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Master's Thesis

BUSINESS CASE OF OPTIMIZATION MODEL FOR SPANISH GRID CONNECTED PHOTOVOLTAIC BATTERY HOUSEHOLD SYSTEM

Author: **Jici Fan**

Supervisor: **Julián Barquín Gil**

Co-Supervisor: **Javier Olea Arias**

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Master's Thesis Presentation Authorization

THE STUDENT:

Jici Fan

....

THE SUPERVISOR

Dr. Julian Barquín Gil

Signed: .... Date: 30../ 06./ 2017

THE CO-SUPERVISOR

Mr. Javier Olea Arias

Signed: .... Date: 29/ 6/ 2017

Authorization of the Master's Thesis Coordinator

Dr. Luis Olmos Camacho

Signed.: .... Date: 29/ 06/ 2017

Abstract

Given the natural advantage in abundant and reliable solar resources, Spain is ideal for developing renewable energy generation with photovoltaics. Thanks to the supportive legislations, advances in technologies and reduction of costs, residential electricity consumers are increasingly incentivized to actively participate in managing their consumption and installing distributed generation units. Several studies have suggested that battery storage coupled with solar photovoltaics (PV) can benefit both households and the electricity grid. These facts call for a model to help households determine the composition of their grid-connected photovoltaic battery system based on the specific situations in Spain.

This paper proposes an optimization-based mixed integer linear programing model for the sizing and scheduling of residential battery storage co-located with solar PV in the context of present self-consumption regulation and three tariff schemes (the 2.0A, the 2.0DHA, and a newly proposed three-period tariff). The objective function for the household is to minimize the annualized electricity expenditure while satisfying the current electricity demand and constraints. To illustrate the model, a 5-spaces household in Sevilla is selected as an example. The load of the appliances is modelled by a load generation model with statistical data of appliances and time-of-use information. The optimization model is built with mixed integer linear programming (MILP) method in GAMS.

Besides the business as usual case, 100 scenarios are created to discover the best combinations when PV/battery prices decrease to different levels. The future scenario analysis is helpful to discover future uncertainties, tipping points, and better regulatory incentives.

The results of the paper contribute in the following three aspects:

- Provide guides for the investment decision of the households to take advantage of PV/batteries to minimize the expenditure.
- Test the performance of the tariff schemes and test the soundness of the future.
- Provide suggestions for the regulators on designing incentives.

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CHAPTER 1:

INTRODUCTION

1.1 Background and motivation

Climate change, limited conventional energy resources and energy security issues drive the integration of renewable energy sources into the modern power grid (Ratnam, et al., 2015). To cope with that situation, the European Union has proposed a 2020 energy strategy to fulfil 20% renewable energy sources in total energy consumption (Red Electrica de Espana, 2010). During the transition towards a more sustainable future, the residential sector is expected to be a key player and has attracted considerable attention from researchers and authorities worldwide (Romero-Jordán, and Pablo del Río, 2014, Santiago, et al., 2014). Consumers' investment in distributed renewable technologies can not only increase the production of renewables but also advantageously substitute generation investments.

Governments around the world have in recent years encouraged grid-integrated residential-scale solar photovoltaic generation and battery installations. In 2013, the Ley del Sector Eléctrico 24/2013 (the Power Sector Law) approved by the Spanish Parliament for the first time touches self-consumption and regulates self-consumption facilities (Aragonés, et al., 2016). Following that, the Royal Decree RD 900/2015 was approved by the Government and set the specific self-consumption regulation. Since then, the residential sector is allowed to invest in self-consumption devices and take advantage of the equipment (Aragonés, et al., 2016). Instead of self-consumption, the residential sector can also manage their demand curve and take advantage of the time-varying tariffs. The smart metering deployment is expected to be finished by 2019 and will allow households to take advantage of the distributed generation units (Leiva, et al., 2016).

Due to both regulatory support and technological innovations, residential electricity consumers are increasingly incentivized to actively participate in managing their consumption and PV or batteries can be attractive for Spanish households (Khatib, et al., 2016, Nguyen, et al., 2017).

However, contrary to the alternatives and expectations, the issue of profitability is not fully perceived by the residential investors due to the information asymmetry and lack of analytical skills. An unwise decision may lead to not only economic loss to the household, but also overinvestment in demand side and loss of social benefit. This fact calls for optimization models to guide the residential investments, including PV/battery sizing, tariff selection and battery scheduling. However, the situation diverse in different countries or different regions. There still lack of research on model for Spanish households.

1.2 Objective and contribution

This project aims to develop an optimization model for the Spanish households. The model is adapted to the context of a single household aiming to optimize its decisions by minimizing its expected electricity related expenditure. This paper applies a MILP method to minimize the annualized electricity expenditure for a household. The household is selected in Sevilla, one of the most suitable cities for solar generation. To better model the real conditions and effects, real data of 2015 is used.

The objective of the household electricity bill optimization model discussed in this project, therefore, is to explore the best investment decisions in household electricity management devices (mainly PVs and batteries) to meet the demand at minimum cost, while guaranteeing compliance with certain constraints such as technical features of the equipment and requirements of the network.

From the consumers' perspective, this model can provide them with guidelines for equipment investing. Meanwhile, the regulators can also take advantage of the model to gain insights about the plausible behavior of the consumers and to facilitate the design of tariffs and incentives.

1.3 Structure of the report

The structure of this paper is organized as follows: Chapter 2 presents the background information about the residential electricity consumption and the electricity tariff schemes in Spain. Chapter 3 introduces the methodology.

Chapter 4 and Chapter 5 describe the load generation model and the optimization model respectively. Chapter 6 shows and discusses the results of the model, including the business as usual case and future scenario analysis. Finally, Chapter 7 gives a conclusion and a brief outlook for the future research.

CHAPTER2:

SPANISH RESIDENTIAL CONSUMPTION AND TARIFFS

2.1 Residential electricity consumption in Spain

The residential sector in Spain is responsible for about 25% of total electricity consumption (IDAE, 2011) and the number is still rising due to the growing residential housing units as well as the increasing quality of life (Santiago, et al., 2014). In 2015, the residential sector as a whole consumed 69.9 TWh electricity and on average 3812 kWh each household (ESIOS, 2016).

2.1.1 Sources of the residential electricity consumption

There are mainly five sources of final electricity consumption. Figure 1 presents the final energy consumption in Spanish households.

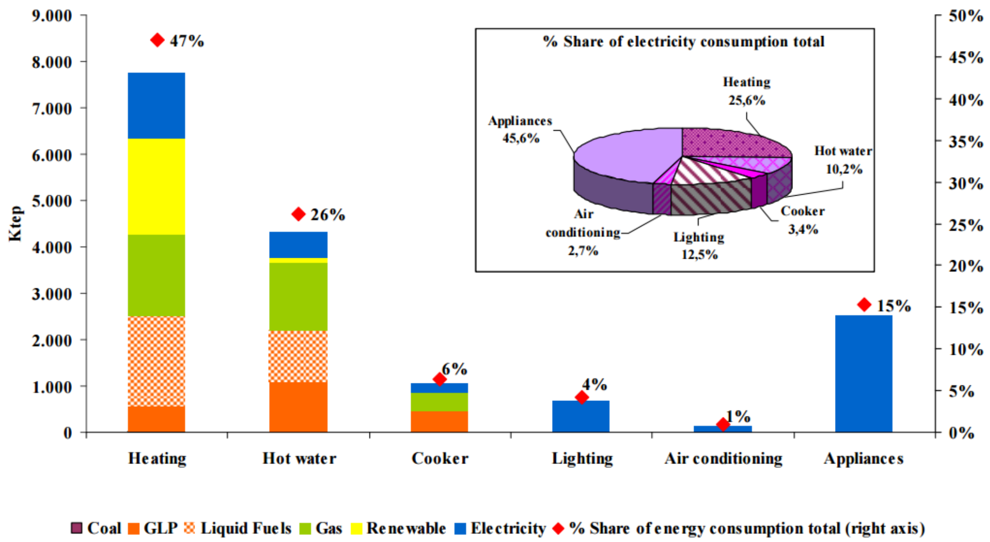


Figure 1 Final energy consumption in Spanish households by fuel and use (2009) (IDAE, 2011, Blázquez, and Filippini, 2012)

Heating is the most relevant destination of electricity consumption of Spanish households, accounting for around 25.6% of the total consumption. Excluding heating, the electricity consumption is most concentrated on hot water, lighting, cooker, air conditioning.

2.1.2 Features of the electricity consumption of Spanish households

The electricity consumption in a Spanish household shows significant seasonality and varies in different regions.

Temperature is an important factor that affects the residential electricity consumption. Figure 2 shows the relation between the temperature and the residential electricity consumption in the year 2015. In Figure 2, it can be observed that the peak electricity load occurred in winter when the average temperature is low and the lowest consumption was observed in spring and autumn when the temperature is mild.

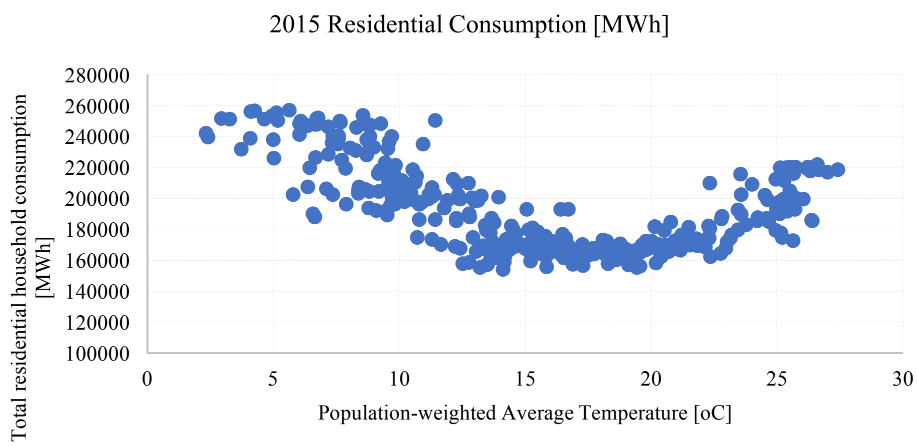


Figure 2 Residential consumption in 2015 (From ESIOS, daily residential consumption is calculated as the sum of measured demand by access tariff 2.0 low voltage general <10 kW and Measured demand by access tariff 2.1 low voltage general ⩾10 kW and <15 kW)

Due to the influence of climate and temperature, the electricity consumptions are different for households in different regions. Blázquez and Filippini (2012) elaborated the climate zones in Spain and compared the electricity consumption per capita per climate zones, as shown in Figure 3.

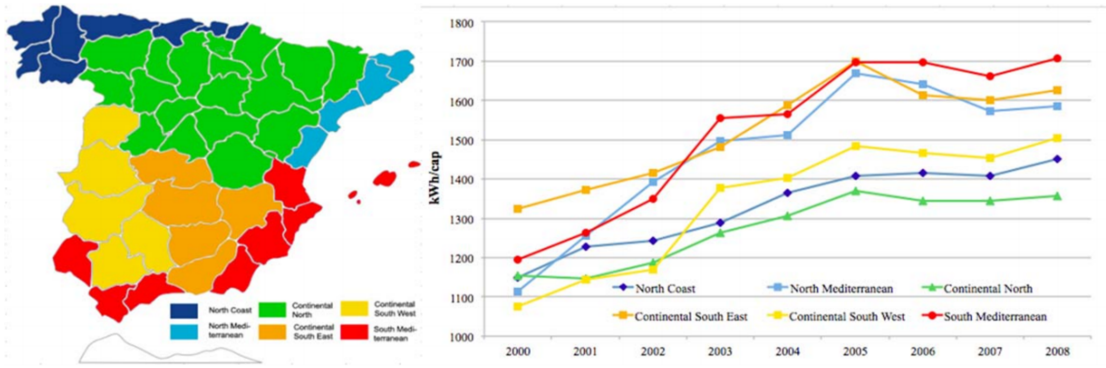


Figure 3 Climate zones (left) and domestic electricity consumption per capita per climate zones in Spain (Blázquez, and Filippini, 2012)

2.2 Spanish electricity tariff schemes

2.2.1 Regulations regarding the self-consumption facilities

A series of radical reforms have been undertaken in the Spanish electricity sector. In 2013, the Ley del Sector Eléctrico 24/2013 (the Power Sector Law) approved by the Spanish Parliament touches for the first time self-consumption and regulates self-consumption facilities (Aragonés, et al., 2016). Following that, the Royal Decree RD 900/2015 was approved and set the specific self-consumption regulations. Since then, the residential sector is allowed to invest in self-consumption devices for own domestic consumption (Aragonés, et al., 2016).

Besides self-consumption, the residential sector can also manage their demand curve and take advantage of the time-varying tariffs. The smart metering deployment is expected to be finished by 2019 and the smart metering deployment can help households to take advantage of the distributed generation units (Leiva, et al., 2016).

Due to both regulatory support and technological innovations, PV and batteries can be attractive for Spanish households.

2.2.2 Spanish domestic tariff

In Spain, the tariff schemes are mainly designed by Comisión Nacional de los Mercados y la Competencia (CNMC, the regulator) to recover the costs of the electricity sector. Spanish residential electricity bills include two components: the market term and the regulated terms.

The market term is calculated based on the amount of consumption and is charged in €/kWh. The market term mainly comprises the cost of the energy purchased the suppliers in the wholesale market, balancing and ancillary services.

The regulated term is further divided into two terms. The first one is based on the contracted capacity and is charged in a €/kW basis. The second terms is volumetric and is charged in €/kWh. Collectively, the regulated part of the bill is aimed to recover network tariffs and policy charges.

Figure 4 presents the breakdown of a typical household electricity bill. The height of the bar is proportional to the yearly payment. It should be noted that some types of cost are recovered from both the €/kW and the €/kWh terms of the regulated part of the tariff. For example, the network costs are mostly recovered through fixed (€/kW/year) charges and the policy charges are mostly recovered through the variable charges. In addition to the determined values, VAT (21% of the bill value) and the electricity special tax (an additional 5.113% of the bill value) have to be added on top.

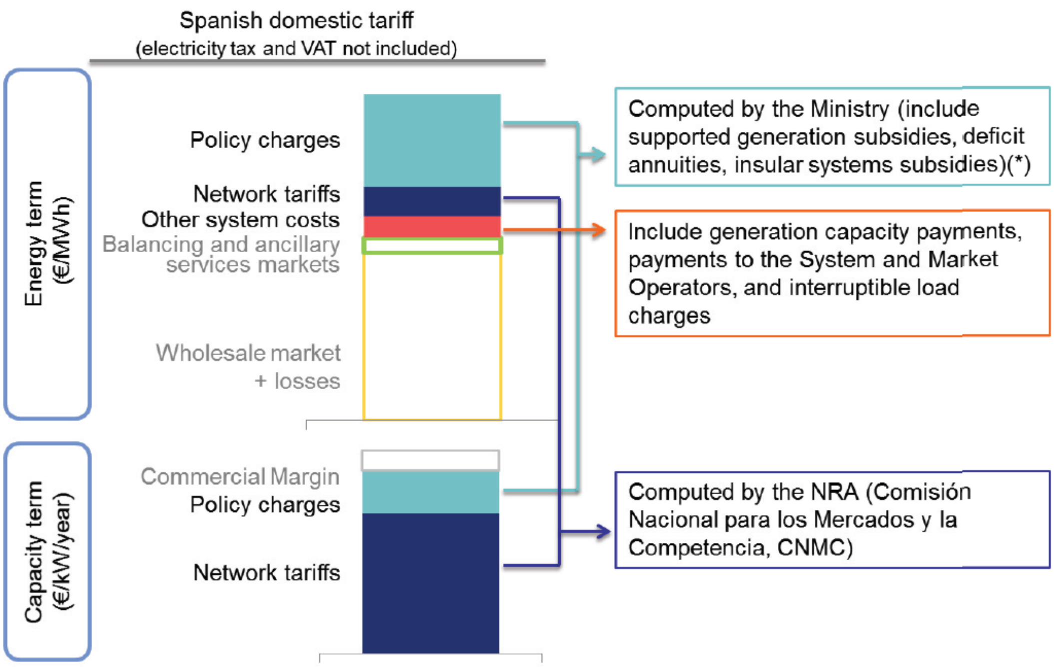


Figure 4 Electricity bill breakdown (Aragonés, et al., 2016)

2.2.2.1 **The market term**

The residential consumers are entitled to request the specific regulated PVPC tariff ('Precio Voluntario para el Pequeño Consumidor', Spanish for 'Willing Price for the Small Consumer'). The PVPC tariff is computed by the Spanish TSO (Red Eléctrica de España) and it is a pass-through of hourly market prices.

2.2.2.2 **The regulated €/kW term**

For the regulated term, the households can select their contracted capacity from standardized values based on their usage pattern. The contracted capacity is charged with a price of 38.04 €/kW/year according to the current tariff schemes.

2.2.2.3 **The regulated €/kWh term**

PVPC 2.0A and 2.0DHA

There are two PVPC tariff schemes that households can choose from: the standard PVPC 2.0A tariff and the two-period time-of-use PVPC 2.0DHA tariff.

The market term based on the wholesale market and ancillary services prices are the same for both the tariffs while the added regulated charges are different: constant along the day or in two periods with higher price in the peak hours and lower price in the off-peak hours.

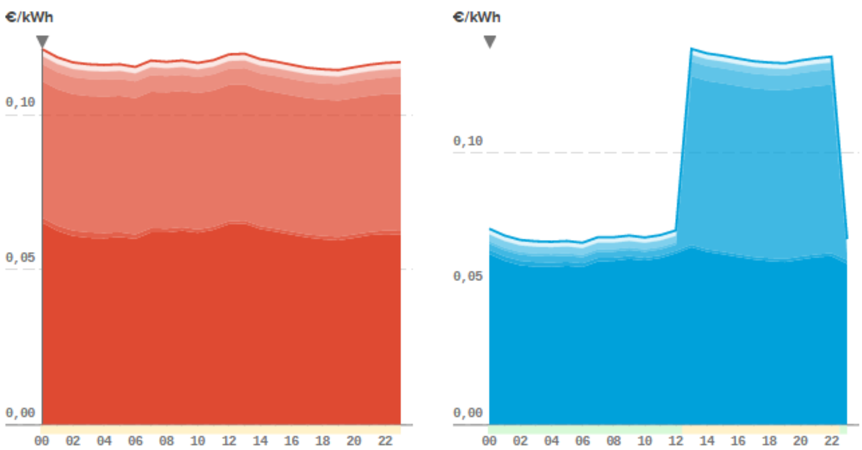


Figure 5 PVPC tariff, July 15th, 2017

2.3 A dynamic effective three-period tariff

A new dynamic, 'real time' access tariff methodology has been proposed by the regulatory affairs department of ENDESA. The newly proposed methodology aims at better reflecting the cost, recovering the tariff deficit, as well as efficiently incentivizing distributed generation and storage deployment (Haro, et al., 2017).

