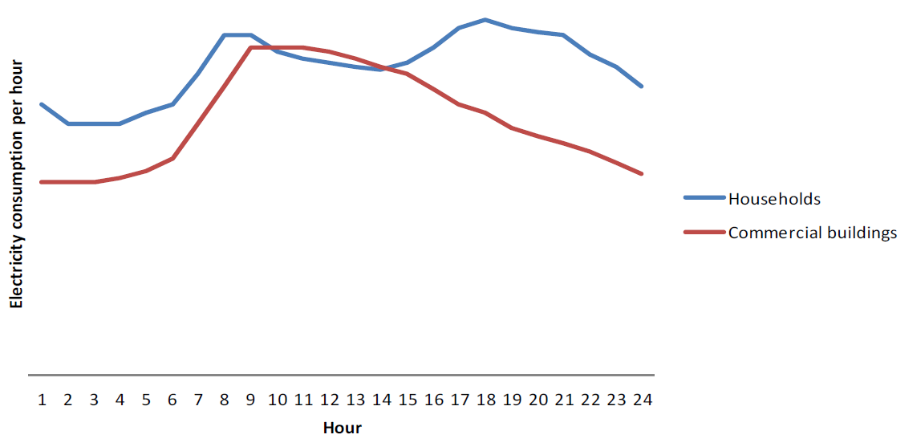


Figure 2.5: Daily Norwegian consumption pattern in households and commercial buildings [3].

Considering the consumption in households, one can observe that there are two distinct usage peaks daily, i.e. one occurring in the morning between 8 and 9 AM, and another increasing in energy consumption in the afternoon. This corresponds to normal end user behaviour where the morning peak is due to the morning routines of household occupants (e.g. showering and lighting), and another increasing in energy consumption caused by afternoon behaviour (e.g. cooking, washing machine, entertainment devices etc.). In between the usage peaks one can observe a significant drop in energy usage consistent with the assumption that household occupants leave home for work or school, causing an overall decreasing in household consumption [3].

2.3 EU directives

Estimations have predicted that by the year 2050 the global energy requirements will more than double from its current level. This fact, accompanied by the need for reducing greenhouse gas emissions, have led to the emergence of several EU directives aimed at reducing and ensuring a more efficient energy consumption. There are in particular three such directives affecting households, all of which are implemented in Norwegian law [3], [7]. These are [3]:

1. **The Renewable Energy Directive**, which purpose is to promote an increased production and use of renewable energy, sets mandatory national requirements for the share of energy consumption which must originate from renewable energy sources. Furthermore, it provides a common framework for stimulating the construction and upgrading of installations to generate more renewable energy. More formally, EU is aiming for 20% of all energy consumption originating from renewable energy sources by 2020, in addition to a 20% increasing in energy efficiency, as part of the EU 20-20-20 initiative.

2. **The Energy Performance of Buildings Directive** concerns improving the energy efficiency in the building stock. That is, establishing schemes for energy efficiency certification of all buildings and energy assessments for the technical installations in buildings.

3. **The Energy Labelling Directive** aims to increase to consumer awareness regarding the energy consumption of products. That is, through energy-labelling of consumer goods the consumers are provided information on the energy-efficiency of products, giving incentives for choosing more energy-efficient alternatives.

2.4 Battery energy storage systems

In [5] they emphasise how Energy Storage (ES) is expected to play an increasingly important role in future power distribution. As power flow no longer will be limited to one direction (i.e. from power sector to consumers), the need for managing distributed generation and demand will require Battery Energy Storage Systems (BES) for maintaining grid stability and flexibility.

In particular, the challenges related to integrating renewable energy sources, given their unpredictable and fluctuating generation patterns, will require significant investment in smaller-scaled and more flexible storage technologies [5].

Currently, BES systems range anywhere from 5 kWh up to 50 MWh and are differentiated by factors such as response time, mobility, and versatility to be fitted to either high power or high energy applications. As stated in section 2.3, EU aims for 20% of all energy consumption originating from renewable energy sources by the year 2020, in addition to increasing the energy efficiency by 20%. Thus, BES systems can ensure a better match between supply and demand, and ease the transition to renewable energy sources amounting to a greater share of the global energy supply [5].

Also, by employing measures for e.g. peak shaving (as described in section 2.5.4) one can compensate with stored energy in high demand periods, which in turn reduces the need for expensive backup generators specifically targeted at handling peak consumption. That is, the electric utility infrastructure costs are primarily driven by the need to serve the load during *peak demand periods*. Thus, by utilizing BES systems to compensate in high demand periods, one can reduce the peak demand seen from the utility company's perspective, which consequently will reduce the electricity costs [25], [5].

There are various services and functions BES systems offer, some of which are [5]:

- **Integration of renewable energy sources:** That is, converting highly variable renewable energy resources into dispatchable ones by use of storage. By using BES systems for decentralized storage one may obtain a dynamic behaviour able to compensate for fluctuating renewable energy generation with fast response times.

- **Peak shaving:** BES systems may store energy when consumption is low, which in turn can be compensated with for shaving usage peaks in high demand periods.

- **Voltage control:** BES systems can help regulate the voltage profile, guaranteeing standard voltage supply within a defined range. That is, by storing energy when the voltage is high and feeding in when voltage is low.

- **Uninterruptible power supply (UPS):** BES systems can act as a backup power source in the event that the external energy supply is disrupted. By temporarily *islanding* the operation (as described in section 2.1.2), e.g. a microgrid can be able to manage the entire energy demand of its participants by utilizing the stored energy of BES systems.

Furthermore, as stated in [25], it is important to consider that the cost of a BES system is largely associated with its *energy* storage rating (Wh) rather than its *power* rating (W). That is, the required discharge period in different applications will greatly affect the costs of implementing a storage system.

2.4.1 Battery technologies

In [5] they emphasize that all four battery technologies (lead-based, lithium-based, nickel-based and sodium-based) can provide distinctive and important functions to grid operators. Below in table 2.1 some of the similarities and differences between the battery technologies are listed based on information gathered from [5].

Technology	Capacity	Efficiency	Life	Cycles	Temperature
Lead	1 Ah - 16 kAh	>85 %	20 years	2000 @ 80% DOD	-30 to +50 °C
Lithium	[1]	≈100 %	20+ years	5000 @ 80% DOD	-30 to +60 °C
Nickel	0.5 Ah - 2 kAh	>90 %	25 years	3000[2]	-40 to +60 °C
Sodium	380 V 40 Ah	92 %	10+ years	4500 @ 80% DOD	-30 to +60 °C

Table 2.1: Similarities and deviations between different battery technologies (DOD = Depth Of Discharge)

Moreover, due to the current relatively high costs of BES systems, most reported installations thus far are considered as pilot projects either partially

[1] One of the main advantages with Li-ion technology is its scalability. It can be adapted to virtually any power or energy requirement, ranging from very high power (i.e. 10 kW / 10 kWh) to very high energy [5].

[2] 3000 cycles of nominal capacity

or fully funded by government entities. Hence, further research and development is needed to reduce the prices and improve the performance of each of the above mentioned battery technologies should they become suitable for smaller-scaled purposes [25], [5].

2.5 Measures for reduced and more efficient household consumption

Households account for around 30 per cent of the total stationary energy consumption in Norway and thus exploring usage patterns and measures for better efficiency is important for achieving an overall reduction in power consumption [3]. In [3] they list several means for both reducing consumption and increasing the energy efficiency, some of which are described in section 2.5.1. Furthermore, in section 2.5.2, the potentials of Smart Grid for better end user management is described, i.e. through providing real time and predictive feedback in terms of electricity usage and pricing details to end users. Moreover, in section 2.5.3, demand shifting is described as a method for reducing the usage peaks in high demand periods, by shifting demand to off-peak periods. Finally section 2.5.4 describes how one can compensate autonomously for daily usage peaks by utilizing the locally generated energy of microgrids in high demand periods with the purpose of ensuring a less fluctuating daily consumption seen from the utility company's perspective.

2.5.1 Energy efficiency measures

Energy efficiency measures concerns reducing the energy requirements, e.g. for buildings, either by properly planning low energy requirements prior to construction, or improving older houses by e.g. better insulation of lofts, basements and walls, in addition to draught proofing windows and doors. As described in section 2.3, the *Energy Performance of Buildings Directive* provides schemes for energy efficiency certification of buildings aimed at ensuring the previously described improvements. Such means can significantly reduce the energy requirements for space heating, which as described in section 2.2 amount to the majority of all energy consumption in Norwegian households [3].

Furthermore, improving the insulation of hot water tanks, installing water-saving showers etc. can also contribute to reducing consumption and improving the energy efficiency. Also, replacing old heating sources (such as oil-fired boilers and paraffin stoves) with better heating systems (e.g., electric heaters or heat pumps) can result in a more efficient heating of households. In addition are consumers increasingly choosing more energy efficient household appliances and entertainment devices due to measures such as the *Energy Labelling Directive* described in section 2.3 [3].

2.5.2 Better end user management of energy consumption

Recent investigations have shown that providing real-time and predictive updates regarding electricity usage and pricing can incentive consumers to reduce their energy consumption [2], [11], [27].

In [11] they have analysed 15 experiments on household response to dynamic pricing of electricity. The study uncovered that households in fact respond to higher prices by lowering their electricity consumption, and that the potential reductions in power generation are considerable. The consumers responded to higher prices during peak periods by reducing the consumption and/or shifting it to off-peak periods and, as a matter of fact, they concluded that providing such information to end users can reduce consumption by 5-15% [11].

However, the experiments mentioned above all used time-varying pricing of electricity, which was only applied during the periods they investigated. In most cases (like e.g. with Norwegian power distribution) the cost of electricity is currently determined day-ahead, and thus provide no economic benefits for consumers to lower their consumption during usage peak periods. Once again, this highlights one of the main advantages that the increased information flow of Smart Grid is intended to provide. That is, we achieve a better foundation for employing such pricing schemes, where we can dynamically determine the cost of electricity based on real-time updates on energy consumption.

Furthermore, as described in [6], the American IT company Opower have studied how providing customers information on neighbouring households' energy usage also can incentive reduction in consumption. That is, they have examined how social pressure can affect consumption behaviour when households are made aware of the consumption patterns in neighbouring homes of similar size and number of occupants. Their results yielded a consumption decrease of 1.9 TWh last year which, in comparison, amount to approximately half of the generated energy provided by the solar power industry in the US [6].

Given a user-centric gathering and dissemination of information we can achieve a foundation for employing measures such as the ones described above. That is, by providing real-time and predictive updates on consumption to households and/or adding pricing incentives, such as the previously described dynamic (demand-dependent) pricing scheme.

2.5.3 Shifting demand from high demand periods

As described in section 2.2, there are variations in power demand daily, and thus, the coinciding habits of consumers causes significant usage peaks to occur at certain times during the day. Consequently, when constructing a power grid, one must take in account the hour of the year for which electricity consumption is at its highest (also known as the power grid's peak load), and ensure that the total energy capacity is great enough to cover this demand [3].

For instance, as described in section 2.2, a daily usage peak usually occurs around 7 or 8 AM on week days due to the morning routines of household occupants. Thus, considering that most hot water tanks in Norway begin heating water as soon as it is drawn, it is plausible to assume that the experienced morning usage peak is caused by this. By employing an automated home energy management mechanism one can shift demand according to a user's preferences with the aim of reducing the overall consumption in usage peak periods. In particular, given the above mentioned water-tank example, it would be feasible to postpone the water heating until mid-day when the overall consumption is significantly less [3].

Considering this, numerous investigations have been performed on measures for reducing usage peaks by shifting usage from high to low consumption periods, with the intention of reducing the peak demand, and consequently the power grid's peak load. For instance, in [1] it is proposed such an energy management system that shifts usage to off-peak hours and lowers the total energy consumption.

2.5.4 Autonomous peak shaving in high demand periods using battery energy storage

Another method for reducing peak demand is by compensating with locally stored energy in high demand periods, henceforth referred to as *peak shaving*. That is, peak shaving in the sense that local energy is used to compensate for usage peaks such that the consumption pattern observed at the utility company appear as constant during high demand periods, while the actual energy usage remain unchanged. Such an approach may also contribute to increased use of renewable energy sources, as this local energy may originate from e.g. solar or wind power.

In [25] it is described a peak shaving study performed performed in Nevada, USA. Here, they have investigated the sizing of a utility-owned BES system that is planned for installation at the substation end of a residential feeder. The purpose was to investigate storing of energy in low-demand periods which in turn could be utilized to compensate for usage peaks. First, they examined the load demand of a residential feeder in the summer months (June - September 2008), amounting to a total of 122 days. After which, the sizing of the BES system was derived from the desired level of peak shaving by *load following*. Load following, or power control, means that the demand dynamically controls the amount of power provided by the battery system. Finally, the BES system power and energy ratings were quantified. In figure 2.6, a sketch of the setup is illustrated [25].

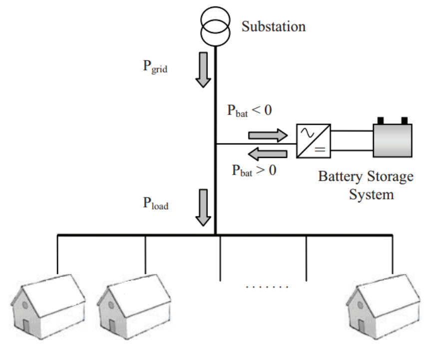


Figure 2.6: Sketch of feeder with BES system and residential area [25]

Below, in the left hand side plot of figure 2.7, the daily load of the residential feeder in the summer months of 2008 is illustrated. Furthermore, the maximum peak load, $P_{load}^{max} = 1.46MW$ occurring on July 8th, was used to determine the boundary for what was considered a usage peak in the whole time period. That is, the desired amount of peak shaving, σ, was defined as a percentage of maximum peak load. In this study they used $\sigma = 0.25$, and thus the maximum net power which had to be supplied by the battery system was [25]:

$$P_{batt}^{max} = \sigma * P_{load}^{max} \tag{2.1}$$

In addition, they assumed a discharge and power conversion loss of 10%, and denoted the overall system efficiency by $\eta = 0.90$. Hence, the maximum power provided by the BES system was defined as [25]:

$$P_{BESS} = \sigma * P_{load}^{max}/\eta \tag{2.2}$$

Given $\sigma = 0.25$, the BES system had to provide a peak power of $P_{batt}^{max} = 0.365MW$, which results in a maximum grid power, $P_{grid}^{max} = 1.095MW$. This boundary is illustrated as the dotted red line in the left hand side plot of figure 2.7, and thus any load change in excess of this threshold was considered a usage peak. The right hand side plot of figure 2.7 illustrates the distribution of hourly consumption with respect to how often they occur, in per cent of total time [25].

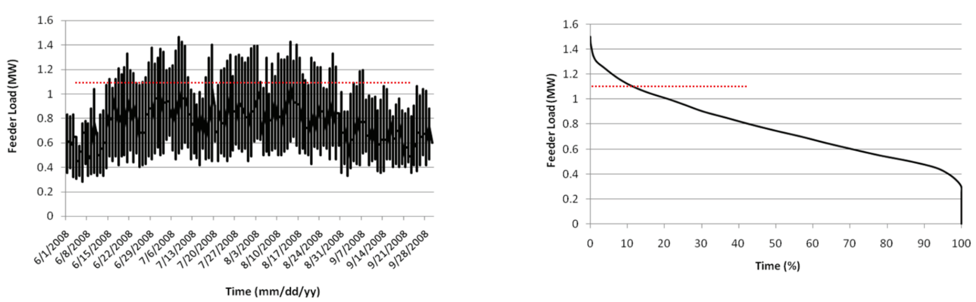


Figure 2.7: *Left:* Daily feeder load during the four investigated months. *Right:* Duration of peak period in per cent. [25]

Given the previously described discharge efficiency, $\eta = 0.90$, the BES system power rating was $P_{BESS} = 0.4MW$. Furthermore, the capacity of the BES system was determined by computing the daily energy demand that must be supplied the battery in order to avoid power flow from exceeding the desired maximum grid power contribution, i.e. $P_{grid}^{max} = 1.095MW$. This was achieved by determining the area between hourly consumption and the maximum grid power boundary [25]. That is [25]:

$$E_{batt}^{i} = \int_{0}^{24} (P_{load}^{i} - P_{grid}^{max})\mathrm{dt}, \;\; P_{load}^{i} \geq P_{grid}^{max} \tag{2.3}$$

After which, the maximum value the BES system had to be able to provide was determined, i.e [25]:

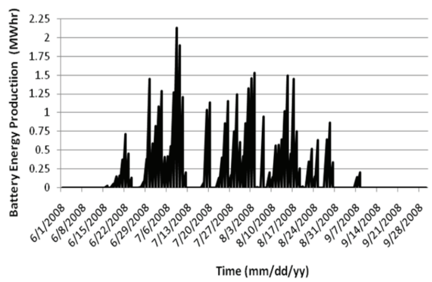
$$E_{batt}^{max} = max\{E_{batt}^{1}, E_{batt}^{2}, ..., E_{batt}^{n}\}, \tag{2.4}$$

where $n = 122$ represents the number of days in the summer period. Finally, they quantified the energy rating of the BES system by dividing the result obtained in equation 2.4 by the discharge efficiency, η, and adding the minimum level of energy must remain at all time in the battery, SOC_{min} (i.e. the *minimum State of Charge*) [25]. That is [25]:

$$E_{BESS} = \frac{E_{batt}^{max}}{\eta} + SOC_{min} * E_{batt}^{max} \tag{2.5}$$

Their investigation revealed the maximum energy rating of the BES system as $E_{batt}^{max} = 2.12MWh$. Consequently, given a discharge efficiency $\eta = 0.90$ and a SOC_{min} set to 20%, results in a BES system capacity of $E_{BESS} \approx 2.75MWh$.

Below, in the left hand side plot of figure 2.8, the daily BES system energy generation of the entire time period is illustrated. Furthermore, the right hand side plot of figure 2.8 illustrates the desired peak power shaving [25].



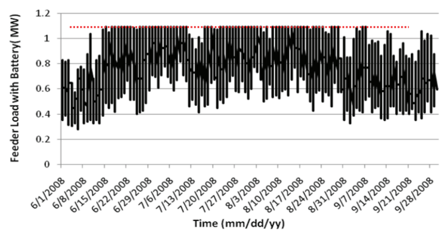


Figure 2.8: *Left:* Daily energy provided by BES system. *Right:* Daily grid power variations after peak shaving. [25]

In this study, the BES system was intended to recharge during the early morning hours when the consumption was low, and thus the right hand side plot of figure 2.8 shows a higher daily minimum load than the base case illustrated in the left hand side plot of figure 2.7 [25].

In the model described in chapter 4, a similar peak shaving approach is attempted using consumption data gathered from the Demo Steinkjer project (described in section 2.6) and photovoltaic solar generation data gathered from elia (described in section 2.7.2).

2.6 Demo Steinkjer

Demo Steinkjer is a Norwegian demonstration project where new solutions for measuring and use of electricity can be tested. The testing site is located in Steinkjer and contains about 1.000 households, of which 321 have agreed to be *active participants* meaning they will participate in consumer oriented tests and projects. The remaining households will participate, without direct involvement, in tests conducted on the grid itself as well as secondary subsystems. The intention of the project is to attract entities to test new technology aimed at an modernization of the power grid with new products and services. Thus, Demo Steinkjer is an arena for which smart energy solutions can be tested with purpose of exploring a suitable design and implementation of the future electricity grid in Norway[3].

Companies such as SINTEF, Nexans, Telenor, Connexion, SagemCom, and others have already shown interest in running projects with Demo Steinkjer, and they will have the opportunity to test new products on real consumers. Entities will have access to customer database including anonymous AMS meter data and high-speed communication capabilities with five net/grid stations. In total, there are about 800 electricity meters installed, including 770 AIDON meters and 30 remotely read units through GSM/GPRS[3].

2.7 Solar energy

In [7] it is stated that the solar energy reaching the surface of Earth every hour is enough to meet the annual global energy needs. The challenge, however, reside in harnessing this energy at an affordable cost. Thus far the cost of large-scale collection, conversion, and storage of solar energy has not been feasible compared to conventional energy generation. Consequently, solar energy currently makes a negligible contribution to the global energy supply. However, predictions on future increasing in energy consumption, in addition to the environmental effects caused by fossil fuels, have arisen the need for further research on solutions for solar energy generation. Other renewable energy sources (e.g. wind, hydro etc.) and non-renewable (e.g. nuclear) are unable to satisfy the expected increased global energy needs, and thus scientists have proposed solar driven production of environmentally clean electricity, hydrogen, and other fuels as the only sustainable long-term solution for global energy needs [7].

In addition to the economic challenges, the availability of solar energy is another source of concern. That is, solar power is not always available where and when needed, and thus daily and seasonal effects have great impact on the energy generation. Moreover, the changing dynamics, non-linearities and uncertainties related to solar energy also make prediction of supply difficult [9].

[3] http://www.demosteinkjer.no

There are several methods for generating solar-sourced electricity. Most commonly used are direct generation using photovoltaic cells (PV) and indirect generation, called concentrated solar power (CSP), where collectors use mirrors and lenses to concentrate sunlight onto a thermal receiver that absorb and convert sunlight into heat, which in turn is used to drive a turbine to provide electric power. In this study, however, only PV energy generation is discussed as it is the most common method of the two, and arguably also easier to implement in microgrid architectures due to the space requirements of CSP generation facilities [18]. This is also supported in [5], where they state that the primary renewable energy source for future Smart Grids will be photovoltaic. In section 2.7.1 below, PV energy generation is described more thoroughly, while section 2.7.2 describe the Belgium transmission system operator elia which publishes data on PV energy generation.

2.7.1 Photovoltaic solar energy generation

Solar cells, or photovoltaic (PV) cells, convert solar radiation directly into electricity and is based on the photovoltaic effect. In general, the photovoltaic effect is defined as the emergence of an electric voltage between two electrodes attached to a solid or liquid system when exposed to light [14]. Below, in figure 2.9, one such PV solar cell installation is depicted [21].

Figure 2.9: A large silicon solar array installed on the roof of a commercial building [21]

The efficiency of solar cells, η, can be derived from equation 2.6 below [14], i.e.

$$\eta = \frac{P_{max}}{E_S * A_c} \tag{2.6}$$

where P_{max} is the nominal power output (i.e. maximum achievable power), E_S is the incident radiation flux (i.e. the amount of sunlight power that reaches the Earth's surface in W/m^2), and A_c is the area of the collector in m^2 [14].

The incident radiation flux is considered to be approximately 1000 W/m^2, and thus, given 100 % efficiency, solar cells generate 1 kW power per square meter during optimal weather conditions. As of now, however, the efficiency of photovoltaic cells averages at approximately 15 % [20]. Furthermore, the daily periods for when solar cells generate power varies significantly in different parts of the world, and thus affect the total amount of energy generated. In figure 2.10 below the *annual* solar energy potential in all of Europe is illustrated [8].

