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Optimal use of resource flexibility in distribution systems

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Optimal Use of Resource Flexibility in Distributions Systems

Master's thesis

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Abstract

To cope with the increasing share of dispatchable renewable energy sources, the consumer needs to evolve from being a regular passive consumer, to being a *prosumer*. The prosumer produces energy through residential solar panels, and tries to adapt his loads to energy production. This is done by shifting flexible appliances, such as a dishwasher, washing machine, tumbler dyer or an electric vehicle charge. The Smart-Meter automatically triggers flexible appliances as a response to low price signals to reduce the user daily cost, and is modelled in this thesis. Three main pricing schemes were tested, to encourage the use of more renewable energy sources and reduce the consumer's expenses: constant pricing schemes, dynamic ones and a main grid fee. The best result was obtained from dynamic pricing schemes with main grid fee, encouraging the use of local renewable power and reducing the daily cost by 9% comparing to a regular passive consumer. Yet, improved performance and reduced cost could be obtained if more flexible appliances were taken into account, making the most of the dynamic pricing schemes.

Acknowledgment

This thesis is the perfect combination of the electric perspective I have developed at NTNU and the project one I have learned at Centrale Marseille, giving a good conclusion to this double degree program.

I am thankful to the Centrale network, to have made this study away possible, in the beautiful Norwegian country.

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Fleur Dubarry
Trondheim, 03/07/2017

Table of contents

List of Figures

List of Tables

Abbreviations

DR	Demand Response
DRM	Demand Response Management
DSO	Distribution System Operator
EV	Electrical Vehicle
LCOE	Levelized Cost Of Energy
PV	Photovoltaics
TSO	Transmission System Operation
UTC	Coordinated Universal Time

1 THEORY

1.1 Introduction

The discovery of fossil fuels has enabled a tremendous transformation during the 19th and 20th centuries: the easy availability of energy has developed transports, communications, health, comfort and technologies to turn the world into the one of the 21st century. However, the overuse of fossil fuels has significantly increased the carbon footprint of humanity, accelerating the global warming affect. The new challenge of the century is to restrain it. Therefore, the European Union has set new energy goals to face climate change : by 2020, greenhouse gases production should be cut by 20%, through an increased share of renewable energies by 20% of the energy consumption, and an increased energy efficiency by 20% [1].

Even though the target is only of 20% of energy production from renewable energies, some countries have set a new target with a 100% renewable production already reached temporally [2], and Norway has about 98% of its electric production covered by renewables[3]. Renewable energies, like solar energy, wind energy and hydropower, are often dispatchable power plants since they rely on the resource distribution around the country. The new power plants are more widespread, and may even belong to consumers. The energy production is also more variable depending on the available resource.

The target of 20% energy savings specially concerns the copper losses from the transportation into the wires, where about 5% of the initial electrical energy is lost [4].

The 20% target also concerns household's efficiency: all appliances are increasingly efficient and controlled by the European Energy Label [1], and house insulation is now very performant. Both aspects have been widely studied in Zero Emission Buildings.

As a summary: the energy production is increasingly variable, widespread and locally-encouraged to reduce wire losses. In the meantime, the energy consumption is more efficient and flexible, especially with the development of dedicated storage and electrical vehicles. The traditional grid where one central power plant was providing the required electricity to the consumer is no longer feasible at long term. The consumer must adjust his consumption to the available energy production, and become more active. *Smart Grids* are the electrical grids of the future: the consumer is now considered as a *prosumer* [5], producing his own energy and actively reacting to the grid condition with *Demand Response Management*. The power plants and DSO give information to the consumer about the grid condition to encourage him to change his consumption, and he gives back his energy consumption profile. The consumer uses from and sells energy to the DSO and various power plants. The information and power flow are now in two directions.

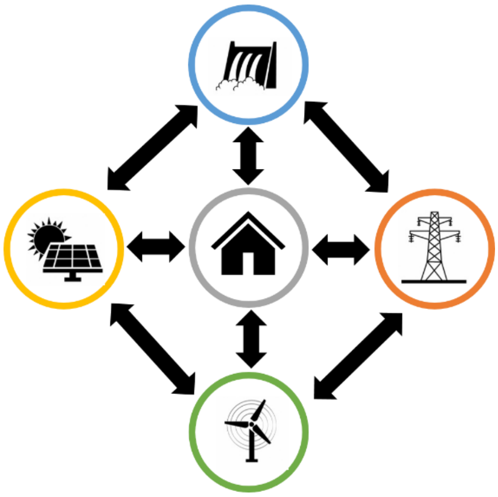


Figure 1.1 Information and Power flow in a Smart Grid

The consumer must become more active, yet he cannot spend his day in front of the power control panel waiting for a production peak. Hence *Smart Meters* are developed, that would not only measure and give precise feedback on the electrical consumption, but also trigger automatically electrical appliances as a response to a grid information.

This automation process is the point of the thesis: the smart meter must know the flexible appliances and their constraints, and optimise their use during the day. A financial optimisation is the most obvious solution, to give benefits and encourage consumers who accept change and invest in new technologies. An algorithm will be designed to model the energy production availability, the consumer flexibility and study the impact of different pricing schemes.

To encourage local power production and consumption, a microgrid will be considered here: the local renewable energy production should be enough to supply for the concerned consumers, but the microgrid may be connected to the main grid in case of unbalance.

Only the power production and consumption are considered here as a simplification, disregarding the reactive power, voltage level, and frequency deviations. These aspects are an entirely new problem widely studied in various papers and projects [6]. Here, the grid stability relies on the perfect balance of power consumption and production, since electricity must be produced and used instantly.

Given the theoretical context of this thesis, no access to an experimental field and data was provided. All the data used for this thesis was provided by different institutions, from different locations and different time zones. The goal of this thesis is to demonstrate a type of demand response management, using relevant datasets but disregarding their spatial and temporal accuracy. Yet every dataset has been adjusted with its local time instead of the Coordinated Universal Time (UTC) often provided, to make the energy production and consumption patterns realistic. The datasets can all be found in the references. The access was free for university purposes, but the institutions should be contacted directly for further use.

1.2 Energy production

The goal of this thesis is to find an economical model using demand response to smooth the variability of renewable energy production. Different renewable energies will be introduced below, and the related datasets selected for the test case. Variable and common renewable energies will be prioritized to demonstrate the relevance of the algorithm.

1.2.1 Solar Power

Solar power is a renewable energy available worldwide: it can be produced everywhere during daylight time, both from direct sunlight exposure and indirect one. Various technologies are still developed and industrialized: from regular solar panels able to produce electricity even from diffuse and indirect solar exposure but for an average efficiency of 15%, to Concentrated Solar Power reaching 40% efficiency but only under direct sunlight [7] to flexible and transparent photovoltaics transforming every surface in a solar power resource of under 10% efficiency [8]. The regular solar panels technology is rather mature, and its cost has been dropping for the past 10 years of about 80%, making it the most emerging renewable energy nowadays. Solar panels are now used both in farms and residential applications, covering about 1% of the global electricity demand in 2015 [9]. Yet the solar energy resource is very variable: always unproductive during the night, very high under direct sunlight exposure, but dropping fast when clouds or shadows make the exposure indirect.

Below is an example of the power production from a residential photovoltaics module in Virginia, US, on the 17th of June 2012. The data is provided by the Electric Power Research Institute [10]. The original database goes from the 16th of June 2012 until the 25th of June 2012, covering nine days of energy measurements with a one second timestep from different solar panels in Virginia, US. The original time of the dataset was in UTC and showing a significant power production during night time. Consequently, the timeframe has been adjusted to the local time, four hours behind UTC and to a ten minutes timestep. In addition, the energy and power production of nineteen different PV systems was provided, both from power plants and single poles. J1 Pole 2 (channel ID 03283) was chosen due to its lack of known issues. It was south oriented with a 30° tilt angle. Finally, the 17th of June is a typical day, with high variability in power production: it's the issue DMR and this thesis are addressing.

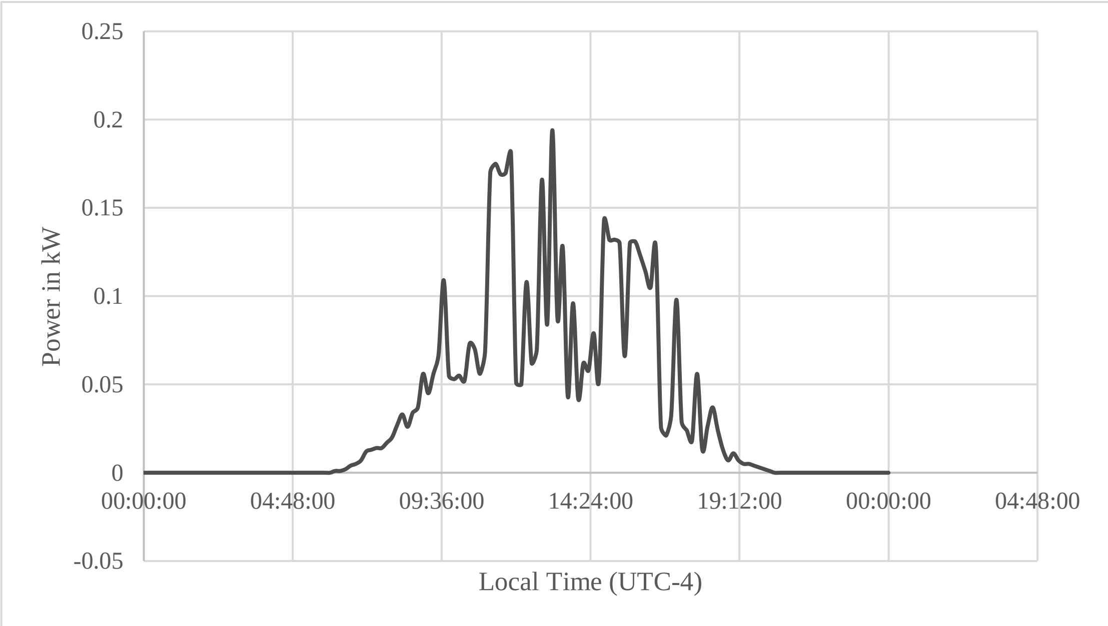


Figure 1.2 Solar power production from a single solar panel in Virginia, 17/06/2012

The lack of power production during night time, and the peak power production during direct sunlight exposure can be directly observed. It can also be noted that the power production is never null during daytime due to diffuse sunlight.

Two more assumptions must be detailed: first, J1 Pole 2 is not a residential solar panel, but a module on a pole. Second, the technology used dates back from 2012, and solar panels performance has improved a lot in the past 5 years. Yet, the AC power rating of this module is 180W, which is a normal rate for residential PV system [7]. Therefore, both inaccuracies are neglected here, but further research should be made with a recent residential solar panel dataset.

1.2.2 Wind Power

Wind power is also available everywhere on the planet: the total wind power potential inland is estimated to 1000TW worldwide [9]. Wind power plants consist of wind turbines from various technologies, all of them having reached a mature stage: from the most common small and large onshore wind farms, to offshore wind farms increasingly numerous due to their higher production potential and lower environmental impact, to small residential wind turbines that are still under development and seldom used. As a result, wind power was covering 2.5% of global electricity demand at the end of 2015 [9]. Yet, just as solar power, it is a very variable source of energy: both at short term (daily variation due to weather conditions) and long term (seasonal variations due to weather patterns).

Below is an example of the power production from a wind farm for one day. The dataset was provided by Sotavento experimental wind farm in Galicia, Spain[11]. The farm consists of 24 wind turbines, from 5 different technologies. It has a power rating of 17.56 MW, and is representative of small wind onshore power plants that are widespread throughout the world land. The original dataset was providing energy measures in kWh, that were converted in power measures in kW. The time also was expressed in UTC with a ten minutes timestep, and has been adjusted an hour ahead of UTC. It should be noted that this time is not the local time zone: indeed, the current Spanish time zone is not its “natural one”. During the second world war, Spain has adjusted its time zone to the German one, and has not switched it back at the end of the war. The “natural time zone” of Spain is GMT (same time as UTC). In addition, the Daylight-Saving Times (DST) is used during summer, when clocks are set to one hour ahead.

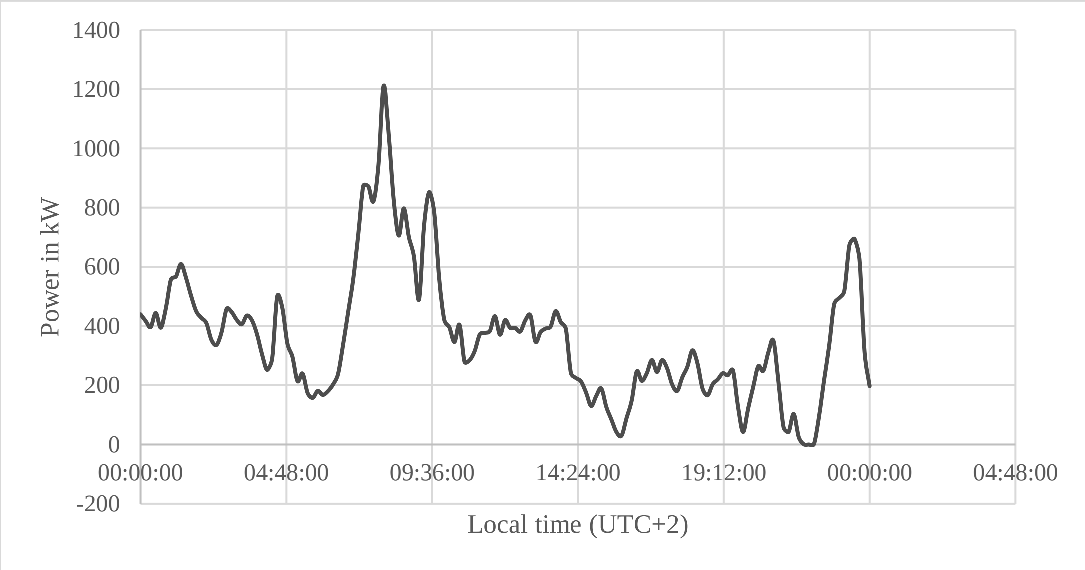


Figure 1.3 Wind Power production from Sotavento experimental farm, 12/06/2017

The date of the 12th of June 2017 was chosen for its up-to-date technologies, and for the high variability of the wind energy production pattern: the production is high when the wind is strong, but drops to zero when the wind stops blowing.