The three-period tariff is an advance of the PVPC 2.0A and PVPC 2.0DHA tariff and determined three periods based on the usage. The design is based on the fact that the relative price of the network cost sharply increases when the network capacity is approached. Figure 6 presents how the hourly network charges vary with the flow through the network.

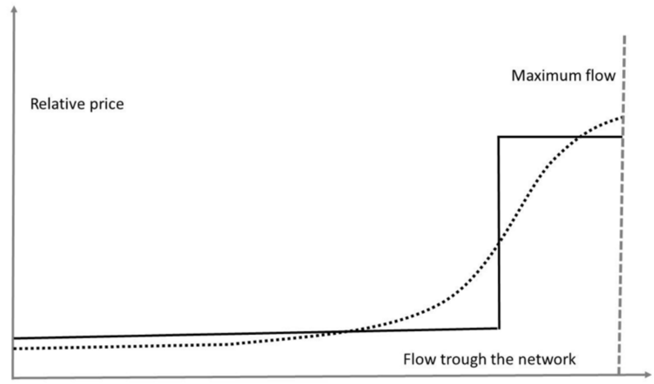


Figure 6 Shape of an ideal network tariff curve based on long-term marginal costs (dotted) and a stepwise approximation (solid) from (Haro, et al., 2017)

In the proposed tariff, a demand threshold of 90% of the peak load was set. To be more specific, 90% of the network costs should be recovered during the peak hours. Figure 7 shows the network tariff-duration monotonic curve for a user connected to the low voltage network.

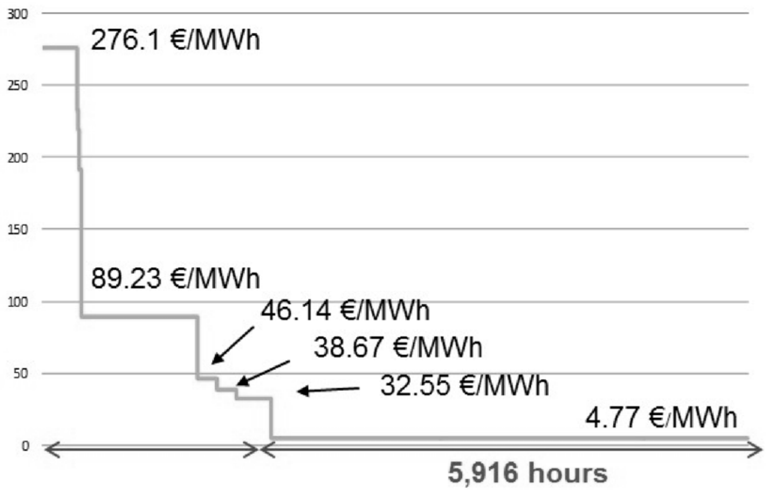


Figure 7 Monotonic network tariff curve from (Haro, et al., 2017)

In the three-period tariff, the hours in a year are categorized into three groups: peak hours, medium hours and off-peak hours. Based on the usage during the hours, the network tariff for each hour is determined. Figure 8 shows a heat map of the low voltage tariffs along a year.

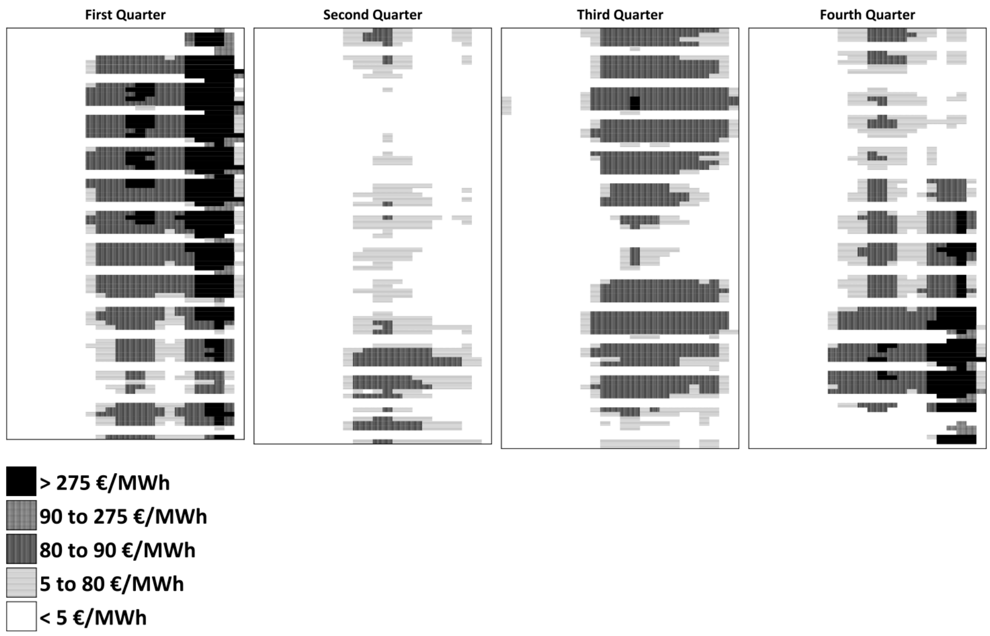


Figure 8 Network tariffs map. Horizontal: hours, vertical: days. From (Haro, et al., 2017)

To simplify the design of the hours, it is assumed that the hours are categorized based on months and the work day or weekends. The definition of the hours in a year is presented in Figure 9. It should be noted that the contracted capacity in the three-period tariff is determined by the maximum consumption in period 1 and period 2.

Month	Day	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	L	3	3	3	3	3	3	3	3	2	2	1	1	1	1	2	2	2	2	2	1	1	1	1	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
February	L	3	3	3	3	3	3	3	3	2	2	1	1	1	1	2	2	2	2	2	1	1	1	1	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
March	L	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
April	L	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
May	L	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
June	L	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
July	L	3	3	3	3	3	3	3	3	2	2	2	2	1	1	1	1	2	2	2	2	2	2	2	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
August	L	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
September	L	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
October	L	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
November	L	3	3	3	3	3	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
December	L	3	3	3	3	3	3	3	3	2	2	1	1	1	1	2	2	2	2	2	1	1	1	1	2
	F	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3

Figure 9 Definition of the hours (L: weekdays, F: weekends)

Similar with the two-period 2.0DHA tariff, the energy and ancillary services prices in the three-period tariff is the same with the 2.0A. However, the regulated charges are added in three periods. The changes in the ways of distributing the total regulated charges are presented as follows:

Table 1 Charges in the three-period tariff (Charges=Energy term + Capacity payment(1+Losses)*

	P1	P2	P3
Energy term (€/MWh)	217,90	54,70	4,10
Capacity Payment (€/MWh)	9,92	9,92	0,00
Losses (%)	14,80	14,80	12,93
Charges (€/MWh)	**229,29**	**66,09**	**4,10**

The values are determined from the work of (Haro, et al., 2017), while small changes are made based on the yearly real situation. The comparison of prices for the energy term under the three tariff schemes are presented in Figure 10, Figure 11 and Figure 12.

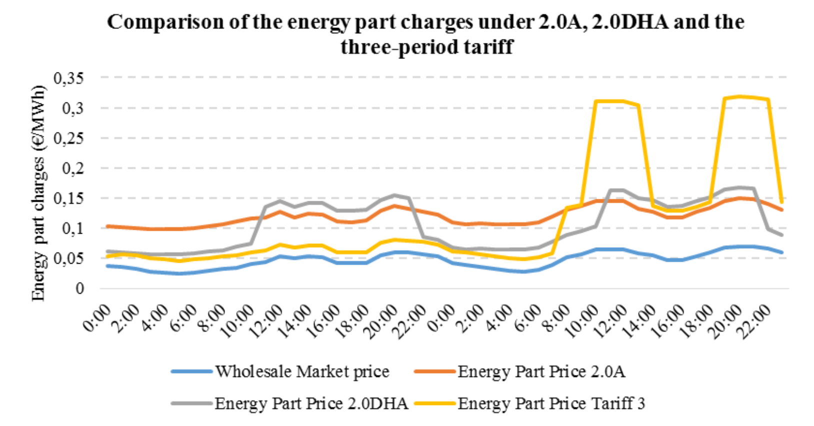


Figure 10 Comparison of the energy part charges under 2.0A, 2.0DHA and the three-period tariff (18th-19th January 2015, Sunday and Monday)

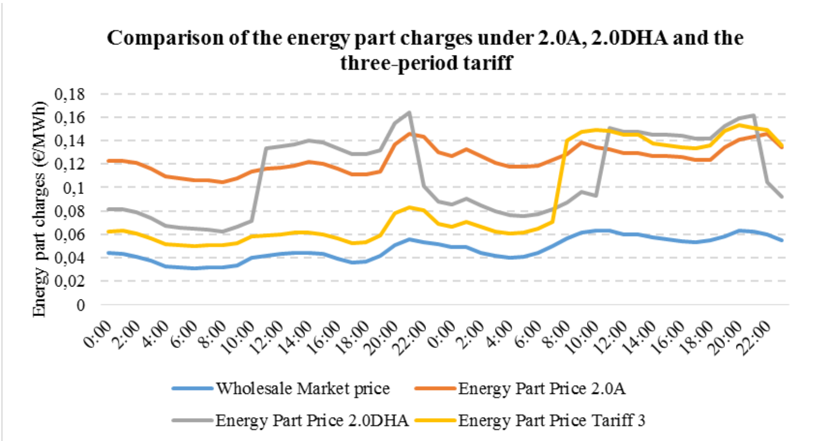


Figure 11 Comparison of the energy part charges under 2.0A, 2.0DHA and the three-period tariff (15th-16th March 2015, Sunday and Monday)

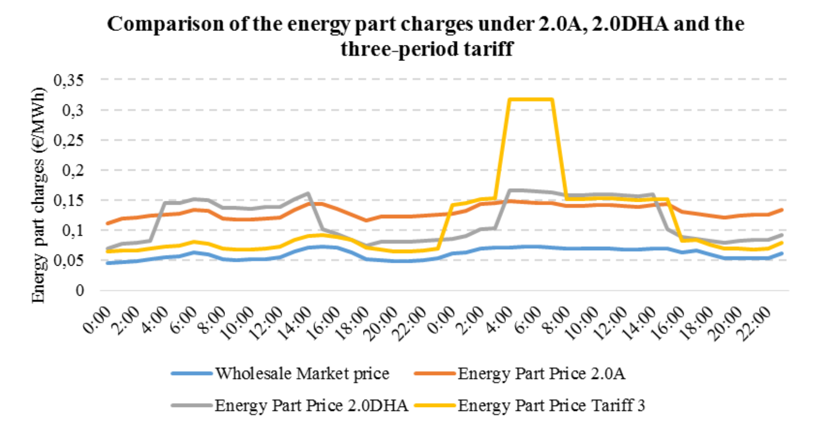


Figure 12 Comparison of the energy part charges under 2.0A, 2.0DHA and the three-period tariff (19th-20th July 2015, Sunday and Monday)

CHAPTER 3:

METHODOLOGY

This part elaborates the methodology adopted in this thesis in order to answer the research questions and to achieve the research objectives mentioned in Chapter 1.

3.1 Optimization method

Many literatures have proposed different approaches for PV/battery expansion or battery hourly scheduling problems (power management problems) with given objective functions and constraints. Four approaches are usually applied in the household PV/battery expansion models: intuitive method, analytical method, numerical method and intelligent method (Posadillo, and López Luque, 2008a, Khatib, et al., 2016, Rawat, et al., 2016). The numerical method, which usually uses simulation-based programs to calculate the optimal size of PVs and batteries, are most widely used (Khatib, et al. 2016).

Techniques of numerical methods include: linear programming (LP) (Kaushika, et al., 2005, Nottrott, et al., 2012) , mixed integer linear programming (MILP) (Ha Pham, et al., 2009, Ru, et al., 2013, 2014), Lagrangian relaxation (LR) (Riffonneau, et al., 2011), dynamic programming (DP), genetic algorithms (Vrettos, and Papathanassiou, 2011) and so on. Linear programming (LP) and mixed integer linear programming (MILP) formulate problems on linear form. LP and MILP requires low computing resources and can provide good results (Riffonneau, et al., 2011, Rawat, et al., 2016). These advantage makes LP and MILP hot methods in solving problems in the electricity sector and they are believed to be the most successful techniques (Gonzalez, 2014). Since the equations in this work are linear equations, the MILP method is applied. A literature review can be found in Chapter 4 with detailed explanation of method selection.

The General Algebraic Modeling System (GAMS) is a high-level modeling system for optimization problems. It consists of a language compiler and a stable integrated high-performance solvers. Through smart links, the optimization capabilities of GAMS are accessed by MatLab. By doing that, the model data are visualized and analyzed in MatLab.

3.2 Topology of the system

A typical household in Sevilla is selected to illustrate the model. The selection of the household is based on Encuesta Continua de Hogares (the Continuous Household Survey, ECH), a survey that provides yearly information on the basic demographic characteristics of the population, the households they make up, and the dwellings they inhabit (Instituto Nacional de Estaadistica, 2015). According to the statistics, the mode of the household type and the number of rooms are couple with children (34%) and 5-space dwelling (40%) respectively. Hence, the model in this paper works with the 5-space (including kitchen and bathroom) household with a couple and children. Figure 13 illustrates the topology of the system under consideration, including solar panels and an energy storage system.

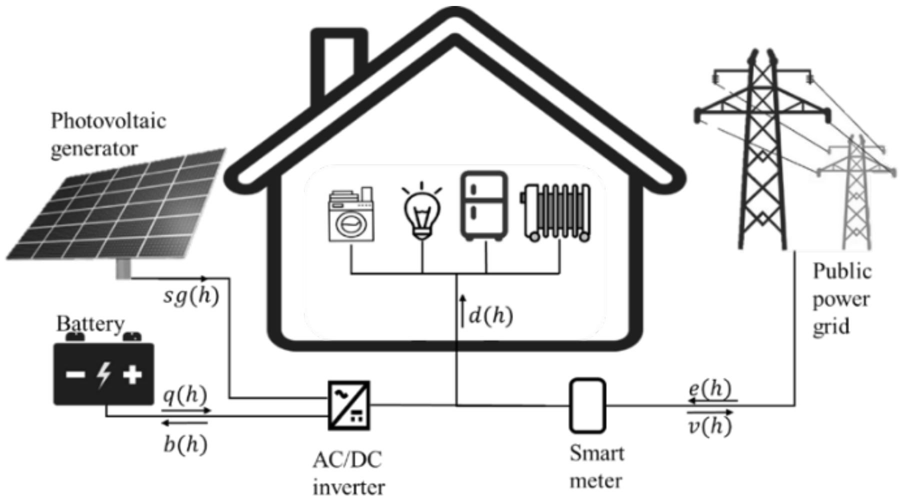


Figure 13 Self-consumption household layout

Appliances, solar panels and energy storage devices are as a whole considered as a household system. The generated electricity can either supply the appliance or be sold to the distributed grid. The battery is connected with both the household and the distributed grid.

It should be noted that the electric circuits in reality are much more complex. According to Royal Decree 900/2015 (Ministerio de Industria Energía y Turismo de España, 2015), generation facilities (including PV panels and storage devices) must be in a different circuit from the load and are metered separately. In this study, the above-mentioned balance is simplified and assumed to take place on a bus connected to the distribution grid.

3.3 Overview of the optimization model

The objective of the study is to maximize the consumers' benefit by optimizing the expansion planning for the appliances including solar panels and batteries. The benefit is defined as the savings a household can recognize by taking advantage of proper installations and optimized scheduling. The process of the proposed optimization model is shown in Figure 14.

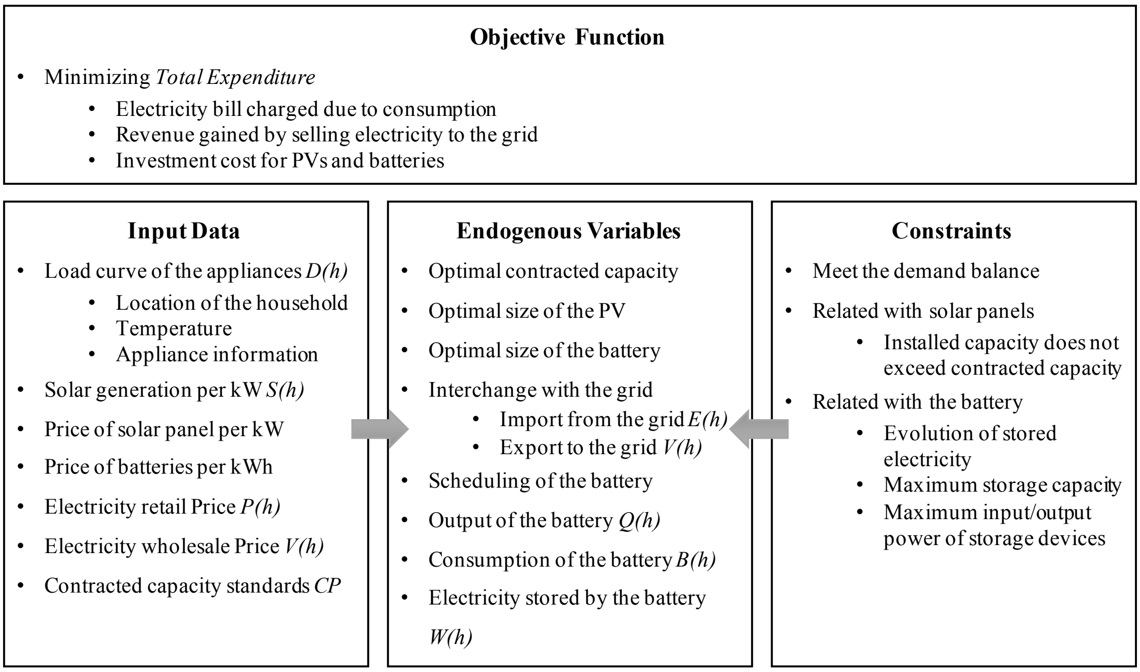


Figure 14 Overview of the optimization model

It should be noted that the load profiling of a household is a crucial however hard to obtain. In this thesis, a bottom-up stochastic model is built to generate load curve of different types of households in different regions in Spain. Bottom-up model build up the total load of a specific household (usually either representative or simply target consumers) from the elementary load components of pieces of single end-uses (Grandjean, et al., 2012, Fischer, et al., 2016, Marszal-Pomianowska, et al., 2016). Compared with using the aggregated data, the bottom-up method shows advantage in reflecting the correct information regarding peaks and random individual factors of a single household.