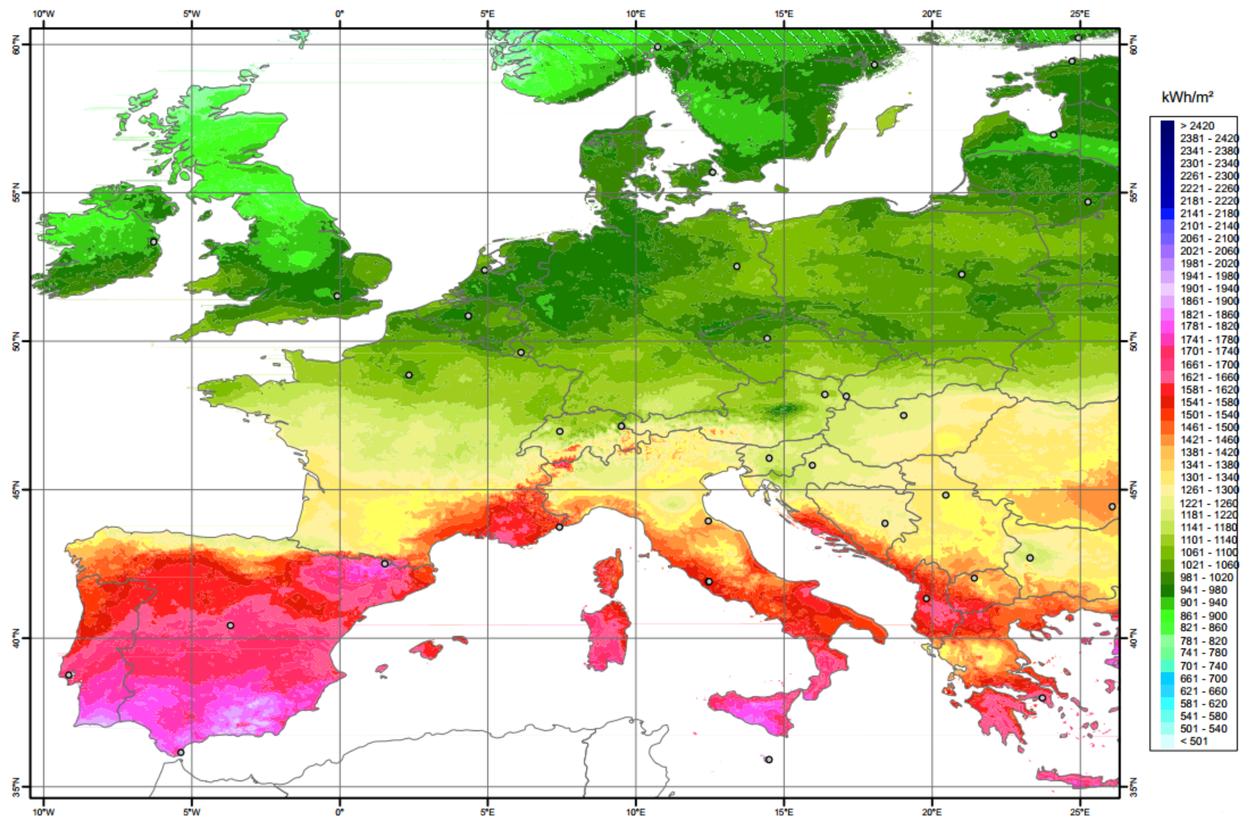


Figure 2.10: Solar energy potential map of Europe [8]

As one can observe the variations are considerable. In particular, comparing the southern parts of Spain and Portugal (1821 - 1860 kWh/m^2) with the southern parts of Norway (861 - 900 kWh/m^2) reveals an annual difference in energy potential of approximately 1000 kWh/m^2.

Furthermore, the power output of solar cell installations are also highly weather dependent, and thus the nominal power output of an installation is achieved only during optimal weather conditions. In figure 2.11 below, the complete solar power output on July 7th 2013 in all of *Germany* is illustrated. In total Germany has, as of 2013, an installed domestic PV capacity of approximately 34 GW. However, due to the varying angles of their solar cell installations, some systems peak at 11 AM while others at 2 PM causing the different installations to achieve generation peaks at different times during the day. Consequently, they achieve maximum power output peaks at about 70-80 % of total capacity [13].

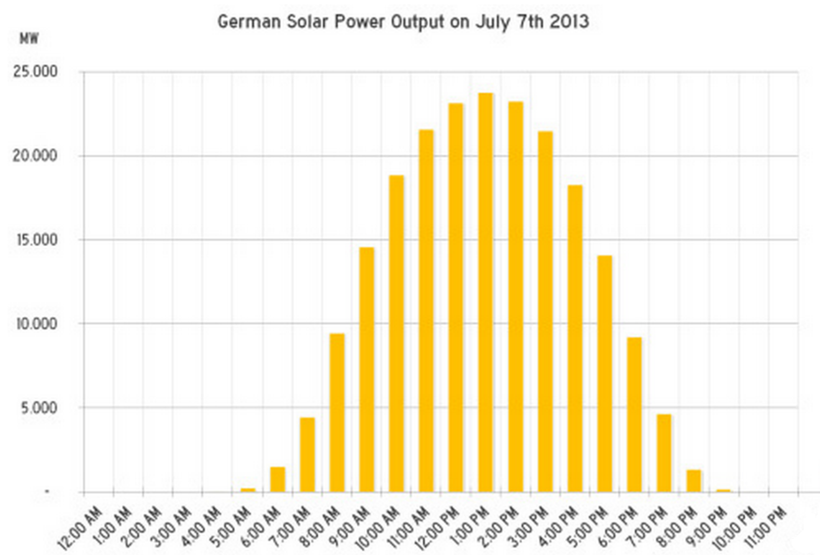


Figure 2.11: German solar energy generation on July 7th 2013 [13]

As one can observe the generation peak this day was 24 GW (occurring at 13 PM), which amounts to approximately 70 % of total capacity [13].

2.7.2 Elia solar cell generation data

Elia is the high-voltage transmission system operator of Belgium responsible for transmitting electricity from generators to distribution systems, which in turn deliver power to consumers. In order to provide transparency in the electricity market, elia publishes generation data from renewable energy sources (such as wind or solar) as both predictive and actual measurements, which consequently can be used for scientific research[4].

In this study, PV solar cell data from elia is used to uncover the potentials for solar energy harnessing, and to determine whether or not it is suitable as a local generation source in microgrids. The data used is gathered from all of Brussels, Belgium in 2013 as *quarter-hourly* updates on power generation, and the total installed PV capacity is 6.92 MW in January until March.

[4]http://www.elia.be

However, in March the nominal capacity was increased to 10.2 MW and thus energy generation becomes greater. Section 3.1.2 describes this investigation.

2.8 Complex network theory

The use of complex network theory is increasing as a measure for analysing and understanding real world networks. Empirical studies on computer networks, social networks and electrical power grids, to name a few, have revealed that behaviour of such networks is not suitable for modelling by use of traditional mathematical graph theory. Real world networks have structures that are irregular, complex and dynamically evolving with time, and thus the models proposed in mathematical graph theory are not able to reproduce the dynamical and functional behaviour of such topologies [4], [24].

In [4] they emphasize several reasons for why the study of complex networks are relevant for real world topologies:

- **Weighted networks:** Often in real topologies the connections between nodes are weighted in terms of edge capacity and intensity, i.e. networks in which a value is associated with each link which may vary as time progresses. Examples of such are existence of weak and strong ties between individuals in a social network, different physical distance between nodes, and different capabilities for transmitting e.g. electric signals.

- **Dynamical behaviour:** Real world networks are composed by large numbers of interconnected dynamical units. Thus, the *collective dynamics* in a complex topology and the local properties of individual nodes greatly affect the interactions in coupled dynamical systems. For instance, studying synchronization phenomena in sociology has become very relevant for acquiring a better understanding of the mechanisms underlying the formation of collective social behaviours, such as e.g. the emergence of new habits, fashions or leading opinions.

- **Adaptive and dynamical wirings:** When networks themselves are dynamical entities, affected by either external or internal actions, the topology is not fixed. That is, as opposed to dynamical processes with static connection schemes, the topology may evolve and adapt with time. A suitable example here is the islanding of a microgrid (described in section 2.1.2) where its external energy supply is disrupted and the cell must adapt by covering the entire energy demand of its participants.

There are some unifying principals and statistical properties common to all complex networks, some of which are listed below [4]:

- **Node degree:** The degree (or connectivity) describes the number of links one node has to other nodes in the network, which can be used to determine a node's importance. In fact, the most basic topological representation of a graph G can be obtained in terms of its *degree distribution*, $P(k)$, defined as the probability that a node in G chosen uniformly at random *has degree* k. If the graph is directed the degree of a node has two components, i.e. out-degree (number of outgoing links) and in-degree (number of ingoing links).

- **Betweenness centrality:** The term betweenness centrality is another measure for deriving a node's importance within a graph. It quantifies the number of times a node acts as a bridge along the shortest path of two other nodes. That is,

$$b_i = \sum_{i \neq j \neq k \in N} \frac{n_{jk}(i)}{n_{jk}} \tag{2.7}$$

  where n_{jk} is the number of shortest paths between j and k, while $n_{jk}(i)$ is the number of shortest paths connecting j and k and passing through i.

- **Graph diameter:** The diameter is the greatest *shortest path* between any pair of nodes in a graph. Thus, to determine the diameter, one first finds the shortest path between each pair of nodes, where the path with greatest length is the diameter.

Moreover, the structure of a network always affects its function. For instance, the robustness and stability of electricity transmission is greatly affected by the topology of the power grid. The traditional power grid (e.g. the one described in section 2.8.1 below) has a moderately heterogeneous topology characterized by an exponential distribution of the number of transmission lines per substation (i.e. degree distribution). However, as described in section 2.1.2, the paper in appendix G proposes a different power grid topology using a preferential attachment structure. Here, the basic idea is that nodes with high degree acquire new links at a higher rate than low-degree nodes, and thus the power generation and storage capacity of each node in the network depends on the number of connection it has to other nodes [4], [24].

2.8.1 Related investigation: Modelling cascading failures in the North American power grid

A related investigation with regards to power grids is described in [16]. Here they have modelled the North American power grid using its actual topology and investigated the damage inflicted in terms of transmission efficiency in the event of substation failure. They made plausible assumptions regarding load and overload conditions of transmission substations and observed how overloads caused by substation malfunctioning leads to cascading effects in the power network [16].

More generally, they modelled the power grid as a weighted graph G, with N nodes (substations) and K edges (transmission lines), and represented it as an N x N adjacency matrix $\{e_{ij}\}$. Each element e_{ij} represent the line between nodes i and j and is a number in the range [0,1], where *0* indicate no direct connection in between the nodes and *1* indicated that the transmission line works perfectly [16].

Initially all the existing transmission lines in the power network were set to *1* and the efficiency of a path between two substations in the network was defined as the *harmonic composition of efficiency* in the transmission lines in between the substations. That is, the harmonic composition of N numbers $x_1, x_2, ..., x_N$ is defined as $[\sum_i^N 1/x_i]^{-1}$. After which, they started to remove nodes from the network and observed how the network progressed. It showed that when removing a substation, its load needs to be redistributed among the remaining neighbouring substations in the network, causing other substations to carry larger loads than their capacity. Ultimately, this leads to overload conditions de-gradating the neighbouring substation's performance as well, which in turn creates an cascading effect on the entire network. In fact, they concluded that the removal of one single substation can, in a worst case scenario, cause a degradation of 25% in terms of overall transmission efficiency [16].

This investigation illustrates how we can use complex network theory to analyse real world networks. In chapter 4, a similar model for autonomy in microgrids is described where the complex network tool NetLogo (described below in section 2.8.2) is used.

2.8.2 NetLogo

NetLogo is a multi-agent programmable modelling environment using an agent-based programming language, meaning that actions and interactions of autonomous agents (i.e. entities or nodes) can be simulated in order to assess their effects on a system as a whole. The tool allows us to facilitate the structural properties of complex systems and examine the collective behaviour of rule-based agents dynamically interacting as in real world networks[5].

As the complexity of a system is closely related to the connectedness and behaviour of different agents, NetLogo allows us to model robustness in terms of adapting to internal and external events in a complex system. Thus, we can model how a complex real world network with dynamically evolving agents progresses with time, and how to handle situations that emerges from the agents' behaviour and interactions[5].

In this study, NetLogo is used for developing the microgrid autonomy model described in chapter 4. The user interface of this model and parts of the NetLogo-code is presented in appendix E, while the model itself is included in the folder "AutonomyModel" on the attached CD-ROM.

[5] http://ccl.northwestern.edu/netlogo/

Chapter 3

Analysing dynamics of energy consumption and generation

In order to model autonomy in microgrids, one must first investigate the dynamics of energy consumption and generation. This chapter describes two analyses, one performed to uncover the dynamics of energy consumption in Norwegian households, and another to reveal the generation potentials of PV solar cells. The data and patterns obtained in these analyses lay the foundation for the subsequent autonomy model described in chapter 4.

3.1 Methodology

Section 3.1.1 describes an investigation of energy consumption in Norwegian households based on data gathered from the Demo Steinkjer project. In section 3.1.2 an investigation on energy generation in solar cells is described which purpose is to reveal the current potentials of solar energy harnessing. Finally, in section 3.1.3, it is described how to setup the database containing the energy consumption and generation data used in these analyses.

3.1.1 Consumption data from Demo Steinkjer project

As described in section 2.6, the Demo Steinkjer project[1] has gathered consumption data from several houses located in the same geographical area as hourly updates over the last two and a half years. Currently this database

[1] http://www.demosteinkjer.no

consists of 7.2 million entries on consumption from 221 buildings, of which the great majority is ordinary households. The intention of this analysis is to examine the consumption data and reveal whether the daily usage patterns of the Demo Steinkjer participants correspond to the description of *normal* Norwegian household behaviour in section 2.2. Furthermore, the obtained consumption patterns gathered from this analysis will lay grounds for the subsequent model (described in chapter 4) where generation and storage features are added in a futuristic microgrid scenario.

More particularly, this analysis will examine usage patterns in a selection of households participating in the Demo Steinkjer project and determine how energy consumption varies by investigating:

- hourly consumption over the course of day in different households
- energy usage in different months over a year
- weekday as opposed to weekend consumption
- total and average consumption when aggregating the patterns of multiple households

Thus, the analysis will uncover e.g. when usage peaks occur, the seasonal effects on energy consumption, and also determine the total daily usage pattern of several households combined. Detecting a daily usage pattern that is consistent when summarizing several households will uncover how we can implement mechanisms for avoiding usage peaks in microgrids, as described in section 2.5.4. The results from this analysis are described in section 3.2.

3.1.2 Generation data from elia solar cells

As described in section 2.1, the futuristic aim of Smart Grid is to achieve a more distributed energy supply infrastructure where local generation and storage sources are added to microgrid cells. Using distributed energy generation the microgrids can autonomously control its own generation and storage in response to variable demand and supply conditions. By adding renewable energy sources (e.g. solar, wind or hydro) to microgrids, one can e.g. compensate for daily high demand periods by utilizing locally stored energy autonomously. Also, in the event that external energy supply from utility company is disrupted, local energy generation and storage can be utilized to avoid power outages.

In this analysis the energy generated from PV solar cells will be examined with purpose of investigating the dynamics and sustainability of solar energy. Furthermore, the analysis will also investigate day-ahead predictions, and reveal with what certainty the harnessing of solar energy can be predicted. The data examined is gathered from elia[2] and concerns solar energy generation in Brussels, Belgium in 2013.

In particular, the analysis will examine solar generation dynamics by investigating:

- the daily variations in generated energy
- the monthly variations in daily generated energy
- the predictability of solar energy

Thus, the aim of this investigation is to derive and analyse the energy generation potential of PV solar cells. Furthermore, the data obtained from this analysis will be utilized in the subsequent model on autonomy in microgrids described in chapter 4. As described in section 2.7.2, elia offer both day-ahead predictions and corrected data on the daily energy generation in solar cells, and thus the investigation will also reveal how accurately solar energy generation can be predicted. The results from this analysis are described in section 3.3.

As mentioned in section 2.7.2, the PV solar dataset from elia has quarter-hourly updates on power generation. For simplicity, this is converted to *hourly average* updates in this investigation, i.e. by summarizing the quarter-hourly updates each hour and dividing it by four. Furthermore, the analysis assumes that this hourly average power output is *constant* each hour.

3.1.3 Database setup

Both the consumption and generation data used in these analyses can be downloaded in .csv format from Demo Steinkjer[1] and elia[2], respectively.

[2] http://www.elia.be

However, as described earlier, the datasets are enormous. In particular, the Demo Steinkjer data alone consists of 7.2 million entries on consumption from the last two and a half years. Therefore, in order to simplify the work of investigating this massive amount of data, I needed to represent it in a more easily accessible manner.

To achieve this, I set up an apache server and configured phpMyAdmin such that I could create a MySQL database consisting of the datasets. The two datasets were then separated in different tables in this database, and made accessible with SQL commands. *See appendix A for a more thorough tutorial on how to set up the database and extract data.*

After which, I extracted data from the database using SQL commands in python scripts, and investigated the dynamics of energy consumption and generation as described in sections 3.1.1 and 3.1.2, respectively. Appendix A describes, as mentioned, how to setup the database and extract data. However, below I have chosen to list some of the most significant and time-consuming issues that needed to be resolved, in order of appearance. These are:

1. The Demo Steinkjer dataset only has a column with the accumulated energy consumption each hour. Thus, one must create a new column called "HourlyConsumption" in phpMyAdmin and then run the python script "addHourlyConsColumn.py". This separate column is needed for deriving the difference between two consecutive measurements, i.e. *the consumption of the last hour*. The script is located both in appendix B and on the attached CD-ROM, and takes approximately four hours to run on the entire database.

2. There are several "gaps" in the dataset from DemoSteinkjer, i.e. missing measurements. Thus, finding longer periods of time, where none of these gaps are present, is extremely time-consuming. However, the 20 households evaluated in the analysis described in section 3.2 have consistent measurements in the time period ranging from October 1st 2012 until June 28th 2013. The User IDs of these households are listed in appendix F.

3. One must manually remove the spaces in column names in the datasets on solar generation. That is, the column "Day-Ahead forecast [MW]"

must be changed to "Day-AheadforecastMW" and "Corrected Upscaled Measurement [MW]" to "CorrectedUpscaledMeasurementMW". If this is not done you get errors when attempting to extract data using python scripts and subsequently in the NetLogo model (chapter 4).

4. The dataset on solar generation provided by elia uses comma as the decimal mark in numbers. This must be exchanged with period, otherwise the extracted data is treated as a string instead of a decimal number in python. The script performing this exchange is "ReplaceCommaWithPeriodInDatabase.py", which is located on the attached CD-ROM.

5. In the solar generation data from elia there exist some duplicate measurements, listed consecutively. This issue is resolved by running the "searchingForDuplicate.py" script located on the CD-ROM, and manually removing the database entry indicated by the output of the python script.

In appendix C and D, two scripts (one for extracting and plotting consumption patterns and another for generation patterns) are presented. These scripts have been included in appendix to give the reader an understanding on how to access the database using python scripts and reproduce the plots and results described in sections 3.2 and 3.3. However, these are just examples, and thus I refer to the folder "pythonworkspace" on the attached CD-ROM to see the complete selection of python scripts used in these investigations.

3.2 Results from analysis: Consumption patterns in Demo Steinkjer households

This section describes the results from the analysis of consumption behaviour in households participating in the Demo Steinkjer project (as described in section 3.1.1). The main purpose of this investigation was to uncover if the consumption patterns of different homes coincide, i.e. to examine whether multiple homes have similar daily usage patterns. If so, the knowledge of these patterns can be used in further modelling of microgrid scenarios where local generation and storage capabilities are added to microgrids. Knowing such patterns can enable means for e.g. utilizing the locally stored energy of microgrids in high consumption periods in order to avoid high electricity prices and power outages as described in section 2.1.

Section 3.2.1 describes the results from an investigation of monthly average consumption in several individual households. The purpose of investigating this was to examine how consumption varies from month to month, and to reveal similarities and deviations in different households. In section 3.2.2 the combined *daily* consumption of several households is examined with purpose of recognizing a common pattern. In section 3.2.3 the investigation concerns a three-month period (i.e. January-March 2013) where the total hourly consumption from ten different houses is summarized. Here we can uncover if a certain usage pattern emerges when the consumption of several households is merged over a longer time period, and also examine the differences between week day and weekend consumption. In section 3.2.4 the total number of homes is increased to 20 and the time period to nine months (October 2012 - June 2013). Here we can examine if the pattern observed in section 3.2.3 remains when increasing the total number of homes and the time period even further. In section 3.2.5 the monthly variations in consumption is examined further with purpose of revealing the differences in monthly average, maximum and minimum hourly consumption. Finally, in section 3.2.6, the findings of this analysis are summarized.

3.2.1 Average hourly consumption from different houses excluding weekends

In figures 3.1, 3.2 and 3.3 below, the *average hourly consumption* from different months in three separate houses is depicted. The consumption patterns of all three households have been gathered from the same time periods, excluding weekends, and we can observe how the average energy usage varies over the course of day in six different months. There are deviations from month to month and in between houses, but common for all houses and months is that they follow *approximately* the same curve. That is, we clearly see a usage peak between 7 and 9 AM and an overall increasing in energy consumption after 15 PM. Considering this, the patterns observed confirms the expected behaviour in Norwegian households described in section 2.2.

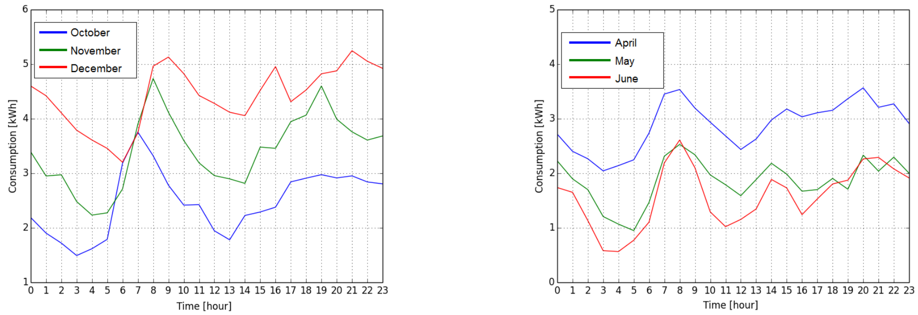


Figure 3.1: **Monthly average consumption (house ID 7350049083690884):** *Left:* October, November and December 2012 *Right:* April, May and June 2013

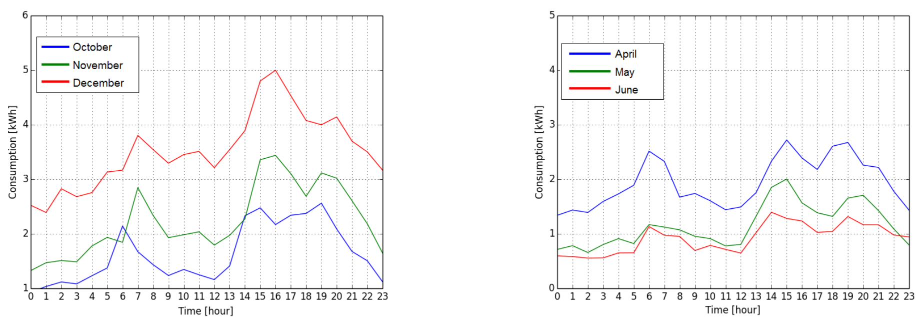


Figure 3.2: **Monthly average consumption (house ID 7350049084529299):** *Left:* October, November and December 2012 *Right:* April, May and June 2013

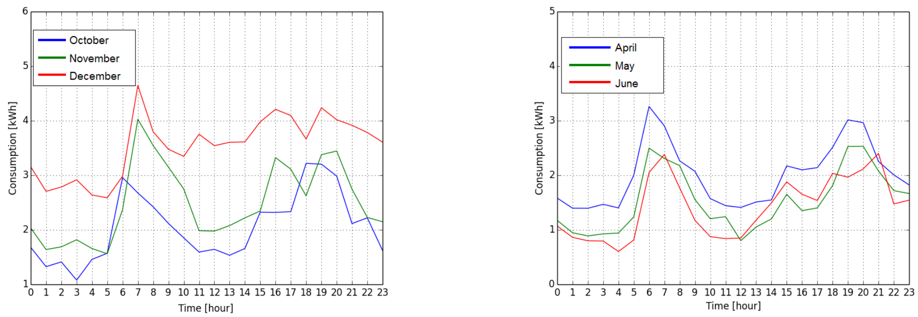


Figure 3.3: **Monthly average consumption (house ID 7350049084529237):** *Left:* October, November and December 2012 *Right:* April, May and June 2013

As stated in section 2.2, 12% of all household consumption in Norway is used for water heating. Given the recurring usage peak between 7 or 9 AM, regardless of household, it is plausible to assume that this increasing in consumption is caused by the morning routines of household occupants. Furthermore, we can observe how the energy usage during daytime (i.e. after the morning peak and before 15 PM) drops significantly. This is consistent with the assumption that household occupants leave home for work or school, which consequently reduces the consumption in the household. Moreover, the fact that 66% of all household consumption is used for space heating (as stated in section 2.2) can explain the monthly variations in terms of overall usage. That is, *colder* months requiring higher energy consumption compared to *warmer* months due to additional need for space heating caused by lower outdoor temperatures.