1.2.3 Hydropower

Hydropower is the largest renewable energy source, as 159 countries have matured the technology [7] and it was covering 16.4% of global electricity production in 2016. There are several types of hydropower: from dams releasing water through turbines, often associated with pumped storage systems pumping back the water into the reservoir, to "run of river" systems generating electricity with the river stream [9]. The latter provide a rather constant power, though subject to seasonal variability. Pumped storage systems work as green batteries: pumping water when the grid has a surplus of electricity, and releasing water when the grid lacks energy. It can provide power at any timescale, from a couple of seconds to cover a peak load, to a couple of months to ensure a constant and base-load production. In 2015, they were standing for 12% of global hydropower capacity. As an overall, hydropower is very reliable, quite constant though flexible, and has especially helped Norway to reach a high share of renewable production, with 99% of generated power coming from hydropower [12]. Norwegian reservoirs mainly rely on rivers supply, and do not require pumped storage systems.

The reservoirs level profile in Norway for 2017 is presented below. Data was provided by Statnett [13]. When all the reservoirs are 100% full, the total potential energy is 82TWh.

Hydropower data of every power plant is aggregated within each one of the five spot market areas database. Only the spot market NO1 is shown below, assuming 16.4TWh of potential energy when the reservoirs are 100% full. The red line shows the maximum level the reservoirs NO1 have reached since 1993, the purple line shows the minimum level, and the green line shows the median level in percentage. Finally, the blue line shows the reservoirs level for 2017. The time zone used is the local one, two hours ahead of UTC. This issue is not very relevant though, since the reservoirs level is quite stable during a day.

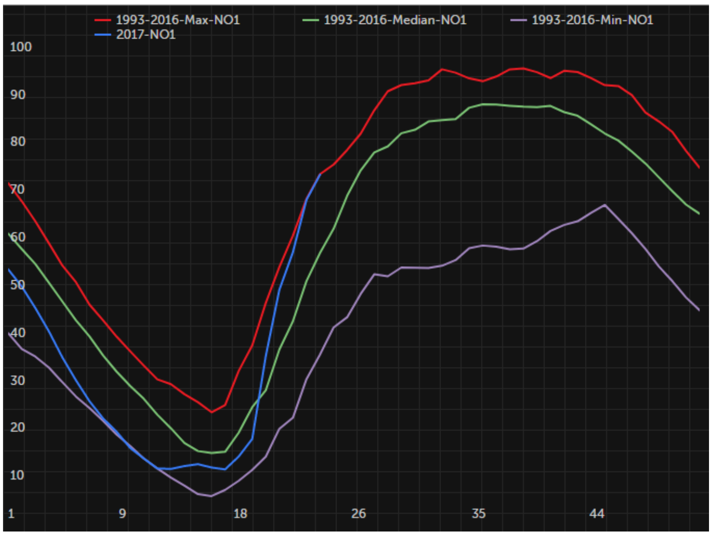


Figure 1.4 Aggregated reservoirs level in % for the spot market area NO1 throughout the year

The highest level is reached in late autumn, when all reservoirs are filled with the melting snow and usual rain. From late autumn on, the rain turns into snow, rivers freeze, and the reservoirs level no longer increases significantly. From late autumn to spring, the hydropower potential is decreasing as reserves are used to balance the grid. In late April, snow melts and fills again the reservoirs.

During the simulation, a winter day will be used to describe the level of the reservoir. We assume there that the reservoirs have no water supply and their level will be only decreasing. These conditions are more demanding than the summer ones, but also well demonstrating the issues renewable energies are facing. For the 19th of February 2017, the reservoir was 23.3% full, corresponding to a potential energy of 3.82TWh.

1.2.4 Other renewable sources

1.2.4.1 Geothermal

Geothermal energy is available everywhere on the planet, but stronger in places with geologic activity where the ground temperature is higher. Geothermal energy is seldom accessed by conductive techniques (in hot dry rock resources), but mainly by convective techniques (in hydrothermal resources). This ground natural heat is used both for heating and electricity production. The latter is done through three main technologies: from the most common flash steam plants where the water resource boils to release steam through a turbine, to dry steam plants directly using dry steam through turbines, to the emerging binary plants, capable of producing energy from low-temperature sources (with an Organic Rankine Cycle or a Kalina cycle) [7]. This renewable energy source is mainly popular in specific places with volcanic activity, such as Iceland or Japan. Yet, with the emergence of binary power plants, more places could use their geothermal energy, which is very valuable: it is not weather nor seasonal dependant, and is consequently a relevant energy resource to replace the former fossil fuels as base-load energy.

Despite its significant advantage of being a baseload energy resource, geothermal only covers less than 1% of the global electricity production. For this reason, geothermal energy resource will not be considered in this thesis.

1.2.4.2 Marine power

Marine power resource is available near-shore or offshore everywhere in the world. It is rather steady throughout the year, despite some seasonal changes due to the tides and weather patterns. Yet its technology is still not mature and expensive: a lot of prototypes exist at a research stage but few have entered the industry stage. There are three main types of ocean energy: tidal energy using tide currents through turbines, wave energy using turbines, pistons or motion energy, and temperature or salt gradients. Despite a total theoretical potential of 32 PWh/year, only 0.53GW were in operation in 2015, 99% of which was provided by tidal energy [9].

Ocean energy is likely to develop in the future, but is currently too expensive and not mature enough to include it in the thesis work.

1.2.4.3 Bioenergy

Bioenergy is made from biomass, usually to produce fuels and gas. It is the most developed renewable energy and covers 10% of the global energy production [9].

Yet it is seldom used for electricity production since its conversion rate is under 20%, and its carbon footprint still significant [7]. Consequently, it is not considered in this thesis.

1.2.5 Main grid

The test case will consist of a theoretical city in island operation powered by renewable energy sources. The latter consist of residential solar PV, one wind power farm, and hydropower reservoirs. In case the local production and consumption would not be balanced, the city may connect to the main grid to compensate for the surplus or lack of power.

The power production from the main grid was provided by Statnett [13]:

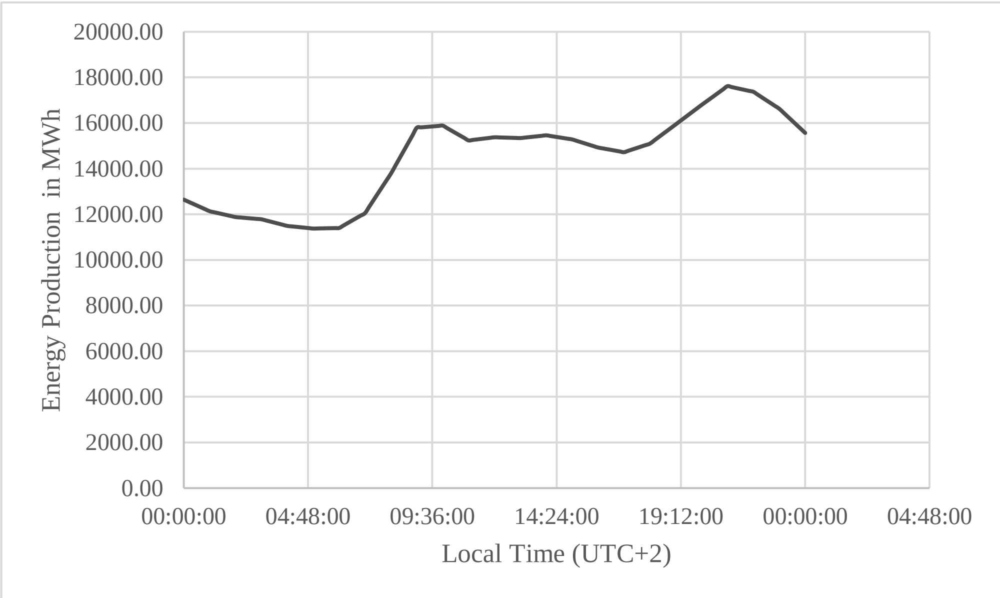


Figure 1.5 Main grid power in Norway, 11/04/2017

The data was provided in local time with summer time (UTC+2).

1.3 Demand-side flexibility

In order to face the mismatch of the energy production to the consumption, recent research interest has been on Demand Response Management [5]. The traditional passive consumer turns into an active consumer, choosing and adapting their load patterns to the energy production. The decision can be actively taken by the consumer himself, entrusted to a third party, or programmed automatically. The prosumer can then not only provide energy through his distributed generator (eg solar panel), but provide flexibility to the grid. There are several ways of making loads flexible: from load shifting, moving the load to a different time, to load shaving, reducing the amount of load, to valley filling, increasing the load to face an energy surplus [14]. Two elements must be considered here: first, the goal of this thesis is to keep the consumers comfort level unchanged, to encourage them to use Demand Response Management in a near future. Second, the houses considered here are assumed to work with 100% electricity -without any gas nor fuel. Consequently, mainly load shifting will be used in this thesis, under the consumer’s comfort restrictions. Loads can then be sorted in three categories depending on their flexibility potential: the must-run, the almost-shiftable and the shiftable units [15].

Table 1.1 Example of household appliances sorted according to their flexibility potential

Must-run units	Almost-shiftable units	Shiftable units
TV-sets, computers, kitchen and bathroom ventilation, lighting, cooking devices.	Refrigerators, kettles and coffee machines, heating.	Water heaters, dishwasher, washing machine and tumble dryer.

The must-run units stand for about 36% of total consumption, and cannot be changed to preserve the consumer’s comfort: when the consumer wants to spend some time on his computer, he does it. The almost-shiftable units represent about 10% of total consumption, and they may be shifted under very restrictive constraints: the refrigerator can cool down anytime, as long as the temperature always remains between 1°C and 4°C for food saving purposes. Finally, the shiftable units cover 54% of total consumption, and can be shifted to more flexible times: the water heater can warm up anytime as long as there is enough hot water for the day.

The model used in this thesis consists of a global must-run power standing for all the must-run appliances and almost-shiftable units neglected (such as kettles, coffee machines and refrigerators), and of several significant flexible units (such as a dishwasher and a washing machine. Their respective dataset and constraints are detailed below.

1.3.1 Must-run appliances

The must-run power stands for all the non-flexible appliances considered in this thesis. It represents the mandatory power consumption profile throughout the day. Two methods were used to try to raise a dataset of daily must-run power.

1.3.1.1 First unsuccessful method

The first method used to determine the consumption profile was to take the global consumption pattern of Norway provided by Statnett [13]. It can be noticed that despite the strong hydropower potential, Norway still occasionally must import energy to cover for national power consumption, proving the need for demand response management.

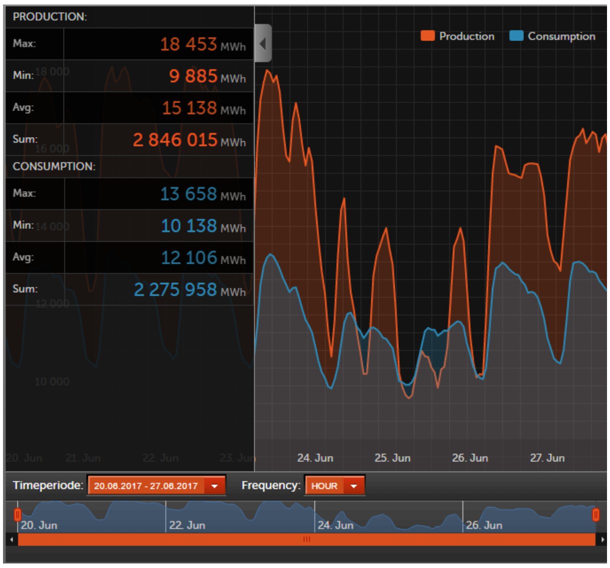


Figure 1.6 Norwegian national power production and consumption for a week in June 2017

The global power consumption was then divided by the number of households: approximating the total Norwegian population to five million and estimating a household of four persons, the resulting consumption power would be

$$P_{household} = \frac{P_{total}}{5.10^6} \times 4$$

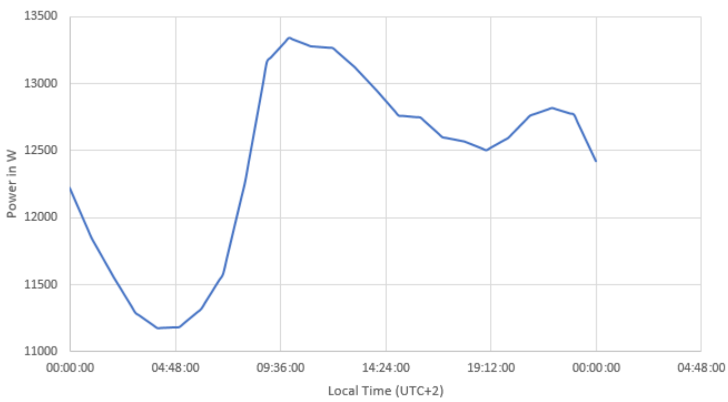


Figure 1.7 Consumption profile for a Norwegian household, with the first method, 11/04/2017

However, this consumption profile does not look very accurate: the consumption power is still high during night time, and the highest consumption is reached between 9am and 2:30pm, when people are supposed to be at work. Stanett calculates the power consumption as the sum of the national power production, the power exports and power imports: all the power consumption is considered, both from residential areas, commercial areas and industries. Consequently, the household consumption profile is twisted and this method had been dropped.

1.3.1.2 Second successful method

The second and final method was found later, and provided by the U.S. Department of Energy open database. The study was conducted by the Office of Energy Efficiency & Renewable Energy (EERE) in 2014, on 936 different locations in the U.S.[16]. With the same time zone as the solar energy resource database (Virginia), Auburn Opelika, Alabama, was selected for convenience.