CHAPTER 4:

LOAD CURVE GENERATION MODEL

Modeling the household electricity consumption is the first step in exploring the possible demand response solutions and determining the optimized combination of renewable devices under different tariff schemes. The chosen approach will be based on load profile modeling. Basically, household load profiling includes the details on the electrical appliances, their consumption pattern and their load distribution in a specific time period with a determined temporal evolution. In this chapter, a bottom-up stochastic model is built to generate load data of households in different regions in Spain.

To achieve the objective of the study, which is exploring the opportunity of minimizing the electricity bill by adopting distributed generation and storage devices under different tariff schemes, the load profiling generation model should fulfil the following requirements:

- The model should be parametric in order to allow scenario analysis.
- The model should be technically explicit: the impacts of specific simulated elements (appliances, equipment) should be modelled explicitly to allow further adjustments and management.
- The model should be suitable for expansion: new elements can be added to allow modeling different households (different size, number of people and regions) and different appliances (i.e. PV panels, batteries, new appliances, etc.).
- The model should be able to return results at different levels to allow further research (i.e. household, building, area, city, etc.).
- The temporal resolution should be smaller than one hour (1-min, 15-min, 60-min).
- The model should include all the major domestic end-uses in Spain: heating, air conditioning, domestic hot water and so on.
- The model should generate stochastic data to better model human behavior.

- The model should be validated with published real data.

This section is organized as follows. Firstly, the literature is reviewed in order to present the current household electricity modeling methods. Then, an outline of the bottom-up model is introduced with mathematical descriptions followed. Following that, it is detailed how the appliances are selected and modeled. Finally, the load curve generated by the model is introduced and validated.

4.1 Literature review on household electricity demand curve modeling

Modelling of household electricity consumption is not a recent research topic. Instead, since 1940s, Hamilton (1942) started load-curve analyses focusing on the properties of synthetic curves (which now are called aggregated load curves). With the increasing need of better power system prediction and planning, many works exploring the household electricity demand curve with different temporal evolutions and space scale considerations have been published (Grandjean, et al., 2012).

4.1.1 Load curve modeling approach

Historically, the methods can be divided into two categories: top-down and bottom-up approaches. This classification is based on the hierarchal position of data inputs as compared to the housing sector as a whole (Swan, and Ugursal, 2009) and is explained by Figure 15 (Grandjean, et al., 2012).

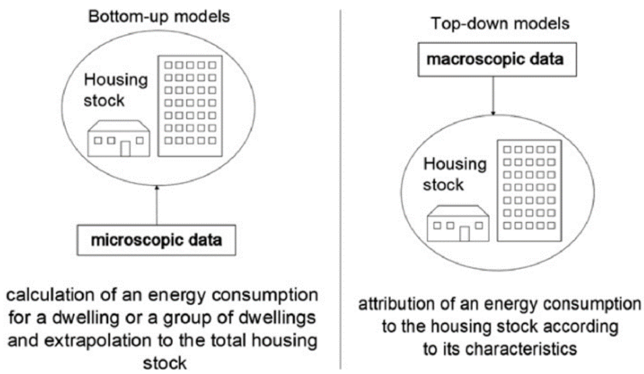


Figure 15 Top-down and Bottom-up Models

To meet the requirements of specific scopes and benefit from both approaches, some hybrid models were also developed. Grandjean, et al. (2012) reviewed the near researches and improved this classification and defined five types of models:

Table 2 Proposed classification of the load curve models by Grandjean, et al. (2012)

Top-down models	Deterministic statistical disaggregation model	This approach consists of disaggregating measured load profiles to identify various appliances. Diversity is not modelled but embedded in the measured data.
Bottom-up models	Statistical random model	This approach is usually used to generate load curve based on appliances usage. Statistical data is used to reconstitute the diversity. Random procedure is applied to generate variations for a given scenario.
	Probabilistic empirical model	Real collected data concerning domestic habits of people is used to reconstitute the diversity. Probabilistic procedures are applied to generate diversity of results.
	Time of use (TOU) based model	Real and precise data concerning the behavior of people (usually Time of Use Survey) is used.
Hybrid models	Statistical engineering model	The diversity can be embedded both in the measured data (i.e. dwelling characteristics, weather data, penetration rates, etc.) and the statistical coefficients that adjust the original results. These coefficients are calculated with the help of measured load curves and socio-economic.

As discussed in Table 2, top down models consider situations as a whole and try to generate or predict the studied variables starting with aggregated data. A typical example is the use of the total load curve (i.e. the aggregated load curve) to differentiate the individual contribution of household appliances (Aigner, et al., 1984, Bartels, et al., 1992, Pipattanasomporn, et al., 2014). Compared with the other two approaches, the method is simple and its requirement for data is less complex. However, aggregated data fails to represent the consumption peaks as well as several random factors of specific households which are important electricity bill determining factors. For example, two households seldom turn on a high-power appliance at the same time. On the other hand, the aggregated load curve represents the average electricity consumption of many households. As a result, the volatility of aggregated load is expected to be smaller than that of a single household.

Bottom-up models, on the contrary, build up the total load of a specific household (usually either a representative one or possibly that of targeted consumers) from the elementary load components of single end-uses (Grandjean, et al., 2012, Fischer, et al., 2016, Marszal-Pomianowska, et al., 2016). Hence, the peak and individual factors can be modeled by this approach, which makes the calculation of household electricity bill more accurate. Another advantage of that approach is that the effects of the different appliances on the total load are modeled individually. That enables the model to be helpful in future studies of smart grid and demand response, when different appliances or different penetration levels of existing ones became prevalent.

4.1.2 Load curve build up methods

One disadvantage of the bottom-up approach is that the construction of the model is quite dependent on detailed and precise data, which are difficult to obtain. The required input data can be the individual consumption of the appliances and their technical properties, weather information, geometrical and thermal properties of the modelled dwellings, electricity bills, human behavior, and so on. This is also reflected in Table 2. Based on the input data's level of detail, Grandjean, et al. (2012) classifies bottom-up models into three categories with increasing complexity and level of detail: statistical random models (Yao, and Steemers, 2005), probabilistic empirical models (Stokes, 2005, Paatero, and Lund, 2006, Chuan, et al., 2014), and time of use models (Walker, and Pokoski, 1985, Capasso, et al., 1994, Widén, et al., 2009, Fischer, et al., 2016). The selection of the approach is therefore dependent on the availability of data. In fact, all the three types of data are available in Spain but are not accurate or reliable enough.

Time of use models are considered to use the most comprehensive information about the timing of human activities. In these models, the consumers' usages of appliances are usually obtained from the national Time Use Surveys. The time use survey in Europe, known as Harmonized European Time of Use Survey (HETU), is compiled by Eurostat at the European level. The study was conducted by asking people to fill in diaries for three days and the results were summarized for 10-minute intervals. Torriti (2014) reviewed the models built with time of use data. However, the nation-wide time use surveys in which HETU is based on are seldom conducted. Actually, the latest time use survey in Europe was the 2009 Spanish Time Use Survey. In this case, the evolution in the use of electronic devices as well as the advancement of the appliances themselves call for a careful consideration of changes in the consumers' usage (Torriti, 2014) and the collection of periodically updated information (Grandjean, et al., 2012). Luckily, though the usage of appliance varies, the occupancy and mobility patterns (i.e. when consumers are at home and awake) may not have changed dramatically(López-Rodríguez, et al., 2013, Torriti, 2014). In any case, residential electricity demand profiles are highly correlated with the timing of active occupancy (lan Richardson, Murray Thomson, David Infield, 2010, Torriti, 2014) This argument creates the opportunity to use occupancy probability taking the place of detailed time of use data. Hence in this study, the probabilistic bottom-up approach is applied taking advantage of real occupancy information and probabilistic process.

After determining the approach, feasible techniques are to be discussed. Based on the former discussed objectives, two factors may limit the selection of techniques: the time resolution and the range of appliances. Grandjean, et al. (2012) reviewed the researches before 2012 and presented them in Figure 16. As can be seen from the works till 2012, there is a lack of model with fine time resolution (1-15 min) and complete range of appliances. lan Richardson, et al. (2010) made use of 10 min 'presence at home and activities' profiles constructed 21,000 daily diaries and determined the probability of turning on the appliances. However, they failed to included seasonal effects and modeled heating as a determined consumption. Stokes (2005) established a very detailed model which can be split into three levels. In her work, she also presented the individual load curves of each appliance. However, her model is built based on large amount of detailed data, such as total load curves of 1200 clients, end-use load curves of 175 households with 9 end-uses, heating and domestic hot water data, and so on. These data are too difficult to reach and thus her method is hard to be reproduced for the case of Spain. Yao and Steemers (2005) presented a bottom-up model called Simple Method of formulating Load Profile (SMLP). In their model, however, the total consumption and working period of each appliance are determined. As a result, they fail to take into account the occupancy factor.

In recent years, load curve generation has remained a hot topic and many new researches has been developed. Chuan, et al. (2014) built a bottom-up mathematical model to simulate the load profile for different type of households. The residential households in their study are classified into 1 or 2-room unit, 3-room unit, 4-room unit and 5-room unit. Depending on the household type, a set of electrical appliances, their saturation level, the power rating and the utilization pattern are determined. The process is simple and the result has been verified. Chuan's model can be helpful for this study as a foundation. However, there are two complements to be added. Firstly, the seasonal effect should be introduced. Chuan's model studies the case of Singapore, where seasonal effect can be neglected. Conversely, the consumption by heating and cooling is significantly influenced by the season in Spain. Secondly, Chuan et al. fail to model households' consumption habits and occupancy. Though their work has been verified against real data, the results can still be criticized as too rough. Hence, this study improves Chuan's work and the occupancy of Spanish household (López-Rodríguez, et al., 2013) is added.

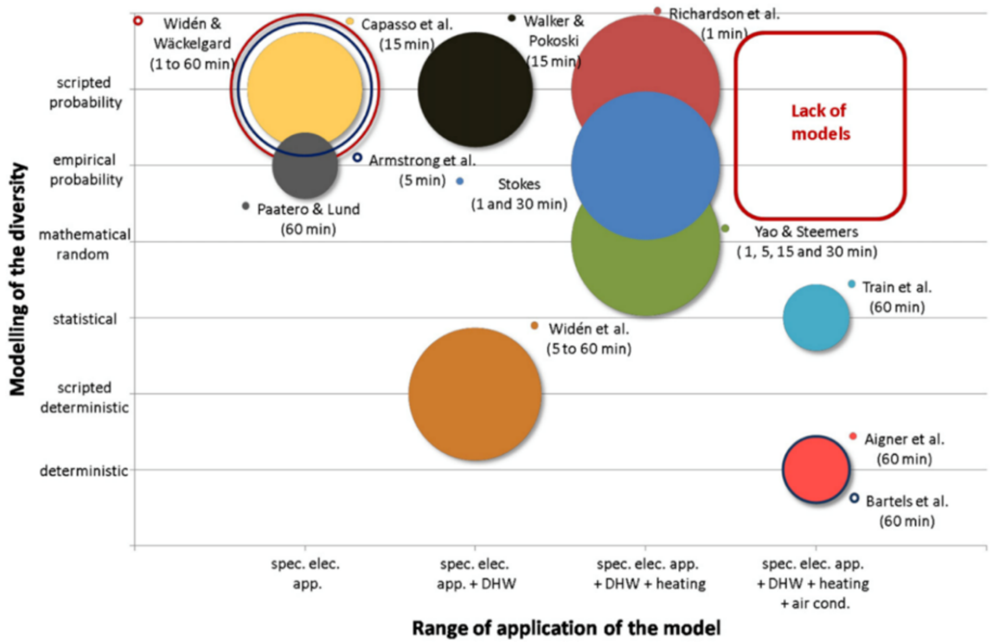


Figure 16 Cross analysis diagram of the load curve models from Grandjean, et al. (2012)

4.2 Outline of the bottom-up model

Based on the above-mentioned requirements as well as the data availability, a bottom-up probabilistic approach is applied in this study. In the model, the appliances are modeled separately with certain input data and their probability of being turned on. It is able to generate three types of curves:

1. 1-min, 15-min and 60-min resolution load curve for a typical family.
2. Status of each appliance along each minute
3. Number of appliances working in each minute for the selected family

The input data and sources for the load curve generation model are presented in Table 3.

Table 3 Input data and sources for the load curve generation model

Data	Details	Source
Temperature data	Daily population-weighted average temperature in 52 provinces in Spain	From AEMET, average daily temperatures of stations are used, population data from National Institute of Statistics
Household information	Household type Number of people	SECH-Project (2011)
Appliance information	List of appliances Saturation level Nominal wattage	(Stevens, et al., 2009, Widén, et al., 2009, IDAE, 2011, Chuan, et al., 2014, Pipattanasomporn, et al., 2014, Marszal-Pomianowska, et al., 2016)
Appliances' consumption pattern	Mean daily starting frequency; Time per cycle; Usage probability distribution	(Ian Richardson, Murray Thomson, David Infield, 2010, Chuan, et al., 2014, Torriti, 2014, Marszal-Pomianowska, et al., 2016)

Figure 17 presents the process of the load curve generation model. Firstly, the start-up probability of the appliances in each minute is calculated with the input data. Secondly, the start-up decisions of the appliances are modeled with a Mathematical algorithm. By adding the working time per cycle, the working conditions (0/1) of the appliances can be modeled and the load curves for single appliances can be calculated by multiplying the working conditions with the nominal wattages. Finally, the overall household load curve is generated by accumulating the entire individual appliance load curve.

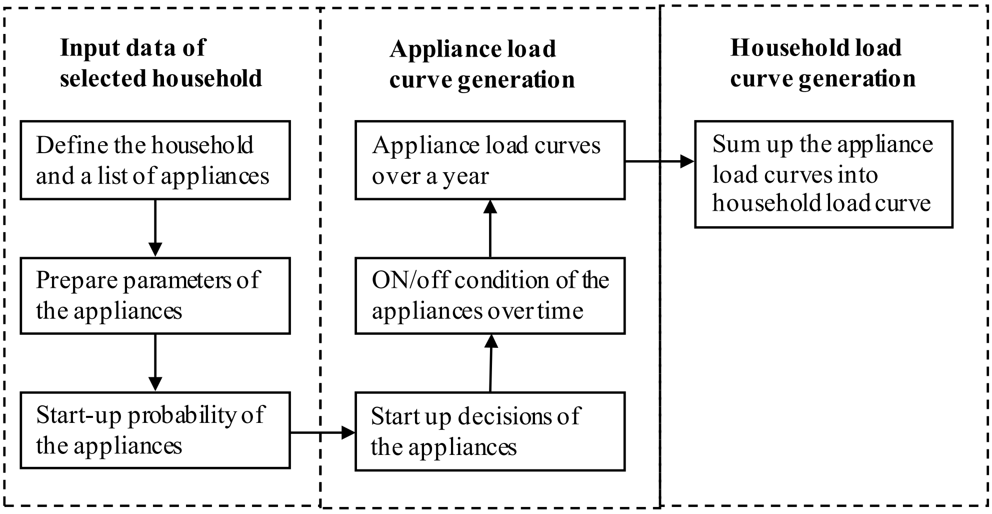


Figure 17 Diagram for bottom-up load generation procedure by Chuan, et al. (2014)

4.2.1 Type of household and appliance possession

The selection of the household is based on Encuesta Continua de Hogares (the Continuous Household Survey, ECH). ECH is a survey that provides yearly information on the basic demographic characteristics of the population, the households they make up, and the dwellings they inhabit (Instituto Nacional de Estaadistica, 2015). The information is disaggregated by autonomous communities and provinces. The latest version, reflecting 2015 data, is dated April 2016.

Table 4 and Figure 18 present the number of households by type of household and number of rooms of the dwelling. As can be seen from the figure, 5-room household takes the highest proportion in almost all types of household. On the other hand, households with couples with children who live at home are 34.08% of the total, exceeding other types and becoming the most common type. Hence the project focuses on modelling 5-bedroom dwellings inhabited by couples with children. However, it should be taken into account that there are other types of dwellings, and that their prevalence is different in the different provinces. On the other hand, keeping the same kind of dwelling nationally allows to assess regional effects.

Table 4 Household types and their composition

Units: thousands of homes	Total	1-room	2-room	3-room	4-room	5-room	6-room	7-room	8-room	9-room	10-room
Total (type of household)	18,346	63	253	768	2,759	7,261	4,185	1,662	770	335	291
One-person	4,584	42	176	390	995	1,709	784	267	125	55	43
Single parent	1,898	4	11	54	270	775	462	182	80	32	28
Couple without children living at home	3,875	11	46	178	642	1,526	880	323	148	62	61
Couple with children who live at home:	6,253	3	12	102	640	2,609	1,640	708	314	128	97
Couple with children living at home: 1 child	2,906	3	7	65	379	1,239	708	295	122	48	40
Couple with children living at home: 2	2,779	..	5	31	224	1,166	766	330	153	61	42
Couple with children who live at home: 3 or more children	569	..	1	6	36	204	166	83	39	19	15
Family nucleus with other people who do not form a family nucleus	786	..	0	12	74	286	195	97	63	29	30
People who do not form any family nuclei	571	3	7	29	111	216	125	42	16	11	11
Two or more family nuclei	380	..	1	5	27	140	100	43	25	18	22

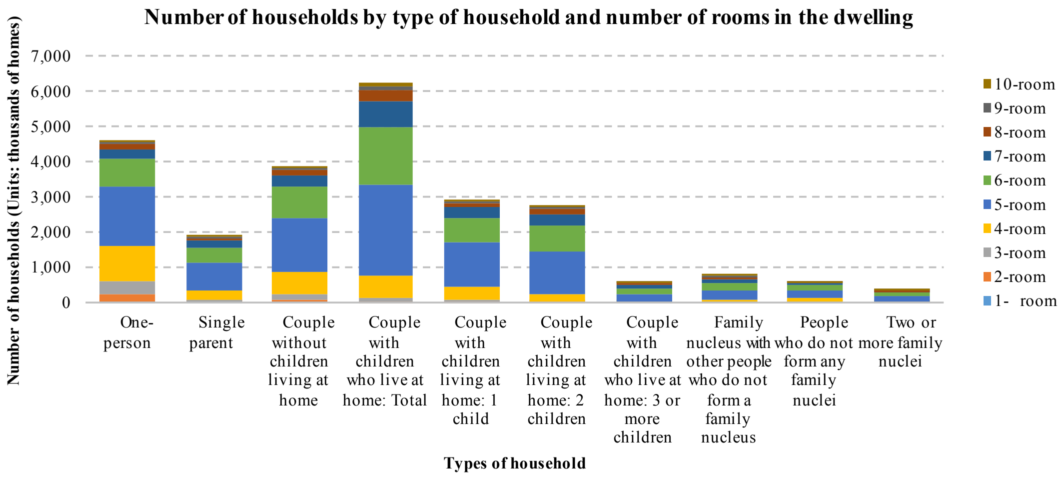


Figure 18 Number of households by type of household and number of rooms in the dwelling

The number of appliances in households are based on the result of SECH-Project (2011). The SECH-Project (2011) divides Spain into three climate zones and presents the equipment ownership of households in each climate zone.