There are, however, variations in the different households. As one can observe in figures 3.1, 3.2 and 3.3, the overall daily pattern described above is consistent in the different homes, but there are slight differences related to the exact occurrence and size of usage peaks. This is consistent with how e.g. size of household, habits of household occupants etc. may vary as described in section 2.2.

3.2.2 Combined daily consumption of multiple households

In figures 3.4 and 3.5 the combined consumption of several households is depicted. The plotted dates are October 1st 2012 (figure 3.4) and February 1st 2013 (figure 3.5), and one can observe how the combined consumption of both 10 and 20 households affect the daily usage patterns on these dates.

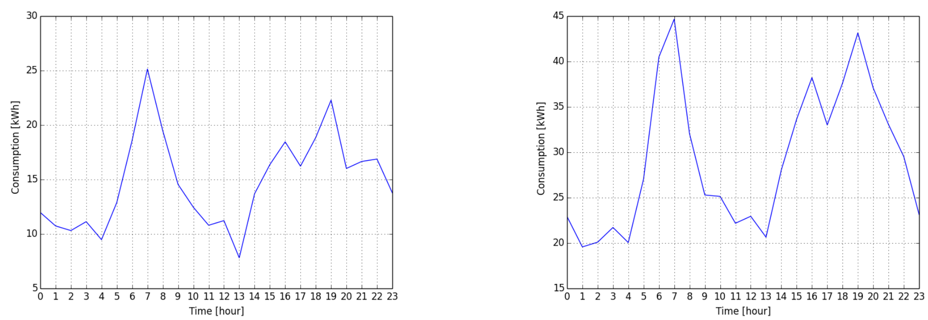


Figure 3.4: **Combined consumption October 1st 2012:** *Left:* 10 households *Right:* 20 households.

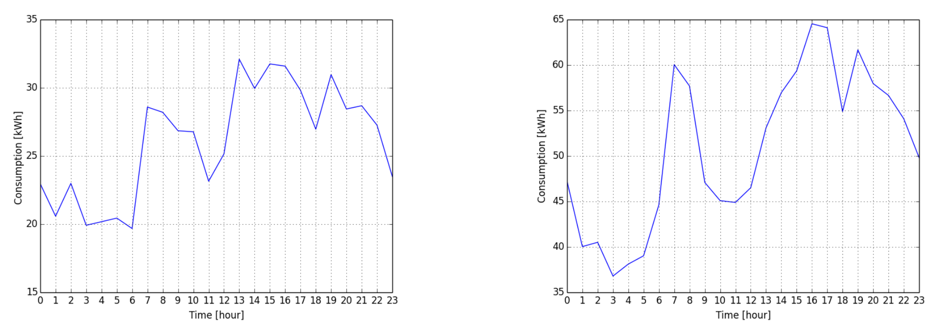


Figure 3.5: **Combined consumption February 1st 2013:** *Left:* 10 households *Right:* 20 households.

As one can see, the expected pattern (described above in section 3.2.1) becomes more and more visible when increasing the number of homes. Hence, the overall pattern when summarizing several homes' energy usage seems to disguise some of the slight differences of the separate homes, and we end up with a pattern that is more similar to what was described as *normal* Norwegian household behaviour in section 2.2.

3.2.3 Combined hourly consumption from ten houses over three months

In figure 3.6 below, the total hourly consumption of ten houses in the months January, February and March 2013 is depicted. The left hand side plot of figure 3.6 is week day consumption, while the right hand side plot is the weekends in the same period. This investigation reveals that when summarizing the total hourly consumption in a group of houses over a three-month period, we get a pattern that more persistently state a behaviour consistent with what is expected in households. That is, a usage peak in the morning, followed by a drop in consumption during daytime, concluded with another increasing in energy usage between 15 PM and midnight. Furthermore, if we compare weekday and weekend consumption we clearly see a change in behaviour particularly related to morning consumption. That is, while the morning usage peak occurs at around 8 AM on weekdays, it appears closer to 11 AM in weekends. Also, the drop in consumption after the morning peak is not as significant in weekends as it is on week days.

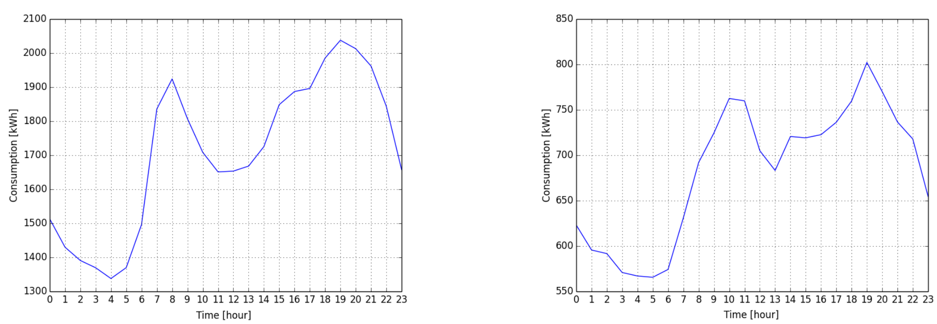


Figure 3.6: **Ten houses total consumption January, February and March 2013:** *Left:* Week days *Right:* Weekends

In figure 3.7 below, the same period is illustrated, only this time as the average hourly consumption *per house*. Here we can observe that average hourly week day consumption in the chosen households varies approximately between 2.1 kWh and 3.2 kWh in this three-month period, while average weekend consumption varies between 2.2 kWh and 3.1 kWh.

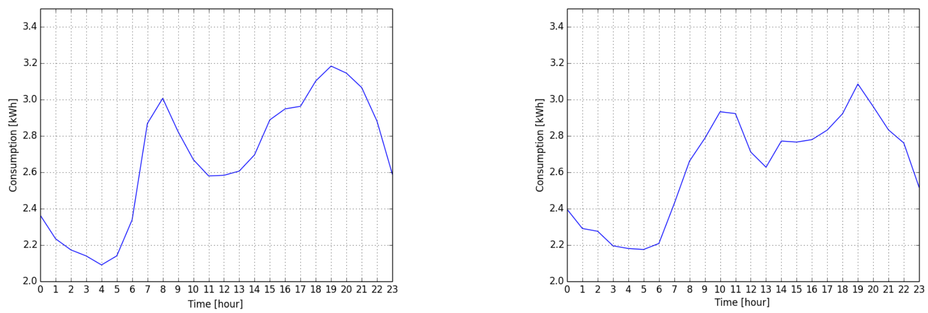


Figure 3.7: **Ten houses average consumption per household January, February and March 2013:** *Left:* Week days *Right:* Weekends

3.2.4 Combined hourly consumption from 20 households over nine months

In figure 3.8 below, the number of houses is increased to 20 and the time period to nine months (October 1st 2012 - June 28th 2013). This shows that the pattern observed in section 3.2.3 remains with further increasing of households and time period. In fact, the expected pattern becomes even more apparent when increasing the number of households and the time period further. That is, the two distinct daily peaks on week days emerges more persistently and the weekend consumption becomes more and more constant from 11 AM until evening.

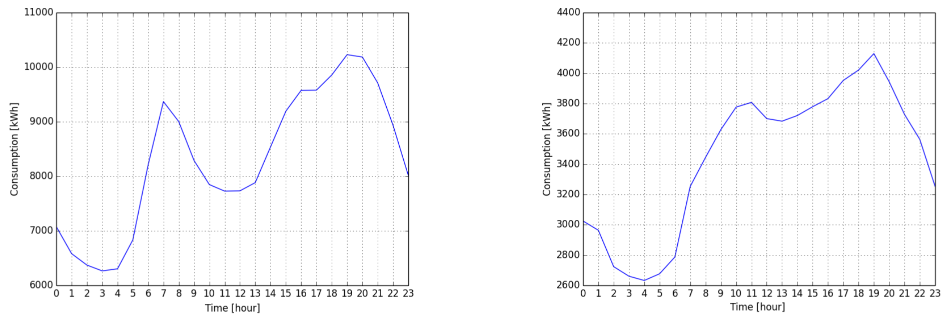


Figure 3.8: **20 houses total hourly consumption October 2012 - June 2013:** *Left:* Week days *Right:* Weekends

Below, in table 3.1, the total consumption of both week days and weekends in all separate months (i.e. October 2012 - June 2013) is listed.

Month	Total *week day* usage [kWh]	Total *weekend* usage [kWh]
October	19865.999 (23 days)	7199.140 (8 days)
November	23881.559 (22 days)	8419.837 (8 days)
December	28184.173 (20 days)	14005.311 (10 days)
January	29775.016 (23 days)	10203.065 (8 days)
February	25292.664 (20 days)	10398.994 (8 days)
March	25226.638 (21 days)	12440.871 (10 days)
April	21536.233 (22 days)	7935.068 (8 days)
May	14977.876 (23 days)	5168.680 (8 days)
June	10578.394 (20 days)	4411.601 (10 days)

Table 3.1: Comparison (20 households): average hourly consumption (week days and weekends)

The fact that total consumption of January is approximately 2.8 times higher than that of June on week days clearly illustrate the impact outdoor temperatures has on energy consumption in Norwegian households.

Furthermore, in table 3.2 the average hourly load of week days and weekends is calculated in the months January - June 2013 (based on the results obtained in table 3.1). What is interesting is that although the usage patterns are different on week days compared to weekends, the *amount* of consumed energy is approximately equal.

Month	Average *week day* usage (hourly) [kWh]	Average *weekend* usage (hourly) [kWh]
October	35.99	37.49
November	45.23	43.85
December	58.72	58.36
January	53.94	53.14
February	52.69	54.16
March	50.05	51.84
April	40.79	41.33
May	27.13	26.92
June	22.04	22.98

Table 3.2: Comparison (20 households): average hourly consumption (week days and weekends)

3.2.5 Examining monthly variations

In figure 3.9 below, the monthly consumption of January and June, and March and April 2013 is depicted. As one can observe, the consumption in January varies significantly from that of June, while March and April are more similar.

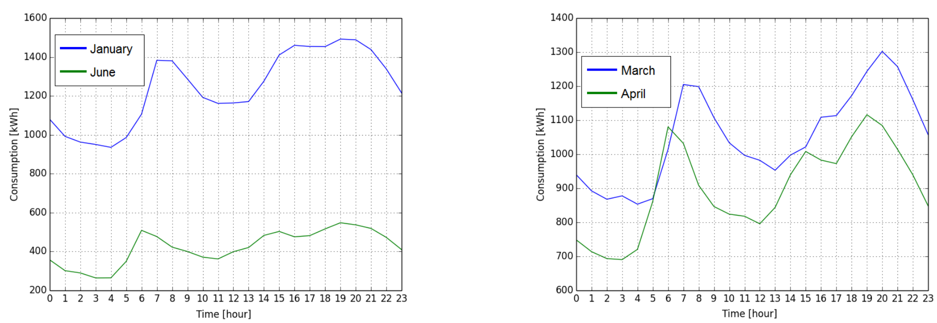


Figure 3.9: **Combined consumption pattern 20 households** *Left:* January and June 2013 *Right:* March and April 2013

Based on the consumption patterns derived we can examine the monthly variations in average and maximum hourly consumption. In the subsequent autonomy model (described in chapter 4) this knowledge will be utilized for determining how to dynamically detect usage peaks in a presumed micro-grid consisting of the 20 households examined in this analysis. In figure 3.10 below, the total hourly consumption pattern of January is illustrated, highlighting the maximum, minimum and average hourly consumption.

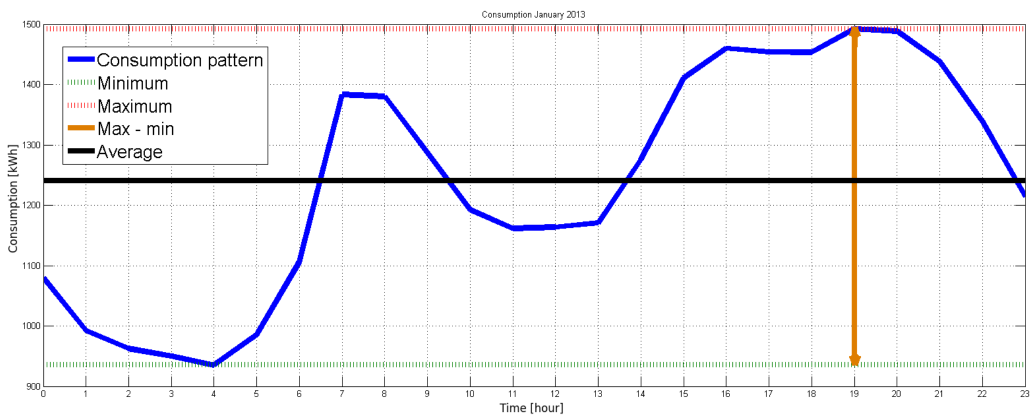


Figure 3.10: Consumption pattern highlighting the maximum, minimum and average hourly consumption in January 2013

Furthermore, in table 3.3 below, the maximum, minimum and average hourly consumption of January through June in the 20 households are listed.

Month	Average [kWh]	Max [kWh]	Min [kWh]	Difference (max - min) [kWh]
January	1240.626	1491.874	935.403	556.471
February	1053.861	1262.196	809.863	452.333
March	1051.110	1302.173	853.439	448.734
April	897.343	1116.093	690.548	425.545
May	624.078	806.253	439.947	366.306
June	440.766	569.496	274.199	295.297

Table 3.3: Aggregated maximum, minimum and average **hourly** consumption of months January through June 2013 (as highlighted in figure 3.10)

3.2.6 Conclusion

This section summarizes the most important and interesting results achieved from the analysis of consumption data in Demo Steinkjer. Based on the households examined in this analysis, the following conclusions were reached:

- Although energy consumption in households varies, the daily usage patterns are somewhat similar in the different houses. In all week day investigations performed, the daily usage curve has *approximately* the same shape independent of household. That is, a usage peak in the morning, followed by a drop in consumption after the morning peak, and finally, another increasing in energy consumption in the afternoon. This is consistent with previous investigations on behaviour in Norwegian households described in section 2.2.

- When summarizing the consumption in several houses over longer time periods, the pattern described above emerges more persistently. That is, the daily consumption curve becomes more and more similar to the expected pattern described in section 2.2. In fact, the investigation shows that further increasing number of houses and time period results in a pattern more and more similar to what is expected.

- There are considerable differences between weekend and week day consumption in households. In particular, the usage peak associated with the morning routines of household occupants deviate, i.e. occurring at 7 AM on weekdays and 11 AM in weekends. Moreover, in weekends the energy usage after the morning peak do not decrease as much as experienced on week days. However, the differences between week days and weekends are primarily related to *when* usage peaks occur, and not the amount of energy consumed daily.

- As mentioned, the shape of the daily consumption curve remains approximately the same in all months evaluated. That is, while the overall consumption increases in colder months we still experience the same usage peaks regardless of season. This supports that the variations in monthly overall consumption is mostly dependent on space heating as described in section 2.2.

3.3 Results from analysis: Generation patterns of elia solar cells

This chapter describes the results from the analysis of solar energy generation in elia solar cells (as described in section 3.1.2). The purpose of this investigation was to examine the dynamics and sustainability of PV energy generation. The knowledge on generation patterns obtained from this analysis will be used in the microgrid autonomy model described in chapter 4.

In section 3.3.1 the daily variations in power output in several months is examined with purpose of uncovering the *day-to-day* fluctuations in energy generation. Furthermore, in section 3.3.2, all twelve months of 2013 are examined in terms of total monthly and average daily generation each month. Moreover in section 3.3.3 the deviations between predicted and actual energy generation is examined. Finally, in section 3.3.4, the results from this analysis are summarized.

3.3.1 Daily variations in power output

In figures 3.11 and 3.12 below, the daily power output pattern from four consecutive days in each of the months January, February, July and August is illustrated. What we can observe here is how the amount of energy generated may vary significantly from one day to another in all months. That is, although overall generation is considerably higher during the summer months, significant day to day variations are present regardless of season. This supports the presumption that solar energy generation is highly weather dependent as described in section 2.7.

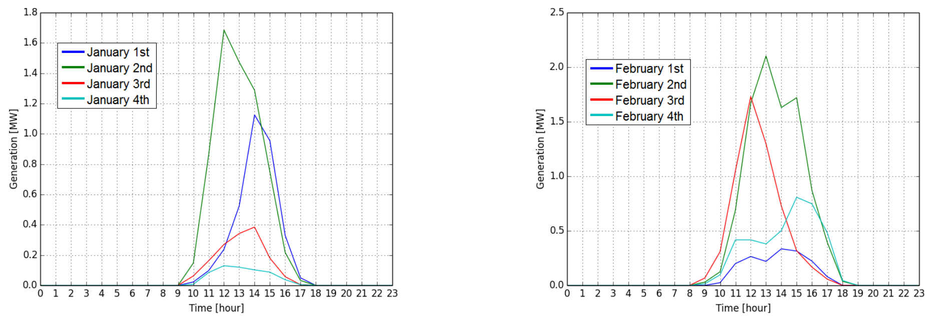


Figure 3.11: **Daily power output on four consecutive days:** *Left:* January 2013 *Right:* February 2013

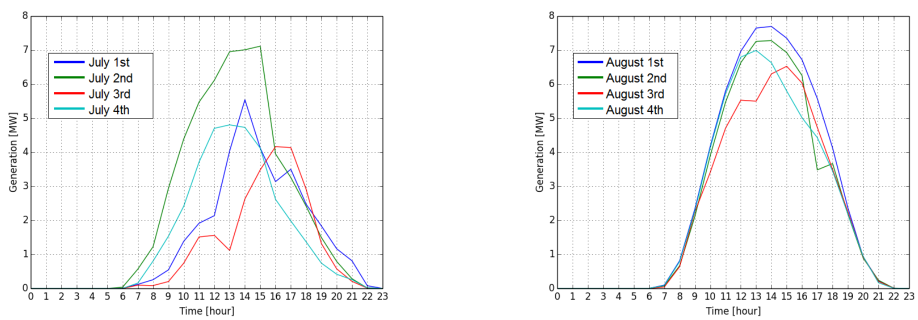


Figure 3.12: **Daily power output on four consecutive days:** *Left:* July 2013 *Right:* August 2013

Furthermore, comparing the generation from January and February (figure 3.11) with the generation from July and August (figure 3.12) reveals that maximum power output is approximately four times greater in the summer months compared to the winter. Furthermore, the daily time period in which the solar cells generate energy is also considerably prolonged during the summer months. That is, while January and February experience an energy generation between 9 AM and 18 PM, July and August generate energy between 7 AM and 22 PM.

3.3.2 Monthly variations in generated energy

In figures 3.13 and 3.14, the total generated energy in each month of 2013 is illustrated. What we can observe here is how the total generated energy varies from month to month, and also how the daily time periods for which the solar cells are active (i.e. generating energy) varies.

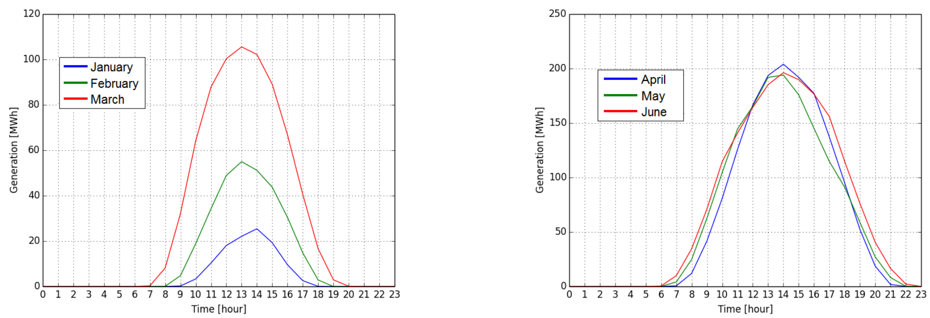


Figure 3.13: **Monthly variations in total generated energy:** *Left:* January, February and March *Right:* April, May and June

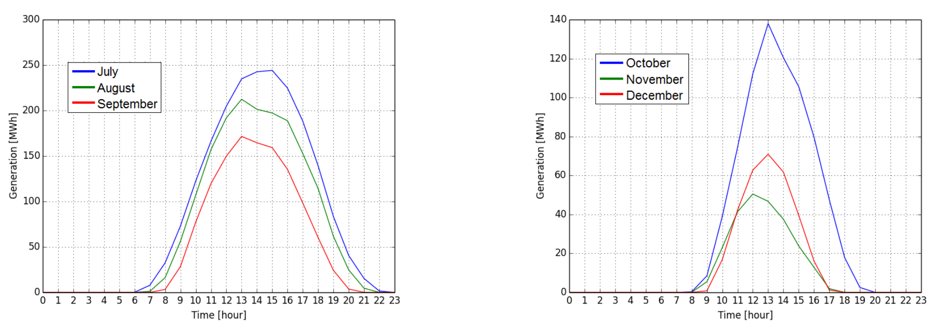


Figure 3.14: **Monthly variations in total generated energy:** *Left:* July, August and September *Right:* October, November and December

In table 3.4 below, the total and average daily generation of each month is listed, in addition to the daily time periods in each month for which the solar cells are active.

Month	Total generation [MWh]	Average daily generation [MWh]	Solar cells active
January	110.78	3.57	9 AM - 18 PM
February	304.76	10.88	8 AM - 19 PM
March	716.61	23.12	7 AM - 20 PM
April	1499.88	49.99	7 AM - 21 PM
May	1513.43	48.82	6 AM - 22 PM
June	1689.93	56.33	6 AM - 22 PM
July	2021.69	65.21	6 AM - 22 PM
August	1687.28	54.42	7 AM - 22 PM
September	1195.60	39.85	7 AM - 21 PM
October	745.91	24.06	8 AM - 20 PM
November	243.23	8.10	8 AM - 18 PM
December	312.08	10.06	8 AM - 18 PM

Table 3.4: Monthly variations in solar energy generation, Brussels 2013

As expected, the energy generation is highest during the summer months, and consequently lowest during the winter. In fact, this investigation shows that total solar energy generation in July is approximately 18 times higher than that of January. Although, as described in section 3.3.2, the Brussels total PV capacity had increased by 3.38 MW in July compared to January, the difference in generated energy is significant regardless. Furthermore, the daily time period for which the solar cells are active is 7 hours longer in July compared to January. Below, in figure 3.15, one can observe how the energy generation through all of 2013 varies from month to month. It shows that energy generation, as expected, increases steadily until reaching its peak in July, after which it starts to decrease.