Three household profiles are available in the database: high load, base load or low load profile. The high load profile was considering large households. The low load profile was assuming very small households with basic appliances -for example there was no tumble dryer but just a drying rack. The household considered for this thesis should demonstrate the possibility of combining demand response and comfort. That is why the base load profile was chosen as the most representative of a typical household. It is following the Building America B10 Benchmark. More details can be found in the web database access.

For a given load profile and location, the database runs for the entire year 2014 with an hour timestep. Local time is used, five hours behind UTC. The date of the 8^{th} of April is chosen, as a compromise between the cold demanding winter power profile -with a high share of heating- and the hot as demanding summer profile -with a high share of air-conditioning. Few heating is still used at this date, moderately increasing the demand profile, which is interesting for the project demonstration.

The database provides hourly power values for the general electricity facility, gas facility, electrical heating, gas heating, cooling, HVAC fans, HVAC electricity, ventilation, interior and exterior lighting, appliances, miscellaneous interior equipment and water heater. No detail composition of the categories is provided. All values are provided in kW. It should be noted that heating is mainly achieved with gas. Consequently, it is assumed that the theoretical electrical heating is using as much power as the data provided for the gas one. The final electrical power consumption is the sum of the general electricity facility, electrical/gas heating, cooling, HVAC fans, HVAC electricity, ventilation, interior and exterior lighting, miscellaneous interior equipment and water heater. Only the gas related data is not used, and the "appliance electricity" is assumed to stand for our flexible components.

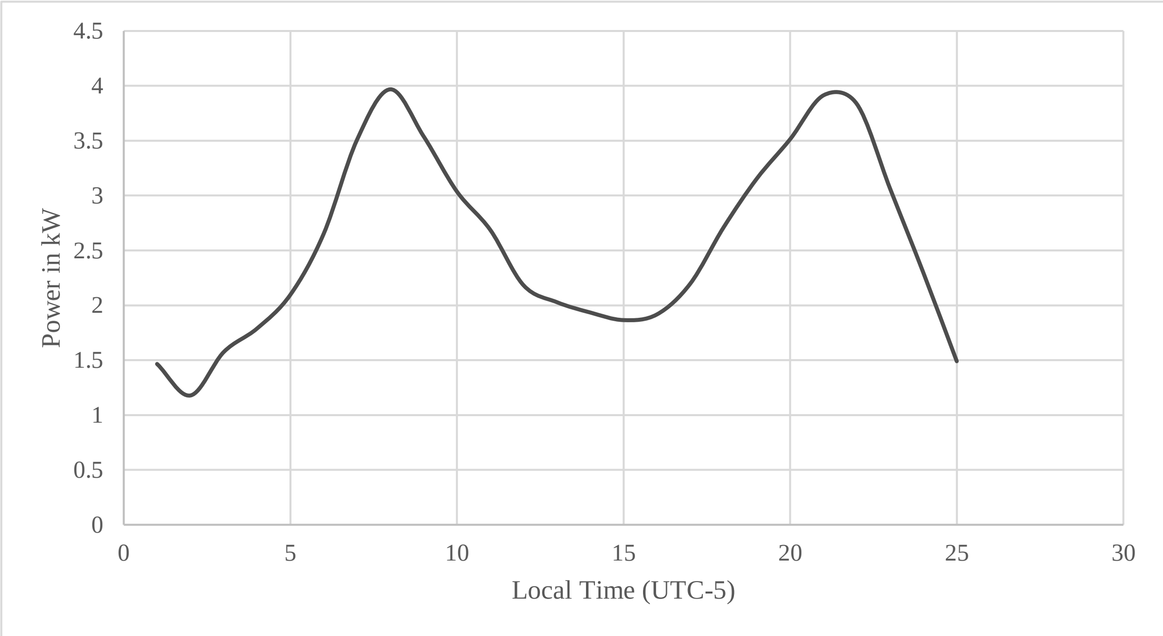


Figure 1.8 Must-run power for a household in Auburn, U.S., 08/04/2014

The two peak loads in the morning before worktime, and in the evening after worktime are very clear here. The high level of power leakage during night time should be noticed, from plugged appliances, water heater and refrigerator. The electric energy consumption of an American citizen was 12 973kWh in 2014, according to IEA statistics [17], which gives an hourly power average of about 1 481W. For a household of four people, the average required power is then 5 924W: it fits the above consumption profile if we count the missing flexible appliances (worth 54% of total consumption [15]). This value is higher than most European countries (for example France has an average power consumption of 793W per capita), but lower than Norway (with 2 626W per capita). This data seems a reasonable compromise for the northern countries, and has a realistic value: consequently, it will be the one used in the simulations.

However, the timestep is only of one hour, against ten minutes for the renewable energy sources. To make the most of the demand response management and resource data availability, the consumption dataset is extended with a ten minutes timestep. Within each hour, the total electric power consumption is linearized:

$$P_{h:m:00} = P_{h:m-10:00} + \frac{P_{h+1:00:00} - P_{h:00:00}}{6} \qquad \forall\, h \in [0, 24], \forall\, m \in \{0,10,20,30,40,50\}$$

h stands for the hour of the day, *m* the minutes. There are six timesteps for each hour. The data is now ready for simulation.

1.3.2 Flexible appliances

1.3.2.1 Dishwasher, washing machine and tumble dryer

The dishwasher, washing machine and tumble dryer are gathered in this first paragraph due to their similar power behaviour and flexibility potential. It should be noted that since demand response management is an innovative concept likely to concern mainly modern households, only modern appliances are considered here. In addition, their energy performance is improving every year, and the most performant ones may be very expensive and difficult to afford. Hence, modern but common appliances are selected below.

The dishwasher used in this study has a typical capacity of 1 200W and works for fifty minutes. Even though it is usually running 48 weeks a year, 5 times a week [18], it is assumed to run at least once during the day of simulation. Regarding the consumer's comfort, the dishes should be cleaned after breakfast and before dinner time, or after dinner and before breakfast time. The dishes are then inaccessible during worktime or night time, and the consumer can use them as soon as he needs them.

Washing machines are rather efficient, and A+++ labelled ones are very accessible and quite common. Consequently, an A+++ one is used here, with a capacity of 2 700 W for a duration fifty minutes. Even though it usually runs 48 weeks a year and 4 times per week [18], it is assumed to run once during the day of simulation. The wash should be finished no more than an hour before the return of the consumer, to avoid water stagnation and smell on the clothes. Hence, it should be finished within an hour before the return of the consumer, during his time at home or within an hour before he wakes up in the morning.

On the contrary, tumble dryers are not very efficient and only B-labelled machines are affordable in the market. A tumble dryer of class C is used here, with a capacity of 2 700W and a duration of an hour and ten minutes. It usually runs 32 weeks a year, twice per week [18], but is assumed to be triggered once during the day. The dryer's flexibility constraints are closely linked to the washing machine ones: the dryer should be turned ON just after the wash ends to avoid moisture stagnation.

1.3.2.2 Electrical vehicle and dedicated storage

Few houses own a dedicated storage nowadays, even though this solution is likely to spread in the future to help the renewable energies integration. However, Electric Vehicles (EV) are increasingly popular, especially in Norway where their share among the total amount of cars has reached 24.4% in 2016 [19]. In addition, Norway has announced its goal of banning fossil fuels use by 2020, which shapes an all-electric-vehicles future. Electric cars have a battery that may be charged at home, at work, or at community spots in populated areas. Recent DRM studies also consider an EV battery as a potential source of energy in case of lack of power grid [20]. Consequently, an EV will be added to the model and used both as an appliance and dedicated storage.

Considering a residential area, electric cars can be plugged to a standard electrical outlet with a maximum charging power of 2.3kW for six about eight hours (six hours until 80%, then up to two hours for the last 20%). Yet, a new dedicated electrical car connector has recently appeared on the market, increasing the charging power to 7kW for about four hours (two hours until 80%, then up to two hours)[21]. These numbers are valid for new batteries (the older the battery is, the lower is its capacity, and the faster is the charge) and average temperatures (charging is less efficient in cold and hot weather). The dedicated electric car connector will be considered in this simulation, and assumed to require 7kW for three hours of charge, neglecting the longer and lower charging rate from 80% on.

The user is likely to require a full battery in the morning, before going to work. We assume there is no charging outlet at his workplace. The EV can charge from his return in the afternoon until his departure in the morning.

1.3.2.3 Heating and Air Conditioning

Eco-friendly space heaters use down to 400-500 watts [22], but back-up heaters can use up to 2 000 W [18]. Space heaters power flexibility is mainly provided by the inertia of the heat inside the house. Some papers have studied its mathematical representation[23].

The consumer will require a minimum and maximum temperature when he is at home for his comfort, maybe different ones during night time, and a minimum and maximum temperature to avoid furniture’s degration when he is away. The heating system can be warming (or cooling) at any moment of the day, as long as the temperature remains within the boundaries set by the consumer.

However, given the difficulty of including thermostat flexibility in the simulation (it requires thermo-dynamic analysis, insulation data, heating efficiency…), this flexibility potential won't be considered in this work. In addition, despite standing for more than half of a household energy consumption in the U.S. [23], heating power is much less significant in Norway where house isolation is very performant. Hence it is neglected and included within the must-run power profile.

1.3.2.4 Water boiler

The usual capacity of a water boiler is 4 000W for a duration of about three hours a day [22] in a four-persons household (45 gallons water volume capacity). Some papers have studied its mathematical representation[23].

The consumer will require a minimum water temperature to have enough hot water available for the day, especially for shower, dishwasher, and washing machine applications. Just as space heating, the water boiler can be warming at any moment of the day as long as the temperature remains higher than the boundary set by the user and lower than the maximum temperature allowed, to avoid any degradation. For usual water heaters, the limit temperatures are 49°C and 82°C [24].

Modelling a water-boiler is as challenging as modelling space heating. Hence, its flexibility potential will be neglected in this work for simplification.

1.3.2.5 Summary

The flexible components used in the simulation are summarized in the table below.

Table 1.2 Flexible appliances selected for further simulation

Appliance name	Power	Duration	Constraints
Dishwasher	1.2kW	1 hour	Started after dinner and over before breakfast, or started after breakfast and over before dinner
Washing machine	2.7kW	1 hour	Over before the consumer's departure, within an hour before his return, or during his time home.
Tumble dryer	2.7kW	1 hour	Started just after washing machine completion
Electric Vehicle	7kW	3 hours	Can be charged after the consumer's return, and must be full at his departure

1.4 Economy of energy

The renewable variable power resource has been defined, as well as the power consumption flexibility potential. Customers now must take the step to use demand response. A natural way to encourage them to move their loads is to optimise their economic benefit from it. As a matter of fact, flexibility has been defined as “the modification of generation injection and/or consumption patterns in reaction to an external price or activation signal in order to provide a service within the electrical system” [25].

However, current pricing schemes relying on regular supply and demand balance market prices are not providing enough benefits to the end-users to them to change their consumption pattern [14]. New economic models for the energy market are needed, and this is the goal of this thesis: to find pricing schemes optimizing the customer benefits while adjusting his loads to the renewable resource.

This part will briefly explain the Norwegian energy market, introduce the aggregator as a third party in charge of flexibility management., and finally present the average current costs of each renewable energy source and the new pricing schemes to experiment in this work.

1.4.1 Presentation

The Norwegian power market consists of four submarkets detailed below. Further information may be found in Stig Ødegaard Ottesen’s work [5].

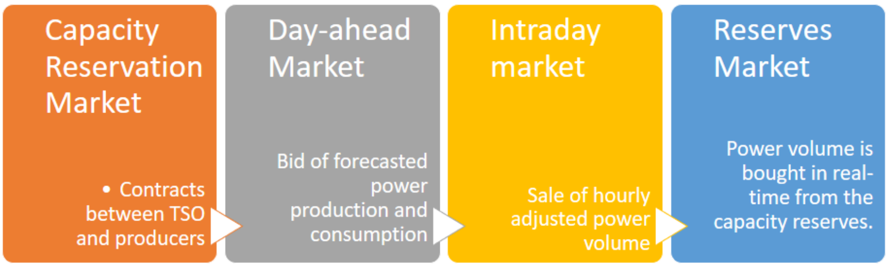


Figure 1.9 Norwegian power market diagram

1.4.1.1 The capacity reservation market

It happens before the day considered. In case of grid imbalance, the TSO (DSO in our case) needs some flexibility reserves to cope with it and avoid blackouts. To that purpose, the TSO signs a contract with an energy producer and consumer (industry or aggregator) for a given period (from a day to several years): the producer is then committed to provide more energy and/or the consumer more loads if the grid gets off balance. Since those reserves are only used in case of problem, and only for real-time adjustments, their price is higher. The TSO makes a priority list of the entities it wants to rely on if imbalance occurs.

1.4.1.2 Day ahead market

During the day-ahead market, producers bid their forecasted power productions and aggregators their forecasted power consumption with an hourly time resolution for the following day. The market closes at 12:00, and the Power Exchange decides of the price of electricity given the supply and demand. The cheapest energy prices are found during the day ahead market.

1.4.1.3 Intraday market

The Power Exchange is organizing the intraday market. It happens every hour of the considered day, closing one hour before each actual working hour: every producer and consumer sells or buys additional power volume to stick to the updated forecast (changes may occur because of the weather, or unexpected events…) to satisfy the demand need.

1.4.1.4 Reserves market

The DSO oversees this market. Despite the previous adjustments, the supply and demand might get off balance, and the TSO needs to adjust it in real time. To cope with that, the TSO buys energy production or flexibility from the priority list.