4.2.2 Appliance data and profiles

Input appliance data for this study includes the saturation level, nominal wattage, mean daily starting frequency, time per cycle and daily usage probability distribution. Saturation level stands for the percentage of possession of a specific appliance. To determine the list of appliances and their saturation level, results from SECH-Project (2011) are used. In the SECH-project, households in Spain are categorized based on the type of dwelling and climate region. The list comes from the most common appliances used in Spanish households. The saturation level is the average saturation of households at the corresponding region. The other three variables (nominal wattage, mean daily starting frequency, and time per cycle) may not be very different from country to country. Besides, there are few sources for Spain. Hence, data from other countries including Sweden (Widén, et al., 2009), Singapore (Chuan, et al., 2014), the U.S. (Stevens, et al., 2009, Pipattanasomporn, et al., 2014) and Denmark (Marszal-Pomianowska, et al., 2016) are used. The appliance data are presented in Table 5. The nominal wattage of heater and air conditioner are not fixed. This is based on the fact that heating and cooling consumption is significantly influenced by the temperature. In this study, it is assumed that the starting frequency and time usage are not constant even though the daily consumption changes.

Table 5 Nominal power, daily starting frequency and time per cycle

Appliances	Saturation [%]	Nominal Wattage [W]	Mean daily starting frequency	Time per cycle [min]
Heating	40.0	-	40.5	6.0
Air Conditioning	49.0	-	40.5	6.0
Sanitary hot water	22.0	3000	10.0	7.0
Lighting	100.0	40	17.0	30.0
Lighting	100.0	40	17.0	30.0
Lighting	100.0	40	17.0	30.0
Lighting	100.0	18	15.0	30.0
Lighting	100.0	20	15.0	30.0
Lighting	100.0	40	15.0	30.0
Lighting	100.0	18	10.0	30.0
Lighting	100.0	11	10.0	30.0
Refrigerator	100.0	120	40.5	12.0
2nd Refrigerator	31.0	120	40.5	12.0
freezer	21.1	190	40.5	12.0
Clothes-washer	100.0	1200	0.8	60.0
Dishwashers	41.7	1100	1.0	40.0
TV	100.0	150	2.0	90.0
2nd TV	28.0	139	0.3	60.0
Hair dryer	16.0	1500	1.8	7.0
Range oven	79.7	2000	3.0	12.0
Microwave oven	87.5	1500	7.5	4.0
Computer (Desktop)	49.5	126	3.9	60.0
Computer (Laptop)	36.8	27	4.0	60.0
Standby	100.0	30	24.0	60.0
Other appliances	100.0	80	8.0	50.0

Daily starting frequency represents the times the appliance is started up in a day. However, in each hour or in each minute, the starting up probability diverse. Hence, it is necessary to take a turning-on probability distribution into account. To better model the minutely start up probability distribution, three types of usage patterns are defined.

(1) Uniform distributed: the start-up probability is the same for every minute in the day. The appliances in this category are refrigerator, freezer, and the standby load.
(2) Heating and cooling: the start-up probability is uniformly distributed in specific time periods (19:01-24:00, 5:01-8:00).
(3) Occupancy distributed: the start-up probability is based on whether there are people at home. The occupancy of Spanish households comes from aggregated data from Santiago, et al. (2014).

Table 6 Three types of turning-on probability pattern

	1	2	3	4	5	6	7	8	9	10	11	12
Uniform	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%
Heating	0.0%	0.0%	0.0%	0.0%	0.0%	12.5%	12.5%	12.5%	0.0%	0.0%	0.0%	0.0%
Occupancy probability	1.9%	0.5%	0.1%	0.1%	0.1%	0.2%	1.9%	4.6%	4.6%	5.6%	5.6%	4.6%

	13	14	15	16	17	18	19	20	21	22	23	24
Uniform	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%	4.2%
Heating	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	12.5%	12.5%	12.5%	12.5%	12.5%
Occupancy probability	5.1%	5.6%	6.7%	6.5%	5.7%	5.6%	5.6%	5.6%	6.5%	7.6%	6.5%	3.7%

4.2.3 Mathematical algorithm for individual appliance load curve

Once the appliance list is known, a mathematical model is required to generate the load curve. The idea is that when the appliance is activated, its rated load will be added to the household's total load consumption at the corresponding time until it completes a full cycle of a single activation.

To deal with that, a turning-on probability factor $P_{start\ (appliance,\ hour)}$ is introduced. $P_{start\ (appliance,\ hour)}$ is defined for each appliance in order to describe the activity level of the appliance in an hourly basis. It is assumed that the probability of turning-on the appliance is the same in each minute. The value of $P_{start\ (appliance,\ hour)}$ represents the probability of turning-on the appliance in each minute of each given hour. Higher $P_{start\ (appliance,\ hour)}$ means higher chance for the appliance to be turned on, and vice versa. $D_{start\ (appliance,\ minute)}$ is defined for each minute as a turning-on decision. At the beginning of each computational time step, a random number between 0 and 1 is generated by the computer and is compared with $P_{start\ (appliance,\ hour)}$. $D_{start\ (appliance,\ minute)}$ is 1 when $P_{start\ (appliance,\ hour)}$ is greater than the randomly generated number. Turning-on probability is calculated using the following equation:

$$P_{start(appliance,hour)} = P_{pattern} * Saturation * Daily\ starting\ frequency * Time\ per\ cycle$$

The minutely turning-on probability of each appliance is calculated applying this equation and is shown in Table 7.

Table 7 Turning-on probability

	1	2	3	4	5	6	7	8	9	10	11	12
Heating	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%
Air Conditioning	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%	100.0%	0.0%	0.0%	0.0%	0.0%
Sanitary hot water	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%
Lighting	0.5%	0.1%	0.0%	0.0%	0.0%	0.1%	0.5%	1.3%	1.3%	1.6%	1.6%	1.3%
Lighting	0.5%	0.1%	0.0%	0.0%	0.0%	0.1%	0.5%	1.3%	1.3%	1.6%	1.6%	1.3%
Lighting	0.5%	0.1%	0.0%	0.0%	0.0%	0.1%	0.5%	1.3%	1.3%	1.6%	1.6%	1.3%
Lighting	0.5%	0.1%	0.0%	0.0%	0.0%	0.0%	0.5%	1.2%	1.2%	1.4%	1.4%	1.2%
Lighting	0.5%	0.1%	0.0%	0.0%	0.0%	0.0%	0.5%	1.2%	1.2%	1.4%	1.4%	1.2%
Lighting	0.5%	0.1%	0.0%	0.0%	0.0%	0.0%	0.5%	1.2%	1.2%	1.4%	1.4%	1.2%
Lighting	0.3%	0.1%	0.0%	0.0%	0.0%	0.0%	0.3%	0.8%	0.8%	0.9%	0.9%	0.8%
Lighting	0.3%	0.1%	0.0%	0.0%	0.0%	0.0%	0.3%	0.8%	0.8%	0.9%	0.9%	0.8%
Refrigerator	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%
2nd Refrigerator	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%
Freezer	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%
Clothes-washer	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%
Dishwashers	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
TV	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%
2nd TV	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Hair dryer	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Range oven	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%
Microwave oven	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.2%	0.5%	0.5%	0.6%	0.6%	0.5%
Computer (Desktop)	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%	0.2%	0.1%
Computer (Laptop)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%
Standby	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%
Other appliances	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.2%	0.6%	0.6%	0.7%	0.7%	0.6%

	13	14	15	16	17	18	19	20	21	22	23	24
Heating	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Air Conditioning	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Sanitary hot water	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.3%	0.2%	0.1%
Lighting	1.4%	1.6%	1.9%	1.8%	1.6%	1.6%	1.6%	1.6%	1.8%	2.1%	1.8%	1.0%
Lighting	1.4%	1.6%	1.9%	1.8%	1.6%	1.6%	1.6%	1.6%	1.8%	2.1%	1.8%	1.0%
Lighting	1.4%	1.6%	1.9%	1.8%	1.6%	1.6%	1.6%	1.6%	1.8%	2.1%	1.8%	1.0%
Lighting	1.3%	1.4%	1.7%	1.6%	1.4%	1.4%	1.4%	1.4%	1.6%	1.9%	1.6%	0.9%
Lighting	1.3%	1.4%	1.7%	1.6%	1.4%	1.4%	1.4%	1.4%	1.6%	1.9%	1.6%	0.9%
Lighting	1.3%	1.4%	1.7%	1.6%	1.4%	1.4%	1.4%	1.4%	1.6%	1.9%	1.6%	0.9%
Lighting	0.8%	0.9%	1.1%	1.1%	1.0%	0.9%	0.9%	0.9%	1.1%	1.3%	1.1%	0.6%
Lighting	0.8%	0.9%	1.1%	1.1%	1.0%	0.9%	0.9%	0.9%	1.1%	1.3%	1.1%	0.6%
Refrigerator	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%	2.8%
2nd Refrigerator	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%
Freezer	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%	0.6%
Clothes-washer	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%
Dishwashers	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
TV	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%
2nd TV	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Hair dryer	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Range oven	0.2%	0.2%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.1%
Microwave oven	0.6%	0.6%	0.7%	0.7%	0.6%	0.6%	0.6%	0.6%	0.7%	0.8%	0.7%	0.4%
Computer (Desktop)	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%
Computer (Laptop)	0.1%	0.1%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.1%
Standby	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%	1.7%
Other appliances	0.7%	0.7%	0.9%	0.9%	0.8%	0.7%	0.7%	0.7%	0.9%	1.0%	0.9%	0.5%

4.3 Appliance data and profiles

4.3.1 Boundary discussion

Many researchers have studied the residential household electricity load characteristics and discovered the existence of some seasonal, daily and hourly periodical patterns. These patterns are often believed to be dependent on external variables such as the outside temperature and the daylight hours (Widén, et al., 2009, Blázquez, and Filippini, 2012). As can be seen in Figure 19 and Figure 20, the electricity consumption in Spain has a high seasonal pattern. A number of researchers has proved that Spanish electricity consumption is significantly correlated with temperature (Pardo, et al., 2002, Blázquez, and Filippini, 2012). Considering the trade-off between simplicity and accuracy, the effect of daylight time is neglected. The idea is that the existence of a correlation between temperature and daylight time may allow temperature to also explain part of the variance explained by the daylight time.

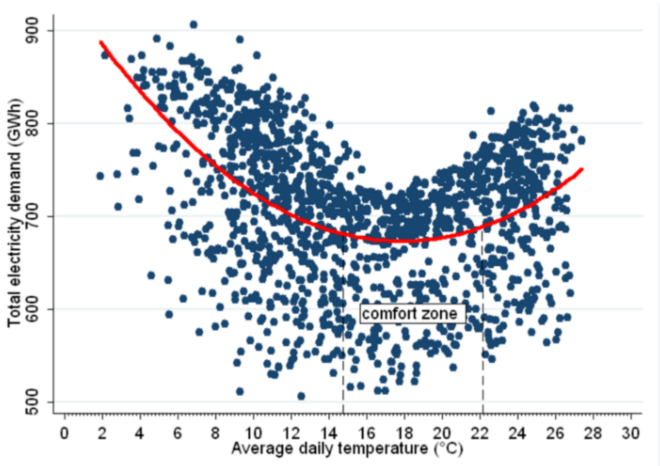


Figure 19 Response of total daily electricity demand to daily average outside temperature 2007-2010 (Blázquez, and Filippini, 2012)

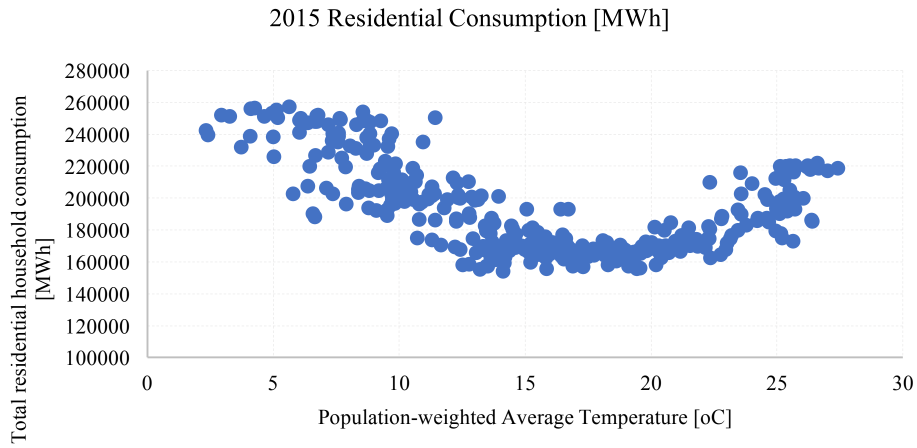


Figure 20 Residential consumption in 2015 (From ESIOS, daily residential consumption is calculated as the sum of measured demand by access rate 2.0 low voltage general <10 kW and Measured demand by access rate 2.1 low voltage general ≥10 kW and <15 kW)

The hourly or daily fluctuation of household loads is also influenced by the effect of consumer availability and activity level. For example, the average daily consumption during day-time is typically lower than that in the weekends due to not present at home, while the consumption is higher in the weekend evenings. However, due to time and resource constraints, the load discrepancy between weekdays and weekends is ignored in the study.

Besides the above-discussed factors, the load curve is also affected by some uncertain factors such as events, holidays, abnormal weather, and so on. For instance, a popular football match or national holiday celebrations may make variations not only to the household load curve, but also to the national network. However, these factors are also neglected in this study for they are too detailed when the scope is focused on a yearly level.

To build a typical household load, a list of commonly used appliances is selected. The selection is based on the result of IDAE (2011) as shown in Figure 21.

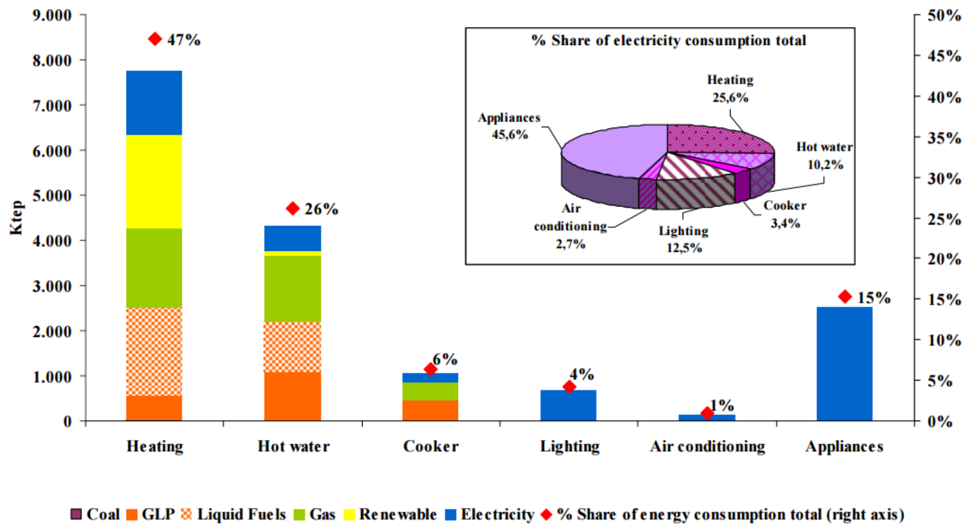


Figure 21 Final energy consumption in Spanish households by fuel and use (2009) (IDAE, 2011, Blázquez, and Filippini, 2012)

In this study, to model the load characteristics of appliances, two categories of appliances are identified: first, loads influenced by the temperature, second, loads not influenced by the temperature. The former category includes heating and cooling and the latter category includes the other appliances.

4.3.2 Heating and cooling

Heating and cooling consumption mostly depends on the temperature. In Spain, heating and cooling account for a large proportion of the total household electricity consumption, reaching 25.6% and 2.7% respectively (IDAE, 2011, Blázquez, and Filippini, 2012). Compared with the heating and cooling consumption, the hot water demand variation due to temperature changes and the lighting demand variation due to changes of sunshine time can be neglected. As a result, heating and cooling consumption becomes the only proportion that changes with temperature. In other words, compared with the electricity usage in spring and autumn, the increases of total household electricity in winter and summer are only caused by using of heaters and air conditioners respectively.

Heating and cooling consumption are modeled in the following steps:

- Firstly, determine the electricity usage without heating and cooling and thus calculate heating and cooling consumption
- Secondly, analyze the relationship between daily average temperature and daily heating/cooling consumption

- Thirdly, distribute the daily heating/cooling consumption to hourly loads

4.3.2.1 **<u>Heating/cooling consumption determination</u>**

Daily residential consumption in Spain and the corresponding daily population-weighted average temperature are plotted in Figure 22 (2015) and Figure 23 (2014). The population-weighted average temperature is calculated with a weighted population average of the provincial temperatures.