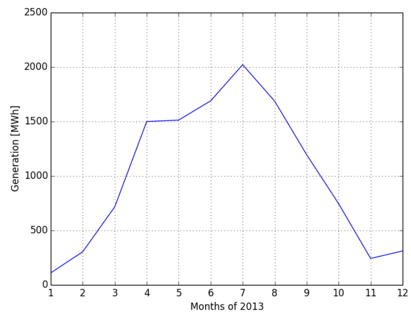
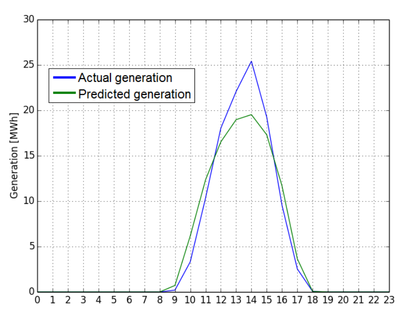


Figure 3.15: Monthly variations in total generated energy 2013

3.3.3 Comparison: predicted and actual energy generation

As described in section 2.7.2, elia also offer day-ahead predictions on energy generation in their solar cells. This investigation concerns comparing predicted and actual energy generation in order to uncover with what certainty one can predict solar energy generation. Below, in figures 3.16 and 3.17, the predicted and actual energy generation of January, March, July and November 2013 is plotted. Furthermore, in table 3.5, the predicted and actual energy generation of each month in 2013 is listed, in addition to the corresponding deviation.



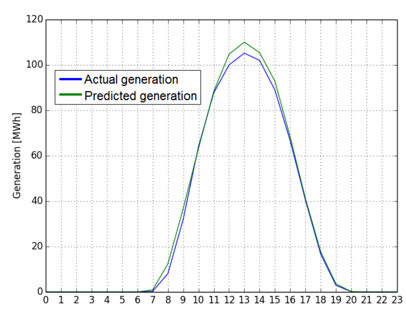
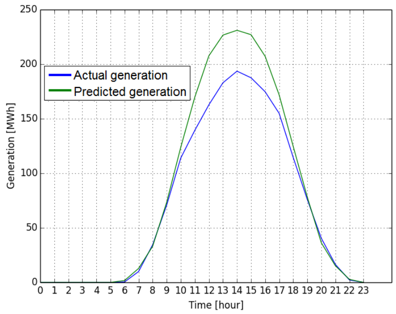


Figure 3.16: **Comparison predicted and actual energy generation:** *Left:* January *Right:* March



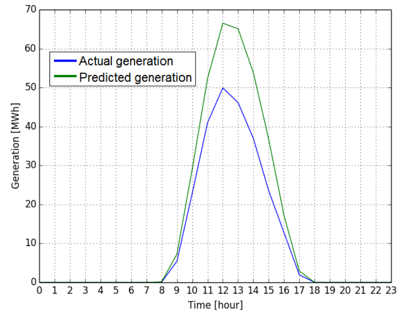


Figure 3.17: **Comparison predicted and actual energy generation:** *Left:* July *Right:* November

Month	Predicted generation [MWh]	Actual generation [MWh]	Deviation [MWh]
January	106.96	110.78	+3.82 (3.57%)
February	402.26	304.76	-97.5 (24.24%)
March	745.83	716.61	-29.22 (3.92%)
April	1404.41	1499.88	+95.47 (6.80%)
May	1482.95	1513.43	+30.48 (2.10%)
June	1943.36	1689.93	-253.43 (13.04%)
July	2152.06	2021.69	-130.37 (6.06%)
August	1821.61	1687.28	-133.33 (7.32%)
September	1362.56	1195.60	-166.96 (12.25%)
October	812.40	745.91	-66.49 (8.18%)
November	330.92	243.23	-87.69 (26.50%)
December	279.69	312.08	+32.39 (11.58%)

Table 3.5: Predicted vs. actual monthly solar energy generation, Brussel 2013

3.3.4 Conclusion

This section summarizes the findings from the analysis of solar cell energy generation in Brussels 2013. The investigation reached the following conclusions:

- Daily energy generation may vary, regardless of month, on a day-to-day basis. That is, the energy generation of two consecutive days may differ considerably, confirming how varying weather conditions greatly affect the amount of generated energy in solar cells. This verifies the suspected dynamics, nonlinearities and uncertainties of solar energy generation described in section 2.7.

- There are substantial seasonal differences in solar energy generation. Table 3.4 in section 3.3.2 shows how the total energy generation varies in each month of 2013, revealing monthly differences with factors as large as 18. However, as shown in figure 3.15, the variations follow a pattern that is expected, i.e. with energy generation increasing steadily from January until the summer months, and decreasing after its peak in July.

- The daily time periods for which the solar cells are active (i.e. generating energy) varies significantly in the different seasons of a year. In fact, the active period in July is as much as 7 hours longer than that of January. The active period off all months is listed in table 3.4 in section 3.3.2.

- The comparison of predicted and actual generation confirms (as stated in section 2.7) the difficulties regarding prediction of solar energy generation. Table 3.5 in section 3.3.3 shows that in some months the total energy generation deviate as much as 26% from the day-ahead predictions. Also, more often than not the predictions are too optimistic, i.e. greater than the actual generation.

Chapter 4

Model

This chapter describes a model for autonomy in microgrids based on the acquired dynamics of energy consumption and generation (described in chapter 3). As described in section 2.8.1 the authors of [16] performed a study where they used complex network theory to model the damage inflicted on transmission efficiency as a result of substation failure in the North American power grid.

In this model complex network theory is used to investigate autonomy in microgrids by modelling consumption, generation and storage, instantiated from different sources. That is, by adding local generation sources and storage capabilities, the model investigates how a microgrid can control its own generation and storage in response to varying demand and supply conditions. In order to provide realistic microgrid dynamics, the model uses the consumption data from Demo Steinkjer and generation data from solar cells analysed in chapter 3.

More formally, the purpose of this model is to investigate peak shaving (as described in section 2.5.4) using the two different microgrid structures *solar farm mode* and *distributed generation mode* (described below in sections 4.1.1 and 4.1.2, respectively). Finally, the mode described in section 4.1.3 concerns a scenario for which external supply is disrupted, and the microgrid need to operate independently of conventional supply from the utility company. Here, the intention is to examine the ability of a microgrid to prevent power outages by covering the entire energy demand of its participants temporarily. Thus, the latter will uncover how long a microgrid can stay operational in different months without external supply by utilizing stored energy and local generation, i.e. as an *islanded* entity as described in section 2.1.2.

Section 4.1 describes the implementation of the model including a description of each separate mode, while section 4.2 presents some of the most interesting results obtained from simulations.

4.1 Modelling autonomy in microgrids

As described above, the purpose of this model is to examine how we can compensate for daily usage peaks in a futuristic microgrid cell by storing and utilizing locally generated energy in high demand periods. In addition, the model also examines how we can avoid power outages when external energy supply to the microgrid is disrupted, again by using local generation and stored energy temporarily. The research performed on consumption patterns in section 3.2 revealed that the usage curve of households has approximately the same shape regardless of season, identified by two distinct daily usage peaks on week days. Thus, this consistent consumption pattern, combined with the dynamics of solar energy generation obtained in section 3.3 lay the foundation for this model.

As described in section 3.1.3, it was difficult to find households in Demo Steinkjer where there was consistent hourly consumption measurements over longer periods of time. This was due to "gaps" in the dataset where measurements were missing. However, the analysis (section 3.2) uncovered 20 households which had consistent measurements over a time period of approximately nine months (Oct 1st 2012 until June 28th 2013). Furthermore, the solar generation data (analysed in section 3.3) used data gathered from the time period January 1st 2013 until December 31st 2013. Hence, this model uses consumption and generation data from the overlapping time period of the two analyses, i.e. from January 1st until June 28th 2013.

For simplicity, as with the analysis described in section 3.3, it is assumed that the solar power output is *constant* in each hour in the model.

The model consists of the three different modes listed below, i.e.

- **Solar farm mode** where there is one large energy source in the microgrid responsible for all local energy generation. Using the energy produced by this local source, the intention is to compensate for daily high demand periods in the microgrid as a whole.

- **Distributed generation mode** where the microgrid consists of several households both generating and storing energy, and the structuring of connections between households is arranged in a preferential attachment manner following the energy availability, as described in section 2.1.2. In other words, households with the largest degree (i.e. most connections to other houses) are the ones with the largest generation and storage capacity. Consequently, this approach aims to compensate for usage peaks in each household individually, as opposed to the solar farm mode which deals with the overall consumption of the microgrid cell.

- **Island mode** stages a scenario where the external supply is disrupted and a microgrid must operate independently, i.e. responsible for covering the entire energy demand of its participants temporarily through local energy generation and storage. Here, the structure is similar as the solar farm mode, i.e. one large generation source responsible for all local energy generation.

Sections 4.1.1, 4.1.2 and 4.1.3 below describes these three modes more thoroughly, while section 4.1.4 describes how the model is set up using the complex network tool NetLogo.

4.1.1 Solar farm mode

In *solar farm mode* the microgrid consists of 20 households, one solar generation farm, and one storage unit. As mentioned, the intention here is to model peak shaving by utilizing the locally generated energy from solar cells in high demand periods. By compensating with local energy during usage peak periods one can dynamically regulate the external energy supply and, from the utility company's perspective, ensure a less fluctuating daily usage curve.

In order to examine realistic consumption patterns the model uses data obtained from households investigated in the analysis in section 3.2. Furthermore, for the solar generation farm, the data analysed in section 3.3 is used.

However, as described in section 2.7.2, the data used in the analysis in section 3.3 concerns solar energy generation in all of Brussels, Belgium. Thus, for simplicity, this energy generation data is scaled down by a factor of 250 making it more suitable for this scenario, while still preserving the dynamics of solar energy generation. As described in section 2.7.1, given 100% efficiency, PV solar cells generate 1 kW per square meter during optimal weather conditions. Thus, if we assume that the nominal power output of the photovoltaic farm is scaled down by a factor of 250 (i.e. from 10.3 MWp to 41.2 kWp), in addition to a 15 % efficiency in solar generation, we can derive the area of solar cells needed in m^2 for this microgrid scenario (using equation 2.6 in section 2.7.1). That is,

$$Required\, solar\, cell\, area\; = \frac{41.2kWp}{0.15 * 1kW/m^2} \approx 275m^2 \tag{4.1}$$

Moreover, the model assumes a BES system with a energy capacity of 1 MWh. Thus, if stored energy at any time exceeds this limit, the surplus energy is immediately used regardless of whether or not a usage peak has occurred. Also, the model has implemented a discharge and power conversion loss of 10% in the BES system, similar to that used in the investigation described in section 2.5.4. Consequently, 10 % of all generated energy in the solar farm is lost in the BES system.

In total we are able to model a period ranging from January 1st until June 28th 2013, with exact and consecutive hourly updates on both consumption and generation throughout this time period. Below, in figure 4.1, the structure of this approach is illustrated.

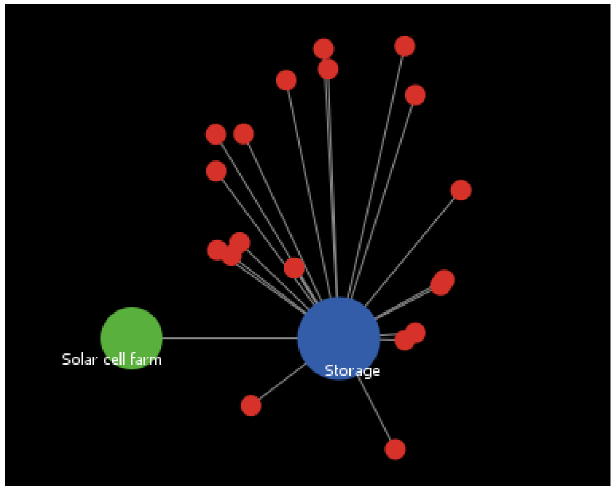


Figure 4.1: Solar farm mode structure, as displayed in model

In order to compensate for usage peaks we must be able to identify when they occur. In the peak shaving investigation described in section 2.5.4 they used the maximum daily usage peak that occurred in a four-month period and determined a constant peak boundary as a percentage of this maximum daily peak load. In this model, a slightly different approach is attempted where *hourly* load is evaluated instead. That is, the identification of usage peaks is based on the results from maximum and average hourly consumption in each month derived in table 3.3 in section 3.2.4. Evaluating this data allow us to derive the boundaries for how to detect hourly usage peaks in each month. That is, by calculating the peak ratio

$$Monthly\,peak\,ratio = \frac{Monthly\,\mathbf{maximum}\,hourly\,consumption}{Monthly\,\mathbf{average}\,hourly\,consumption} \tag{4.2}$$

we can derive an upper boundary for normal hourly consumption in different months. Consequently, an hourly load exceeding this boundary can be considered a usage peak, in need of compensation.

Below, in table 4.1, the peak ratios (calculated by equation 4.2) for the months January through June 2013 is listed based on the results derived in section 3.2.4. Furthermore, the suggested *start boundary* for identifying peaks is for each month proposed as the acquired peak ratio multiplied by the last day average hourly usage. That is, the last day average usage is a variable dynamically calculated and updated after simulating each day in the model.

Month	Peak ratio (PR)	Start boundary
January	1.203	PR_{Jan}∗Last day average
February	1.198	PR_{Feb}∗Last day average
March	1.240	PR_{Mar}∗Last day average
April	1.244	PR_{Apr}∗Last day average
May	1.292	PR_{May}∗Last day average
June	1.292	PR_{Jun}∗Last day average

Table 4.1: Start boundaries in each month

However, as described in section 3.3.2, there are significant monthly variations in solar energy generation and thus the boundaries need to dynamically adjust dependent on how much energy is generated. That is, months where the solar energy generation is higher have the potential of compensating for a larger share of the energy consumption, while months with less energy generation primarily must focus on shaving the most significant usage peaks. Thus, the model has implemented a dynamic scheme which determines the peak boundaries based on the amount of stored energy available. Consequently, months with a modest energy generation (e.g. January or February) have boundaries close to or equal with their *start boundary*, while months with greater energy generation have boundaries that deviate more.

In table 4.2 below, the dynamic relationship between stored energy amount relative to storage capacity, and peak boundaries are listed. If the stored amount is less than 20% the peak boundary equals the *start boundary* described in table 4.1. However, if stored power exceeds 20%, the peak boundary decreases by 10% relative to previous peak boundary for each 10% increasing in storage capacity. That is,

Storage status	Peak boundary (PB)
<20%	$PR*$Last day average (*start boundary*)
>20%	$(PR - PR * 0.1)*$Last day average
>30%	$(1 - 0.1) * (PR - PR * 0.1)*$Last day average
>40%	$(1 - 0.1)^2 * (PR - PR * 0.1)*$Last day average
>50%	$(1 - 0.1)^3 * (PR - PR * 0.1)*$Last day average
>60%	$(1 - 0.1)^4 * (PR - PR * 0.1)*$Last day average
>70%	$(1 - 0.1)^5 * (PR - PR * 0.1)*$Last day average
>80%	$(1 - 0.1)^6 * (PR - PR * 0.1)*$Last day average
>90%	$(1 - 0.1)^7 * (PR - PR * 0.1)*$Last day average

Table 4.2: Relationship between stored amount and peak boundary

Thus, the peak shaving procedure with the solar farm mode structure is as follows:

1. After each day of simulation, the microgrid's last day average hourly usage is calculated.

2. For each hour the following day, the hourly usage is compared to the last day average and potential peaks are identified by the monthly boundaries described in tables 4.1 and 4.2.

3. If a peak occurs, the amount of energy which can be compensated for is determined according to the available energy in the storage unit as described in table 4.2. Hence, the compensation is calculated as:

$$Compensated\,amount = Total\,hourly\,usage - PB * LDA \tag{4.3}$$

   where PB is the current peak boundary according to storage status, and LDA is the last day average hourly usage.

4.1.2 Distributed generation mode

As with *solar farm mode* (described in section 4.1.1) the intention of the *distributed generation mode* is also to compensate for daily high demand periods by utilizing local energy generation and storage in microgrids. However, unlike the previous mode where there was one large generation source in charge of all local energy generation, the *distributed generation mode* attempts a more distributed approach where households themselves are capable of both generating and storing energy. Hence, in this mode the model attempts to compensate for usage peaks in each household individually.

In figure 4.2 below, a simple model representing the end user of a microgrid is depicted, as proposed in the paper in appendix G. The user is represented as a circle which diameter indicates the storage capacity, the arrow **to** the node indicate consumption, and the arrow **from** the node indicate generation. The loop (denoted charging) represent energy produced locally being stored or consumed.

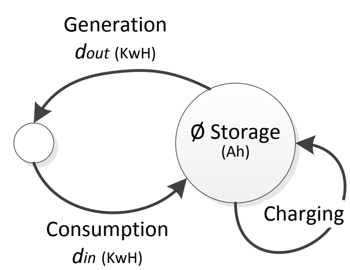


Figure 4.2: End user data model (as described in the paper in appendix G)

By modelling several end users as depicted in figure 4.2 we can observe the microgrid behaviour when it is consisting of several dynamical entities consuming, generating and storing energy individually. That is, by modelling the network as a complex directed graph G(N,E), with N nodes (users) and E edges (transmission lines). The structure of this approach is illustrated in figure 4.3 below, where the diameter of each node indicate its generation and storage capacity.

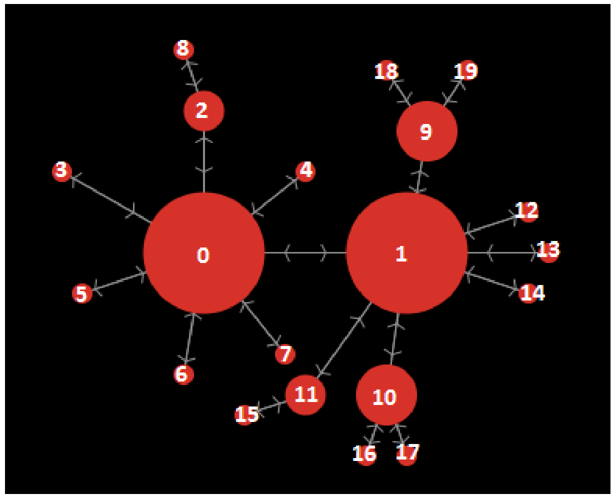


Figure 4.3: Distributed generation mode structure, as displayed in model.

In this mode the energy generation occurs in each of the households, and the structuring of connections between households is arranged in a preferential attachment manner following the energy availability (as described in section 2.1.2). Once again, the solar data analysed in section 3.3 is used, and as with *solar farm mode* described above, this generation data is scaled down by a factor of 250. However, the amount of generated energy in each household is set to vary depending on the out-degree of each node in the network (i.e. number of connections to other nodes). The total number of edges in this model is 38, and below the distribution of energy generation for each node is listed based on their respective out-degrees.

- **Two nodes with out-degree 7:** $Energy_{generated} = \frac{7}{38} * Total\, generation$
- **Two nodes with out-degree 3:** $Energy_{generated} = \frac{3}{38} * Total\, generation$
- **Two nodes with out-degree 2:** $Energy_{generated} = \frac{2}{38} * Total\, generation$
- **14 nodes with out-degree 1:** $Energy_{generated} = \frac{1}{38} * Total\, generation$

Hence, the total energy generated in the microgrid is equal to that of the *solar farm mode*, only here it is divided among the different nodes based on the degree distribution.

Potential usage peaks are identified in the same manner as with the *solar farm mode*, i.e. by using the boundaries as described above in section 4.1.1. However, as the peak shaving now is enforced on each household, the model calculates last day average hourly usage in each individual household as opposed to just the overall microgrid average. Also, once again the model assumes a discharge and power conversion loss of 10%.

Furthermore, in order to achieve a more optimal utilization of available energy, it is implemented upper storage boundaries in each of the nodes except the two most central (i.e. the ones denoted 0 and 1 in figure 4.3). Consequently, any surplus energy in smaller-degree nodes exceeding their respective boundary is transferred to connected higher-degree nodes, with purpose of ensuring a better utilization of the available energy resources in the microgrid as a whole. The boundaries are set as follows:

- **Nodes with out-degree 3:** maximum energy capacity 30 kWh
- **Nodes with out-degree 2:** maximum energy capacity 20 kWh
- **Nodes with out-degree 1:** maximum energy capacity 10 kWh

Thus, the peak shaving procedure using *distributed generation mode* is as follows:

1. After each day of simulation, the last day average hourly usage of *each* household is calculated.

2. For each hour the following day the hourly usage is compared to the last day average and potential peaks are identified using the monthly boundaries described in tables 4.1 and 4.2.

3. If a peak occurs, the amount of energy which can be compensated for is determined according to the available energy in the storage unit as described in table 4.2. Hence, the compensation is calculated as:

$$Compensated\,amount = Total\,hourly\,usage - PB * LDA \tag{4.4}$$

   where PB is the current peak boundary according to storage status, and LDA is the last day average hourly usage. Also, if the stored amount at smaller-degree nodes is insufficient to cover the required peak shaving, the smaller-degree node may receive contributions from connected higher-degree nodes if there is available resources there.

4. Finally, if an household has generated more energy than it is allowed to store, the surplus energy is transferred to the neighbouring household with the largest out-degree.

4.1.3 Island mode

In *island mode* we are able to investigate how long a microgrid can manage the entire energy demand of its participants, as an islanded entity (as described in section 2.1.2). The purpose of enabling such a feature is to prevent potential power outages when the external energy supply is disrupted. Thus, the intention here is to examine the duration for which a microgrid can stay operational in different months using local generation and stored energy reserves. Obviously, this will vary as both consumption and generation varies significantly in the different months of the model. The structure of this approach is similar to that of the *solar farm mode* described in section 4.1.1, i.e. one solar farm, one storage unit and 20 households.

At any time during simulation one can cut the external energy supply and observe how the microgrid starts to utilize its stored energy reserves in accommodation to local generation to prevent a power outage. Moreover, the model assumes a discharge and power conversion loss of 10 % and a BES system with a energy capacity of 1 MWh.