1.4.2 Pricing Schemes

Current trends in energy production costs in USD/kWh were found in the 2016 World Energy Resources report [9]. They are presented below:

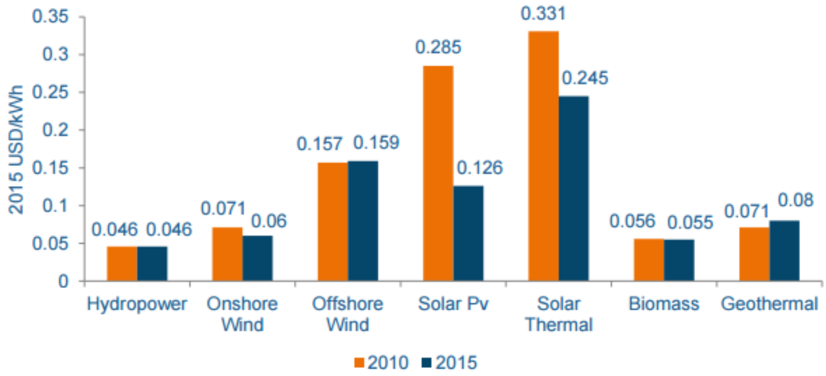


Figure 1.10 Trends in global renewable energy LCOE in the time period from 2010 until 2015 [9]

For further use, the LCOE from the renewable sources used in this work were adjusted to Norwegian currency, using the exchange rate r = 8.33847 the 19/02/2017[26]:

C_{hydro} = 0.384 NOK/kWh $C_{wind\text{-}onshore}$ = 0.5 NOK/kWh C_{solar} = 1.051 NOK/kWh

These prices are a world average, considering the cost of small and large installation in different countries. It can be observed that the significant development of solar PV has resulted in a major drop of cost, of about 56%. Yet, solar power is still more expensive than hydropower, onshore wind and geothermal, due to the high price of some of its components.

The Levelized Cost of Electricity is an economic tool to compare the total cost of different energy sources over their lifetime. It includes the initial investments, the operational and maintenance costs, the fuel costs, the financial costs, and the energy production per year [4]. As a result, the LCOE gives the energy production price per kWh. Considering it as the minimum price of electricity to pay back for the installation, some financial profit should be added as well as the grid facilities levelized cost to get the actual price paid by the end-user.

The overall usual market price of electricity was provided by Nord Pool. The dataset concerns the Nordic grid[26], with the local time UTC+1 (winter time). The day 19/02/2017 was chosen to fit the hydropower database, since Norwegian electricity mainly remains on hydropower.

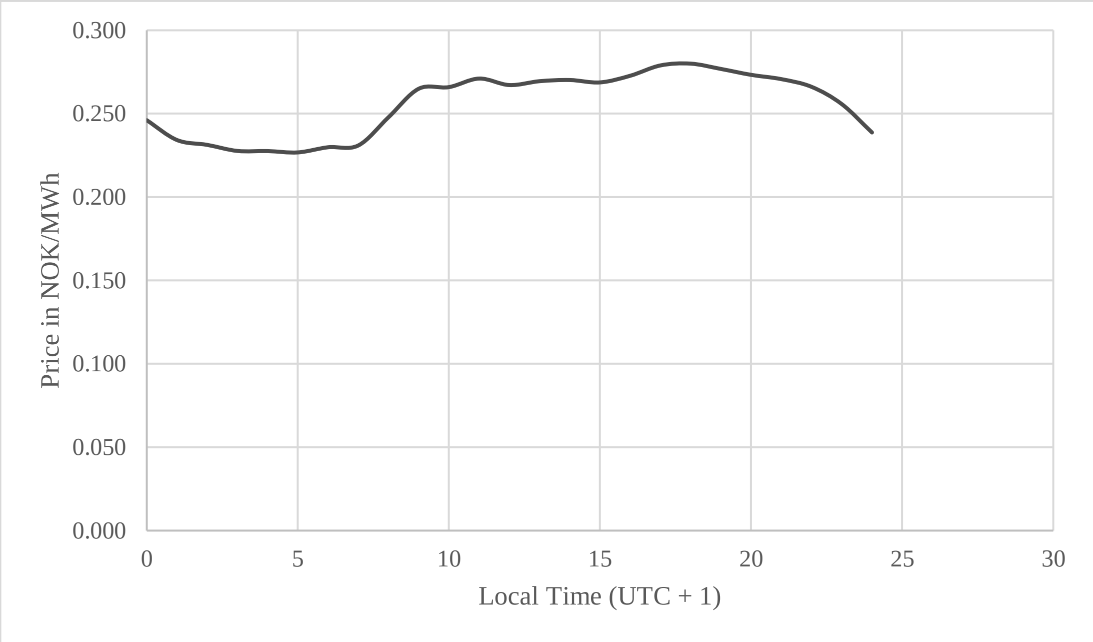


Figure 1.11 Electricity cost of the Norwegian grid, 19/02/2017

Even though the dates from the main grid energy production and the costs differ, it can be noticed that they follow a similar pattern: increasing in daytime, decreasing in nighttime. In both cases, they are rather different from the consumption pattern: the on-peak and off-peak times are not easy to spot on the graph. That may explain why the current pricing scheme is not enough to encourage consumer to move their loads off-peak: the different in tariffs is not significant enough.

To encourage the use of consumption flexibility as a response to resource flexibility, and to demonstrate the interest of new economic models, the following pricing schemes will be modelled:

Table 1.3 Pricing Schemes used in the simulation

Base case	Main grid fee	Sale of flexibility	Peak fee
Usual market conditions	An additional fee is imposed to the consumers if they use power from the main grid. This is to encourage consumers to use mainly local and green energy.	The consumers “sell” their flexibility potential to the DSO through the Aggregator during the capacity reservation market.	An additional fee is imposed to the consumers during peak load

2 MODELLING

First, the whole model was made with an hour timestep to ensure its behaviour. Each operation was tested and controlled separately. Then, the model was updated with the 10-minutes database.

The algorithm consists of a preparation phase, a definition phase, an acting phase, and finally a result data extraction.

2.1 Defining the parameters

2.1.1 Initialisation

The energy production and consumption must be weighted prior to database creation. Indeed, the data collected come from various projects of different size. For demonstration purposes, it is relevant to have realistic proportion of production and consumption. Assuming a city of 100 000 inhabitants with an average power consumption of 5.924kW per household, it gives a global power consumption of about 148.1MW. The solar power production is given per household solar panel, and no adjustment is necessary. A single panel power rating is 0.18kW, which gives a total solar power of 4.5MW. The wind farm consists of 24 wind turbines, and stands for a small-scale farm. Its power rating is 17.56MW. Assuming three similar wind farms spread in the surroundings of the theoretical city, the total wind power now accounts for 52.68MW. Finally, since the reservoir NO1 stands for a fifth of the country, the local hydropower will be reduced to a tenth of NO1, with a new potential energy of 382GWh. It can be noted that there are five million inhabitants in Norway; one fifth of which is one million people, corresponding to NO1; one tenth of which makes 100 000 inhabitants, the size of the theoretical city. To save the reservoir's reserves until the snow melts, the reservoir's energy capacity is assumed to be calculated for 71 days (to reach the 30th of April):

$$Power_{rating} = \frac{Energy}{24\ hours \times 71\ days}$$

The reservoir's power rating is therefore 224.18MW.

The data was provided under `.xls` format, from different places and different timesteps. The first step consists in cleaning the data to form a homogeneous database.

All files were first opened under excel: the timestep was adjusted to ten minutes by deleting lines (eg for solar power data) or by linearizing the hourly values as explained in the previous section (eg consumption data) and the time values were converted from hours to minutes, from midnight in the morning to midnight in the evening (total of 1440 values for the day).

Since the data was provided in the context of larger studies, the additional columns not needed for this work were deleted. The relevant columns were converted from MWh, TWh or Wh to kW. The headers were then deleted for an improved further extraction. Finally, the files were save with a `.csv` format, separated by semicolons.

After preparing the files, an SQL database was created. SQL is the most accessible computing language for database management. Considering an industrial application, the Smart Meter or Aggregator will get remote access to both the energy production and energy consumption. The timeframe will then be as close as possible to continuous, and the DR actors will have to compute the inputs and give a response at every instant. For further analysis, improvement and maybe complaints, it is important that all this data is stored safely on a regular basis, both to ease the -in this case- python computation and not rely on a single python connection. In this context, even though it is not needed in this short-term case, the `.csv` files were imported in the SQL database through a small script entitled `Initialisation.sql`. This script also prints all the tables created to ensure its correct operation.

2.1.2 Database creation

Once the data collection has been imported in SQL, a python file `CreateEnergyDatabase.py` creates new tables adapted to the further work. A python script using an SQL database connection was chosen to combine both the database potential of the SQL language, and the calculation and loops skills of Python.

All tables were created with a loop, inserting a count with ten minutes timestep as time values and zeros for the rest of the row. Tables were then updated with fixed values (eg hydro in battery level and Energy Production), or values from the tables created during initialisation (eg all Energy Production but hydro, must-run Energy Consumption and main grid cost).

As a result, the following tables were created:

- The table *EnergyProduction*: it contains the timeframe in the first column, and the corresponding solar, wind, hydro and main grid power production in kW. This table will be used as a base for power potential at each instant.

- The table *PowerUse*: it contains the timeframe in the first column, and the corresponding solar, wind, hydro, EV and maingrid power use in kW. This table will be updated to count the amount of energy and compare the different resources used as a response to the pricing schemes.
- The table *EnergyConsumption*: it contains the timeframe in the first column, and the corresponding must-run, dishwasher, washing appliances and EV consumption in kW. This table will be updated to show the time when each appliance was triggered.
- The table *BatteryLevel*: it contains the timeframe in the first column and the corresponding EV and hydro energy storage level in kWh. This table is made to see how the battery potential is used, and how sustainable it is. Both hydropower and EV dedicated storage behave differently than other renewable productions: wind and solar's power production depends on external conditions, whereas hydro and EV's power production relies on their previous battery level and power production. To comply this special feature with their energy source function, the BatteryLevel table is dedicated to them. The hydropower potential found in the theoretical part is entered at time 00:00, beginning of the day, as a battery base level. Since EV behaves differently from hydropower due to its appliance co-function, its battery base level will be provided later.
- The table *PricingScheme*: it contains the timeframe in the first column, and the corresponding costs of solar, wind, hydro, EV and main grid power in NOK/kWh.

2.1.3 Definition of parameters

The first version of the program was accessing the database every time a value was needed or updated. Yet, the connection time was long and demanding, and another solution had to be found to speed up the computation. That's why the second and final version connects to the database at the beginning of the day to extract the values from the database, and at the end of the day to save the changes. In a real-life application, this connection can be made every minute, or every ten minutes, depending on the amount of data.

The script `SmartMeter.py` starts with a database connection extracting all the values from the tables inside lists of tuples. To make the data more accessible, the lists of tuples are converted in regular lists of values, containing 144 objects for each time of the day. The lists containing data are the following:

- The time in minutes throughout the day `timeframe`.

- *Energy Production*: Solar production `Psolar`, wind production `Pwind`, hydro potential production `Phydro`, EV potential production `Pev`, and main grid production `Pmg`. `Pev` represents the potential power production for each time and will be defined later in the code. The four other lists directly come from the database.
- *Power Use*: Solar power use `PUsolar`, wind power use `PUwind`, hydro power use `PUhydro`, main grid power use `PUmg`. They all come from the corresponding SQL table. `PUmg` concerns both the electricity used from the grid in case of lack of power (positive values), and delivered to it in case of surplus (negative values).
- *Energy Consumption*: Must-run consumption `Pmr`, dishwasher consumption `Pdish`, washing appliances -both washing machine and tumble dryer- consumption `Pwash`, EV power use `PUev`. `PUev` concerns all the power flows between the battery and the consumer, both charging and discharging, both consuming and producing. The values are negative when power is produced, and positive when power is consumed -EV values are defined from the appliance point of view.
- *Battery Level*: the EV energy battery level `batteryEV`, and the hydro energy battery level `batteryHydro`. Both come from the corresponding SQL table.
- *Pricing Schemes*: solar power cost `csolar`, wind power cost `cwind`, hydro power cost `chydro`, the equivalent EV storage cost `cev` and main grid cost `cmg`.

2.2 Defining the actors

Before starting with the rest of the program, the time issue should be discussed. Indeed, ten minutes timestep is not continuous nor a round number in hours:

$$10\,min\ =\ 0.16666666\ldots h$$

To cope with that, two functions `hconversion` and `mconversion` have been created: the former to convert minutes in hours, and the second to convert hours in minutes.

$$t_{hour} = 60\ \times t_{minute}$$

$$t_{minute} = 60 \times int(t_{hour}) + 10\times int(\frac{t_{hour} - int(t_{hour})}{10}\times 60)$$

In addition, the functions floor10, ceil0 and round10 rounding times to the lower, upper and closer tens minutes were built, using the functions floor, ceil and round from the math package.

For the rest of the simulation, it must be kept in mind that values may not match exactly the theoretical one due do the not finite timestep value.

2.2.1 Pricing Schemes

Basic costs lists have been extracted from the database, and they now need to be updated depending on the pricing scheme applied. The class `PricingScheme` has been created in this purpose and is detailed below.

Table 2.1 PricingScheme class

	Name in the program	Description
Instance variables	`costtype`	type of cost as a string.
	`costlist`	Cost for each time of the day as a list.
	`PAlist`	Available power production for each time of the day as a list.
Methods	`constant` (cvalue)	Updates the `costlist` with a constant a value `cvalue` for each time.
	`Proportional` (factor)	Updates the `costlist` with a value proportional to a given list of values.
	`weighted` (factor)	Updates the `costlist` with a value proportional to the inverse of the power production for each time.
	`fee` (factor)	Updates the `costlist` by adding a fee to its initial value for each time.
Instances	`solarc`	Represents the solar resource's cost: `"solar", csolar, Psolar`
	`windc`	Represents the wind resource's cost: `"wind", cwind, Pwind`
	`hydroc`	Represents the solar resource's cost: `"hydro", chydro, Phydro`

	`mgc`	Represents the solar resource's cost: `"maingrid", cmg, Pmg`
	`evc`	Represents the solar resource's cost: `"EV", cev, cmg`
	`avgc`	Represents the solar resource's cost: `"average", cavg, cmg`

Since the electrical vehicle is buying electricity from the grid, its equivalent cost relies on the main grid's one.

The cost `avgc` is a cost indicator for the Smart-Meter: if the average energy cost is lower than this limit, it should trigger flexible appliances. Hence it should be proportional to the main grid tariffs to encourage local consumption. More detailed explanation about the decision process is available in further subsections.

2.2.2 Energy Production

The class PowerAvailable is created to represent the energy production. Its characteristics are detailed in the table below.