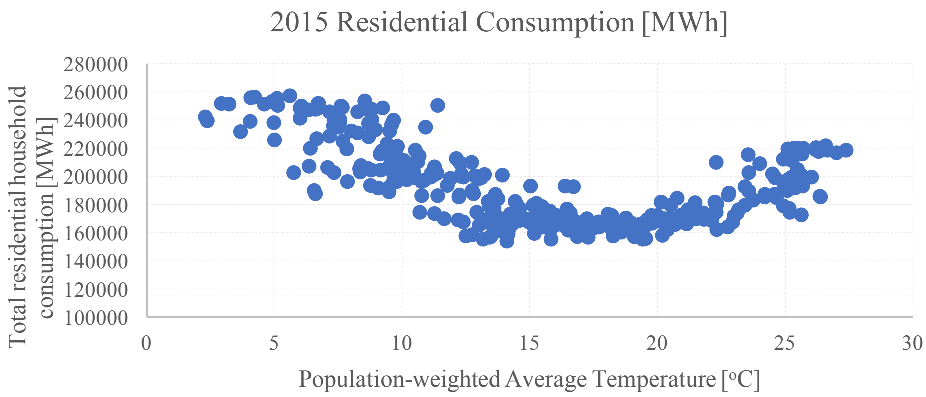


Figure 22 Residential consumption in 2015

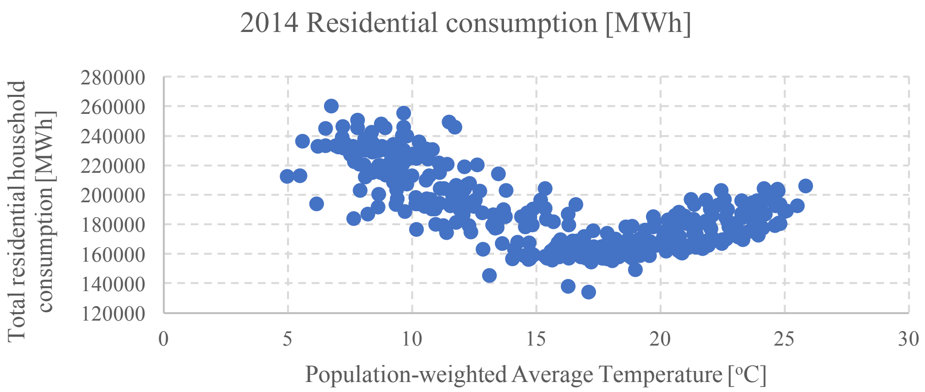


Figure 23 Residential consumption in 2014

As can be seen in the two figures, the consumption reaches the lowest at around 15-20ºC. This region is called 'comfortable zone' or 'temperature-barrier' in literatures (Blázquez, and Filippini, 2012). The 'temperature-barrier' is a threshold over or under which the heating and cooling appliances will be switched on. In order to take into account the non-linear relationship between residential demand and temperature, equations for heating and cooling are discussed separately and two climate variable, heating degree days (HDD) and cooling degree days (CDD) are applied (Moral-Carcedo, and Vicéns-Otero, 2005, Blázquez, and Filippini, 2012). HDD and CDD are defined as follows (Moral-Carcedo, and Vicéns-Otero, 2005):

$$HDD = \sum_{nd} T^* - T_t; 0$$

$$CDD = \sum_{nd} T_t - T^*; 0$$

Here, *nd* stands for days of a particular year, T^* stands for the threshold temperature of cold or heat, and T_t is the observed temperature on day t. Hence, HDD and CDD can represent the number of days on which the temperature is respectively below and above the predetermined thresholds. However, there is no absolute threshold for the comfortable zone and value is expected to be different between countries. From literatures shown in Table 8, there are several sets of thresholds for HDD (heating degree days) and CDD (cooling degree days). In this work, 15/21 threshold is used as it fits the figure best.

Table 8 Thresholds used in Spanish

HDD threshold	CDD threshold	Source
15	22	(Blázquez, and Filippini, 2012)
18	18	(Valor, et al., 2001, Pardo, et al., 2002, Blázquez, and Filippini, 2012)
13	23	(Labandeira, et al., 2011)
15	21	(Termodina, et al., 2001)

It should be noticed that the number of households is increasing with time. As shown in Table 9, the number of household increased from 18.303.100 to 18.346.200 in 2015 from 2014 level. To deal with that, the number of households should be divided by the corresponding total amount.

Table 9 Number of households in 2014 and 2015 (Instituto Nacional de Estaadistica, 2015)

	Year 2014	Year 2015
Households	18,303,100	18,346,200
Average size of the household	2.51	2.51
Most common types of household:		
Single person younger than 65	2,681,400	2,724,400
Single person older than 64	1,853,700	1,859,800
Childless couples	3,978,600	3,874,800
Couples with children	6,333,800	6,253,100
Mother and children or father and children	1,754,700	1,897,500

Average daily consumption without heating or cooling (AC), daily heating ($C_{heating}$) and cooling ($C_{cooling}$) consumptions are calculated based on the following equations:

$$AC = \frac{\sum_{d}^{365} C_d}{365 - HDD - CDD}$$

$$C_{heating} = C_t - AC; \quad t \in HDD$$

$$C_{cooling} = C_t - AC; \quad t \in CDD$$

Applying the equations to the data, the following statistics (shown in

Table 10) based on 2015 data can be obtained. The correlation between heating/cooling consumption and HDD/CDD are checked and presented in Figure 24 and Figure 25.

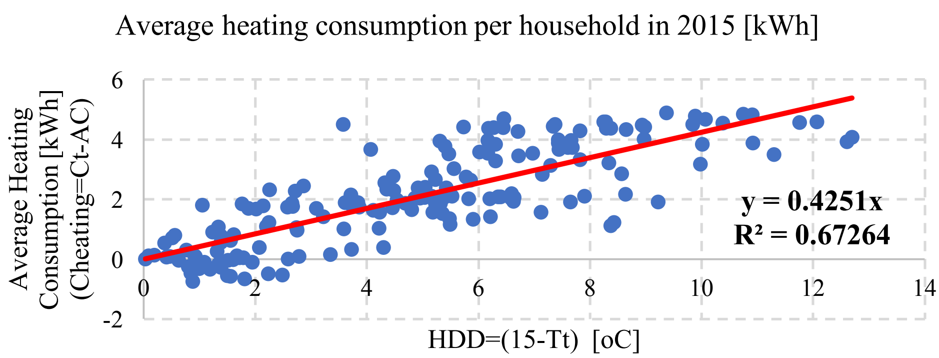


Figure 24 Average heating consumption and HDD

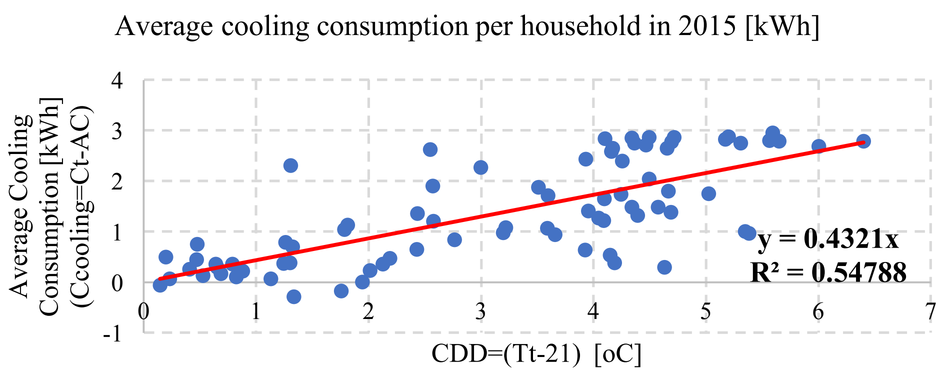


Figure 25 Average cooling consumption and CDD

Table 10 Statistics and comparison with data from IDAE (2011)

	Year 2015	Year 2009
HDD days	177	
CDD days	78	
AC [kWh]	9.14	
Sum of residential consumption per year [MWh]	6.99E+07	6.00E+07
Average yearly residential consumption [kWh]	3812.60	
Average yearly heating consumption [kWh]	370.75	
Percentage of heating consumption	9.72%	7.41%
Equation	Cheating= 0.4251*HDD	
Explained variance	0.67	
Average yearly cooling consumption [kWh]	97.95	
Percentage of cooling consumption	2.57%	2.31%
Equation	Ccooling= 0.4321*CDD	
Explained variance	0.55	

Unlike other appliances, the load coming from heaters and air conditioners has the following features: firstly, the operation of heaters and air conditioners is continuous. In other words, once the appliance is turned-on, consumers prefer to keep it working for a long cycle. Secondly, those two appliances seldom work on their nominal power. Instead, their power is dependent on the temperature. As a result, the working powers of heaters and air conditioners are determined by the daily consumption rather than their nominal power. Once the daily consumption on heating or cooling is determined, the consumption is uniformly distributed during 19:01-24:00 and 5:01-8:00.

4.3.3 Other appliances

As discussed before, the appliances modeled in this study are categorized into three categories based on the pattern of usage: heating and cooling (power determined by the temperature), uniformly working (such as refrigerators and stand-by power), and working depending on occupancy (such as lighting or TV).

In this study, the usages of the following appliances are supposed to be dependent on occupancy: sanitary hot water, range oven, microwave oven, lighting, clothes-washer, dishwasher, TV, hair dryer, computers, and some other appliances.

Arguments may arise regarding the treatments of sanitary hot water, range oven and microwave, whose usage might be distributed in specific time periods. Treatment of sanitary hot water consumption is especially important since it accounts for, on average, more than 10% of the total electricity consumption for a household, while cookers account for around 5%. Hence, in depth studies should be carried on for the usage pattern of sanitary hot water. Stokes (2005) and Pipattanasomporn, et al. (2014) analyzed the real usage data of households in the U.K. and the U.S. and presented the 1-minute water-heating demand (as shown in Figure 26 and Figure 27). Pipattanasomporn's research indicates that the water-heater starts several times a day for shower, sink and retaining temperature. Unlike the Stokes' case in 2005, current usage of sanitary hot water is more divers and more spread. Hence, taking into account the spread and differences in consumers' habits, the treatment in this study is acceptable.

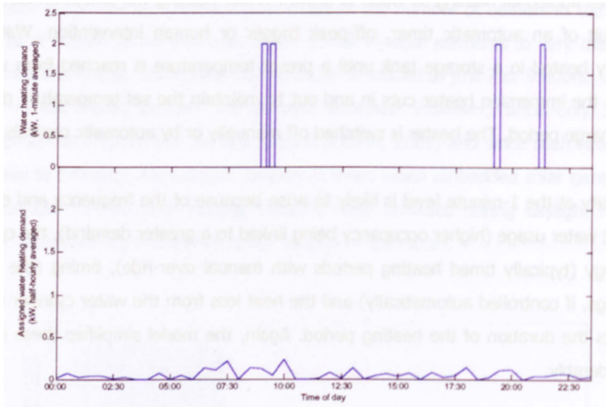


Figure 26 1-minute (top) and half-hourly (bottom) averaged water-heating demand on 21st December, 2005, U.K. (Stokes, 2005)

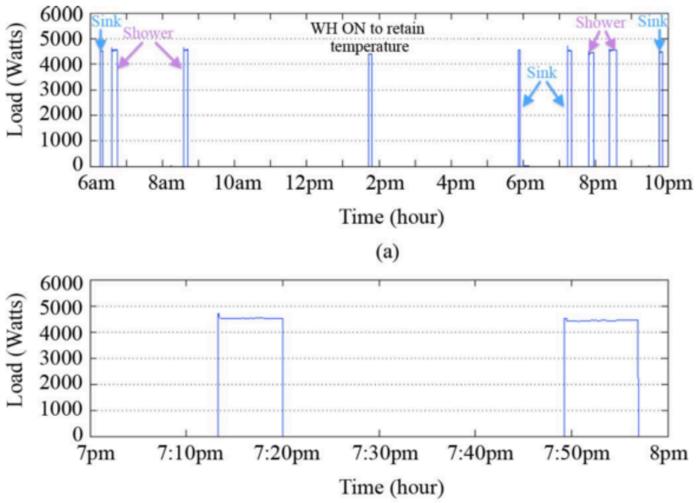


Figure 27 Load profiles of the 50-gallon water heater, showing its 14-hour operation (top) and 1-hour operation between 7 P.M. and 8 P.M., the U.S. (Pipattanasomporn, et al., 2014)

4.4 Load curve result

A case study on household with 3-4 people (a couple with 1-2 children) in Sevilla is presented to show the results of the load generation model.

4.4.1 1-minute and 60-minute load curve

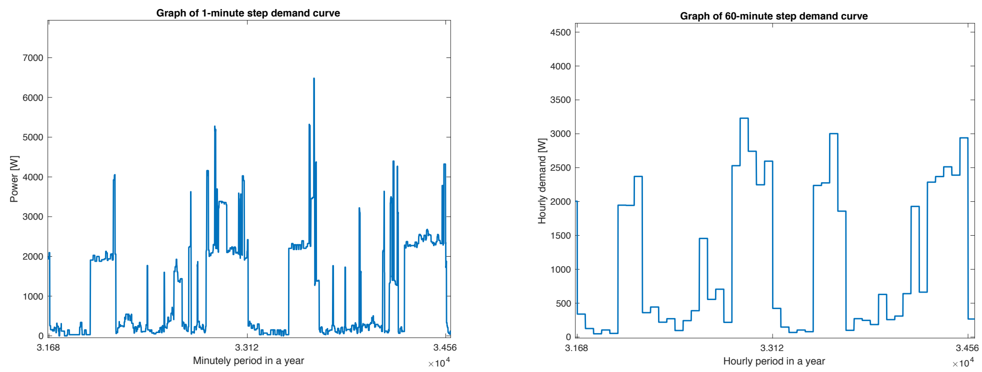


Figure 28 1-minute (left) and 60-minute (right) load curve of two random days in winter

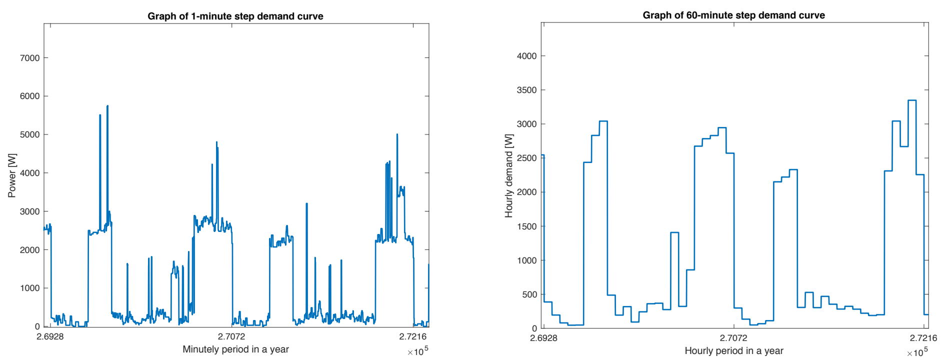


Figure 29 1-minute (left) and 60-minute (right) load curve of two random days in summer

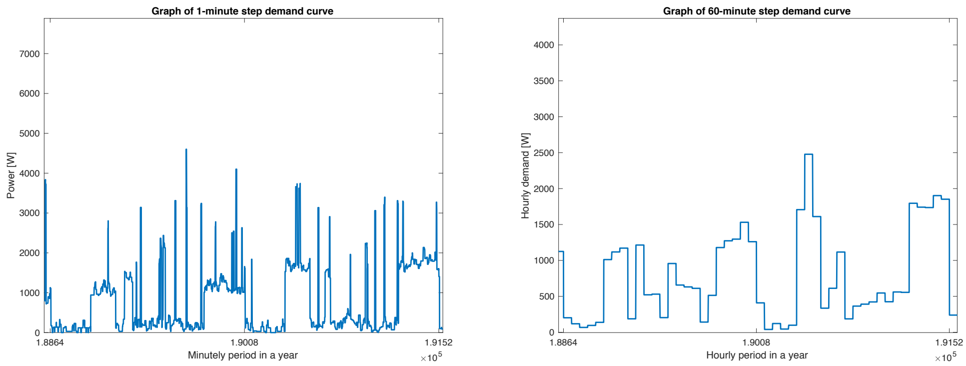


Figure 30 1-minute (left) and 60-minute (right) load curve of two random days in spring

4.4.2 Number of working appliances

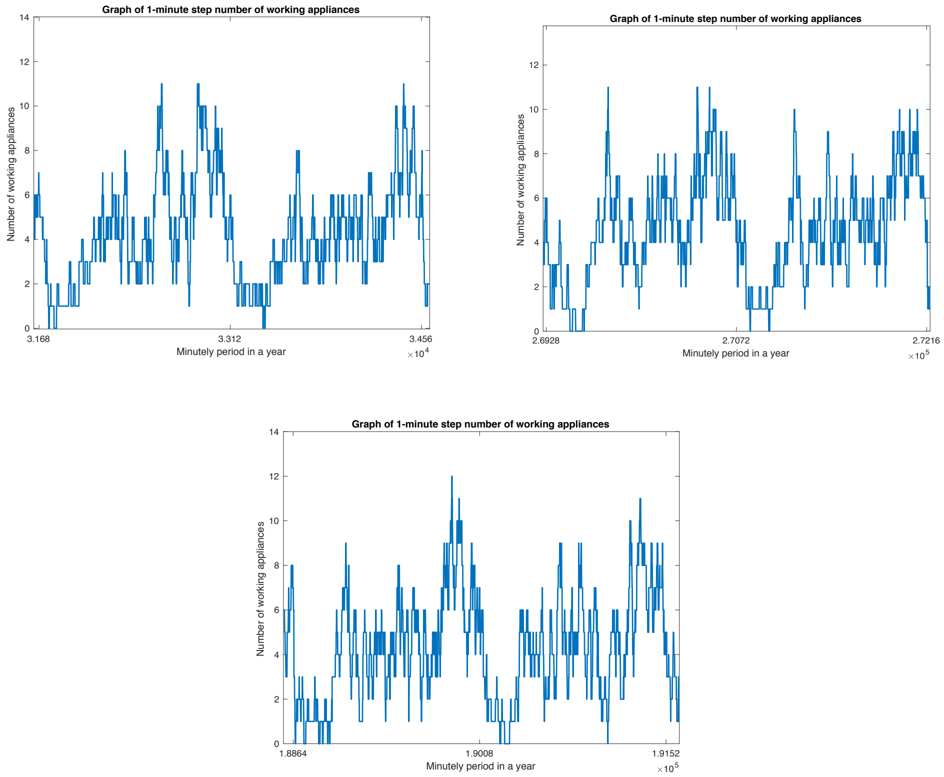


Figure 31 Number of working appliances in winter (left top), summer (right top) and spring (bottom)