4.1.4 Model setup and user interface guide

The model is developed using the complex network tool Netlogo, described in section 2.8.2. Thus, to open the model (located in folder "AutonomyModel" on attached CD-ROM) one must install NetLogo, which can be downloaded from[1]. Furthermore, the model is also connected to the database containing the consumption and generation data analysed in chapter 3, and thus *will not work before the database is set up as described in section 3.1.3.* Moreover, to be able to set up a connection with a MySQL database one must first download a MySQL wrapper for NetLogo that needs to be included in the same directory as the model. However, this wrapper is currently included as required in the model on the attached CD-ROM. Below, a code extract

[1]http://ccl.northwestern.edu/netlogo/

illustrating how to set up the database connection in NetLogo is described, i.e.

```
to setup-database-connection

  sql:configure "defaultconnection" [["host" "localhost"] ["
     port" 3306] ["user" "root"]
  ["password" "root"] ["database" "demosteinkjer"]]

end
```

The user interface in the model (presented in appendix E) shows the different user settings which can be manipulated in order to investigate different scenarios. These are:

- **Mode:** This setting determines which of the three previously described modes the model should run.
- **Number of homes:** Here one can choose the number of households in the microgrid. Maximum amount and default setting is 20.
- **Choose house ID for individual plots (1 and 2):** Here the user can choose specific household IDs for individual consumption plots. This is particularity useful when running the *distributed generation mode* of the model as you then can observe the peak shaving in *individual* households. One may choose any of the model's 20 households for this purpose.
- **Number of days for simulation:** The simulation starts at January 1st 2013, however the user may choose the number of days for which the simulation lasts. Maximum amount of days is 179, i.e. until June 28th.
- **Initial storage state:** Here the *initial* stored amount in per cent of total storage capacity can be specified. By default this is set to 20 % (i.e. 200 kWh).
- **External supply:** This setting is restricted to the island mode of the model. The external supply can be switched off at any point in the simulation, causing the microgrid to solely depend on stored energy and local generation to handle the demand of its participants.

The user interface and parts of the NetLogo-code is presented and explained in appendix E, while the model itself is included in the folder "AutonomyModel" on the attached CD-ROM.

4.2 Simulations

This section describes some of the most interesting results obtained from simulating the three different modes of the autonomy model described above in section 4.1.

4.2.1 Results: Solar farm mode

Using solar farm mode I have simulated the entire time period (i.e. January 1st until June 28th) and investigated how peak shaving varies in different months. The number of households was set to 20 and the initial storage status was set to 20 % of total capacity (i.e. 200 kWh). Below, some of the most interesting results from this investigation is presented.

As suspected, the model achieved a modest peak shaving in January and February. In figure 4.4 below, the total consumption pattern of January 4th 2013 is illustrated with the corresponding peak shaving. This day, usage peak compensation only occurred in two hours, i.e. at 16 and 17 PM. However, during these two hours the most significant usage peak this day occurred, and thus the most critical peak was handled.

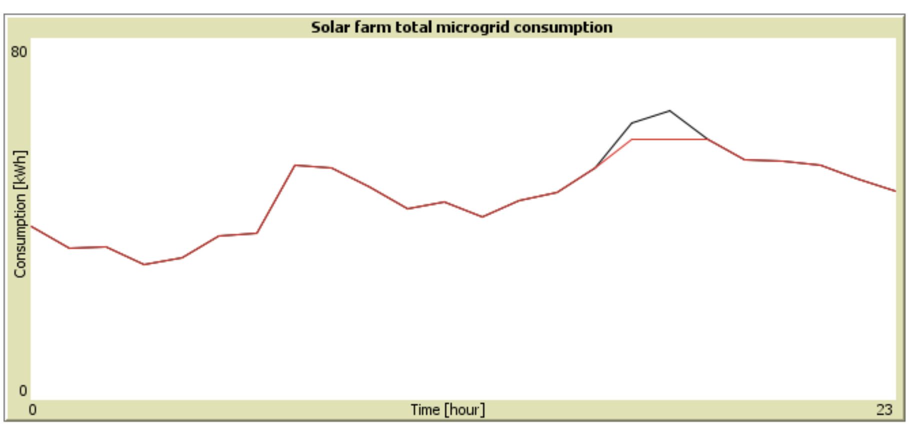


Figure 4.4: Consumption pattern January 4th (solar farm mode)

In figure 4.5 below, the consumption pattern of the last day of the model, June 28th, is illustrated. Here, one can observe how we achieve a far greater peak compensation than that of January 4th above. In fact, each hour from 5 AM until 23 PM the energy supplied by the utility company to the microgrid is held constant at 15.2 kWh, while the actual usage varies significantly.

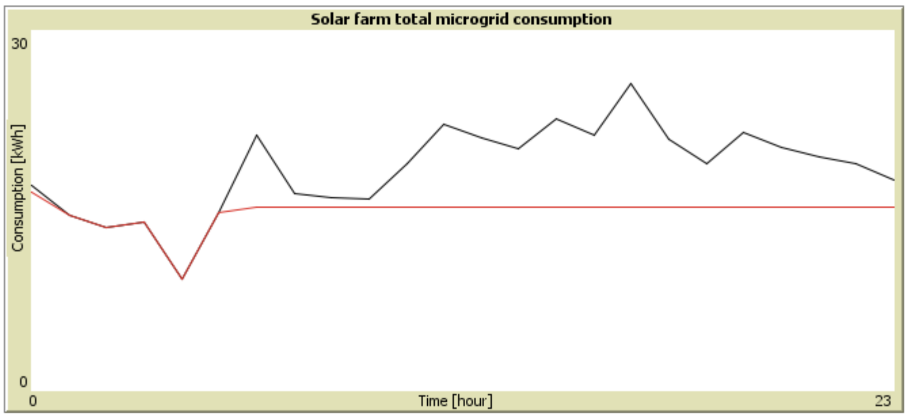


Figure 4.5: Consumption pattern June 28th (solar farm mode)

Figure 4.6 below illustrates the greatest *hourly* peak shaving that occurred in the entire time period. It occurred at 19:00 PM on April 2nd, and the energy compensated for was $\approx 29kWh$ of the total consumption this hour.

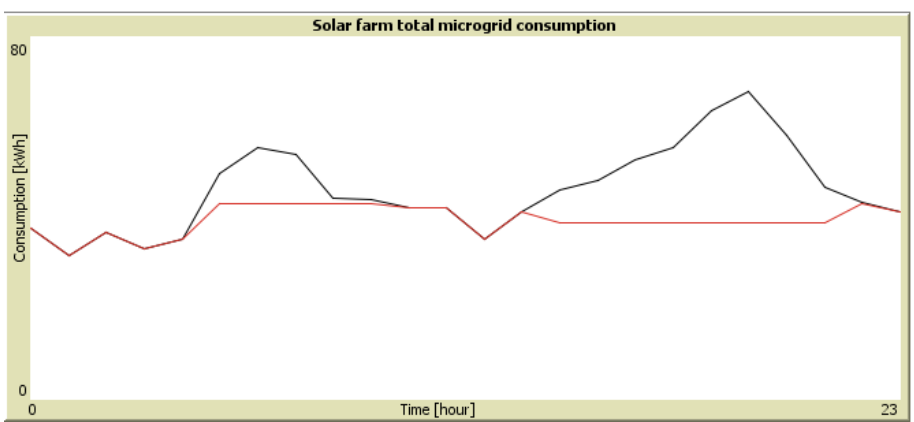


Figure 4.6: Consumption pattern April 2nd (solar farm mode). Maximum peak occurring at 19 PM.

Furthermore, in figure 4.7 below the maximum *daily* usage peak shaving in the entire time period is illustrated. This occurred on April 24th, and the total energy compensation was 275.15 kWh.

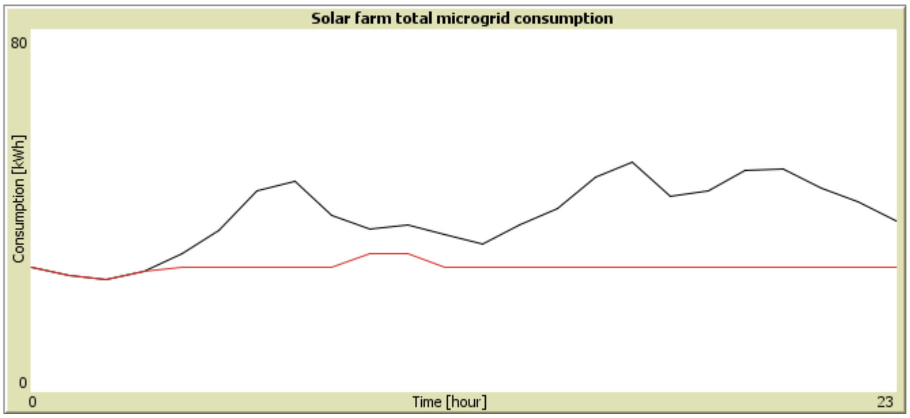


Figure 4.7: Consumption pattern April 24th (solar farm mode)

In table 4.3 below the maximum hourly peak shaving, maximum daily peak shaving, and total monthly peak shaving of each month is listed.

Month	Max *hourly* peak shave	Max *daily* peak shave	Total peak shaving
Jan	17.21 kWh	105.66 kWh	402.21 kWh
Feb	12.67 kWh	99.81 kWh	750.50 kWh
Mar	23.15 kWh	180.74 kWh	1804.84 kWh
Apr	28.89 kWh	275.15 kWh	3940.15 kWh
May	23.73 kWh	234.56 kWh	3968.24 kWh
June	25.55 kWh	250.04 kWh	4370.21 kWh

Table 4.3: Max hourly, max daily and total monthly peakshaving in each month (solar farm mode)

In figure 4.8 below, the status of the BES system in use over the entire time period is illustrated, revealing how the amount of stored power varies.

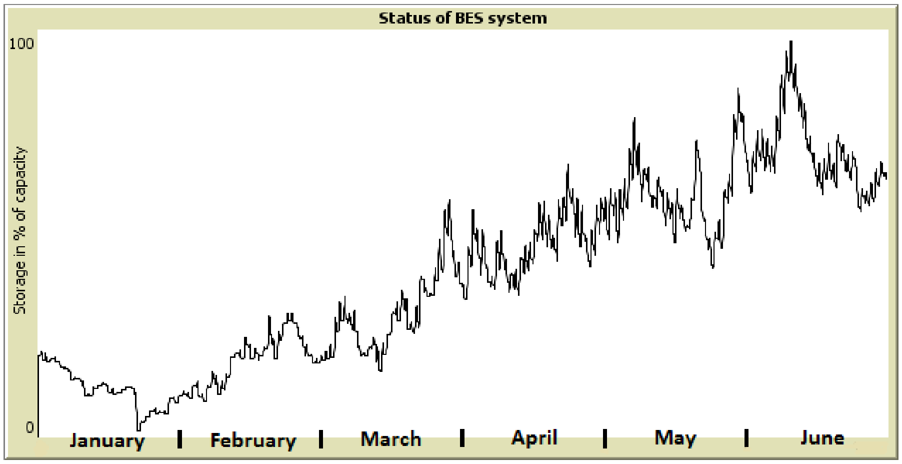


Figure 4.8: Variations in stored power (solar farm mode)

Furthermore, in table 4.4 the maximum stored power in each month is listed. Here one can observe how the maximum amount for the entire time period is 972.14 kWh, occurring on June 8th.

Month	Max stored energy [kWh]
Jan	210.52
Feb	304.19
Mar	582.00
Apr	667.99
May	855.45
June	972.14

Table 4.4: Maximum amount of energy stored in each month (solar farm mode)

4.2.2 Results: Distributed generation mode

When simulating the *distributed generation mode* I used the same initial settings as with *solar farm mode*, i.e. 20 households, initial storage status at 20 % of total capacity and simulation period January 1st until June 28th. However, the resulting peak shaving is significantly different.

In general, the *distributed generation mode* achieve in most cases a worse overall peak shaving than that of the *solar farm mode*. As peak shaving is attempted on each household individually, the varying usage patterns in different homes causes the peak shaving of the total microgrid consumption to suffer. In *solar farm mode*, the model considers the total load demand of the microgrid participants when attempting to shave peaks, and thus achieve a better overall result. In *distributed generation mode*, however, the available stored energy is not concentrated on handling the most critical usage peaks of the microgrid as a whole. This is especially the case in periods where the generation is low (e.g. January and February), as one can see in figure 4.9 below. This is the same day as illustrated with *solar farm mode* in figure 4.4, and what one can observe is how the most critical peak this day (occurring at 19 PM) is not handled at all.

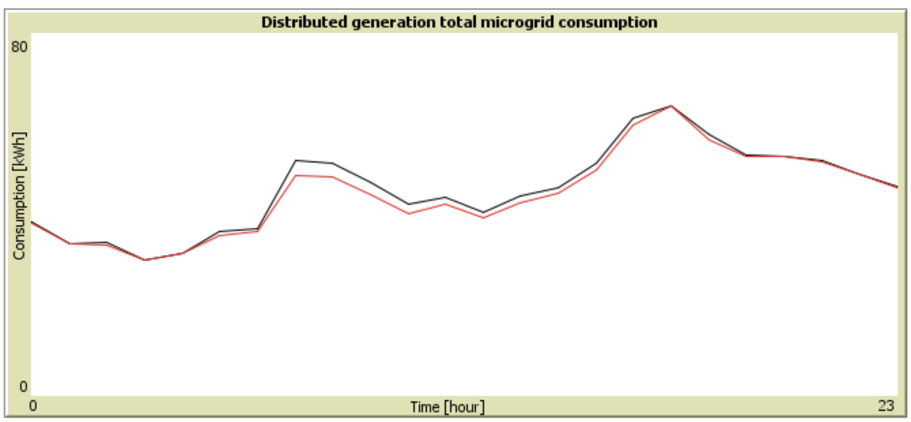


Figure 4.9: Consumption pattern Jan 4th (distributed generation mode)

Furthermore, in figure 4.10 below the peak shaving of June 28th is illustrated. If one compares this to the *solar farm mode* peak shaving of the same day (illustrated in figure 4.5), one can observe how the total amount compensated for actually is greater using *distributed generation mode*. However, the energy provided by the utility company is varying far more as opposed to *solar farm mode* where it was held constant at 15.2 kWh.

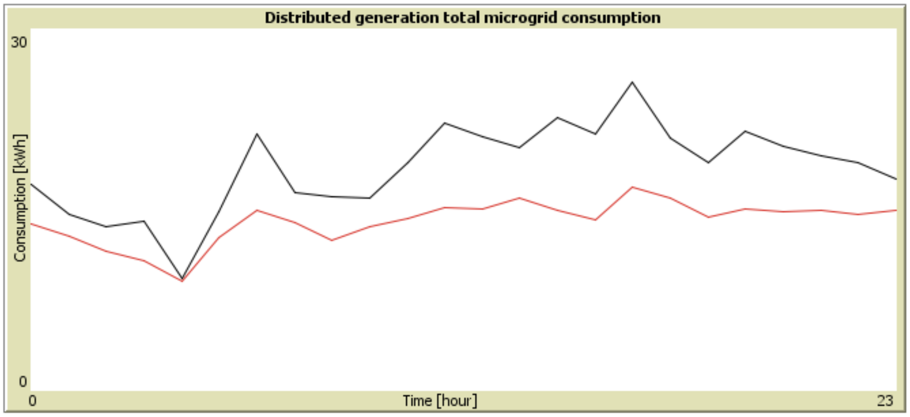


Figure 4.10: June 28th

Below, in figure 4.11, the greatest *hourly* peak shaving in the entire time period using *distributed generation mode* is illustrated. This occurred at 18 PM on June 2nd, and the total compensation was $\approx 23kWh$ of total consumption this hour.

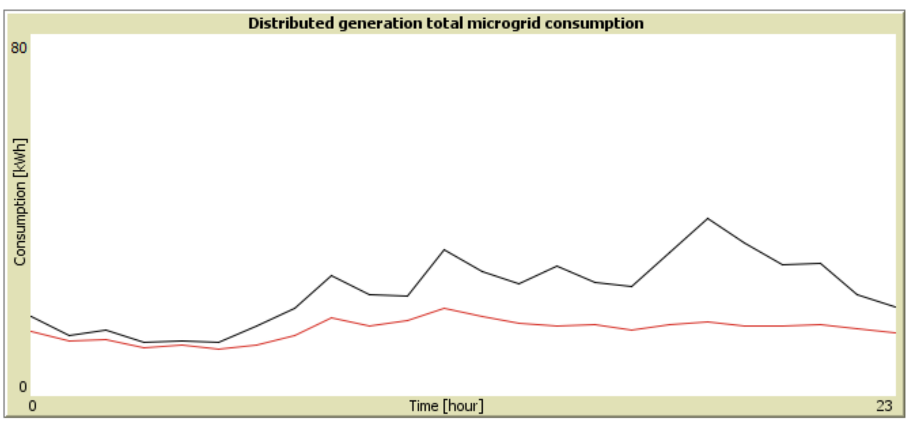


Figure 4.11: Consumption pattern June 2nd (distributed generation mode)

In figure 4.12 the maximum *daily* usage peak shaving in the entire time period using *distributed generation mode* is illustrated. As with *solar farm mode*, this occurred on April 24th. However, the total compensation was less, i.e. approximately 237 kWh.

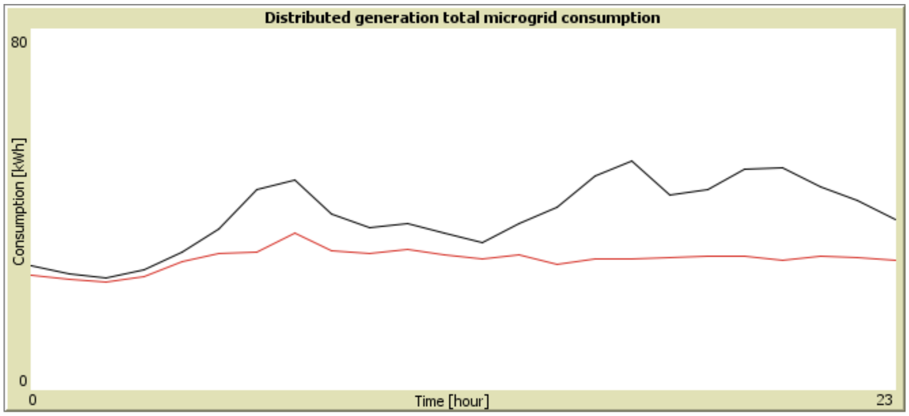


Figure 4.12: Consumption pattern April 24th (distributed generation mode)

In table 4.5 below the maximum hourly peak shaving, maximum daily peak shaving, and total monthly peak shaving of each month is listed, using *distributed generation mode*. Comparing this to table 4.3, one can observe how the *total* peak shaving of each month in fact is greater using *distributed generation mode* than that of *solar farm mode*. However, the maximum *hourly* and *daily* peak shaving is less in each month.

Month	Max *hourly* peak shave	Max *daily* peak shave	Total peak shaving
Jan	10.26 kWh	87.47 kWh	516.14 kWh
Feb	11.09 kWh	75.66 kWh	847.09 kWh
Mar	14.94 kWh	137.34 kWh	1812.35 kWh
Apr	21.68 kWh	236.65 kWh	3999.59 kWh
May	20.96 kWh	212.07 kWh	4158.68 kWh
June	22.72 kWh	229.24 kWh	4479.18 kWh

Table 4.5: Max hourly, max daily and total monthly peakshaving in each month (distributed generation mode)

In figure 4.13 below, the combined status of the BES systems in use over the entire time period is illustrated, revealing how the amount of stored energy varies in *distributed generation mode*. Comparing this to *solar farm mode* (figure 4.8) one can see how the utilization of stored energy is significantly greater using *distributed generation mode*. Particularly in the three first months (January - March) the stored amount is rarely significant, indicating that all produced energy is used immediately to compensate for usage peaks.

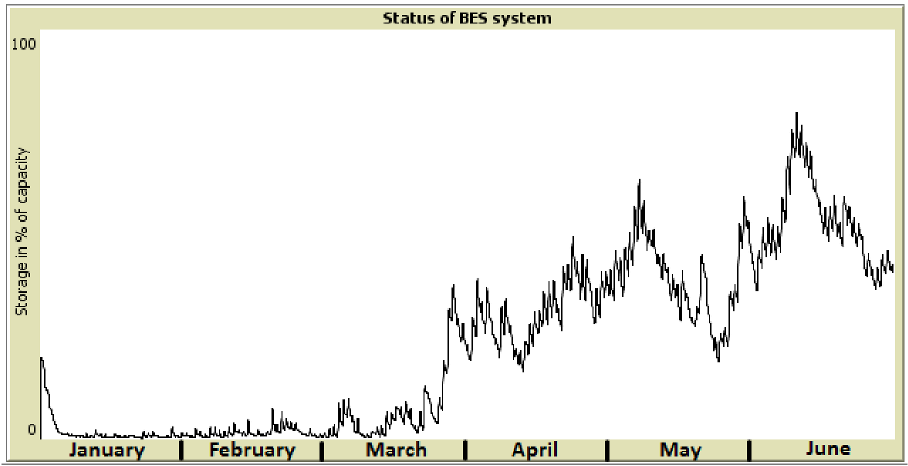


Figure 4.13: Variations in stored power (distributed generation mode)

In table 4.6 below the maximum stored power of each month is listed. As with *solar farm mode* the maximum amount for the entire simulation period occurred on June 8th, however the amount was less (i.e. 799.79 kWh).

Month	Max stored energy [kWh]
Jan	198.59
Feb	71.73
Mar	376.06
Apr	492.02
May	630.60
June	799.79

Table 4.6: Maximum amount of power stored in each month (distributed generation mode)

4.2.3 Results: Island mode

Using the island mode of the model it is examined how long a microgrid can stay operational without external supply. The external supply was turned off at 2 AM on the 15th of each month and what we can observe is how the island mode duration varies in different seasons. When the external energy supply was turned off the BES system was fully charged (i.e. 1000 kWh), and thus this investigation reveals how long the microgrid can stay operational using its stored reserves in addition to local generation in different months. As with the investigations described in sections 4.2.1 and 4.2.2 above, the number of households was set to 20.

In figure 4.14 below the island mode duration on January 15th is illustrated. Average hourly energy usage in the microgrid this day was 55.03 kWh. As one can observe the microgrid is able to manage the entire demand of its residents for 16 hours.

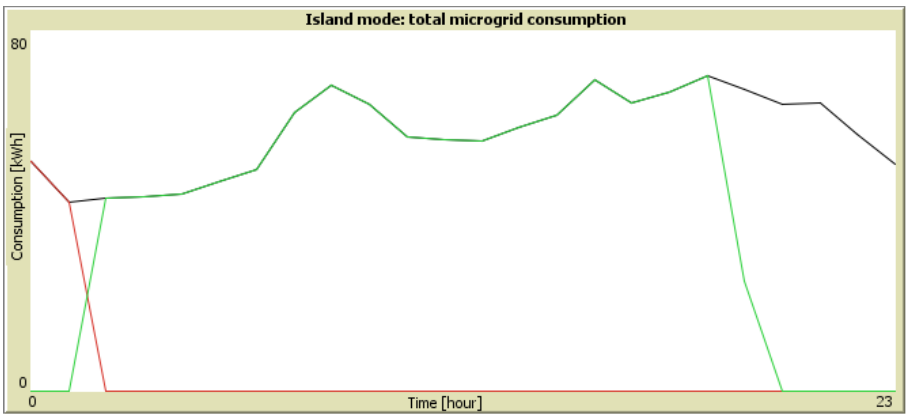


Figure 4.14: Island mode January 15th

In figure 4.15 below the island mode duration on March 15th is illustrated. Average hourly energy usage in the microgrid this day was 52.88 kWh. As one can observe, the island mode duration is one hour longer in March, i.e. 17 hours.