Table 2.2 PowerAvailable class

	Name in the program	Description
Instance variables	`resourcetype`	type of resource as a string.
	`PAlist`	Power production potential for each time of the day as a list.
	`PUlist`	Power use for each time of the day as a list.

	`costlist`	Cost of the energy for each time of the day as a list.
Methods	`updatePower` (timeindex, Pused)	Updates the power production potential after a power use Pused at a given time index.
	`createResourceUse` (timeindex, Pused)	Updates the resource power use after a power use Pused at a given time index.
Instances	`solarpower`	Represents the solar power resource with the variables: `"solar", Psolar, PUsolar, csolar`
	`windpower`	Represents the wind power resource with the variables: `"wind", Pwind, PUwind, cwind`
	`mgpower`	Represents the main grid power resource with the variables: `"maingrid", Pmg, PUmg, cmg`

The instances hydropower and EV are not defined yet, since they require some adjustments detailed in the next subsection.

The method `updatePower` takes an index `timeindex` and power `Pused` as arguments. It adjusts the available power at the given `timeindex` by adding `Pused` to the current power potential. This method is important when power is assigned in several stages within a same timestep: when the second task starts, it must have access to the remaining power volume for that time.

The method `createResourceUse` takes an index `timeindex` and power `Pused` as arguments. It registers the total power volume used at the given `timeindex` by adding the used power `Pused` at each stage.

2.2.3 *Storage class*

Hydropower and EV also deliver energy, but have additional features to the previous energy production class: a battery level at each instant and a battery power delivery rate. Since they still behave as power sources, the class `Storage` is defined as a child class of `PowerAvailable`. Therefore, in addition to the variables and methods detailed above, the `Storage` class has the following properties:

Table 2.3 Storage Class

	Name in the program	Description
Instance variables	`Resourcetype, PAlist, PUlist, costlist`	See `PowerAvailable` class.
	`battery`	Battery level for each time of the day as a list.
	`ratedpower`	Maximum power of discharge as a REAL number.
Methods	`updatePower, createResourceUse`	See `PowerAvailable` class.
	`initialisation` (timeindex, batt0)	Sets the initial battery energy batt0 and power production potential at a given time index
	`updateBattery` (timeindex, Pnew)	Updates the battery energy after charging or discharging Pnew at the given time index.
Instances	`hydropower`	Represents the hydropower resource with the variables: `"hydro", Phydro, PUhydro, chydro, batteryHydro, 224.18.106`

The instance EV is not defined yet, since it requires some more adjustments that can be found in the next table.

The method `initialisation` takes an index `timeindex` and battery energy `batt0` as arguments. Since all the power production and battery levels rely on their previous values, the first battery energy level `batt0` defines the instance's behaviour for the whole simulation. For hydropower, the first battery energy level is the one for the first time of the day considered, at midnight, and is the one provided by Statnett database. However, and it is the reason why `batt0` is defined within a method and not a variable, an EV may be connected to the grid at any moment of the day: the battery level is then detected by the grid and stands for the new initial battery level. Therefore, initialisation changes the battery energy level to `batt0` at `timeindex`. The battery is assumed to be 86% full in the morning, and 29% full after a day work. Since the power production potential is directly proportional to the energy stored, the power production potential is also updated. The storage energy sources are defined with a maximum power capacity during discharge: the power potential is therefore the rated power during most hours, but is lower in the last hour.

$$P_{hour} = ratedpower, \qquad \text{hour} \neq \text{lasthour}$$

$$P_{lasthour} = \frac{Battery\ Level}{time\ step}$$

The method `updateBattery` takes an index `timeindex` and power `Pnew` as arguments. `Pnew` stands for a power production or consumption (mainly in EV's case since it is assumed that the hydropower reservoirs are only discharging) at time `t = timeframe[timeindex]`. This method updates the energy level of the battery in kWh:

$$battery_{new} = battery_{old} + P_{new} \times timestep$$

Where the timestep is expressed in hours. If the battery level gets higher than 100% due to the discontinuous timestep, the battery level is set back to its maximum capacity (mainly applicable in the EV case, with a maximum energy level of 17.5kWh). Given the new battery level at instant `t`, the battery level at instant `t+1` is also updated if applicable (i.e. the end of the day is not reached yet):

$$battery_t = battery_{t+1}$$

Then, the power potential at time `t+1` is updated -there is no need to change the one at time `t` since it has already started. The same process than in `initialisation` is used.

2.2.4 Energy Consumption

The reason why the EV object has not been created before, is because it also consumes energy. Consequently, it is also an instance of the class Appliance, created to represent the energy consumption actors. This class is defined by the following table:

Table 2.4 Appliance class

	Name in the program	Description
Instance variables	`apptype`	Type of appliance as a string.
	`power`	Power consumption of the appliance as a real number.
	`duration`	Duration of the appliance as a real number in minutes.
	`timelimits`	Time constraints defined by the consumer, as a list [$time_{start}$, $time_{stop}$] with the format: time = hour.min
	`powerlist`	Power used by the appliance for each time of the day as a list.
	`condition`	State of the appliance as a string, default value set to "passive".
Methods	`_get_timelimits`	Parameter of timelimits: returns the input as a time in minutes.
	`ON` (timeindex, batt_adjust)	Turns ON the appliance: condition is set to "running", and the powerlist is updated.
	`OFF` (timeindex, batt_adjust)	Turns OFF the appliance: condition is set to "passive" and the power list is updated.
Instances	`mustrun`	Represents the must run appliances with the variables: `"mustrun", -1, -1, -1, Pmr`
	`dishwasher`	Represents the dishwasher appliance with the variables: "dishwasher", 1200, 50, [8.30, 17.0], Pdish

	wash	Represents the washing appliances with the variables: “washingappliances”, 2700, 120, [14.0, 20.0], Pwash

apptype, power, duration and timelimits are variables linked to the flexibility constraints provided by the end user. Timelimits should be provided with the format hour.minutes for an improved comfort on the user side (counting in minutes in inefficient after the first two hours). Consequently, the function _get_timelimits is defined as a variable parameter to use the converted time in minutes in further calculations. Timenew is in minutes, time is in the input format, int if a function taking the integer part of a number, and i stands for the starting time or the ending time:

$$time_{i,new} = int(time_i)\times 60 + (time_i - int(time_i))$$

The variable powerlist will be used during analysis part to know when the appliances were triggered.

condition is a variable indicating the Smart Meter what is allowed to do with the appliance: if it is set to “passive”, time is outside the time limits set by the consumer or is already completed, and in both cases cannot be triggered; if it set to “waiting”, time is inside the time limits set by the consumer and is waiting to be triggered; if it set to “running”, the appliance is turned ON and is not flexible anymore.

The method ON takes an index timeindex and a time adjustment factor batt_adjust as arguments. The variable condition is set to “running”, and the power consumption is updated: from the time the appliance is triggered, and during all its duration, the powerlist is updated to its rated power value. To give the Smart Meter an indication about termination, its power consumption value is set to -1 a timestep after completion. One more detail is to be commented: for a typical appliance, duration and power are the intrinsic variables. However, it is different for EVs: the duration depends on the battery level, and is likely to not be rounded to tens minutes. To include this case in the function ON, the time adjustment factor is added to the appliance duration. The upper value rounded to tens minutes is taken: the ON time might be longer than it should be in the battery case, but at least ensures the 100% have been reached.

$$ONtime = ceil10(duration - batt_{adjust})$$

$$batt\_adjust = \frac{battery\ level}{rated\ power}$$

The method `OFF` is triggered when the Smart Meter finds the power value -1 set earlier. It takes an index `timeindex` as an argument, changes back the power value at `timeindex` to zero, and sets the condition to “passive”: the appliance has been triggered and completed successfully.

The washing machine and dryer are gathered under the same instance `washingappliances` because the tumble dryer must be triggered quickly after the washing machine is completed, to avoid stagnating water. Consequently, to simplify the model, both appliances are modelled by one with the same power (since they have the same power requirements; else an average value would have been calculated) and during as long as their cumulated duration.

2.2.5 Electric Vehicle

Since it has a battery, produces and consumes energy, it belongs to all previous classes `PowerAvailable`, `Storage` and `Appliance`. Consequently, a child class `ElectricVehicle` is created with the following parameters:

Table 2.5 ElectricVehicle class

	Name in the program	Description
Instance variables	`resourcetype, PAlist, PUlist, costlist, battery, ratedpower`	See `Storage` class.
	`apptype, power, duration, timelimits, powerlist, condition`	See `Appliance` class.
Methods	`updatePower, createResourceUse, initialisation, updateBattery`	See `Storage` class.
	`_get_timelimits, ON, OFF`	See `Appliance` class.
Instances	`EV1`	Represents the “morning” electric car.

	`EV2`	Represents the "evening" electric car.

The `ElectricVehicle` class inherits all the methods from its parents' class. However, a lot of variables are now doubled, which makes the creation of an instance more confusing.

`resourcetype` and `apptype` have the same value "EV". power and ratedpower have the same value 3.5 as a real number, since it's the EV's charging power and rated power during discharge. The duration variable stands for the time needed to fully charge the battery, and is set to 5 hours x $60 = 300$ minutes.

Electric cars can charge from the end of the workday, to the beginning of the next workday. However, since only one day is considered starting at midnight, the time when the EV is connected to the grid is divided in two parts. To make the most of the EV's flexibility potential, two `ElectricVehicle` instances are created: `EV1` stands for the "morning" electric car plugged in the morning, and passive after the user leaves the house for work; `EV2` stands for the "evening" electric car, passive until the user returns from work, and plugged until midnight. The former has the list [0.0, 8.30] as `timelimits`, and the latter [17.0, 24.0].

`powerlist` and `PUlist` both stand for the EV's power use, and are consequently defined by the same list `PUev`. This list will show both the power production and consumption of the electric car.

`PAlist` stands for the EV's power potential at each time of the day, and is provided by the list `Pev`. `costlist` is the equivalent cost for each time of the day, from the list `cev`. Finally, the battery energy level throughout the day is provided by `batteryEV`.

It should be noted that the EV's behaviour was very challenging to model, and some redundancies might appear inside the algorithm.

2.3 Smart-Meter decision process

To ease the script and process understanding, the process will mainly be explained through a diagram and punctual comments.

For each time, the appliances are split in two lists for flexible and must-run appliances. Then the Smart Meter assigns the cheapest energy source to `Pmustrun`. Then it covers the running appliances with the following cheapest resources. And finally, it triggers the flexible appliances if the cost signal is interesting enough.

2.3.1 Preparation

First, the Storage instances are initialized if applicable.

Then the Smart-Meter receives information from all the appliances and must decide which ones can be used for flexibility purposes.

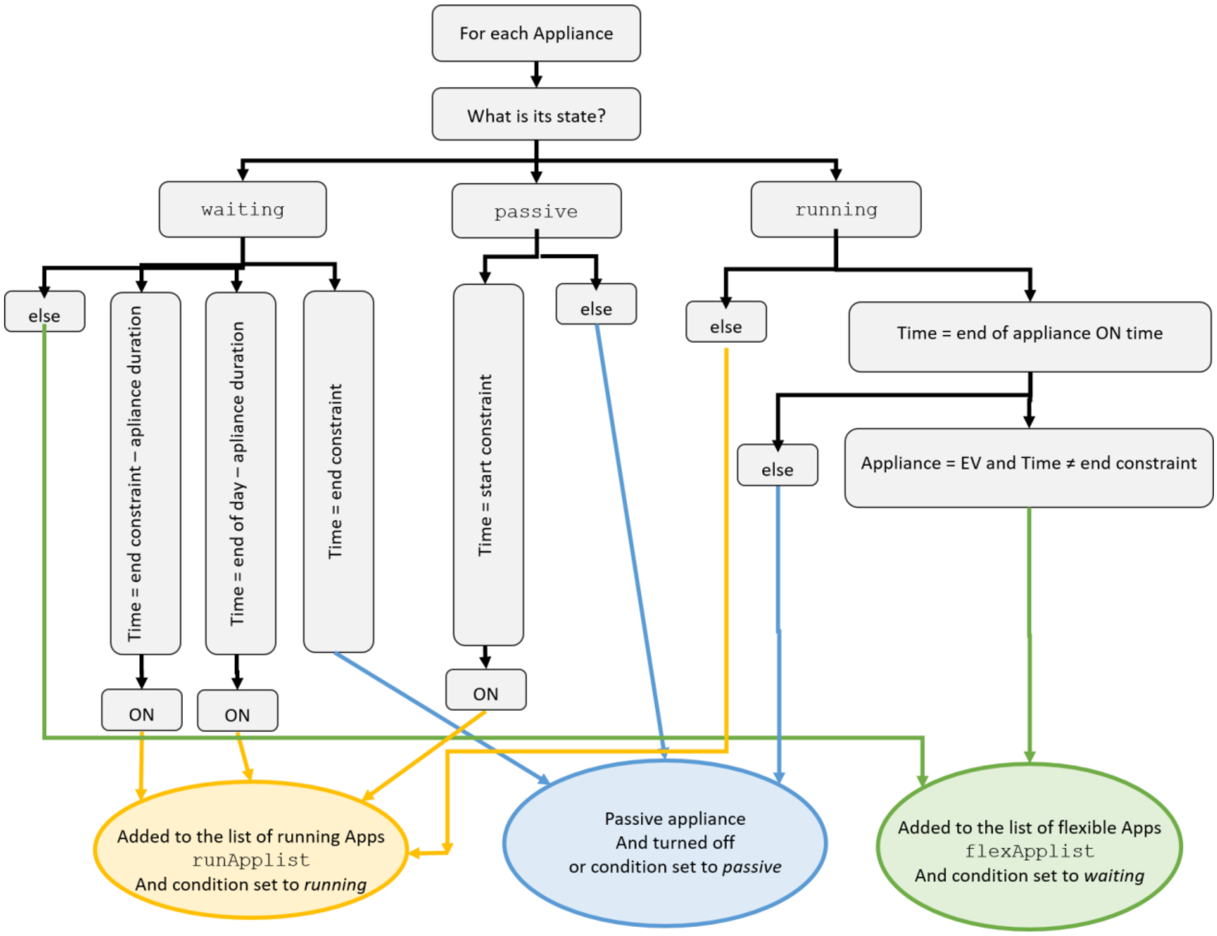


Figure 2.1 Diagram of the decision process to elect the flexible appliances

The lists runApplist and flexApplist are created, and the appliances are added to it following the previous algorithm. In general, appliances are flexible if they are "waiting", unless they need to be triggered to be finished before the end constraint defined by the user. If the end constraint is reached, all appliances must be set to "passive". When appliances are running, they can no longer enter the flexible appliance list, unless it is an electric vehicle: EVs task is never completed, whereas other appliances should not be triggered twice.