4.4.3 Consumption of appliances

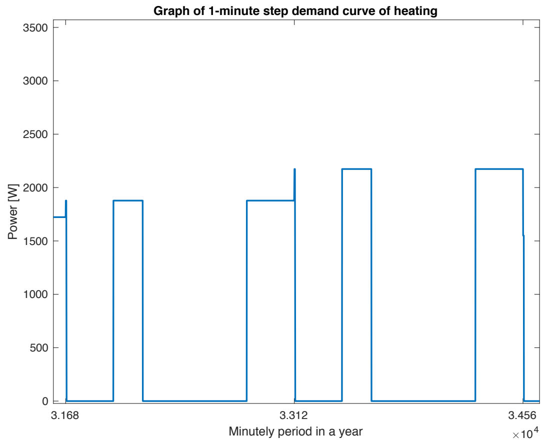


Figure 32 Heating load in winter

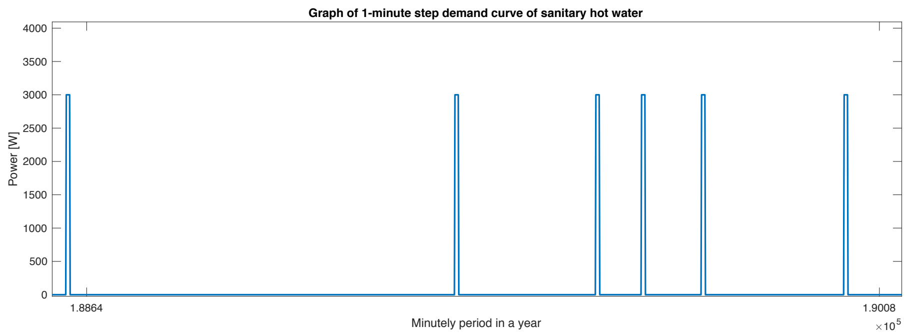


Figure 33 Sanitary hot water load

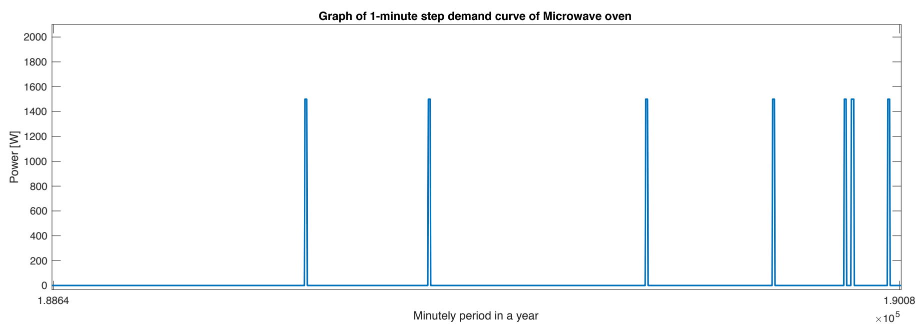


Figure 34 Microwave oven load

CHAPTER 5:

GAMS OPTIMIZATION MODEL

5.1 Objectives

As discussed in the former chapter, the residential sector is one of the major contributors in national electricity balances and is expected to be a key player in the transition toward a more sustainable future. Instead of being passive and inelastic with respect to the power grid conditions and price signals, consumers now have opportunities to actively manage their electricity consumption and benefit from their changes. However, the rapid increase and sheer number of alternatives make consumers easily dazzled due to information overload and vulnerable, as information asymmetry and lack of analytical skills become relevant issues. For example, supposing a household wants to take advantage of the different electricity prices by installing a battery, the following questions have to be answered:

Is it profitable to purchase the battery? How large the battery capacity should be?

To go one step further:

Is buying a battery the best alternative to minimize the electricity expenditure?

An unwise decision may lead not only to an economic loss for the household, but also to an overinvestment in demand side and a loss of social benefit. Fortunately, it is clear that the above-mentioned questions are to some extent linked: determining the quantity and dispatch of alternative techniques is necessary to minimize the total cost. To address these issues, studies on optimally managing the resources of users are essential.

In any case, a perfectly rational and informed customer will be assumed. That might be justified, if retail markets are competitive enough. In any case, it is an interesting reference scenario. The objective of the household electricity bill optimization model discussed in this chapter, therefore, is to explore the best investment decisions in demand side management devices (mainly solar panels and batteries) to meet the demand at minimum cost, while guaranteeing compliance with certain constraints (technical features of the equipment, requirements of the network, etc.). As discussed below, the model may be adapted to the context of a single household aiming to optimize its decisions by minimizing its expected electricity related expenditure.

The model is a one-year-term model with hourly periods, which involves working with a total of 8760 hours. To some extent, this model is indeed treated as an optimization problem for expansion planning of PV and batteries in a household. Investment in solar panels or storage devices is usually a long-term decision, ranging from 10 to 30 years. One year (the minimum cycle time) is selected as the modeling period to take into account the seasonality in household consumption, electricity prices and solar generation. Based on the current metering techniques and tariff charging standards, the electricity consumption is measured and charged in hourly periods.

Input variables for the optimization model are household demand, solar panel generation profile, estimated investment cost of solar panels and batteries, parameters of three tariff schemes.

Household´s optimal decisions are endogenous variables to be determined. From the consumers´ perspective, the model covers the best solution of investment on devices and the selection of the tariff scheme that maximizes savings. Meanwhile, the model will also return the corresponding hourly exchange (consumption and supply) with the network and the hourly management of the battery. Hence, regulators and electricity companies can also benefit from the model by having an idea of plausible demand-side changes.

The model is a long-term expansion model with both long-term and short-term decisions. In the long term, households can determine the optimal installed capacity of solar panels and batteries. These long-term decisions are endogenous variables. Once determined, they are supposed to remain the same for the whole year and the hourly electricity exchange with the network are determined based on them. In the short term (such as one day), the household has to manage the scheduling of battery’s input (consuming) and output (feeding the network or appliances) if batteries are used. It is noteworthy that batteries play a very relevant role in influencing the electricity exchange with the network and helping consumer benefit from the price differences.

To summarize, the model covers:

1. Economic profitability: the maximum saving a household can achieve while satisfying the current demand.
2. Tariff selection: which tariff scheme to select, how much capacity to contract.
3. Investment decision on devices: optimized installing capacities for solar panels and batteries.
4. Hourly optimal scheduling for battery operation and electricity exchange from the network.

5.2 Literature review on household electricity optimization modeling methods

There are a huge number of publications proposing different approaches for PV/battery expansion or battery hourly scheduling problems (power management problems) with given objective functions and constraints.

The optimization of the system is usually assessed on some economic or environmental criteria (e.g., expenditure, savings, energy savings, carbon emissions, etc.). Khatib, et al. (2016) and Rawat, et al. (2016) reviewed the objective functions of past publications and found that most of them are economic valuation ones. Some of the economic tools used are net present cost (NPC), net present value (NPV), levelized unit cost of electricity (LUCE), simple payback period (SPP) and discounted payback period (DPP) (Kandpal, and Garg, 2003, Rawat, et al., 2016). NPC is the present value of all the costs incurred during the lifespan, including initial investment, operation and maintenance cost and financial cost. NPV is the net present value that subtract the NPC from all the benefits. LUCE is the annualized cost per kWh of electricity. The SPP and DPP periods are the time it takes to recover the investment cost without/with considering the time value of money. As discussed in the former chapter, this study aims to implement a one-year-term model to maximize the net present value of all the electricity related expenditure. However, the installation of solar panels and batteries are on-off decisions with a long economic life. Hence, it is assumed that the investment cost of solar panels and batteries are paid yearly intervals and the annuity, therefore, is calculated given the net present cost and lifespan.

Four approaches are usually applied in the household PV/battery expansion models: intuitive methods, analytical methods, numerical methods and intelligent methods (Posadillo, and López Luque, 2008a, Khatib, et al., 2016, Rawat, et al., 2016).

The intuitive method is the simplest among the four methods. In this method, simplified calculations are used based on the designer's experience. The input data in this method are usually the average values, such as averages of daily load demand and daily solar radiation. Chel, et al. (2009) evaluated the optimum size of PV power system components for a location in India. The work was based on simplified mathematical expressions using daily electrical load (kWh/day) and peak sunshine hours on optimally tilted surface specific to the country. The optimum PV/battery sizing combination was obtained by minimizing the unit cost of electricity, system life cycle costs and capital costs. Many other examples can be found in Egypt (Ahmad, 2002), Bangladesh (Bhuiyan, and Ali Asgar, 2003), Jordan (Al-Salaymeh, et al., 2010) and so on. Due to the use of simplified equations and averaged estimates, the results are thought to be rough estimates and less accurate (Rawat, et al., 2016).

The analytical method is more accurate. It makes use of empirical or analytical relationships. This method tries to realize a reliable or cost effective system with mathematical modeling techniques such as time series fitting function (Markvart, et al., 2006) or distribution functions (Posadillo, and López Luque, 2008b).

The numerical method usually uses simulation-based programs to calculate the optimal size of PVs and batteries. Khatib, et al. (2016) has reviewed the size optimization techniques for PV systems and concluded that simulation based numerical methods are the most widely used technique. In this method, the input data (e.g. solar radiation, demand load) varies according to time intervals (i.e. minute, hourly or daily). Meanwhile, the output data (i.e. power generation, load requirement, battery state of charge and battery I/O power) are also calculated for each time interval. This method requires heavy computations and long-term data. Simulation software (i.e. PVSYST, Hybrid Optimization Model for Electric

Renewables (HOMER), Retscreen, System Advisory Model (SAM) etc.) or simulation environments (i.e. MATLAB, Python, TRANSYS, LABVIEW etc.) are also usually used (Rawat, et al., 2016).

Techniques to perform numerical analyses include: linear programming (LP) (Kaushika, et al., 2005, Nottrott, et al., 2012) , mixed integer linear programming (MILP) (Ha Pham, et al., 2009, Ru, et al., 2013, 2014), Lagrangian relaxation (LR) (Riffonneau, et al., 2011), dynamic programming (DP), genetic algorithms (Vrettos, and Papathanassiou, 2011), merit lists, neural networks, expert systems and so on. Among these methods, the first four are mostly applied to optimize systems with PV and batteries (Riffonneau, et al., 2011, Rawat, et al., 2016).

Linear programming (LP) and mixed integer linear programming (MILP) formulate problems on linear form. Unlike LP where variables are continuous, MILP can solve problems with binary variables and discrete integer variables (Ha Pham, et al., 2009). Kaushika, et al. (2005) presents a simulation model for the sizing of stand-alone solar PV systems with interconnected arrays and battery storage corresponding to zero values of LPSP on diurnal basis. Nottrott, et al. (2012) implemented a model to optimize the energy storage dispatch schedules for demand charge management in a grid-connected, combined photovoltaic-battery storage system. Pham, et al. (2009) calculates an optimum planning of solar PV production and the load rescheduling to satisfy the demand of user to minimize the energy cost. Ru, et al., (2013, 2014) developed a mixed integer linear program (MILP) to determine the optimal battery energy capacity for a PV system, in the context of marginal energy cost reductions to minimize the net cost of energy purchased by the customer. LP and MILP requires low computing resources and can provide good results (Riffonneau, et al., 2011). This advantage makes LP and MILP a hot method in solving problems in electricity sector and they are believed to be the most successful techniques (Gonzalez, 2014). However, the main drawback is that it is unable to accommodate large-scale problems without specific mathematical solvers (Borghetti, et al., 2008, Riffonneau, et al., 2011, Gonzalez, 2014). Besides, another limitation to be noticed is that LP and MILP are unsuitable for reactive optimization according to actual measurement. Moreover, as given in the definition, LP and MILP require the objective functions and constraints to be linear. To deal with nonlinear object functions, Lagrangian relaxation (LR) method formulate problems in a relaxing form through the

Lagrangian multiplier. The objective functions in LR are usually convex (or concave). This makes the LR a strong candidate for reactive optimization, especially used in HEV applications (Riffonneau, et al., 2011). However, LR requires longer computation time and works only with continuous variables. Hence, this method is only suitable for small problems with less than 50 variables (Riffonneau, et al., 2011).

Dynamic programming (DP) is a graph-based technique corresponding to the shorter path algorithms (Riffonneau, et al., 2011). Riffonneau, et al. (2011) presented a predictive control system that optimizes the power flow management into a grid connected PV system with storage at the lowest energy cost from an electric utility. Compared with LP and MILP, DP shows advantages in reactive optimization. Moreover, DP's performance index and constraints can hold all the natures (linear or not, differential or not, convex or concave, etc.). However, DP approach requires high memory and computation when the studied period is long or discretized with small time steps (Riffonneau, et al., 2011).

To sum up, the numerical method with simulation-based programs outperforms the others in optimizing sizes of PVs and batteries. However, the numeric methods are faced with a trade-off between computation time and feasibility of constraint's nature. LR and DP enable all natures of constraints while they both require longer computation time and memory. Linear programming (LP) and mixed integer linear programming (MILP) are only suitable for linear problems but are simpler. This study only takes into account the balance of active power. As a result, the objective function and all the constraints are linear. Besides, there are integer variables involved (such as the selection of contracted capacity from standard values). Therefore, the MILP is applied in this study.

5.3 Model overview

Enabling and increasing customers' participation is one of the major objectives of the future grid. Newly deployed technologies include distributed generation, energy storage systems, advanced smart meters, controllable appliances, and new legislations. By the year 2019, the smart metering deployment will be finished and new dynamic pricing policies might be implemented.

Figure 35 illustrates the topology of the system under consideration, including solar panels and an energy storage system. Positive power flows are presented as vectors showing the direction and name. h is set to stand for the chronically hourly periods ($h \in \{1,2, \dots ,8760\}$) and the values of the power flows varying with h.

$d(h)$ represents the load profile of appliances in the house, which is discussed before. $sg(h)$ stands for the generation of PV panels. The generated electricity can meet part or the whole demand, charge the battery or be sold to the grid. The battery is connected to both the stand-alone system and the distributed grid. Discharge/charge power of the battery (electricity delivered from the battery and stored in the battery) are respectively represented by $q(h)$ and $b(h)$. Appliances, solar panels and energy storage devices are as a whole considered as a household system. The interexchange between the household system and the distribution grid is represented as $e(h)$ and $v(h)$ for the purpose of billing and compensation. $e(h)$ stands for the consumption of household system from the grid and it is charged at the retail price. $v(h)$, on the other hand, stands for the feeding in to the grid and is sold at the market-clearing price of market exchange.

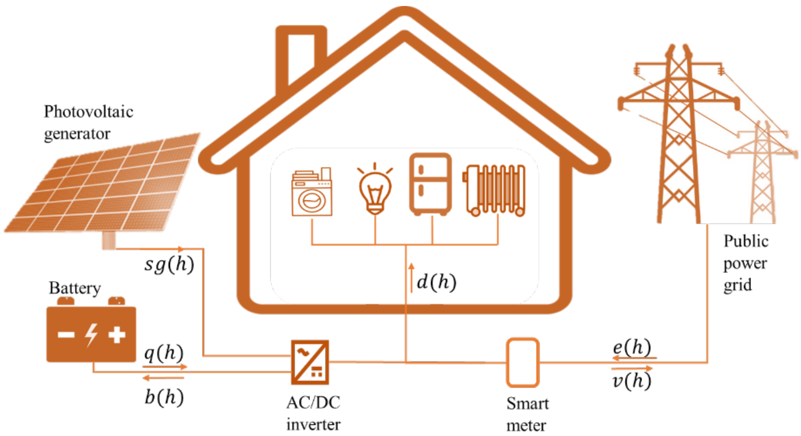


Figure 35 Self-consumption household layout

In order to maintain a balance between the supply and demand sides at each time period h, the condition of the following equation should be met:

$$e(h) + sg(h) + q(h) = d(h) + b(h) + v(h)\ ; \ \ \forall h$$

It should be noted that the circuits in reality are much more complex. According to Royal Decree 900/2015 (Ministerio de Industria Energía y Turismo de España, 2015), generation facilities (including PV panels and storage devices) must be in a different circuit from the load and are metered separately. In this study, the above-mentioned balance is simplified and assumed to take place on a bus connected to the distribution grid. There are other two main assumptions in the model:

1. The first assumption is that that the tariff schemes are unchanged during the lifespan of PV and batteries. By assuming that, households can calculate their yearly savings with the annualized investment cost (annuity). Besides, the effect of different tariff schemes on electricity bills and investment decisions can be compared.
2. The other main assumption is that customers are assumed to have full knowledge of future data, such as retail price, solar generation and so on. However, considering the unstable demand change, the complex market-clearing mechanism and the unpredictable weather condition, households can never have a perfect forecast for the future. The optimization model works with real data of 2015. Hence, the scheduling and savings of households can approximate (i.e. by implementing better forecasting techniques) but can never exceed or equal to the modelled results. This may lead to an overoptimistic bias: the result might be overoptimistically estimated and the savings might be overstated.

5.4 Demand and time horizon

To incorporate with the dynamic pricings and demand, a chronological list is a requisite and the intervals used here are always hourly. The demand curve generated in the former chapter is used here. This result in 8760 periods in the model.

For a medium-term model with hourly periods, many researches (Hubert, and Grijalva, 2012, Gonzalez, 2014) prefer to assign variable durations to periods. Specifically, consecutive hours with similar characteristics are grouped to reduce the size of the problem. However, this method is not applied in this study because of two reasons: Firstly, the model is simple enough and there is no need to simplify it further by sacrificing accuracy. Although there are 8760 periods, the algorithm is not complex. For each period, only the performance of battery (quantity of input or output) is different. As a result, it only takes seconds to get the results. Secondly, grouping the consecutive hours will reduce the variance of the demand and the peak load information. To some extent, grouping hourly load means smoothing the load. This action will for sure reduce the total cost and affect the evaluation of the battery's benefit.