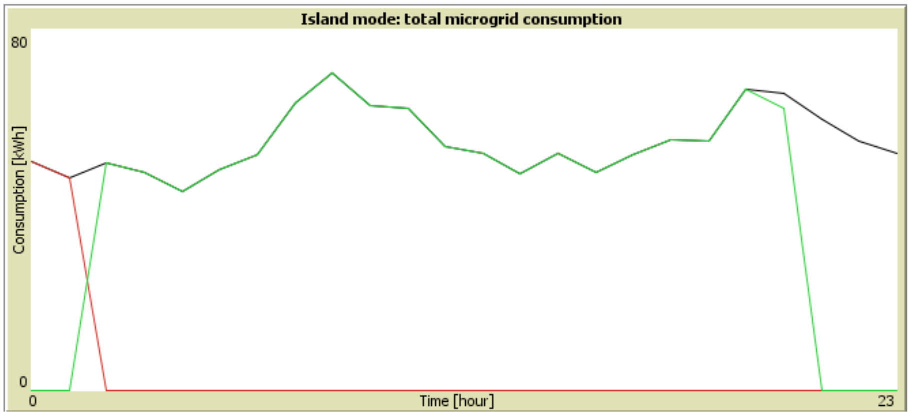


Figure 4.15: Island mode March 15th

Furthermore, in figure 4.16 island mode on May 15th is illustrated. Here, the average hourly energy usage in the microgrid was 27.90 kWh, and one can observe that the microgrid is able to manage the entire demand the rest of the day. In fact, it is able to manage the demand until 21 PM on May 16th (43 hours in total).

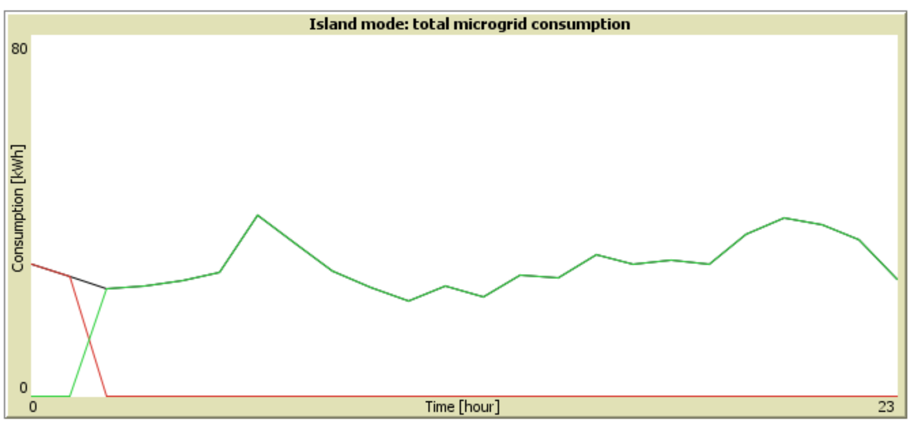


Figure 4.16: Island mode May 15th

Below, in table 4.7 the island mode duration on the 15th in each of the months in the model is listed.

Month	Average hourly energy usage [kWh]	Island mode duration
Jan	55.03 (Jan 15th)	2 AM - 18 PM (16 hours)
Feb	51.48 (Feb 15th)	2 AM - 20 PM (18 hours)
Mar	52.88 (Mar 15th)	2 AM - 19 PM (17 hours)
Apr	32.01 (Apr 15th)	2 AM (15th) - 7 AM (16th) (29 hours)
May	27.90 (May 15th)	2 AM (15th) - 21 PM (16th) (43 hours)
June	24.90 (June 15th)	2 AM (15th) - 7 AM (17th) (53 hours)

Table 4.7: Island mode duration in each month

Chapter 5

Discussion

This chapter reflects on some of the results obtained and key issues arisen during this study.

5.1 Demo Steinkjer consumption patterns

There are some issues worth addressing regarding the results obtained in the analysis of consumption patterns in Demo Steinkjer (section 3.2). First off, even though the monthly differences in total energy consumption varies considerably, the usage peaks are present *regardless of season*. The analysis showed that we experience the same usage peaks in all months, occurring at approximately the same time during the day. Hence, as concluded in section 3.2.6, this supports how monthly differences in consumption is mostly dependent on space heating caused by the seasonal variations in outdoor temperatures. Clearly, this consistency in daily high and low demand periods emphasize the potentials of many of the efficiency measures made possible by a transition to a smarter distribution grid, such as the ones presented in section 2.5. In particular, the potential benefits gained from enabling means for shaving and shifting of demand in usage peak periods are evident, given the knowledge of this consistent daily pattern.

Secondly, the investigation of daily usage patterns in *single* households (section 3.2.1) revealed a much more fluctuating pattern than what was achieved when analysing the combined energy usage of several homes. The analysis showed, however, that when aggregating the consumption patterns of several households, the fluctuating behaviour of different homes is disguised, and we achieve a pattern more similar to what is expected. This is also important to take in account with regards to efficiency measures in microgrids. That is, in order to achieve the best overall microgrid efficiency, using measures such as autonomous peak shaving, one must focus on handling usage peaks in the microgrid as a whole as opposed to treating usage peaks in each household individually. Once again, this emphasizes the importance of the increased information flow that Smart Grid technology is intended to provide. That is, given real-time reporting on consumption from each of the users in a microgrid one can enforce efficiency measures on the microgrid as a whole, and thus ensure a better overall efficiency in energy usage. As discussed in section 5.3 below, this was also the conclusion reached from the peak shaving modelling described in sections 4.2.1 and 4.2.2.

Furthermore, the analysis also revealed the apparent differences between week day and weekend consumption in households. While the week day pattern revealed two distinct high demand periods daily (one between 7 and 9 AM, and another in the afternoon), weekends had a more constant high consumption from 11 AM until evening. However, as described in section 3.2.4, the differences between the two was primarily related to *when* usage peaks occur, and not the amount of energy consumed daily. In fact, as one can observe in table 3.2 in section 3.2.4, the collective *average hourly consumption* of 20 households is approximately equal when comparing week days and weekends. Thus, if peak detection is determined according to last day average hourly usage (as proposed in the model described in chapter 4), we do not need to distinguish between week days and weekends in terms of identifying a usage peak.

Finally, as discussed earlier, the consumption data provided by Demo Steinkjer had numerous measurement gaps in the dataset. Thus, finding longer periods of time, where none of these gaps were present, was extremely time-consuming. However, the 20 households used in both the analysis (section 3.2) and the autonomy model (chapter 4) all have consistent and consecutive measurements in the time period ranging from October 1st 2012 until June 28th 2013. The database IDs of these households are presented in appendix F. The reason for these measurement gaps is unknown. One could argue that it is caused by packet losses in the communication infrastructure, however this is unlikely due to the fact that when measurements are missing it is not just one hourly update that is lost, it is usually between 10 and 48 hours worth of *consecutive* consumption updates. Thus, it is likely to assume that the missing data is caused by individual or multiple households ceasing to report as result of e.g. system maintenance or improvement.

5.2 Solar cell energy generation

The investigation of solar cells (section 3.3) also revealed some results worth addressing. In particular, the substantial seasonal differences in energy generation calls into questioning the suitability of solar energy for Norwegian conditions. As a matter of fact, the analysis showed that total generated energy in July was as much as 18 times greater than that of January. Although, as described in section 3.3.2, the Brussels total PV capacity had increased by 3.38 MW in July compared to January, the difference in generated energy is significant regardless. Hence, given the weather conditions in Norway, whereas winter months are the clearly most energy demanding, would suggest that solely relying on solar energy in Norwegian microgrids might not be the best choice compared to other renewable resources. That is, the potential benefits of solar energy harnessing is clearly greater in parts of the world with a milder climate and greater generation potentials.

Also, one must bear in mind that the data used in the analysis in section 3.3 originates from Belgium, and consequently does not give a precise impression of what the potentials are for solar energy harnessing in Norway. As described in section 2.7.1, photovoltaic energy generation is highly weather dependent, and nominal power output (i.e. maximum achievable generation) will only occur during optimal weather conditions. Thus, installing a capacity similar to that of Brussels might, or most probably will, result in a different power output pattern in Norway. In fact, given the variations in solar energy potentials in Europe (figure 2.10, section 2.7.1) it is plausible to assume that total energy generated in Norway would be significantly less than that of Belgium. Considering this, it would have been interesting to study solar generation data gathered in Steinkjer in order to provide dynamics more representative for Norwegian conditions, and consequently more suitable with regards to the consumption patterns analysed.

Furthermore, the main problem with solar energy, or any other renewable source for that matter, is that supply cannot be manipulated (i.e. we are unable to control the power output). Consequently, this causes the difficulties with regards to prediction of supply. The analysis showed that day-ahead predictions on solar energy supply could vary as much as 26 % from the actual generated amount each month. Also, more often than not these predictions were optimistic (i.e. greater than actual generation). Moreover, as described in section 3.3.1, the day-to-day variations in supply was considerable, once again confirming the suspected weather dependency of solar energy generation. These observations clearly state the challenges associated with solar energy, and emphasize the need for a storage technology capable of transforming this highly variable resource into a dispatchable one. That is, the most efficient utilization of solar energy would depend on a storage system capable of charging during high generation periods, and discharging in non-generating hours.

Finally, in section 4.1.1 the area of PV cells required to obtain the capacity used in the *solar farm mode* of the autonomy model was derived (i.e. nominal power output of 41.2 kW). The calculation revealed that one needs an area of approximately 275 m^2 of photovoltaic cells, given 15 % cell efficiency, in order to obtain the desired capacity. Arguably, such a size for a solar farm installation is manageable in futuristic microgrids, and will be possible to implement regardless of geographical location. That is, by e.g. installing PV cells on several rooftops one would easily meet such a space requirement.

5.3 Autonomy model

The purpose of the microgrid autonomy model (chapter 4) was to investigate usage peak shaving and islanding of microgrid operation. As described in sections 4.2.1 and 4.2.2, the two different modes for which peak shaving was attempted (i.e. *solar farm* and *distributed generation mode*) resulted in significantly different utilization of available stored resources. The simulations showed that although *total* peak shaving performed in *distributed generation mode* was greater than that of *solar farm mode* in each month, the maximum *hourly* and *daily* peak shaving was less. That is, as peak shaving in *distributed generation mode* was performed on each individual household, the different usage patterns caused a suboptimal storage utilization in the microgrid as a whole, as available resources was not concentrated on handling the usage peaks of the overall microgrid consumption.

Furthermore, when comparing the variations in stored energy throughout the entire simulation period in both modes (depicted in figures 4.8 and 4.13), one can observe the differences in available stored energy in different months. This revealed that using *distributed generation mode* the capacity in storage was in the first three months rarely significant, indicating that most of the produced energy was used immediately. Using *solar farm mode*, however, there was at all times some resources available, and thus critical usage peaks (i.e. peaks exceeding the *start boundary* described in section 4.1.1) was never ignored. On the other hand, in the three first months using *distributed generation mode* all BES systems was often completely discharged, consequently causing critical usage peaks to be ignored, both in individual households and in the microgrid as a whole. In particular, this is illustrated in figure 4.9 in section 4.2.2 where one can observe how the most critical usage peak this day (occurring at 19 PM) is not handled at all.

The observations made by these simulations clearly emphasize the potentials of the increased information and power flow provided by a smarter distribution grid. As mentioned, employing peak shaving on individual households in a microgrid, as opposed to the combined consumption of all microgrid participants, results in a significantly worse utilization of available resources. Thus, in order to achieve the best overall result it is more feasible to take a subsystem approach that considers a microgrid's total consumption and generation when enforcing efficiency measures. This, however, will require a continuous collaboration between the microgrid users, and a centralized control system for utilizing the stored reserves most optimally.

Simulating islanding of microgrid operation also showed significant monthly differences. In fact, comparing the island mode duration in January (16 hours) and June (53 hours) revealed a difference of 37 hours for which the microgrid was able to manage its entire energy demand. The simulation also showed that midday energy generation in May and June in fact often was greater than the consumption, causing the battery to start charging. Worth addressing, however, is that in *island mode* the microgrid instantaneously took over when the external energy supply was switched off. This assumption is unlikely as some response time is required to switch between the two modes of operation.

Regarding the development of the model there are several issues worth addressing. First off, as described in section 4.1, to simplify I assumed that the solar power output is constant in *each hour*. As discussed in section 5.2, this is rarely the case given the high weather dependency of solar energy generation. Furthermore, I have used the same peak boundaries in both the *solar farm mode* and *distributed generation mode* of the model for detecting usage peaks. In retrospect, given the varying consumption patterns of individual households (discussed in section 5.1), this might not have been the best approach. That is, a better solution would clearly be to calculate individual peak boundaries for each household. Finally, as described in section 2.7.2, the nominal solar generation in the data used had an increasing in power output capacity in March, which greatly affected the energy generation. Perhaps it would have been more feasible to use a dataset that had a constant power output capacity in the entire modelling period.

Also, the model uses hourly updates on both energy consumption and generation. This simplification is inaccurate as the actual load in households and power output from solar cells may vary significantly within one hour. Thus, in order to achieve a better model it would have been feasible to use data with greater precision.

5.4 Storage in microgrids

As described in chapter 1, the main focus of this study has been to analyse and model consumption and generation patterns in residential area microgrids. Thus, the potential issues related to storage of energy is not well covered. In the model in chapter 4 it is implemented a discharge and power conversion loss of 10 % in the BES system used, however other storage-related issues such as e.g. minimum state of charge (SOC_{min}, as described in section 2.5.4), and further energy loss in the battery system is not taken into consideration. Also, as described in section 2.4, the cost of a BES system is mainly associated with its energy capacity rather than its power rating. Thus, the required period of discharge will greatly affect the costs of the storage system. In the model (chapter 4) it was simply assumed a 1 MWh battery system, not considering issues such as response time and required period of discharge etc. In particular, as described in section 4.2.1, by simulating using the *solar farm mode* of the model we achieved a maximum *hourly* consumption shaving of ≈29 kWh and a maximum *daily* energy compensation of 275.15 kWh. Clearly, these observations must be addressed if one is to design a suitable storage system for this purpose.

5.5 NetLogo

NetLogo proved to be a useful tool for developing the model in chapter 4, and can be recommended for others attempting to model something similar. The agent-based programming language is easy to learn, and there is a lot of online support (e.g. tutorials, troubleshooting forums etc.) that can be of help. On the downside, however, as one can see from the code in the folder "AutonomyModel" on the attached CD-ROM, you are required to use a large amount of global variables in order to connect the user interface with the code. That is, every user-setting, plotting variable, monitoring variable etc. must all be defined as global. This combined with all other shared global variables results in a somewhat messy code. Furthermore, when accessing the database using SQL commands in the NetLogo model, the data extractions can be extremely slow. The advice is to reduce the amount of SQL queries executed in the model, by e.g. providing the start-IDs in the database of the different households' consumption and generation measurements in the code.

Also, NetLogo is not a supported programming language in editors such as notepad++. On the attached CD-ROM (in folder "AutonomyModel") the code of the model can be viewed by either opening the actual NetLogo model and pressing the "code-bar", or by opening the file "NetLogoCode.py". However, the latter interprets it as a python code, and thus the advice is to view the code as intended in NetLogo.

Chapter 6

Conclusion

This study has focused on addressing the energy usage patterns of households, and investigating means for reduced and more efficient household consumption in futuristic microgrids. Furthermore, two analyses have been performed with purpose of examining the dynamics of energy consumption in households and the energy generation potentials of photovoltaic solar cells. Finally, I have attempted to model autonomy in a microgrid cell using the acquired dynamics of energy generation and consumption obtained from the two previously described analyses. The purpose of this model was to examine:

- usage peak shaving in high demand periods using local energy generation and storage.
- how long a microgrid can stay operational using stored energy reserves and local generation when external energy supply is disrupted, i.e. with purpose of avoiding power outages.

To conclude the thesis, I will summarize the study's main findings.

The analysis of Demo Steinkjer households (section 3.2) revealed that consumption patterns are consistent with previous investigations on behaviour in Norwegian households. The analysis showed that when aggregating the consumption of several households over longer periods of time, we obtain a daily pattern that varies as expected, with two distinct usage peak periods on week days. Furthermore, the analysis also showed that there are considerable differences in consumption when comparing week day and weekend consumption. That is, while we experience these two distinct usage peaks on week days (one between 7 and 9 AM, and another in the afternoon), the weekend consumption has a different pattern. In particular, the usage peak associated with the morning routines of household occupants is shifted several hours in weekends, from approximately 7 AM to 11 AM. However, as discussed in section 5.1 the differences between week day and weekends are primarily related to *when* usage peaks occur, and not the amount of energy consumed daily.

Moreover, the expected patterns of both week day and weekend consumption seem to emerge even more persistently when increasing the time period and the number of households further, despite the monthly variations in total consumption. This supports the presumption that usage peaks are consistent regardless of season, and that monthly differences in overall consumption is mostly due to the varying need for space heating in households depending on outdoor temperatures. However, even though the aggregated consumption results in this presumed pattern, the behaviour of individual households may vary significantly. That is, the investigation of consumption in *single* households (section 3.2.1) revealed a much more fluctuating daily usage pattern as opposed to what was experienced when the consumption of several households was aggregated. Once again, this is consistent with previous investigations (described in section 2.2) as consumption in different households may vary depending on factors such as geographical location, size of household and behaviour of household occupants.

The analysis of solar energy potentials (section 3.3) clearly verified the unpredictable dynamics, nonlinearities and uncertainties of solar energy harnessing described in section 2.7. In particular, the investigation on day-to-day variations (section 3.3.1) revealed how the power output on consecutive days may differ considerably, confirming the great impact weather conditions have on energy generation in solar cells. The analysis also showed that day-ahead predictions on supply could vary as much as 26 % from actual generation each month, and that the predictions more often than not were too optimistic. Furthermore, as discussed in section 5.2, the considerable seasonal differences in solar energy generation questions the suitability of solely relying on solar energy for local microgrid generation given Norwegian conditions. In particular, the analysis showed that energy generation in July was significantly greater than that of January. Thus, given that winter months are the clearly most energy demanding in Norway would suggest that, in addition to solar power, it perhaps would be feasible to include other renewable energy sources (e.g. wind) in Norwegian microgrids.

As discussed in section 5.2, to obtain a nominal capacity of 41.2 kW, given 15 % cell efficiency, one needs an area of approximately 275 m^2 of photovoltaic cells. However, this nominal capacity represent the maximum achievable output power which only occurs during optimal weather conditions. Hence, given that global solar radiation varies, installing such a capacity will result in considerably different energy supply potentials in different parts of the world. Thus, Norwegian conditions will require a significantly greater installed capacity in order to achieve a given energy supply compared to other parts of the world with a milder climate and greater solar generation potentials.

The potential benefits of local energy generation and storage in microgrid cells are evident. In particular, given the consistent daily usage pattern in households, much can be gained from employing measures such as e.g. peak shaving. However, as discussed in section 5.3, the modelling of peak shaving showed that in order to achieve the most optimal result, it is important to consider a microgrid's total consumption and stored reserves when compensating in high demand periods. Such a centralized monitoring and control can be achieved with the increased information and energy flow intended with Smart Grid. Furthermore, the varying dynamics of solar energy generation emphasizes the need for a storage system capable of charging during generation periods, and discharging in non-generating hours. However, as described in section 2.4, one of the main advantages with BES systems is this ability to convert highly variable renewable energy resources into dispatchable ones.

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Appendix A

Tutorial for setting up database and extracting data

Setting up database:

*The following three steps **must** be taken in order for the attached python scripts and the autonomy model to work.*

1. Set up apache server and configure phpMyAdmin and MySQL, e.g. as described in [1]

2. Create a database named "demosteinkjer" in phpMyAdmin.

3. Upload .sql files on consumption and generation (located in folder "Database" on the attached CD-ROM) to database "demosteinkjer" in separate tables (four tables in total), i.e.

    - Create one table called *"consumption"* in the *"demosteinkjer"* database and import the "consumption.sql" dataset. Worth noticing, however, is that this import must be done via *command line* as the file is to large to be imported directly in phpMyAdmin.
    - Create one table called *"generationjanfebmaraprmayjun2013"* in the *"demosteinkjer"* database and import the "generationjanfebmaraprmayjun2013.sql" dataset.
    - Create one table called *"generationjulaugsept2013"* in the *"demosteinkjer"* database and import the "generationjulaugsept2013.sql" dataset.
    - Create one table called *"generationoctnovdec2013"* in the *"demosteinkjer"* database and import the "generationoctnovdec2013.sql" dataset.

As described in section 3.1.3 there are some preprocessing steps that needs to be performed on the consumption and generation datasets, i.e.

- Add a column called "HourlyConsumption" to the "consumption" table in the database, and run python script "addHourlyConsColumn.py", located on the attached CD-ROM (in folder "pythonworkspace").

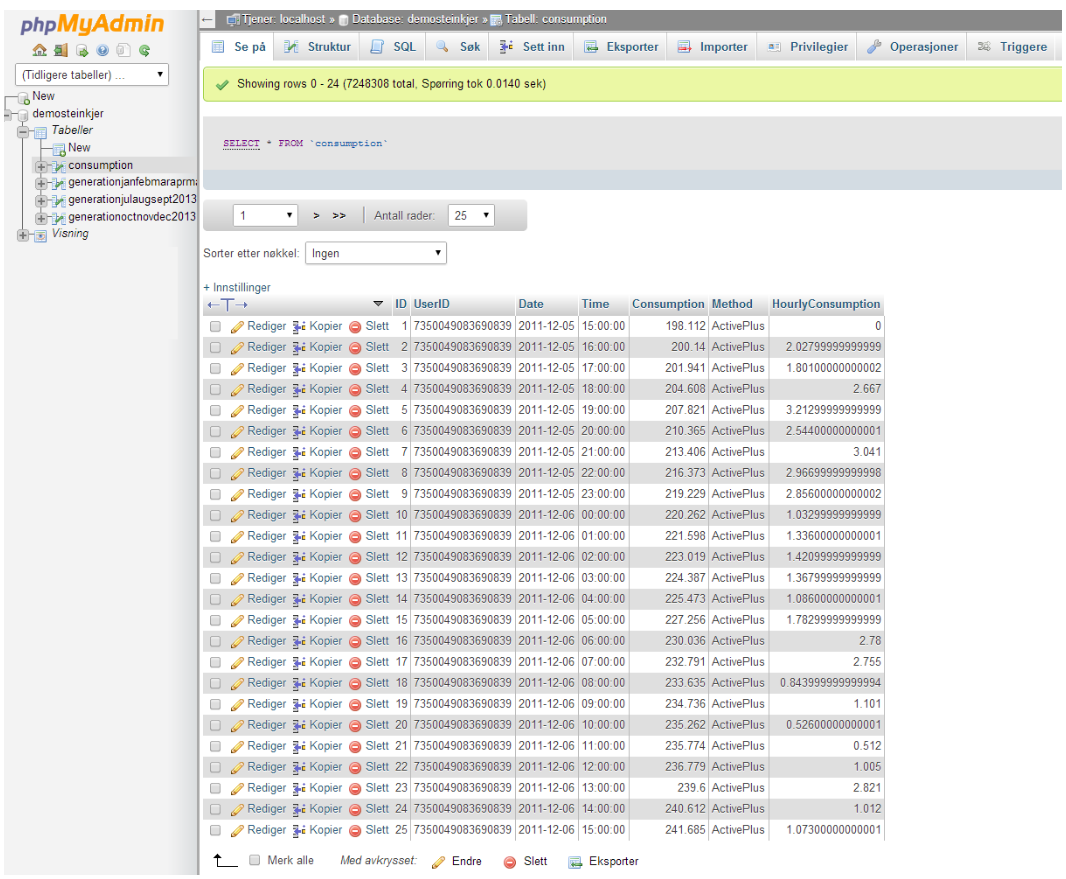
- Remove spaces from **all** column names in **all** three generation tables.