For each case, decision making for electric cars are specified due to their adjusted duration.

2.3.2 Must-run appliances

First, the must-run consumption is run, and the Smart-Meter choses the cheapest source of energy. PA is the power available for the given resource. The resources are sorted from the one with the lowest cost, to the one with the highest. The resources are then used in this order.

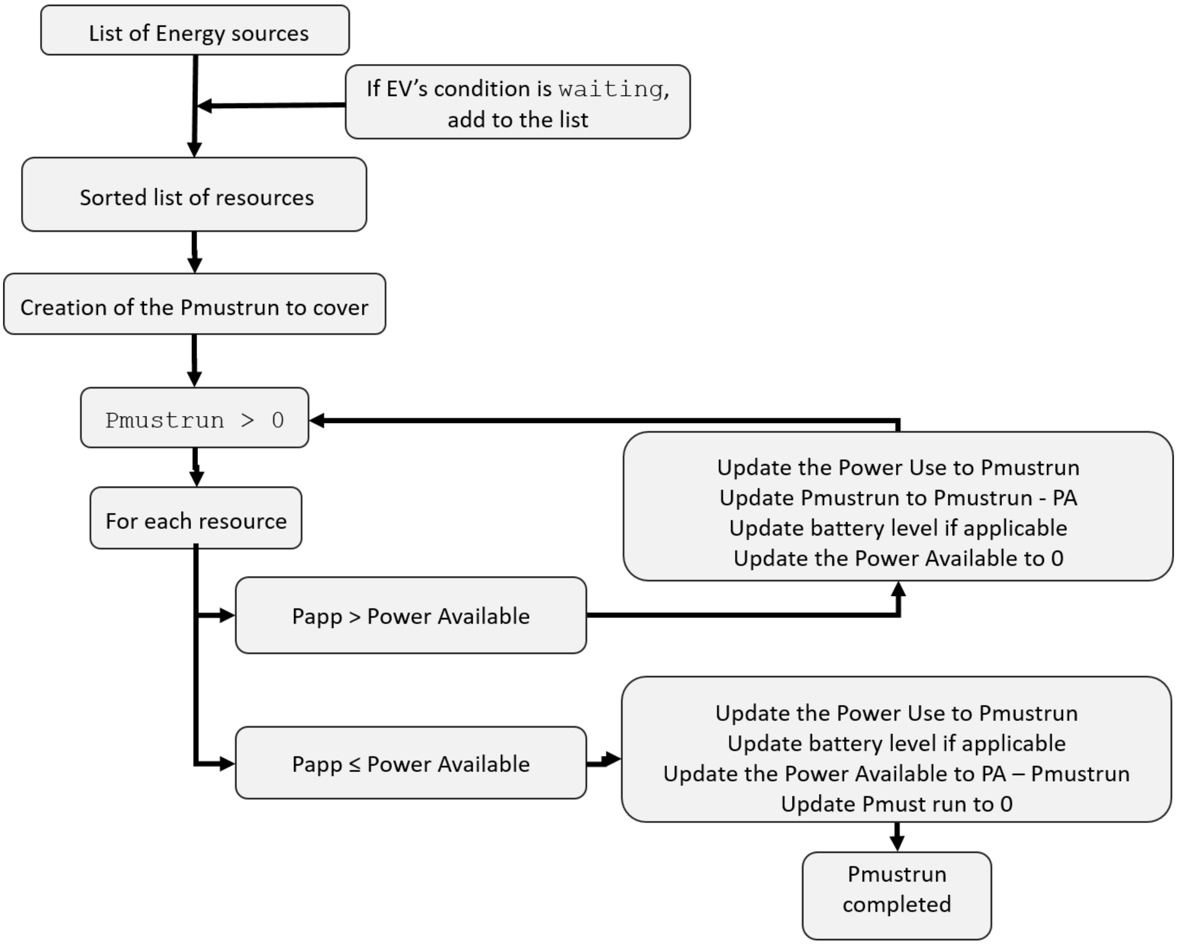


Figure 2.2 Diagram of decision process to minimise the cost to cover Pmustrun

2.3.3 Running appliances

The running appliances are following a similar decision-making process than the must-run power. The power available for each resource decreases each time it used to cover for one appliance consumption. The resources are sorted from the one with the lowest cost, to the one with the highest. The resources are then used in this order.

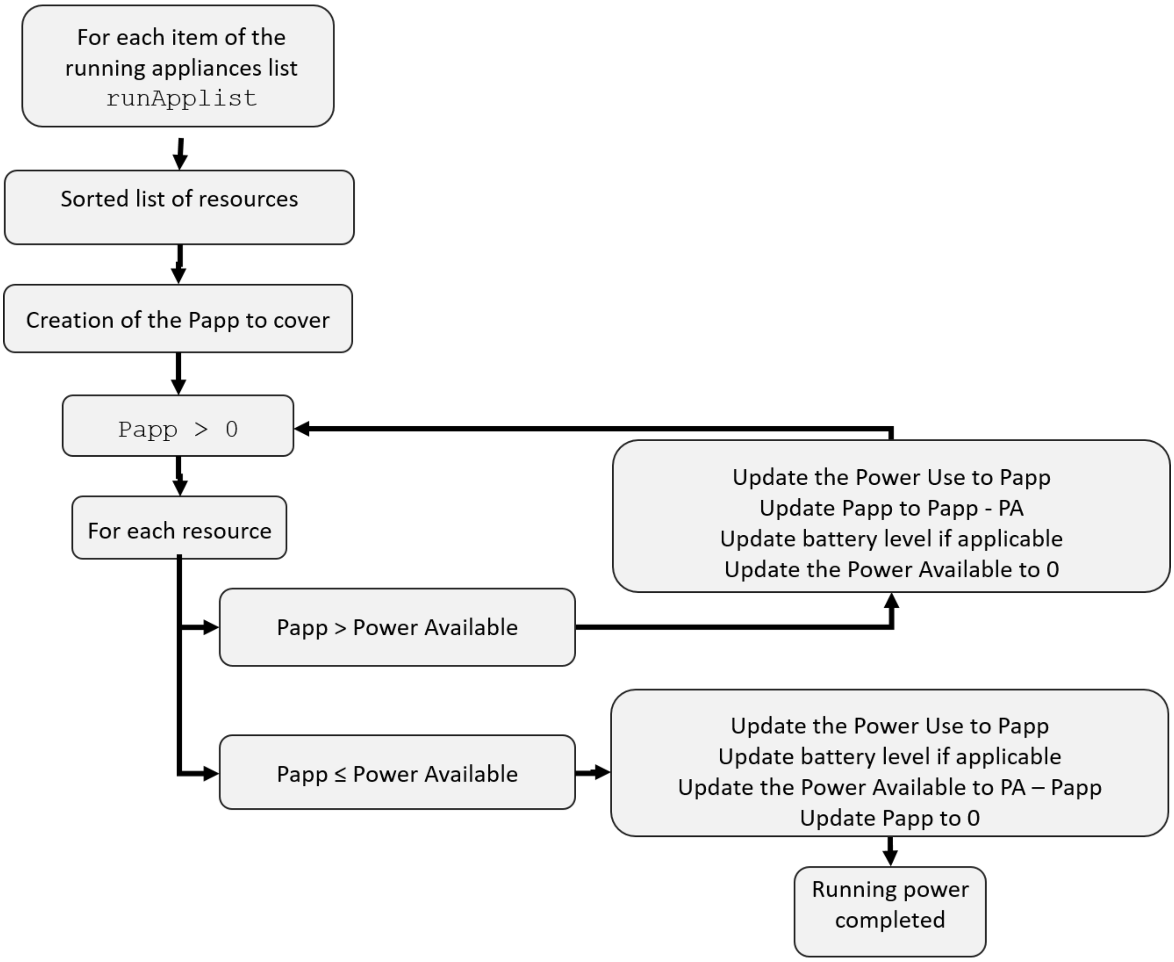


Figure 2.3 Diagram of the decision process to minimise the cost to cover for running appliances

In addition, a special loop dedicated to EVs is inserted: if the appliance is running, the battery should still be updated to keep on a continuous battery level. In addition, the electric car cannot be charged and discharge in the same time. The EV cannot be part of the resource list if it is already running or passive as expressed in the previous subsection. The reverse case is now considered: if EV is used as an energy resource, it can no longer be part of the flexible appliances list. This constraint was also inside the code of the previous subsection.

2.3.4 Flexible appliances

The flexible appliances are only triggered if the Smart-Meter receives an interesting price signal. First, the Smart Meter calculates the average cost of energy available: if it is smaller than the limit `cavg` determined by the pricing schemes, the Smart-Meter will trigger one flexible appliance. It calculates the average cost of each appliance if it was to be triggered, finds the minimum, and triggers it. The power available is updated, the appliance removed from the list, and the loop goes on as long as the consumption of energy is cheap.

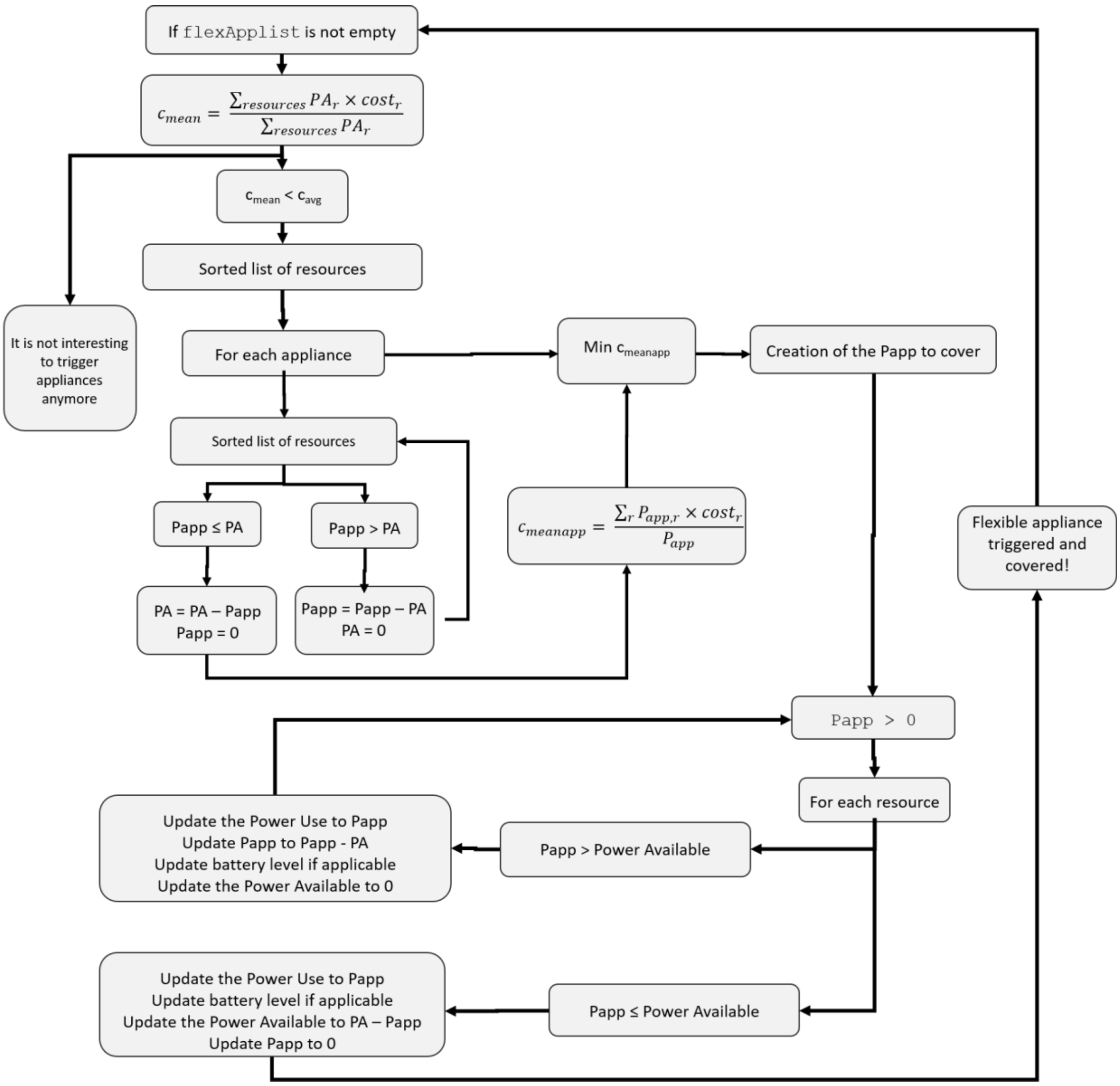


Figure 2.4 Diagram of decision process to trigger the flexible appliances and minimise the costs

3 Results and Discussion

3.1 Constant prices

3.1.1 Base case

First, the costs for each renewable resource are defined as constants, with the value defined in the theory sections:

Table 3.1 Constant pricing schemes for the base case

c_{solar}	c_{wind}	c_{hydro}	c_{EV}	c_{avg}
1.051 NOK/kWh	0.5 NOK/kWh	0.384 NOK/kWh	0 NOK/kWh	1 x $c_{maingrid}$

This situation is assuming that the residents will buy the solar energy from the grid: solar power is then produced by solar farms instead of residential solar panels. The equivalent cost of EV is set to zero, as the consumer has already paid for it when it was charging the car. The indicator cost `cavg` is set equal to the main grid ones: in this way, the Smart Meter will trigger appliances as soon as the price is lower than the main grid distant one.