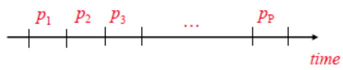


Figure 36 Chronological representation of time (Gonzalez, 2014)

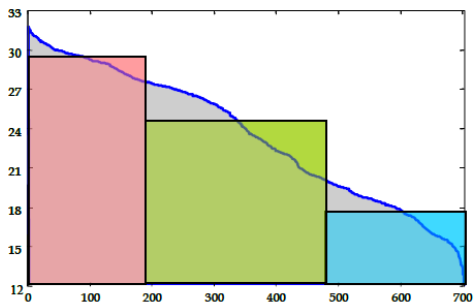


Figure 37 Division of the monotonic load curve into three levels from Gonzalez (2014)

5.5 Solar PV generation and related constraints

Estimating the production and cost of potential PV installations is a tough task. Currently, the most commonly used nameplate rating is in watts (W) or kilowatts (kW). Power rating of the system is a measure of how big the generation system is, instead of how much it will produce.

5.5.1 Cost of solar panels

The cost of solar panels has decreased dramatically in the past years due to the development of the technology and an increase of the numbers of competitors in the market. The decrease in price is mainly due to a decrease of the price of the PV modules. As shown in Figure 38, price for PV modules in 1975 was $101.5/watt, that is 227 times higher than it is today (0.447/watt).

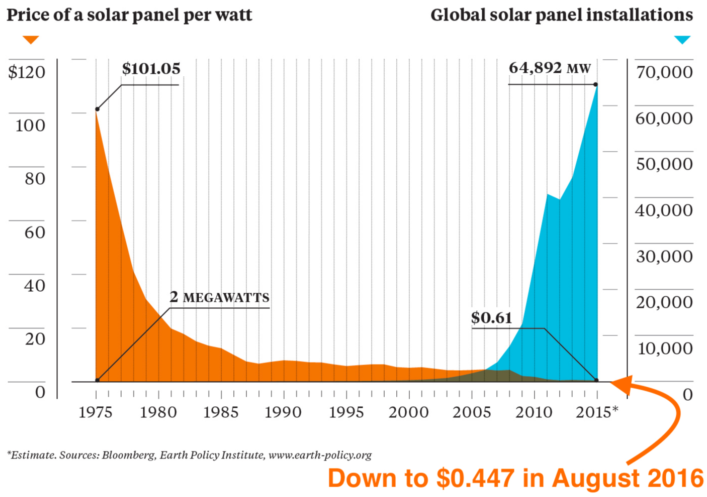


Figure 38 Price of a solar panel per watt and global solar panel installations (Zachary Shahan, 2014)

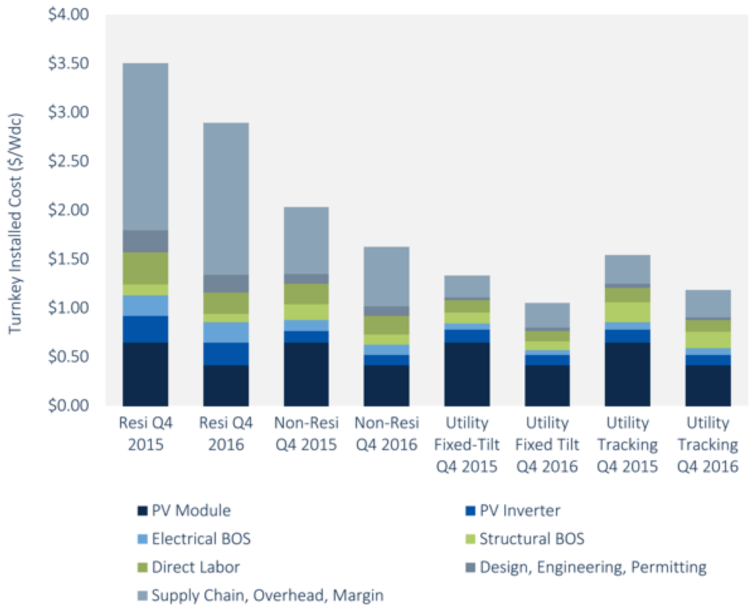


Figure 39 Modeled U.S. national average system costs by market segment, Q4 2015-Q4 2016 (Wood Mackenzie Limited/Energy Industries Association, 2016)

The price of a residential rooftop system is different from the market price of solar panels. In fact, the bulk of the turnkey installed cost for households is currently the 'soft cost' (supply chain, installation, perming, etc.). Consequently, prices vary tremendously from less than €3/watt to €8/watt (Zachary Shahan, 2014). However, current prices can hardly be found on the Internet due to the lag in updating information. At the time of this writing, the most recent and reliable data is published by Wood Mackenzie Limited/Energy Industries Association (2016) (as shown in Figure 39). Accordingly, the average pricing for residential rooftop systems landed at $2,89/watt (€2,66/watt) in Q4 2016 in the U.S. In this study, it is assumed the price in Spain is €3/watt, a little higher than that of the U.S. Based on advanced testing conducted by PV manufactures, solar panels have a useful lifespan of 25 to 30 years (Richardson, 2017). Here a life span of 25 years is used. To calculate the annuity of the system, a straight-line depreciation method was used. Considering the time value of money, the annuity of solar panels (PV_Price in euro per watt) are calculated with the equation below, where r represents the discount rate for the future.

$$3000 = \sum_{n=1}^{25} \frac{PV\_Price}{(1+r)^n} = \frac{PV\_Price}{1+r} + \frac{PV\_Price}{(1+r)^2} + \cdots + \frac{PV\_Price}{(1+r)^{25}}$$

Here an inflation rate (r = 6%) is applied and therefore $PV\_Price = 234{,}7$ euro per kilowatt per year. Many utility companies and governments offer incentives or feed-in tariffs. However, there are no incentives or subsidies in Spain for household installations. The optimal installed solar capacity ($PVCapacity$) is determined by the model and the total expenditure on solar panels every year is calculated as:

$$PV\ Expenditure = PVCapacity * PV\_Price$$

5.5.2 Generation profile

To determine the optimal size of the system, a PV generation profile is necessary. However, the generation profile depends on many factors:

- Locational constant factors: number of daylight hours, intensity of the sunlight
- Locational random factors: weather (i.e. cloudy days)
- Household specific factors: orientation and tilt of the installation, whether there are shadows cast over (due to trees, buildings etc.)

Among the above-mentioned factors, location is the primary and the most influencing one. Household specific factors, on the contrast, are not representative for all households and can be to some extent controlled over.

Hence, households in different regions should be modelled with different solar generation profiles.

Two kinds of solar generation curves can be reached: regional average production profile and real data from solar panel stations. An average production profile (Figure 40) stands for an estimated average profile in a specific region with the same daily production and hourly distribution. Compared with real solar station data (Figure 41), average production profiles fail to take the random factors into account.

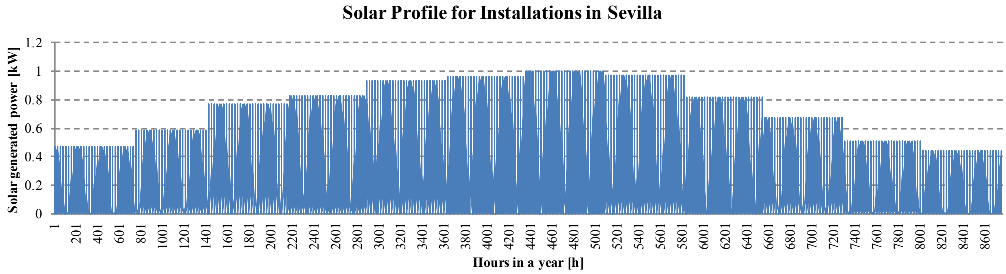


Figure 40 Profile for installations in Sevilla

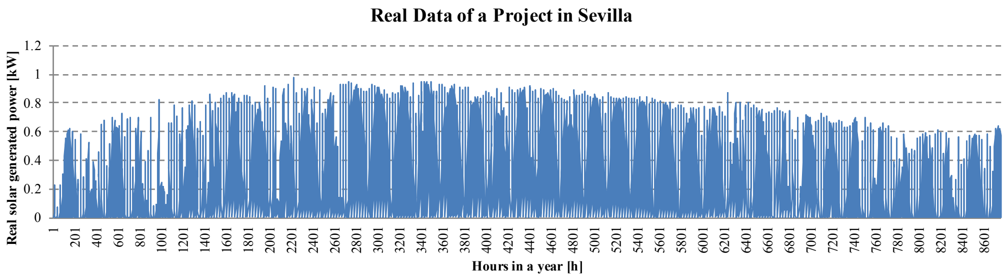


Figure 41 Real data of a project in Sevilla

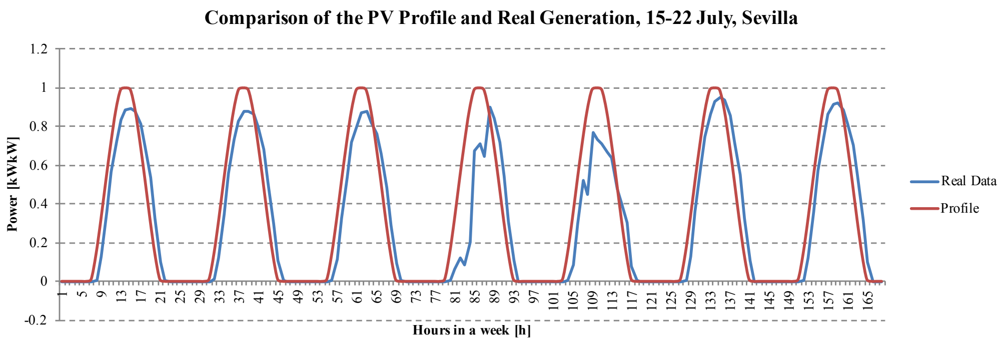


Figure 42 Comparison between the generation profile and real generation data, 15-22 July, Sevilla

Figure 42 presents the differences between real data and regional average production profile. Hence, real generation data from solar plants are used in this study. $s(h)$ stands for the generation real curve of a 1-kW solar panel and it varies in different regions. $PVCapacity$ is determined by the model and the household's solar generation $sg(h)$ therefore equals:

$$sg(h) = s(h) * PVCapacity; \;\; \forall h$$

5.5.3 Constraints regarding solar generation

There are two constraints regarding the power of the PV installation: the contracted capacity and the charges to self-consumption. According to Royal Decree 900/2015 (Ministerio de Industria Energía y Turismo de España, 2015), self-consumption PV installations should always be smaller than the capacity contracted between the customer and the electricity company. Besides, self-consumption PV owners have to pay charges to self-consumption if their installations are larger than 10 kW. Considering that the installation is smaller than the contracted capacity and the contracted capacities are less than 10 kW, no charges to self-consumed energy are applied in the model.

$$PVCapacity \leq Contracted\ Capacity$$

5.6 Storage capacity, cost and related constraints

Cost-effective batteries would be charged from the grid during low price periods while the stored electricity would be used to feed the appliances (or sell to the grid) when prices are higher. During this process, four factors are expected to affect the performance and therefore to influence the cost-effectiveness of installations: maximum storage capacity, maximum input/output power, efficiency and cost. Currently, there is a considerable variety of household batteries in the market. Table 11 compared 43 available household storage devices that are available in the market.

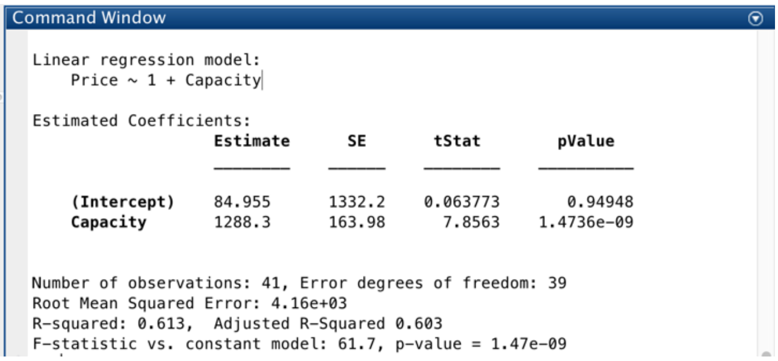
Table 11 Price and parameters of present available batteries

Product Name	Price [€]	Capacity [kWh]	Pmax [kW]	Round Trip Efficiency
ABB REACT		2	1.5	94%
Akasol neeoQube	11280	4.95	1.5	98%
Alpha-ESS ECO S5	11632.5	12.96	5	95%
Ampetus "Super" Lithium	2162	2.7	1.5	95%
Ampetus Energy Pod	10701.9	11.52	5	97%
Aquion Aspen 48S-2.2	2068	2.2	0.68	90%
BMZ ESS3.0	7238	5.4	8	97%
BYD B-Box LV Residential	9390.6	9.8	10	TBD
DCS PV 5.0	5546	5.12	5	99%
Delta Hybrid E5	7990	4.8	3	90%
ElectrIQ	12350	10	8	98%
ELMOFO E-Cells ALB52-106	7698.6	4.4	5	96%
Enphase AC Battery	1880	1.14	0.26	96%
Fronius Solar Battery	14617	9.6	4	90%
Fusion Power Systems Titan-3	12925	8	3.5	94%
GCL E-KwBe 5.6	3431	5.6	3	95%
GridEdge Quantum	18800	7.68	4.5	95%
Hybrid "Home" Plus	10340	8.2	3	92%
Leclanche Apollion Cube	8648	5.4	3.3	97%
LG Chem Resu 10	8272	8.8	5	95%
LG Chem RESU 6.5	6204	5.9	4.2	95%
Magellan HESS	19364	11.52	5	97%
Mercedes-Benz Energy Storage Home		2	1.25	97%
Nissan	4275	4.2	3	
Orison	1610	2.2	1.8	90%
Orison	2013	2.2	1.8	90%
Panasonic		8	2	93%
PowerOak ESS	12267	9.8	3	TBD
Powervault	2215	3	0.8	95%
Powervault	2689	4	0.8	95%
Powervault	2689	2	0.8	95%
Powervault	4034	4	1.2	95%
Powervault	6360	6	1.2	95%
Pylontech US2000B	1879.06	1.92	2	TBC
Redflow Zcell	11844	10	3	80%
SENEC.home Li 10.0	19608.4	10	2.5	95%
SimpliPhi PHI3.4 Smart-Tech battery	4841	2.75	3.1	98%
SolaX BOX	13254	11.52	4.6	97%
SolaX Lead Carbon	6570.6	4.5	4.6	90%
Sonnenbatterie	28670	16	3	93%
Sunverge SIS	24440	9.86	5	96%
Tesla Powerwall 2 (AC)	8272	13.2	5	89%
Tesla Powerwall 2 (DC)	7520	13.5	5	92%
ZEN Freedom Powerbank FPB16	20445	14.4	5	TBD

Compared with the other three factors, the round trip efficiency can be determined easier. As shown in Table 11, most of the batteries are designed with an efficiency between 90% and 97%, with 95% as an average. Therefore, an efficiency of 95 % is used in this study.

Determining the other three factors requires some artful guesses. Table 11 listed 43 household storage devices with maximum capacities ranging from 2 kWh to 13,5 kWh. The wide selection and the advancing technique make it inappropriate to model the batteries with real parameters. Therefore, estimations have to be made to calculate cost based on the other parameters.

As discussed at the beginning of this chapter, maximum storage capacity (w_{max}) and maximum input/output power (b_{max}, q_{max}) are exogenous variables optimized by the model. Cost, on the contrary, is further determined by w_{max}, b_{max} and q_{max}. This is based on the fact that batteries with larger capacity and input/output power are more expensive. To check whether there are correlations between cost and other three variables, a linear regression of battery price (cost) is constructed and tested with capacity (w_{max}) and input/output power (b_{max}, q_{max}) as independent variables. Stepwise regression is a method of regressing multiple variables while automatically removing those that are not significant (Draper, and Smith, 1998). The stepwise regression model and the corresponding histogram of residuals are shown in Figure 43 and Figure 44.



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Linear regression model:
    Price ~ 1 + Capacity

Estimated Coefficients:
                   Estimate     SE       tStat        pValue
                   ________   ______   ________   __________

    (Intercept)     84.955    1332.2   0.063773      0.94948
    Capacity        1288.3    163.98     7.8563   1.4736e-09