- Run python script "searchingForDuplicate.py" (located in folder "pythonworkspace" on attached CD-ROM) on the database, and manually remove the database entry indicated by output of the python script.

[1] https://www.youtube.com/watch?v=kZ2zbO6PABk

- Run python script "ReplaceCommaWithPeriodInDatabase.py" on "DayAheadforecastMW" and "CorrectedUpscaledMeasurementMW" columns in **all** generation tables in order replace comma with period as decimal mark in numbers.

However, these last four steps are necessary only if one intends to use the data downloaded from Demo Steinkjer and elia directly. In other words, using the datasets included on the CD-ROM makes it unnecessary to perform these last four steps. Below, in figure A.1 the resulting representation of the database in phpMyAdmin is illustrated.



	ID	UserID	Date	Time	Consumption	Method	HourlyConsumption
Rediger Kopier Slett	1	7350049083690839	2011-12-05	15:00:00	198.112	ActivePlus	0
Rediger Kopier Slett	2	7350049083690839	2011-12-05	16:00:00	200.14	ActivePlus	2.02799999999999
Rediger Kopier Slett	3	7350049083690839	2011-12-05	17:00:00	201.941	ActivePlus	1.80100000000002
Rediger Kopier Slett	4	7350049083690839	2011-12-05	18:00:00	204.608	ActivePlus	2.667
Rediger Kopier Slett	5	7350049083690839	2011-12-05	19:00:00	207.821	ActivePlus	3.21299999999999
Rediger Kopier Slett	6	7350049083690839	2011-12-05	20:00:00	210.365	ActivePlus	2.54400000000001
Rediger Kopier Slett	7	7350049083690839	2011-12-05	21:00:00	213.406	ActivePlus	3.041
Rediger Kopier Slett	8	7350049083690839	2011-12-05	22:00:00	216.373	ActivePlus	2.96699999999998
Rediger Kopier Slett	9	7350049083690839	2011-12-05	23:00:00	219.229	ActivePlus	2.85600000000002
Rediger Kopier Slett	10	7350049083690839	2011-12-06	00:00:00	220.262	ActivePlus	1.03299999999999
Rediger Kopier Slett	11	7350049083690839	2011-12-06	01:00:00	221.598	ActivePlus	1.33600000000001
Rediger Kopier Slett	12	7350049083690839	2011-12-06	02:00:00	223.019	ActivePlus	1.42099999999999
Rediger Kopier Slett	13	7350049083690839	2011-12-06	03:00:00	224.387	ActivePlus	1.36799999999999
Rediger Kopier Slett	14	7350049083690839	2011-12-06	04:00:00	225.473	ActivePlus	1.08600000000001
Rediger Kopier Slett	15	7350049083690839	2011-12-06	05:00:00	227.256	ActivePlus	1.78299999999999
Rediger Kopier Slett	16	7350049083690839	2011-12-06	06:00:00	230.036	ActivePlus	2.78
Rediger Kopier Slett	17	7350049083690839	2011-12-06	07:00:00	232.791	ActivePlus	2.755
Rediger Kopier Slett	18	7350049083690839	2011-12-06	08:00:00	233.635	ActivePlus	0.843999999999994
Rediger Kopier Slett	19	7350049083690839	2011-12-06	09:00:00	234.736	ActivePlus	1.101
Rediger Kopier Slett	20	7350049083690839	2011-12-06	10:00:00	235.262	ActivePlus	0.52600000000001
Rediger Kopier Slett	21	7350049083690839	2011-12-06	11:00:00	235.774	ActivePlus	0.512
Rediger Kopier Slett	22	7350049083690839	2011-12-06	12:00:00	236.779	ActivePlus	1.005
Rediger Kopier Slett	23	7350049083690839	2011-12-06	13:00:00	239.6	ActivePlus	2.821
Rediger Kopier Slett	24	7350049083690839	2011-12-06	14:00:00	240.612	ActivePlus	1.012
Rediger Kopier Slett	25	7350049083690839	2011-12-06	15:00:00	241.685	ActivePlus	1.07300000000001

Figure A.1: Database representation in phpMyAdmin

Extracting consumption and generation data from database:

In the folder *"pythonworkspace"* on the attached CD-ROM the python scripts used for extracting and plotting consumption and generation patterns in the analyses in chapter 3 is located. However, in order to run any of these scripts there are some python packages that must be installed, these are:

- MySQLdb
- dateutil
- pyparsing
- matplotlib
- numpy
- re
- six

After having set up the database as described earlier, and installed the necessary python packages, all scripts in the folder *"pythonworkspace"* can be run without any other preprocessing steps. Hence, one can reproduce the results obtained in the analyses described in sections 3.2 and 3.3. As described in section 3.1.3, in appendix C and D two of these scripts is presented (one for extracting and plotting consumption patterns and one for generation patterns).

Worth noticing is that the consumption dataset provided by Demo Steinkjer has a lot of "gaps", i.e. missing measurements. However, the 20 UserIDs presented in appendix F all have consistent and consecutive hourly measurements in the time period October 1st 2012 until June 28th 2013. As mentioned, these are also the households analysed in section 3.2.

Appendix B

Code: Adding hourly consumption column to Demo Steinkjer dataset

```python
'''addHourlyConsColumn.py -                                '''
'''This script calculates the consumption update each hour in
    the entire database'''
import MySQLdb
import sys

conn = MySQLdb.connect(host="localhost", # host
                      user="root", # username
                       passwd="root", # password
                       db="demosteinkjer") # name of database

conn.autocommit(True)
cur = conn.cursor()

idcount = 2, data1 = 0, data2 = 0, maxID = 0, hourlycons = 0

cur.execute("SELECT MAX(`ID`) FROM `consumption` WHERE `
   Method`='ActivePlus'")
for row in cur.fetchall():
    maxID = row[0]

while(idcount <= maxID):
    idcount = idcount - 1
    cur.execute("SELECT `Consumption` FROM `consumption`
       WHERE `ID`= %s AND `Method`='ActivePlus'", idcount)
    for row in cur.fetchall():
        data1 = row[0]

    idcount = idcount +1
    print "IDCOUNT: %d" % idcount
    cur.execute("SELECT `Consumption` FROM `consumption`
       WHERE `ID`= %s AND `Method`='ActivePlus'", idcount)
    for row in cur.fetchall():
        data2 = row[0]

    hourlycons = data2 - data1
    cur.execute("UPDATE `consumption` SET `HourlyConsumption
       `= %s WHERE `ID`= %s AND `Method`='ActivePlus'", [
       hourlycons, idcount])
    print "Hourly cons: %.3f" % hourlycons
    idcount = idcount + 1

cur.close()
conn.close()
```

Appendix C

Code: Extracting consumption data from database

```
'''ConsumptionTwentyHouseholdsNineMonths.py -
This script extracts and plots the aggregated daily
   consumption pattern on week days of 20 households in
   January and February 2013.
'''
import MySQLdb
import sys
import dateutil
import pyparsing
import matplotlib.pyplot as plt
import numpy
import re
import six

#Connect to database
conn = MySQLdb.connect(host="localhost", # host
                     user="root", # username
                      passwd="root", # password
                      db="demosteinkjer") # name of database

conn.autocommit(True)
cur = conn.cursor()

maxID = 0, prevID = 0, IDcount = 0
cons = [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]
howmany = [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]

#Get max measurement ID in database
cur.execute("SELECT MAX(`ID`) FROM `consumption` WHERE `
   Method`='ActivePlus'")
for row in cur.fetchall():
    print(maxID)
    maxID = row[0]
    print(maxID)

#The 20 chosen households in Demo Steinkjer database
IDs = [7350049083690884,
7350049084530592,
7350049084529299,
7350049084531155,
7350049084529251,
7350049084529213,
7350049084531209,
7350049084529565,
7350049084529497,
```

```
7350049084529459,
7350049084529404,
7350049084531339,
7350049084531292,
7350049084531537,
7350049084531469,
7350049084531346,
7350049084530974,
7350049084530912,
7350049084530813,
7350049084530745]

#Define x axis for plot
x =
    [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23]


#JANUARY#
for IDcount in range(0,20):
    prevID = IDs[IDcount]
    cur.execute("SELECT `ID` FROM `consumption` WHERE `UserID
        ` = %s AND `Date` = '2013-01-01' AND `Time` =
        '00:00:00' AND `Method`= 'ActivePlus'", prevID)
    for row in cur.fetchall():
        ID = row[0]
        print "ID = %d" % ID

    for day in range (1,32):
        if (day !=5 and day !=6 and day !=12 and day !=13 and
            day !=19 and day !=20 and day !=26 and day != 27)
           :#Week days only
            for hour in range(0,24):
                cur.execute("SELECT `HourlyConsumption` FROM
                    `consumption` WHERE `ID` = %s", ID)
                for row in cur.fetchall():
                    cons[hour] = cons[hour] + row[0]
                    howmany[hour] = howmany[hour] + 1
                ID = ID + 1
            print "day = %d" % day
        else:
            ID = ID + 24 # Skip weekend
            print "Skip weekend"

#FEBRUARY#
for IDcount in range(0,20):
```

```python
    prevID = IDs[IDcount]
    cur.execute("SELECT `ID` FROM `consumption` WHERE `UserID
       ` = %s AND `Date` = '2013-02-01' AND `Time` =
       '00:00:00' AND `Method`= 'ActivePlus'", prevID)
    for row in cur.fetchall():
        ID = row[0]
        print "ID = %d" % ID

    for day in range (1,29):
        if (day !=2 and day !=3 and day !=9 and day !=10 and
           day !=16 and day !=17 and day !=23 and day != 24):
           #Week days only
            for hour in range(0,24):
                cur.execute("SELECT `HourlyConsumption` FROM
                   `consumption` WHERE `ID` = %s", ID)
                for row in cur.fetchall():
                    cons[hour] = cons[hour] + row[0]
                    howmany[hour] = howmany[hour] + 1
                ID = ID + 1
            print "day = %d" % day
        else:
            ID = ID + 24 # Skip weekend
            print "Skip weekend"

#IF AVERAGE
#for hour in range(0,24):
#     cons[hour] = cons[hour] / howmany[hour]

cur.close()
conn.close()

plt.plot(x,cons)
plt.xticks
   ([0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23])

plt.ylabel("Consumption [kWh]")
plt.xlabel("Time [hour]")
#plt.axis([0,23,2600,4400]) #To specify axis
plt.grid()
plt.savefig('test.png')
plt.show()
```

Appendix D

Code: Extracting generation data from database

```
'''
SolarGenerationJanFebMar2013.py - This script gathers and
   plots the solar energy generation from January 2013
'''
import MySQLdb
import sys
import dateutil
import pyparsing
import matplotlib.pyplot as plt
import numpy
import re
import six

conn = MySQLdb.connect(host="localhost", # host
                     user="root", # username
                      passwd="root", # password
                      db="demosteinkjer") # name of database

conn.autocommit(True)
cur = conn.cursor()

IDcounter = 1, hour = 0
gen = [0] * 24

x =
   [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23]


howmany = [0] * 24

tempgen = [0] * 24

total1 = 0


#JANUAR 2013#

cur.execute("SELECT `CorrectedUpscaledMeasurementMW` FROM `
   generationjanfebmaraprmayjun2013` WHERE `ID` = %s",
   IDcounter)
for row in cur.fetchall():
    gen[hour] = float(row[0])
IDcounter = IDcounter + 1
howmany[hour] = howmany[hour] + 1
```

```
for hour in range(1,24):
    cur.execute("SELECT `CorrectedUpscaledMeasurementMW` FROM
        `generationjanfebmaraprmayjun2013` WHERE `ID` = %s",
       IDcounter)
    for row in cur.fetchall():
        gen[hour] = float(row[0])
        howmany[hour] = howmany[hour] + 1
    IDcounter = IDcounter + 1
    cur.execute("SELECT `CorrectedUpscaledMeasurementMW` FROM
        `generationjanfebmaraprmayjun2013` WHERE `ID` = %s",
       IDcounter)
    for row in cur.fetchall():
        gen[hour] = gen[hour] + float(row[0])
    IDcounter = IDcounter + 1
    cur.execute("SELECT `CorrectedUpscaledMeasurementMW` FROM
        `generationjanfebmaraprmayjun2013` WHERE `ID` = %s",
       IDcounter)
    for row in cur.fetchall():
        gen[hour] = gen[hour] + float(row[0])
    IDcounter = IDcounter + 1
    cur.execute("SELECT `CorrectedUpscaledMeasurementMW` FROM
        `generationjanfebmaraprmayjun2013` WHERE `ID` = %s",
       IDcounter)
    for row in cur.fetchall():
        gen[hour] = gen[hour] + float(row[0])
        gen[hour] = gen[hour] / 4
    IDcounter = IDcounter + 1

print "IDcounter before rest of January = %s" % IDcounter

for day in range(0,30):
    for hour in range(0,24):
        cur.execute("SELECT `CorrectedUpscaledMeasurementMW`
            FROM `generationjanfebmaraprmayjun2013` WHERE `ID`
             = %s", IDcounter)
        for row in cur.fetchall():
            tempgen[hour] = tempgen[hour] + float(row[0])
            howmany[hour] = howmany[hour] + 1
        IDcounter = IDcounter + 1
        cur.execute("SELECT `CorrectedUpscaledMeasurementMW`
            FROM `generationjanfebmaraprmayjun2013` WHERE `ID`
             = %s", IDcounter)
        for row in cur.fetchall():
            tempgen[hour] = tempgen[hour] + float(row[0])
        IDcounter = IDcounter + 1
```

```
        cur.execute("SELECT `CorrectedUpscaledMeasurementMW`
           FROM `generationjanfebmaraprmayjun2013` WHERE `ID`
            = %s", IDcounter)
        for row in cur.fetchall():
            tempgen[hour] = tempgen[hour] + float(row[0])
        IDcounter = IDcounter + 1
        cur.execute("SELECT `CorrectedUpscaledMeasurementMW`
           FROM `generationjanfebmaraprmayjun2013` WHERE `ID`
            = %s", IDcounter)
        for row in cur.fetchall():
            tempgen[hour] = tempgen[hour] + float(row[0])
            tempgen[hour] = tempgen[hour] / 4
            gen[hour] = gen[hour] + tempgen[hour]
        IDcounter = IDcounter + 1

#IF average
#for hour in range(0,24):
#    gen[hour] = gen[hour] / howmany[hour]

cur.close()
conn.close()

for hour in range(0,24):
    total1 = total1 + gen[hour]

print total1

total1 = total1 / 31

print total1 # average daily generation

print("Disconnect OK")

plt.plot(x,gen)
plt.xticks
   ([0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23])

plt.ylabel("Generation [MWh]")
plt.xlabel("Time [hour]")
#plt.axis([0,23,0,12]) #To specify axis
plt.grid()
plt.savefig('test.png')
plt.show()
```

Appendix E

Autonomy model: user interface and code extracts

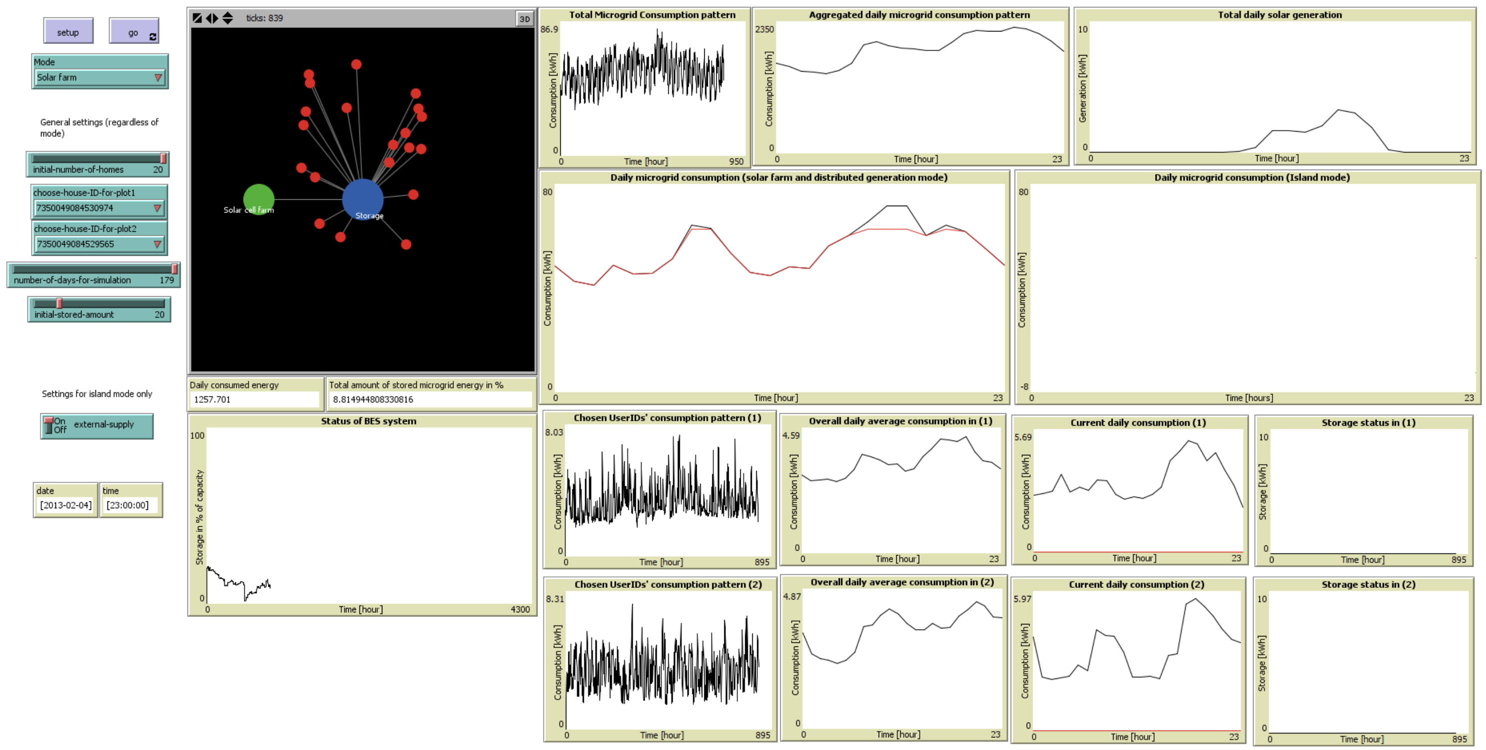


Figure E.1: User interface of autonomy model (solar farm mode)

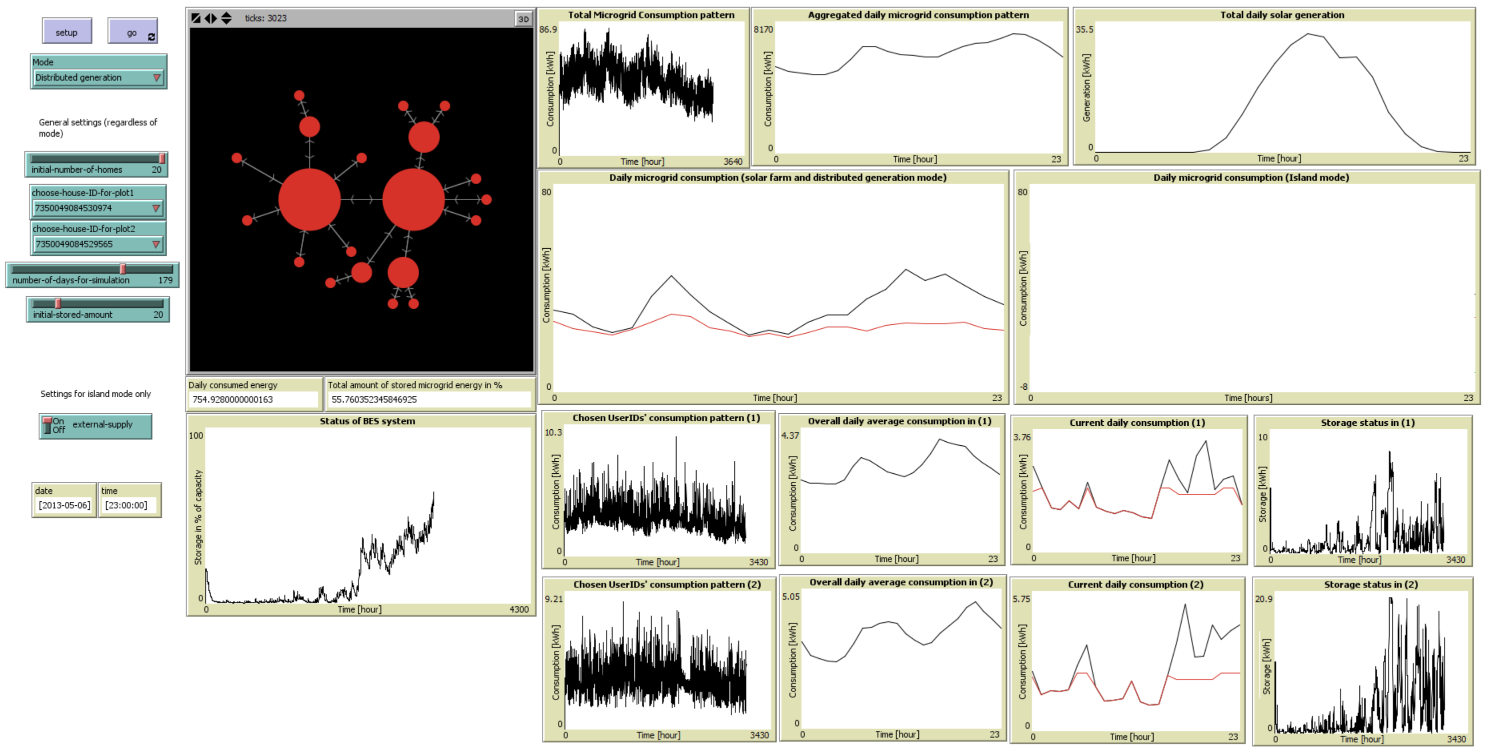


Figure E.2: User interface of autonomy model (distributed generation mode)

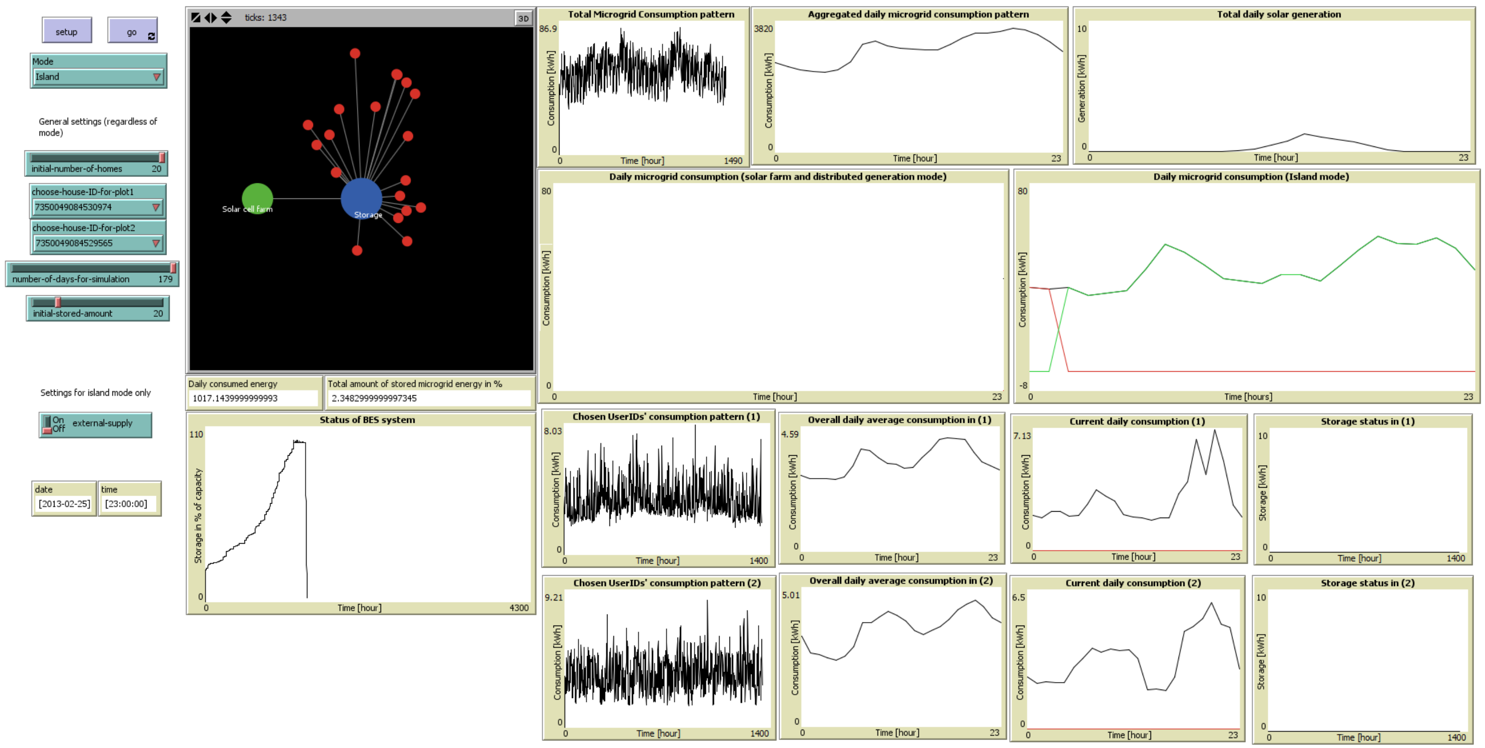


Figure E.3: User interface of autonomy model (island mode)

Below I have included some parts of the NetLogo code, however the complete code is 42 pages long and thus **not** included in appendix due to space requirements. To see the complete code either

- open the NetLogo model located in folder "AutonomyModel" on the attached CD-ROM and click the "code-bar",
- or open the file named "NetLogoCode.py" in the folder "AutonomyModel" on the attached CD-ROM.