The total cost spent on energy for the whole day is 143.48NOK., and some simulation details are available below:

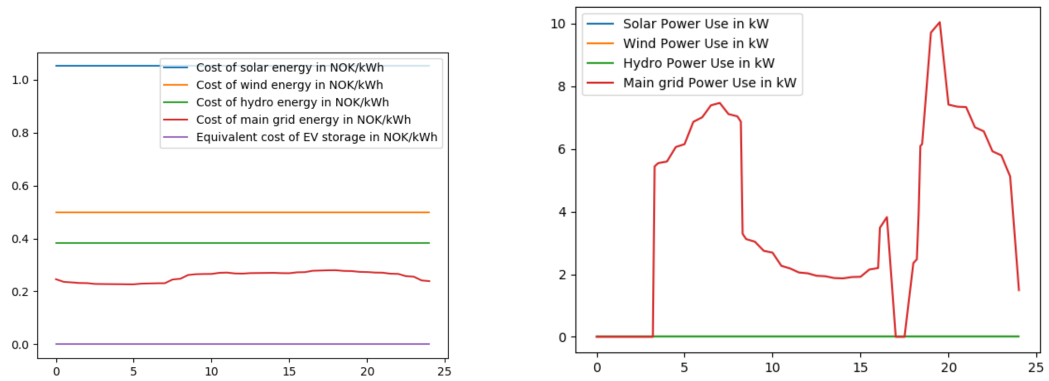


Figure 3.1 Price per resource (left) and energy resource use (right)

It can already be noted that since the costs from renewable sources are higher than the one of the main grid (the latter is in between 0.225 and 0.28 NOK/kWh for the considered day), the energy source used during the day is exclusively from the main grid. The Smart Meter has well optimised the energy cost, to the detriment of the expensive renewable energies.

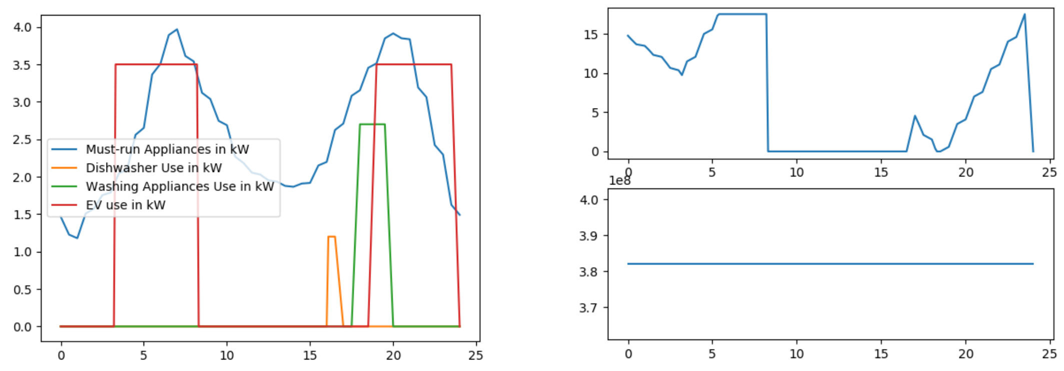


Figure 3.2 Power consumption from the appliances (left) and battery level of the EV (upp) and hydro reservoir (down)

It can also be observed in the previous figure that all appliances are triggered just before reaching their ending constraints. This is because the indicator `cavg` is equal to the lowest cost: there is no time during the day when the average cost gets lower than `cavg`. Flexible appliances are therefore only triggered when they must, wasting their flexibility potential.

Some comments can be given as well on the battery levels: the battery is charged at 86% when it is connected at the beginning of the day, then is discharged to cover the must run appliances in the early morning, and charged back to 100%. A gap down to 0kWh is observed during the day, and stands for the time when the battery is disconnected from the grid while the user is going to his workplace. Finally, it is connected when the consumer returns with a battery level of 29%, then is discharged down to 0% and charges back to 100%. The charge and discharge does not appear linear, probably due to the rounded values.

Since no hydropower has been used due to its high cost, the reservoir's capacity has remained steady during the whole simulation.

3.1.2 Constant prices adjustment

The previous prices assumed that the consumers would buy the solar energy: yet, in this case of residential solar panels, the energy is free.

In addition, since the renewable costs provided by the theory part were a world average, it will be assumed in this part that the actual cost in European countries is about half cheaper for wind power.

Hydro power is considered as an exception, since no less than 159 countries have access to the fully mature technology [7]. Its cost will just be assumed lower, which is a valid assumption given than the Norwegian electricity grid relies on hydropower, and provides cheaper energy.

The following values will hence be used:

Table 3.2 Constant adjusted pricing schemes

c_{solar}	c_{wind}	c_{hydro}	c_{EV}	c_{avg}
0 NOK/kWh	0.25 NOK/kWh	0.27 NOK/kWh	0 NOK/kWh	1 x $c_{maingrid}$

The total cost of the day is 135.45 NOK, or a reduction of 8NOK/day. That makes total annual savings of 2931NOK, or 6% of the total amount. This reduction is mainly due to the lower prices, and especially the free availability of solar power.

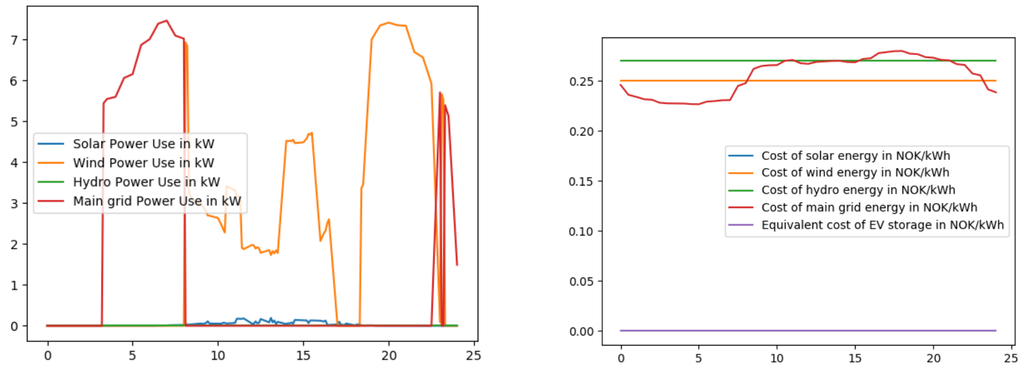


Figure 3.3 Power use per resource (left) and cost of each energy source (right)

The energy resource repartition is already much more encouraging: all the solar power resource is used as the instant it is produced since it is much cheaper than others.

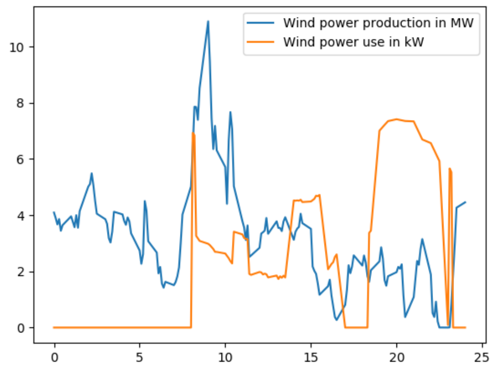


Figure 3.4 wind power use (right)

Wind power is also widely used, but hydro power is still neglected: this is likely due to the very low cost of wind energy and high one of hydropower. On one hand, half the world average value might be a too optimistic price for wind power production. On the other hand, the hydropower cost is higher in average than the main grid cost: since the main grid electricity is mainly produced by hydropower in Norway, it is reasonable to think that 0.27 NOK/kWh is a too pessimistic value. Yet, this value will be kept in further simulations to demonstrate the challenge most countries are facing: having renewable energy production cheaper than coal and nuclear power, main electricity providers.

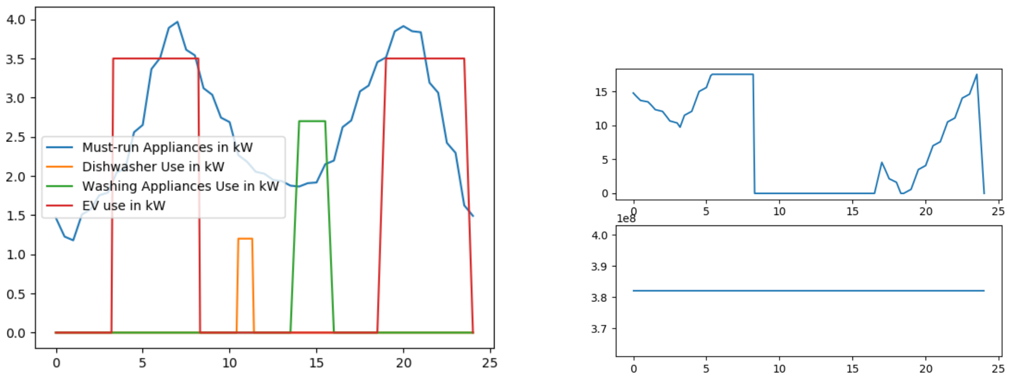


Figure 3.5 Appliances power consumption (left) and batteries level (right)

Thanks to the cheaper solar and wind power, the cost indicator gets higher than the average energy cost, and the appliances may be triggered during their flexibility time. Both washing appliances and dishwasher are triggered during the day, especially the dishwasher which is triggered during a peak of wind production.

The battery level profiles have not changed from the previous case.

Despite some interesting results, constant pricing schemes are not very realistic: the main grid costs are very variable, and it is to be assumed that renewable energy sources' cost behave in a similar way. The supply and demand balance ruling the market costs also applies to energy sources, and the price should be lower when the available power volume increases.

3.2 Dynamic Prices

3.2.1 Weighting factor

As explained previously, more dynamic prices are needed to better represent the reality, and encourage even more the Smart-Meter to trigger appliances when the renewable power production is high.

Yet, as solar power price is set to zero, and hydro power production is rather constant, both energy sources are limited to constant representation. The main price flexibility potential comes from the wind energy. The following pricing schemes are used in this simulation:

Table 3.3 Dynamic pricing Schemes

C_{solar}	C_{wind}	C_{hydro}	C_{EV}	C_{avg}
0 NOK/kWh	800/ P_{wind} NOK/kWh	0.27 NOK/kWh	0 NOK/kWh	1 x $C_{maingrid}$

The total cost of the day is down to 127.65NOK, which represents another 6% cost reduction from the constant adjusted pricing schemes.

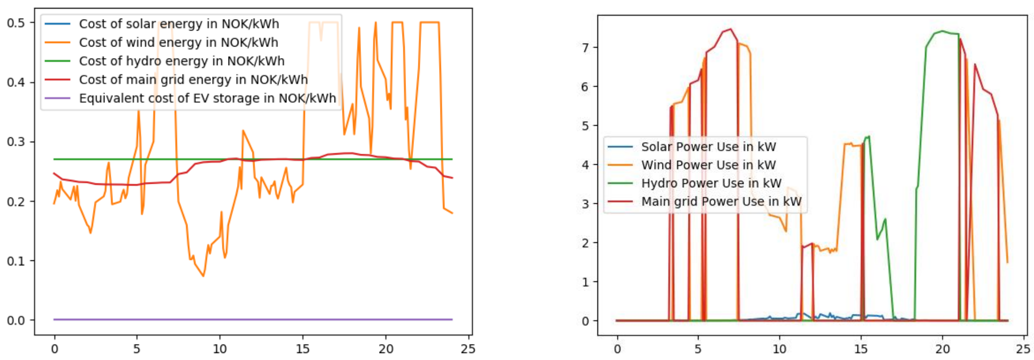


Figure 3.6 Cost of energy sources (left) and power use per resource (right)

The wind power cost is closer to real prices, and has an average value of 0.3NOK/kWh, which is still higher than the constant one set earlier.

The Smart-Meter accesses more often to the main grid than the previous case, where the wind cost was set to 0.25 (which was a low value). Solar power is entirely used again. This time, some hydropower is taken from the reservoirs instead of the main grid. It was previously covered by the wind power, which had a cheaper constant value.

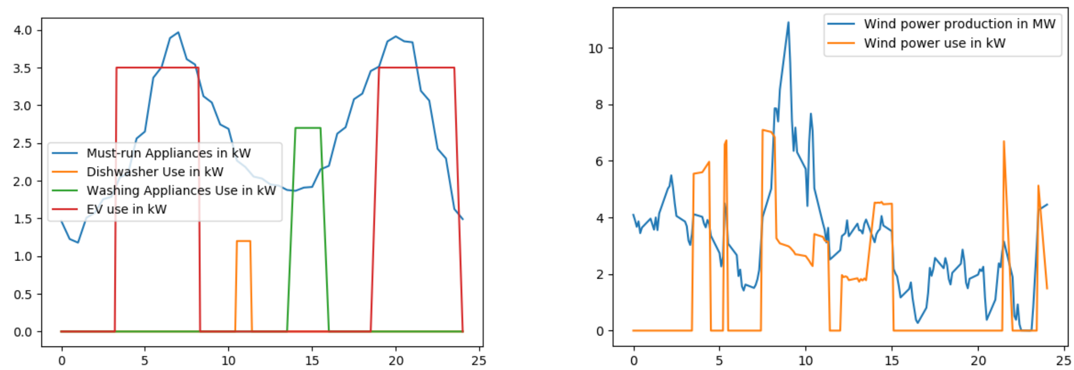


Figure 3.7 Appliances power use (left) and wind power production and use (right) for dynamic pricing schemes

Not as much benefits are taken from the wind power production as the previous case: the wind energy production is likely to have more surplus power to sell to the main grid. The main grid may be a strong grid, but this is not optimum for its balance if many similar microgrids are connected to it.

It can be observed here, and just like in the previous case, that solar power and wind power are mainly used to cover for the must run applications. Yet, the dishwasher is triggered during a peak of wind power production, of which about 1kW is used to cover for this flexible appliance at about 10:30. The same is observed for the washing appliances: they are triggered by the wind power production around 14:00, and entirely covered by wind production until 15:00. From 15:00 until 16:00 (tumble dryer use), the power consumption is covered by hydropower though.

The battery levels have not been shown here, since the EV battery behaviour is identical to previous cases, and the hydropower reservoir variations are too small to be noticed.

3.2.2 Cost indicator

Another variable cost is the indicator cost. Its optimum value was found for 1.1 times the main grid cost:

Table 3.4 Dynamic pricing schemes with higher cost indicator

c_{solar}	c_{wind}	c_{hydro}	c_{EV}	c_{avg}
0 NOK/kWh	800/ P_{wind} NOK/kWh	0.27 NOK/kWh	0 NOK/kWh	1.1 x $c_{maingrid}$

A slightly lower daily price of 126.92NOK is reached.

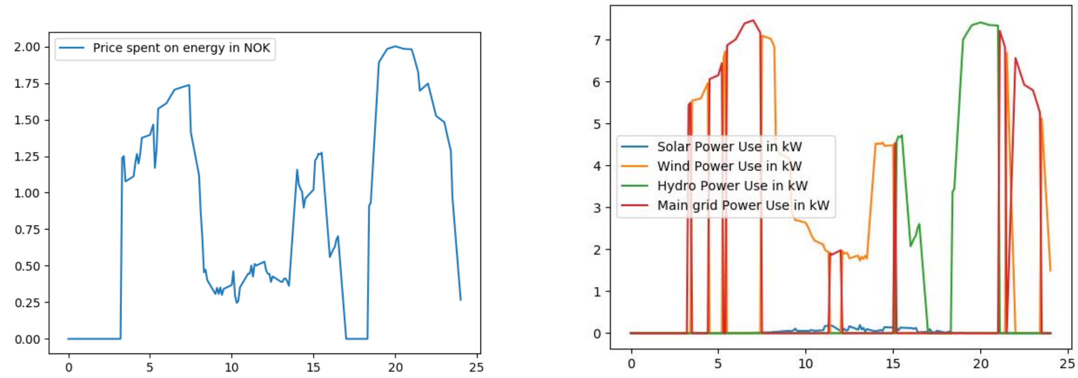
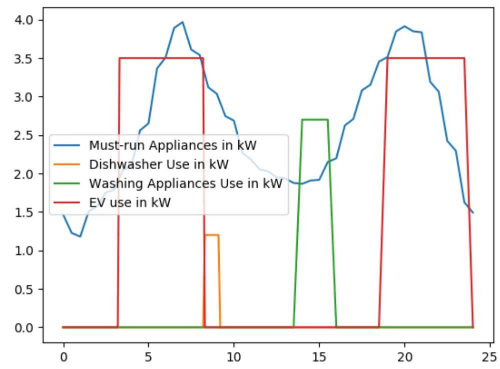


Figure 3.8 Instant price spent on energy (left) and power use per resource (right)

The power volume use repartition is identical to the previous case, with still an important share of main grid connection.

The money spent on energy expenses for each time of the day follows the flexible appliances use: it is low during the night when the must run appliances power to cover gets lower than 1.5kW; high around 5:00 when the electric car is charged, even more when the peak must run power is reached around 7:00; low during the workday but reaching a peak cost when the washing machines are triggered from 14:00 to 16:00; and high again when the electric car is charged. It can also be noted that the trigger of the dishwasher at 8:30 does not induce a significant peak cost: it is likely due to the solar power resource which is more productive from that time.



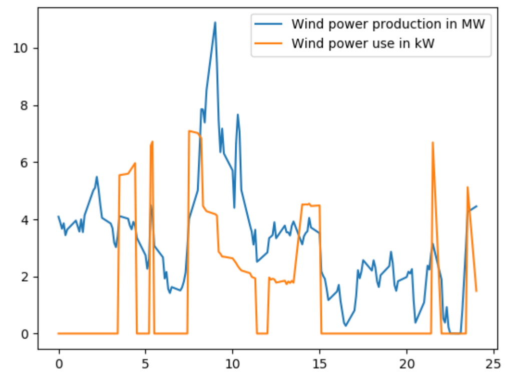


Figure 3.9 Appliances power use (left) and wind power production and use (right) for dynamic pricing schemes

Even though the resource power use repartition has not changed much comparing to the previous case, the appliances use has changed: the EV charging and washing appliances are identical, but the dishwasher is triggered in the morning, resulting in a 0.7NOK reduction cost.

3.2.3 Main grid fee

One last pricing scheme case must be studied: the case when a fee is added each time main grid power is used. This is likely to result in a higher total cost, since one of the resources becomes more expensive. The fee was taken high enough to show some changes, but low enough to be realistic: it is here an increase of the original value by 10%. This is already larger than what most facilities would accept.

Table 3.5 Dynamic pricing schemes with a main grid fee

C_{solar}	C_{wind}	C_{hydro}	C_{EV}	C_{avg}	$C_{maingrid}$
0 NOK/kWh	800/ P_{wind} NOK/kWh	0.27 NOK/kWh	0 NOK/kWh	1.1 x $C_{maingrid}$	$C_{maingrid}$ + 0.025

It results in a total daily cost of 130.10NOK, higher than previous dynamic values but still lower than for the constant ones.

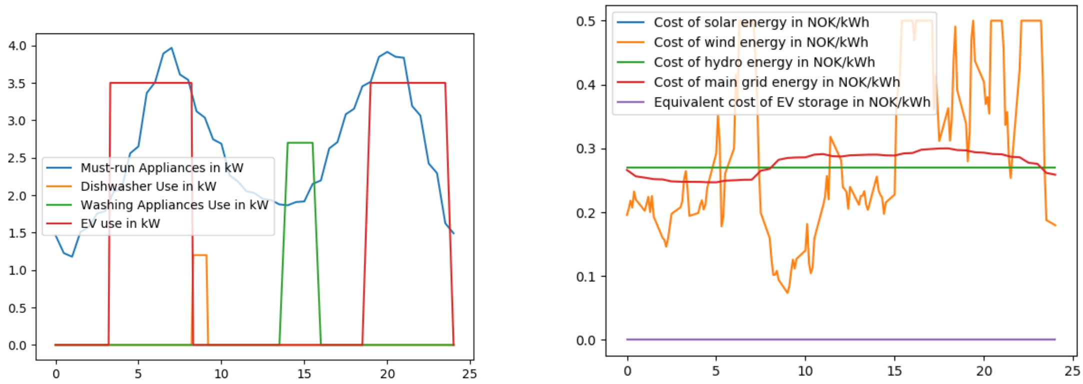


Figure 3.10 Appliances power use (left) and cost of each resource (right)

It can be observed on the right figure that the main grid cost is slightly higher than in previous cases, why all other costs have not changed.

The appliances consumption is also identical to the previous case.

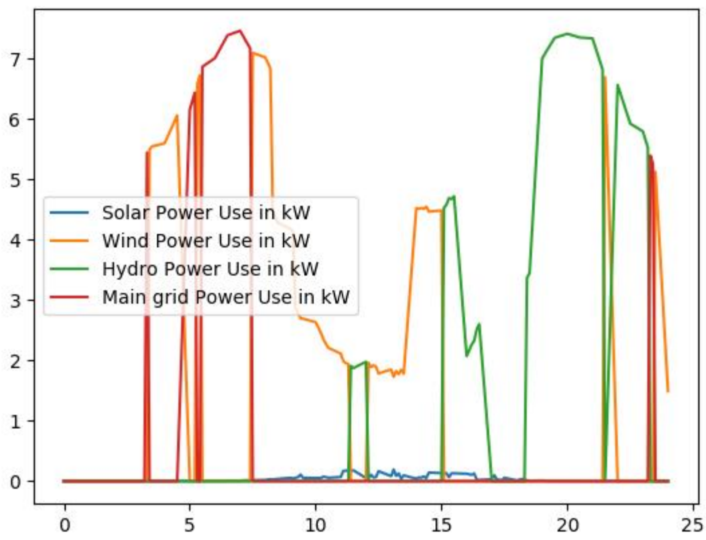


Figure 3.11 Power use repartition per resource

The main change is observed in the power production repartition: fewer connections to the main grid are made, all replaced by hydropower.

3.3 Discussion

3.3.1 Renewable Energy Use

Both constant pricing schemes and dynamic ones have decreased the main grid connections and encouraged the use of more renewable resources of energy: the Smart-Meter has done what it was expected to. The best overall results were obtained by the dynamic pricing schemes with an increased indicator and a main grid fee: it has the lowest main grid requirements, and uses the most local renewable resources. Yet, main grid connections remain and are not entirely avoided. This might be due to the Smart-Meter decision making process: the average overall cost of electricity `cmean`, which is compared to the indicator cost, is defined as follow:

$$cmean = \frac{\sum_{resources} c_{resource} \times PA_{resource}}{\sum_{resources} PA_{resources}}$$

Where $c_{resource}$ is the resource's cost, and $PA_{resource}$ its remaining available power. That gives:

$$cmean = \frac{c_{solar} \times PA_{solar} + c_{wind} \times PA_{wind} + c_{hydro} \times PA_{hydro} + c_{maingrid} \times PA_{maingrid} + c_{EV} \times PA_{EV}}{PA_{solar} + PA_{wind} + PA_{hydro} + PA_{maingrid} + PA_{EV}}$$

Since PA_{hydro} and $PA_{maingrid}$ are much higher than the power provided by the other resources, their costs weight too much in the average price, and `cmean` is not representative of the renewable energy production. Consequently, flexible appliances are not triggered depending on a high production of renewable energy as they should. Once they are triggered, renewable production is well prioritized by the Smart-Meter, but it does not match the actual need of power consumption from the grid. This could be adjusted by introducing a weighting factor inside the equation above, increasing the share of wind and solar production.

Even though dynamic prices were inducing the highest share of renewable energy, the best use of it as a resource of flexibility was made with constant costs: even though hydropower is scarcely used, wind power is widely used. And this is the most important regarding the new stakes of including a high share of renewables in the electric grid: hydropower is a base load energy already adapted to the traditional grid, whereas wind power is very variable and challenging for the grid to handle. Demand Response Management was introduced to help the DSO smooth the production variability, to make consumers move their loads to peaks of renewable power production. Constant prices with the adjusted costs were best answering this issue, using wind power instead of hydro power to cover for appliances. This is likely due to the low price of wind power, set down to 0.25NOK/kWh, more cost competitive than hydropower and the main grid in this case. These simulations prove once more the need for cheaper renewable energy sources to ease their social acceptance and wide integration.

Finally, it can be noted that solar power and wind power are scarcely used to cover for flexible appliances: this is due to the renewable energy prioritization for must-run power. All the solar power produced is used before reaching the flexible appliances. This may also have an impact in the calculation of `cmean`: even though their relative higher production is noted, the weight of wind and solar power is even lower, since `cmean` only considers the remaining amount from each power resource. An improved `cmean` calculation should include, as well as the weighted factors mentioned earlier, the initial and full renewable power production.

3.3.2 Consumer's flexibility and benefits

A typical consumer saves about 6% of total energy cost from being a prosumer, i.e. producing solar power, having an electric car and have flexible appliances (with renewable energy constant cost). This is too low to encourage him to invest in all the new expensive technologies. Introducing dynamic pricing schemes (and the indicator's cost as 1.1 times the main grid's one), the cumulated savings from a typical household gets up too 11.54%. This value is more encouraging, and, depending on the amount of initial investments, might induce a reasonable pay back time. Hence, even though flexible prices do not imply very significant changes in the energy use repartition, it increases significantly the consumer's benefits. In addition, the renewable energy producer also gains from it, since the average cost of wind power is higher there than with a constant cost.

Yet, the flexible appliances were used in similar times of the day for all computations, probably due to the limited number of flexible appliances. Only a dishwasher, washing machine and EV were considered in this work: a water heater, space heating and other almost-shiftable appliances should be considered in further study. The dynamic pricing schemes might reveal even higher potential if facing more flexible consumption.

After all, the cost indicator responsible for the trigger of appliances has proven to be more relevant for flexibility purposes than pricing schemes: if too low, the condition is seldom met, and appliances are triggered only when they must; if too high, the condition is often met and appliances are triggered in the first minutes. In both cases, the appliances flexibility potential is wasted. This issue is challenging to fix, since the Smart-Meter only takes instant-decision, and does not consider the best scenario over the day.

3.3.3 Introducing a new entity: the aggregator

To complete the work made by a Smart-Meter, another entity, the *Aggregator,* working in the day ahead market is introduced in many studies. It will optimise the consumer's benefit and power use over the whole day, based on energy production's forecasts.

In addition, the industry has been selling its load flexibility to the TSO to cope with grid instability for years, especially in the reservation markets. Consumers could "sell" their flexibility potential as well: yet each consumer's flexibility potential doesn't have a lot of weight in the overall energy market. That's how the Aggregator has been thought: it can bid the consumers' aggregated flexibility, optimize their profit and send a signal to the Smart-Meter for it to activate appliances. The task of triggering the flexible elements of consumption that used to belong to the Smart-Meter alone at a single household scale is now handled collectively. The relevance of using an Aggregator has been proven in some studies[5]. However, it was not modelled in this thesis due to the lack of time, lack of data and its difficulty. Further work should include both entities, the Aggregator working in the day ahead and reserve market and the Smart-Meter working in the instant market, in order to find the most flexible and efficient demand response.

If modelling the aggregator, it would be interesting to develop an economic modelled dedicated to electric vehicle: its equivalent selling cost has been assumed to zero, but truly is the charging cost. Smart charging at low-cost should be encouraged to increase even more the benefit for a consumer to own an electric car. Both entities, the Aggregator working in the day ahead and reserve market and the Smart-Meter working in the instant market, should succeed to optimise the renewable power consumption.

4 Conclusion

The Smart-Meter algorithm has proven its functionality, and has succeeded to decrease the consumer's daily cost related to energy, and increase the renewable energy share. The optimum compromise between cost reduction and renewable energy use were reached for dynamic pricing schemes with a main grid additional fee. Even though the highest consumer benefit was obtained with dynamic pricing schemes and no additional fee, the optimal use of resource flexibility was made with low constant pricing schemes. Low prices have once more shown their importance in increasing the use of renewable energy sources. Yet, the use of more flexible appliances might improve the Smart-Meter and dynamic pricing scheme's performance. A reduction of 11.54% of the total energy cost has been proven for a prosumer behaviour with limited flexibility potential, and is an encouraging result for further technological and management improvements.

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