Below the code executed when pressing *setup* in the user interface is presented (see user interface above). This function sets up the model with the chosen user settings. That is, it connects the model to the database, sets the initial values on consumption and generation, ensures the correct layout of the microgrid according to chosen mode etc.

```
to setup
  clear-all
  reset-ticks

  setup-database-connection
  setup-mode

  setup-generation
  setup-inital-houses
  setup-initial-date-and-time

  set prevmonth 1 ; start January
end
```

Below the code executed when pressing the button *go* in the user interface is presented. This button starts the simulation, and thus must be executed after first setting up the model. For each "tick" of simulation (i.e. each hour) this function runs one time until the time period (determined by the initial setting number-of-days-for-simulation) is finished. Here, new hourly consumption and generation updates in the microgrid is continuously extracted from the database and the peak shaving (solar farm and distributed generation mode) or islanding of microgrid operation (island mode) occurs.

```
to go
  if ticks >= (number-of-days-for-simulation * 24 - 1) [stop]

  update-consumption
```

```
  update-total-consumption
  update-date-and-time
  update-generation

  tick
end
```

Finally, the code extract below describes the peak shaving procedure using the solar farm mode of the model. Here, the total consumption each hour is compared to the current peak boundary according to storage status in the microgrid (as described in section 4.1.1), and the resulting peak shaving is performed.

```
to peakshaving-solar-farm

...

ifelse (totalcons > currentpeakboundary * lastdayaverage)[

    set need totalcons - (currentpeakboundary *
       lastdayaverage)

    ifelse (totalstoredenergy > 200 and totalcons < (item
       index peakboundaries) * lastdayaverage )[

      ifelse (need > totalstoredenergy - 200)[

        set need totalstoredenergy - 200
        set totalstoredenergy totalstoredenergy - need
        set macrogrid totalcons - need

      ]
      [

        set totalstoredenergy totalstoredenergy - need
        set need need + need2
        set macrogrid totalcons - need

      ]
    ]
    [
      set need totalcons - (currentpeakboundary *
         lastdayaverage)

      ifelse (totalstoredenergy > 0)[
```

```
        ifelse (need > totalstoredenergy)[
          set need totalstoredenergy
          set totalstoredenergy totalstoredenergy - need
          set macrogrid totalcons - need

        ]
        [
          set totalstoredenergy totalstoredenergy - need
          set need need + need2
          set macrogrid totalcons - need
        ]

      ]
      [
        set macrogrid totalcons
        set need 0
      ]

    ]
  ]
  [
    set macrogrid totalcons
    set need 0
  ]

end
```

Appendix F

20 Demo Steinkjer households with consistent measurements

Below in table F.1, the 20 households analysed in section 3.2 are listed. These households all have consistent and consecutive hourly measurements on consumption in the time period October 1st 2012 until June 28th 2013.

Household ID
7350049083690884
7350049084530592
7350049084529299
7350049084531155
7350049084529251
7350049084529213
7350049084531209
7350049084529565
7350049084529497
7350049084529459
7350049084529404
7350049084531339
7350049084531292
7350049084531537
7350049084531469
7350049084531346
7350049084530974
7350049084530912
7350049084530813
7350049084530745

Table F.1: Consistent households in time period October 1st 2012 until June 28th 2013

Appendix G

Paper: Towards a user-centric mechanism to compile the microgrid status collaboratively

Towards an user-centric mechanism to compile the microgrid status collaboratively

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***Abstract*—The system envisioned to create smarter power grids allows the end users take an active role in their electricity management. Recent investigations reported significant reduction in consumption by users accessing the amount and price of the electricity being used at home. Precise information can incentive the users reduce consumption and behave in accordance to collective interests (e.g., avoid outages and high prices). Here, we go further reusing the crowd sensing concept to gather electricity-related data in a continuous loop of collaboration among users sharing a microgrid. It is done modelling electricity consumption, generation and storage in a graph-based data model instantiated from different sources. The research reported here is the first steps towards the development of an user-centric mechanism to compile the microgrid status collaboratively.**

***Index Terms*—Crowd sensing, user-centric electricity data, power consumption/storage models.**

I. Introduction

Smart grid's users are organized in cells called *microgrids* which would operate autonomously by managing its own consumption coupled with its generation and storage capacities [11]. To achieve autonomy, the information system relies on sensors and intelligent services to process the sensed data and actuate properly (e.g., identify usage peak and shift the operation of certain appliances). As a result, the users can control their electricity usage in response to variable supply conditions or prices [7], [13]. To achieve it, the future *energy management systems* (EMS) will rely on an *internet of things* (IoT) sensing and actuating in the environment.

Here, we reuse the *crowd sensing* concept, [4], [9] also called *people-centric sensing*, to create a continuous loop of interactions to compile the microgrid status, as illustrated in Fig. 1. This figure shows the status being compiled from different sources and shared through the gateways available at the user, such as broadband links, private wide area networks and mobile networks. This scenario makes feasible the deployment of user-centric systems to gather, compile and share electricity-related data. From a software engineering perspective, the smart house will be an open platform for new applications.

This investigation was motivated by recent papers reporting that accurate information about the amount, the price and the sustainability index of the electricity being used can drive users to reduce consumption and achieve collective aims [2], [7], [12], [13]. We go further designing the tools to allow the users compile the microgrid status in a collaborative way. It is an attempt to merge the typical IoT monitor and control loop with people-centric sensing.

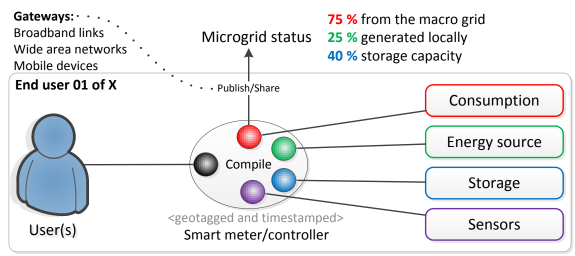


Fig. 1: Gathering user-centric data.

Gather and compile data are important tasks because smart services may require a certain amount of information to make well-timed decisions [6], [11]. The future challenges include response to the varying demand meeting the users preferences and collective interests. Given the diversity of electricity suppliers and the growing deployment of local generation/storage at the end user, the microgrid status should also be compiled from the users perspective. The data gathered is structured in a graph-based data model to represent consumption, generation and storage. The present investigation will unfold towards a strategy to disseminate good consumption practices from the users to the users.

This paper is organized as follows. The next section summarizes the background listing the information used in smart grids, presenting the microgrids functionalities and describing the state-of-the-art of the feedback mechanisms for users. Section III discuss the design and development of the continuous loop to gather, compile and share user-centric data. Then, in section V, the data model employed to represent user-centric data is detailed. Finally, we conclude and provide further work.

II. Background

A. Information used in smart grids

Smart grids rely on information systems to efficiently match production and demand of electricity. The power grid is divided in cells called *microgrids* which has a local system aiming at integrate distributed generation. This system gathers a diverse set of information regarding electricity generation (centralized or distributed), consumption (real-time or predictive) and storage (batteries) through a communication infrastructure [5], [11]. The information gathered or learned are the input for intelligent control algorithms. Examples of information are:

- Network topology: power network topology, including the geographical localization of suppliers, distribution grid and end users;
- Supplier information: characteristics of each electricity provider such as reliability, capacity, price and sustainability index;
- User-centric data: consumption history, preferences, local generation and storage.

This information is likely to be structured in standard formats with well-defined semantics, such as Common Information Model (CIM) [13]. More importantly, the distributed information flow must be created and maintained autonomously [11]. In this paper, we propose a user-centric information flow to compile the microgrid status and measure the users participation in terms of consumption, generation and storage.

B. Microgrids functionalities

Microgrids are power grid cells using distributed electricity generation and storage [11]. It is an important design decision because distributed generation/storage can use renewable energy sources such as sunlight and wind [2]. The microgrid information system can control the electricity generation and storage (e.g., solar panels and batteries) in response to variable energy supply conditions or prices [7], [13]. The aim is reach a certain level of autonomy to be able to prevent usage peaks, avoid outages and provide a better user-centric control.

The open challenges towards autonomy include the deployment of electric vehicles without overloading the power grid and the integration of dispersed battery storage systems. Moreover, different local suppliers, including small generators at end users, should be able to sell some of their production to the grid [2]. Another challenge is design a communication architecture for energy trading among the suppliers and users.

At the end users, smart meters and local controllers act as interfaces between the distribution and communication networks, measuring/controlling consumption (e.g., shifting appliances operation when the price is over a defined threshold) [2]. These devices are part of an *advanced metering infrastructure* (AMI) which can monitor electricity consumption, quality and generation/storage.

As a result, smart services can exploit the metering data and price to pre-emptively identify failures and take appropriate countermeasures, or to implement techniques to control electricity consumption [10]. In the present investigation, we assume the availability of an open platform to deploy these smart services at the end user. In practice, it requires the adoption of standardized technologies to integrate EMSs and other systems at home.

C. Feedback mechanisms

If we combine the set of informations previous described in the subsection **A** and the microgrid's functionalities at subsection **B**, we can provide feedback services. Recent investigations suggest that provide accurate feedback to the users is the first step to incentive them reduce consumption and behave towards collective aims [1]–[3], [13].

More specifically, studies have shown that providing real-time electricity usage information reduces consumption by 5-15% [3]. Adding pricing incentives and automated home energy management tools can double the savings, i.e. 10-30%. It requires EMSs to monitor/control the consumption applying user defined preferences. Finally, incentives could be given to promote the adoption of cleaner energy sources (e.g., lower prices for renewable sources) [2].

Concerning electricity sources, the investigation in [2] proposed a framework to footprint the electricity provided by multiple suppliers and compile its respective sustainability index. Given a set of suppliers at a microgrid, the framework determines the compound sustainability index considering the amount of electricity provided to the grid by each supplier [2].

Regarding automated management systems, the survey in [1] compared eight EMSs using as criteria features such as monitoring/controlling, data disaggregation, information integration, security and intelligence. Most of the systems have a web or mobile user interface and are integrating data from others systems or sensors. However, just one of them provides control mechanisms.

It is still subject of research how to track the users consumption/storage and how to show its impact in the microgrid. Here, we start with the hypothesis that crowd sensing concept can be used to gather user-centric electricity data to compile the microgrid status in a continuous cycle of interactions. We argue that given the fast deployment of distributed generation/storage the microgrid status should also be compile from the users' perspective.

III. Gathering and sharing user-centric data

A. Designing

The challenge is how to compile the user-centric data related to consumption, generation and storage. Fig. 2 illustrates the continuous loop of data sensing which orchestrates the system to compile and share the microgrid status. This figure highlights the components to (**1**) *gather*, (**2**) *compile* and (**3**) *share* the user-centric information [4], [9]. Empowered by the data model, later described in section V, the loop is also able to track new users, generators/storages and consumption behaviours.

The *gathering* component collects sensors data (e.g., current amount of energy stored in a battery at the user), and the *compiling* component extracts information from the data set (e.g., total amount of energy stored in the microgrid). Then, it is necessary do something useful with the information e.g., use the stored energy to avoid outages. Finally, this data set should be *shared* within the microgrid to collaboratively measure and map the current status.

The loop in Fig. 2 supports the necessity of continuously match supply and demand, because both can change over time [7], [13]. The aim is provide better quality electricity-related

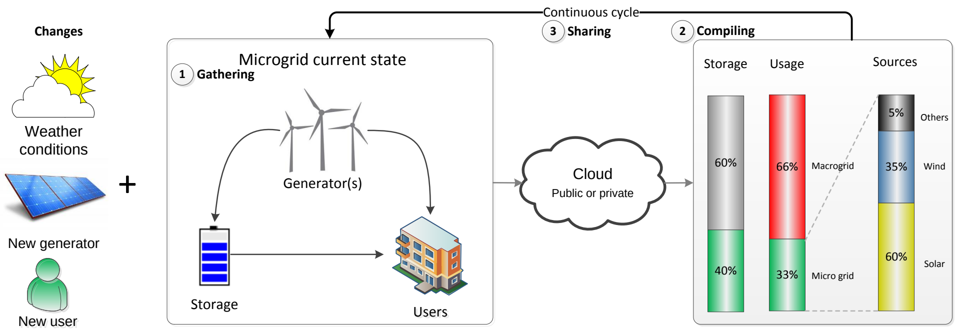


Fig. 2: Loop to compile the microgrid status: (1) gathering, (2) compiling and (3) sharing.

data in terms of freshness and accuracy. Moreover, consumers need to be informed about the current status of the microgrid in a comprehensible format and given incentives to reduce their consumption [7]. The next step is use this loop disseminate good consumption practices based on real users experiences.

B. Developing

Picturing the whole process, it starts with the sensors at the user gathering data such as electricity consumption, generation and storage. In sequence, all the microgrid users asynchronously send this data to a common server or central controller in charge of compile its status. Once compiled, the information is shared among the users ending the process. Then it starts again to update the status and keep track of changes such as new users or generators. Regarding connectivity, this loop requires a two-way communication channel between the users and the server at the cloud.

One way to connect such a large scale system is plug all the entities to an *representational state transfer* (REST) framework, as illustrated in Fig. 3. It is a web-based architecture which allows data exchange using publish/subscribe services (e.g., *Enterprise Service Bus* - ESB and *Constrained Application Protocol* - CoAP). At the web is possible to assign a naming authority to assure the semantic validity of the objects in the system. In addition, a REST framework can provide the basic communication infra-structure for an open platform among users, providers and third party services.

It can be summarized as a cyber-physical system developed to give automatic or human controlled feedbacks, here called *opportunistic* or *participatory* respectively:

- Opportunistic sensing: requires no user involvement to gather data [9] (e.g., automatic metering reading). We assume the availability of an open software platform for data gathering at the user. Then, the local controller can run a routine to gather data in a specific time interval or when it is available. To illustrate, this routine could be implemented as an EMS module;
- Participatory sensing: the user manually determines what, how and when to collect the data (e.g., post a good practice to save energy). May occur when the user want to report a new generator/storage, buy or sell energy or share a information about a supplier (e.g., price and sustainability index).

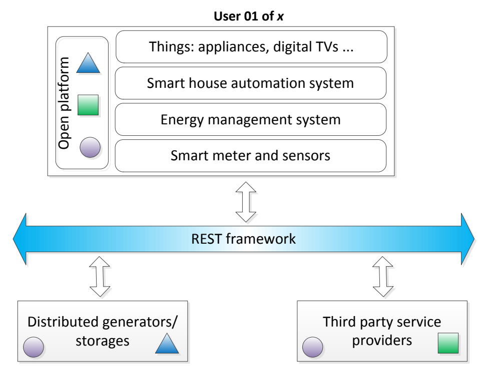


Fig. 3: System components connected to a REST framework.

These two sensing paradigms can track the incremental deployment of alternative generation and storage aiming at increase the microgrid autonomy level. The awareness of the microgrid status can motivate the community invest in renewable energy.

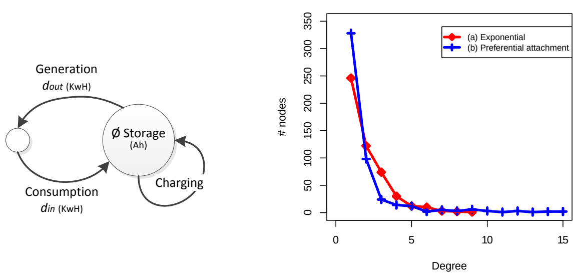
IV. DEMOSTEINKJER

Demo Steinkjer is a Norwegian demonstration project where new solutions for measuring and use of electricity can be tested. The testing site is located in Steinkjer and contains about 1.000 households, of which 321 have agreed to be *active participants* meaning they will participate in consumer oriented tests and projects. The remaining households will participate, without direct involvement, in tests conducted on the grid itself as well as secondary subsystems. The intention of the project is to attract entities to test new technology aimed at an modernization of the power grid with new products and services. Thus, Demo Steinkjer is an arena for which smart energy solutions can be tested with purpose of exploring a suitable design and implementation of the future electricity grid in Norway[1].

Companies such as SINTEF, Nexans, Telenor, Connexion, SagemCom, and others have already shown interest in running projects with Demo Steinkjer, and they will have the opportunity to test new products on real consumers. Entities will have access to customer database including anonymous AMS meter data and high-speed communication capabilities with five net/grid stations. In total, there are about 800 electricity meters installed, including 770 AIDON meters and 30 remotely read units through GSM/GPRS[1].

V. Compiling the user-centric data

Complex network theory has been used to understand the power grid behaviours from a system perspective [8]. We reuse this approach defining a graph-based data model to represent consumption, generation and storage, as show in Fig. 4a. In this figure, the user or supplier is represented as a circle which diameter indicates the installed storage capacity. The arrow **to** the node indicate consumption, the arrow **from** the node is generation, and the loop means electricity produced locally being stored or consumed. To simplify, we use the terms *user*, *generator* and *node* interchangeably.



(a) Data model (b) Degree distribution

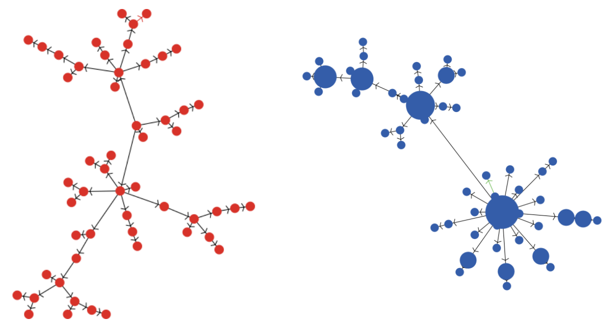
Fig. 4: Data model semantics and degree distribution of random networks.

For instance, the microgrid's autonomy in a specific point in time can be compiled by the Equation 1. First we sum up the storage capacity available at the nodes, N. Then we subtract the generation and consumption, which are the sum of the *in degrees*, d_{in}, minus the sum of *out degrees*, d_{out}, respectively. In sequence we divide it by the voltage in use to get the result in *Ah* (ampere hour). Then we subtract it from the storage capacity previously calculated. The low complexity of this computation highlights the advantage of such a simple model.

$$Autonomy = \sum_{i=1}^{N} Storage_i - \left(\frac{\sum_{i=1}^{N} d_{in_i} - \sum_{i=1}^{N} d_{out_i}}{Volts} \right) \quad (1)$$

[1]http://www.demosteinkjer.no

Formally, it is as a weighted graph $G(N, E)$, with N nodes (users, generators and storages) and E edges (the transmission and distribution lines). Fig. 4b shows the degree distribution of two network growing models: exponential (a) and preferential attachment (b). Both models have an inverse exponential degree distributions, however preferential attachment has a longer tail. It means that few nodes have several connections, high degree, and the difference can be visually compared in Fig. 6 (a) and (b). The exponential model, in Fig. 6a, is used to represent the current power grid distribution network [8]. The nodes are towers or substations and the edges are the power lines, it is used to simulate failures observing its cascade effects in the network.



(a) Exponential (b) Preference attachment

Fig. 5: Examples of random networks.

The preferential attachment, in Fig. 6b, can represent the microgrid operating autonomously which requires a rearrange in the grid following the energy availability. As a result, the nodes with generation and storage, bigger nodes in Fig. 6b, keep the microgrid functioning. The next step is model the microgrid's dynamics, which can widely vary depending on the geographical localization, type of energy generation (e.g., hydro, solar, wind and biomass) and weather conditions.

VI. Data model

A. Structure

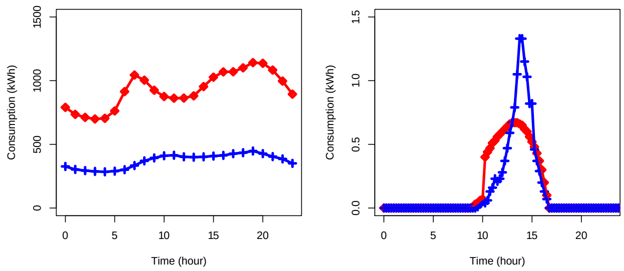
The structure of the microgrid will vary in case of an outage or when it is necessary operate in island mode.

TODO: find papers with different structures...

B. Dynamics

VII. Conclusion

In this paper, we discussed the design and development of a mechanism to compile the microgrid status in terms of consumption, generation and storage from the end user perspective. We reused the crowd sensing concept to orchestrate the functions to gather, compile and share electricity-related data. We assume the availability of an open platform at the end user for third party services. The data is compiled in graph-based model to represent consumption, generation and storage. By means of the research reported herewith, we are closer to achieve an model to disseminate good consumption behaviours among the users.



(a) Consumption (b) Generation

Fig. 6: Examples of random networks.

References

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