Number of observations: 41, Error degrees of freedom: 39
Root Mean Squared Error: 4.16e+03
R-squared: 0.613,  Adjusted R-Squared 0.603
F-statistic vs. constant model: 61.7, p-value = 1.47e-09
```

Figure 43 Stepwise regression model

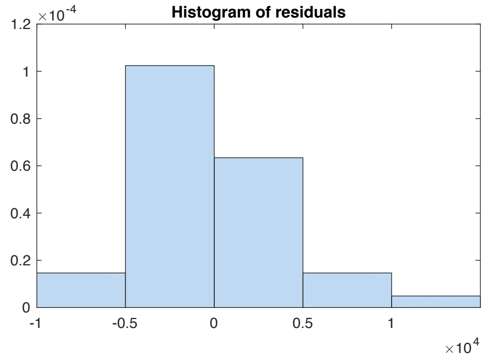

Figure 44 Histogram of residuals of the stepwise regression model

It can be seen that cost is solely determined by the capacity (w_{max}) with an adjusted R-square of 0,603 (R-square equals 0,613). The equation to determine the battery price (€) is as follows:

$$Battery\ Expenditure = 1.288{,}3 * w_{max} + 84{,}96$$

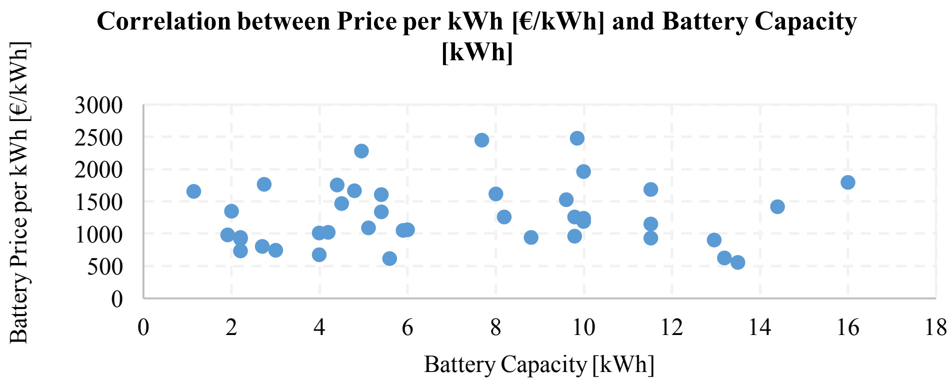

Figure 45 Correlation between Price per kWh [€/kWh] and Battery Capacity [kWh]

In the GAMS model, the interaction part has to be modeled with a binary variable depending on whether the battery is installed or not. To make it simpler in the model, whether the interaction part can be set to zero is tested. As can be seen in Figure 46, the zero-interaction lines has high degree of similarity with the original one and the R-square remains almost the same. Therefore, the interaction part is eliminated from the equation and the new equation is as follows:

$$Battery\ Expenditure = 1.297{,}4 * w_{max}$$

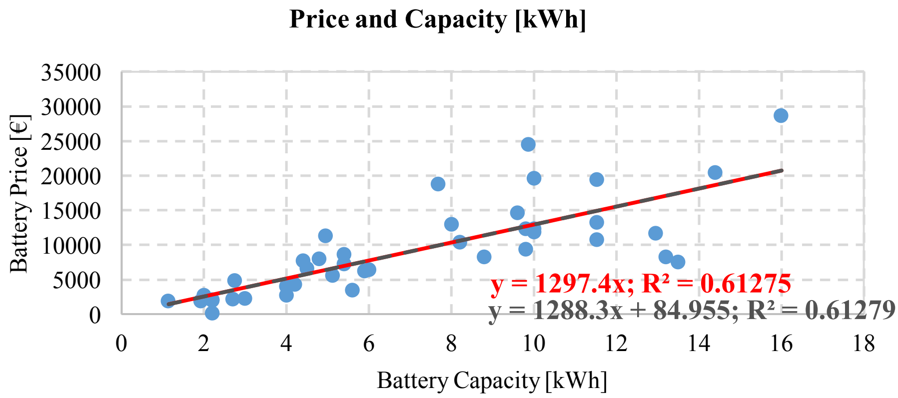

Figure 46 Comparison of equations with or without interaction part

As can be seen in both the two approaches, the spread of the price per kWh is quite large. This spread leads to the result that the variance explained by the second approach (R square) is around 0,61, which is not large but acceptable. To calculate the annuity, the same method (discounting future cash flows) is applied for batteries. The warranty for batteries are 10 years on average and the annuity $Price\_Battery$ is calculated as follows. Here $r = 6\%$ is applied and therefore $Price\_Battery = 176{,}3$ euro per kWh per year.

$$1.297{,}4 = \sum_{n=1}^{10} \frac{Price\_Battery}{(1+r)^n} = \frac{Price\_Battery}{1+r} + \frac{Price\_Battery}{(1+r)^2} + \cdots + \frac{Price\_Battery}{(1+r)^{10}}$$

$$if\ r = 6\%, \qquad Price_{Battery} = 176{,}3\ €/kWh$$

Both the cost and the output power are endogenous and modeled by a function of max storage capacity. The correlation between the maximum output power and the capacity of the battery is presented in Figure 47.

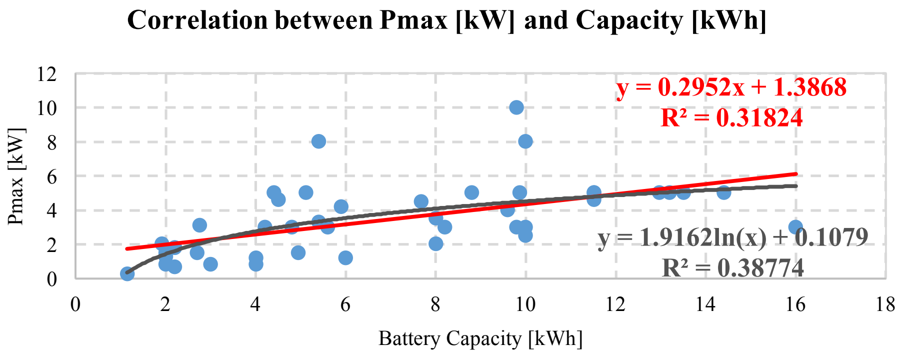

Figure 47 Correlation between Pmax [kW] and Capacity [kWh]

Maximum input/output power is modeled as:

$$b_{max} = q_{max} = 0{,}2952 * w_{max} + 1{,}3868$$

An argument may rise concerning whether the average price (€/kWh) or the cheapest price for each capacity should be used. It is true that the lowest price can lead to the consumers' highest profitable and, all else equal, rational households should definitely choose the cheapest product. However, that is not the case in reality. Consumers' behavior may be influenced by many factors such as advertisements, availability of the products, brand attraction and appearance of the products. As a result, the real selection of storage might be remarkably diverse.

Equations regarding parameters are listed as follows:

$$BAPrice\ (€/kWh \cdot year) = 176{,}3 * w_{max}$$

$$b_{max} = q_{max}\ (€/kW \cdot year) = 0{,}2952 * w_{max} + 1{,}3868$$

Regarding the usage of household batteries, two types of constraints should be considered: (1) energy balance and (2) physical parameters of the battery.

The first constraint is the energy balance of the battery. $w(h)$ stands for the energy stored in the battery at the end of period h. There are three inflows or outflows that affect $w(h)$: remaining electricity at the end of the previous period ($w(h)$), the output $q(h)$ if the battery provides electricity and the input $\eta * b(h)$.

The evolution is presented as follows;

$$w(h) = w(h-1) - q(h) + \eta * b(h); \qquad \forall h > 1$$

It is assumed that the equation works for $h > 1$. $w(1)$, the initial value of the stored electricity, is an input and is set to be zero.

It should be noted that $b(h)$ stands for amount the battery consumes and η stands for its round trip efficiency. The equivalent stored electricity (electricity that the battery can provide) is $\eta * b(h)$.

Other constraints regarding the physical parameters are listed:

$$w(h) \leq w_{max}; \qquad \forall h$$

$$q(h) \leq q_{max}; \qquad \forall h$$

$$b(h) \leq b_{max}; \qquad \forall h$$

5.7 Tariff schemes and related constraints

In Spain, network and other regulated costs are recovered by an access tariff designed by the Comisión Nacional de los Mercados y la Competencia (CNMC, the regulator), energy costs are pass-through from the wholesale market, and a variety of taxes, levies and other charges are established by the Ministry of Energy. In summary, residential electricity bills comprise mainly two parts: market term and regulated term.

The regulated term includes both volumetric €/kWh and fixed €/kW charges. kW based charges are determined by the contracted capacity between households and utility companies. Currently, the contracted capacity is chosen among standardized values and households can choose the value based on their usage pattern.

Considering that the CP can have significant impact on the total expenditure, the CP is treated as a discrete variable to be selected by the model. The standard values are listed as $CP(i)$ where i varies from 1 to 7 and the corresponding values are listed as follows.

$$CP(i) \in \{2{,}3;\ 3{,}45;\ 4{,}6;\ 5{,}75;\ 6{,}9;\ 8{,}05;\ 9{,}2\}$$

$$scp(i) \in \{0;\ 1\}$$

The selection from the standard values is realized by a set of decision variables $scp(i)$. When $scp(i) = 1$, $CP(i)$ is selected as the most suitable contracted capacity for the household. Considering that changing the contracted capacity requires application and fees, the household is assumed not to change its contracted capacity during the year. Hence, only one $scp(i)$ can equal to one and the corresponding $CP(i)$ is then selected. This process is realized by the following equations:

$$CP = \sum_{i=1}^{7} (CP(i) * scp(i))$$

$$\sum_{i=1}^{7} scp(i) = 1$$

The contracted capacity is the maximum amount of power that can be consumed simultaneously. Hence, the contracted capacity is a natural constraint for the consumption of a household system from the grid $e(h)$. Besides, the contracted capacity is also a constraint for the installed solar panels. Based on the new mandatory regulations set by Royal Decree 900/2015, the generation installed power cannot exceed the contracted capacity. The two constraints based on current scheme are presented as follows:

$$e(h) \leq CP \quad \forall h$$

$$PVCapacity \leq CP$$

Three tariffs schemes are to be tested in this study. Among them, there are already two tariff schemes that consumers can chose from (PVPC 2.0A and PVPC 2.0DHA) and a newly proposed one. Except for the changes in prices, there are also differences related to contracted capacity.

The newly proposed tariff scheme aims to recover the costs mainly during the two peak periods and relax the restriction in off-peak hours by 15 kW. Hence, the constraints are edited as follows:

$$P_{max} = 15$$

$$v(h) \leq P_{max} \quad \forall h$$

$$period1(h), period2(h), period3(h) \in \{0, 1\} \quad \forall h$$

$$period1(h) + period2(h) + period3(h) = 1 \quad \forall h$$

$$e(h) \leq \left(period1(h) + period2(h)\right) * CP + period3(h) * P_{max} \quad \forall h$$

5.8 Objective function (cost calculation)

The objective of the study, as discussed before, is to maximize the consumers' benefit by optimizing the expansion planning for the appliances including solar panels and batteries. The benefit is defined as the savings a household can recognize by taking advantage of proper installations and optimized scheduling.

The benchmark to calculate the savings is the yearly electricity bill without solar panels or batteries ($Cost_{\_without}$). Based on the load curve generated in Chapter 4, the contracted capacity should reach 5.75 kW. $p(h)$ stands for the retail price with taxes added. Hence, $Cost_{\_without}$ can be calculated as follows:

$$Cost_{\_without} = \sum_{h=1}^{8760} (p(h) * d(h)) + 38{,}043426 * 5{,}75$$

The total cost in the expansion-planning model is composed of three parts: electricity bill charged due to consumption, revenue gained by selling electricity to the grid, and the investment cost for PVs and batteries. Note that $wmax$ and $PVCapcity$ are exogenous variables determined by the model. If it is not profitable to install PVs or batteries, $wmax$ and $PVCapcity$ will equal to zero. $pv(h)$ in the equation stands for the wholesale price in the wholesale market.

$$Total\ cost = \sum_{h=1}^{8760} \big(p(h) * e(h)\big) + 38{,}043426 * CP - \sum_{h=1}^{8760} \big(pv(h) * v(h)\big) + Price\_Battery * wmax + Price\_PV * PVCapacity$$

Compared with the expenditure without PVs or batteries, the household's electricity bill is changed in three aspects:

(1) Consumers' hourly consumption from the grid is changed from $d(h)$ to $e(h)$.
(2) Contracted capacity (CP) can be changed due to batteries (reduce CP by shifting the peak) and PV installation (increase CP in order to be able to install a larger PV facility).
(3) Consumers can also sell electricity to the grid. It should be noted that consumers' production can only be sold at the wholesale price ($pv(h)$) instead of retail price. Therefore, the consumption cost and production

revenue are calculated separately and households cannot be charged by the net consumption ($e(h) - v(h)$).

Royal Decree 900/2015 establishes new mandatory regulations related with self-consumption and has been into force since 11 April 2016. Accordingly, households who want to sell the surplus energy to the wholesale market have to pay the €0,5/MWh power generation grid charge and a 7% generation tax introduced by Law 15/2012 (Industria, and Turismo, 2015). These amounts should be deduced from the revenue of surplus selling:

$$revenue = \sum_{h=1}^{8760} \big((pv(h) - 0{,}0005) * v(h)\big) * (1 - 7\%)$$

Note that $wmax$ and $PVCapcity$ are exogenous variables determined by the model. If it is not profitable to install PVs or batteries, $wmax$ and $PVCapacity$ will equal to 0. Hence, $Total\ cost$ is never larger than $Cost_{\_without}$, and $Total\ cost = Cost_{\_without}$ if $wmax = PVCapacity = 0$.

$$\begin{aligned}\text{Min } Savings &= Cost_{\_without} - Total\ cost \\ &= \sum_{h=1}^{8760} (p(h) * (d(h) - e(h)) + 38.043426 * (5.75 - CP) \\ &+ \sum_{h=1}^{8760} \big((pv(h) - 0.0005) * v(h)\big) * (1 - 7\%) - (Price\_Battery \\ &* wmax + Price\_PV * PVCapacity)\end{aligned}$$

Further information regarding the formulation of the optimization model can be found in the Annex.

CHAPTER 6: MODELLING RESULTS AND IMPLEMENTATION

This chapter applies the optimization to a 5-room household in Sevilla to illustrate the optimization model.

Firstly, a business as usual case in performed with the present values as input data. The business as usual model aims at testing the current profitability of PV and batteries, discovering the optimal combination of the grid-connected PV battery system, as well as evaluating the performance of the three tariff schemes.

Following the business as usual scenario, a future scenario analysis is performed. With the continuous decrease in PV/battery prices, the status quo is challenged by many uncertainties and an exploration for the future trends is important for all stakeholders. 100 scenarios are created to represent the future price levels of PV and batteries. The future scenario analysis aims to compare the influences of the three tariff schemes, to discover the dynamic aspects for the future challenges on technologies and to provide suggestions for better incentives to support a more sustainable environment.

6.1 Business as usual case in Sevilla

6.1.1 Overview of the expense under different tariff schemes

Table 12 provides a first glance of the optimized expenses under the three tariff schemes. Here in the three experiments, the same load curve is used. Three basic conclusions can be drawn from the results:

Table 12 Summary of results

	2.0 A	2.0 DHA	3-period Tariff
Consumption [kWh]	5.962,3	5.962,3	5.962,3
Expenditure without [€]	1.158,2	1.054,9	1.056,2
Expenditure with [€]	1.146,3	1.027,8	1.049,1
Saving [€]	11,9	27,1	7,1
Contracted Capacity [kW]	5,75	5,75	4,6
PV Capacity [kW]	0,43	0,61	0,35
Battery Capacity [kWh]	0	0	0

Firstly, 2.0DHA and the three-period tariff outperform 2.0A for the household. The expenditure under 2.0A is the highest with the current demand curve. Without installing solar panels or batteries, the consumer has to spend €1.158,2 under tariff 2.0A. Its expenditure under 2.0 DHA and the three-period tariff is similar around €1.055. Interestingly, the consumer can save around €100 just by changing from 2.0A to other two tariff schemes.

Secondly, solar panels have already been profitable though the optimal installation is still small. Batteries, on the other hand, are not profitable for the household.

Under current solar panel prices and a discount rate of 6%, the maximum saving is €27,1 and it is achieved under 2.0DHA combined with 0,6kW solar panels. However, it should be noted that the estimated yearly saving might be too small to attract households taking actions. Consequently, the households might be reluctant to install PVs and the tipping point for PV installation has not been reached. Meanwhile, the household's saving by installing the PV system is smallest under the three-period tariff, indicating that implementing the three period tariff may cut the benefit of households who already installed PV systems.

In terms of batteries, the optimal sizes of the battery for the household are both zero under the current two tariff schemes. Though the time-varying tariffs are implemented, the price differences are not strong enough to compensate the high cost of the batteries.

Thirdly, the three-period tariff will not increase the expenditure of the household dramatically. The expenditure is similar with the current expenditure under 2.0 DHA though the contracted capacity can be reduced to 4.6 kW. This implies that the household's peak consumption is not fully overlaps with the peak hours defined in the three-period tariff scheme.

Detailed information about the solar generation, battery scheduling and household-network exchange is presented in Figure 48, Figure 49 and Figure 50. The demand used in these three experiments are identical (the dark blue line) and it varies with seasonal effects. The retail prices (including taxes) are green and the wholesale market prices are light blue. As can be seen in the figures, the retail price under tariff 2.0A is the flattest, with very slight fluctuation every day. On the contrast, 2.0DHA and the three-period tariff try to differentiate the hourly prices by defining different peak hours. In tariff 2.0DHA, the peak hours are identified in a daily level, hence the fluctuations can be identified with stable variance. The three-period tariff differentiates the peak hours in a yearly view in three categories. By doing that, it can take into account the seasonality as well as the daily variation.

The orange line presents the electricity exchange between the household and the network, where positive values stand for consuming from the network and vice versa. From a yearly angle of view, the hourly demand is greater in winter and summer. Under tariff 2.0A and 2.0DHA, the seasonality of hourly demand is not reflected in the retail prices. Although the retail price is slightly higher in winter and summer, the increase rate is not comparable with that of the demand. However, the three-period tariff outperforms in dealing with the seasonal demand changes: the peak price is highly overlaps with the peak consumption from the network.

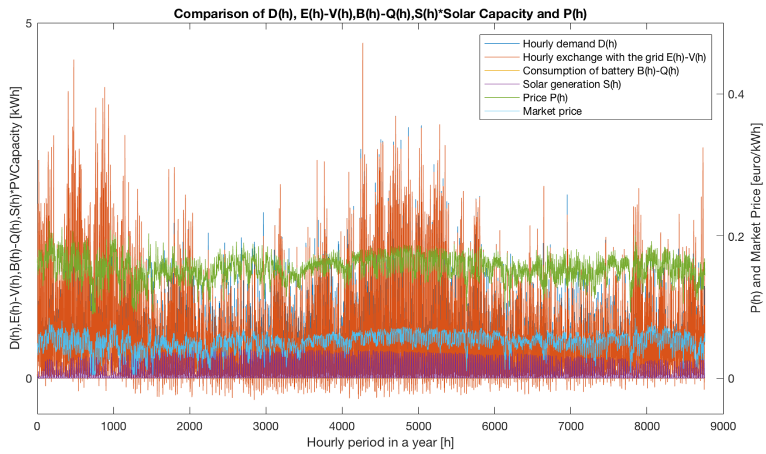

Figure 48 Comparison of demand, solar generation, household´s exchange with the network, and electricity prices under three types of tariff schemes (2.0A tariff)

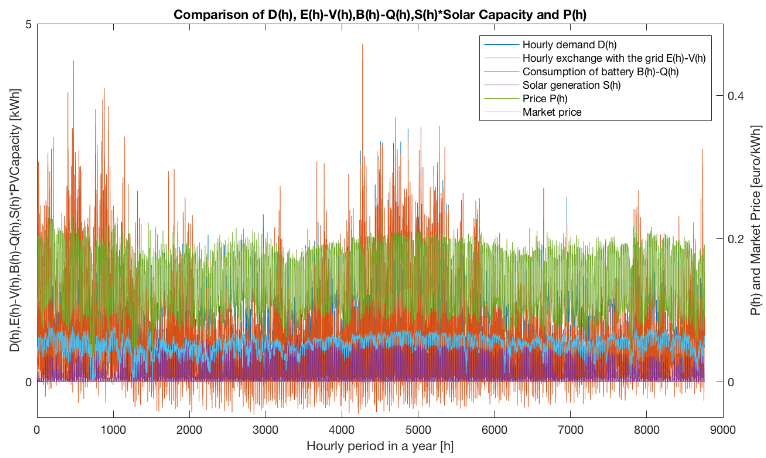

Figure 49 Comparison of demand, solar generation, household´s exchange with the network, and electricity prices under three types of tariff schemes (2.0DHA tariff)

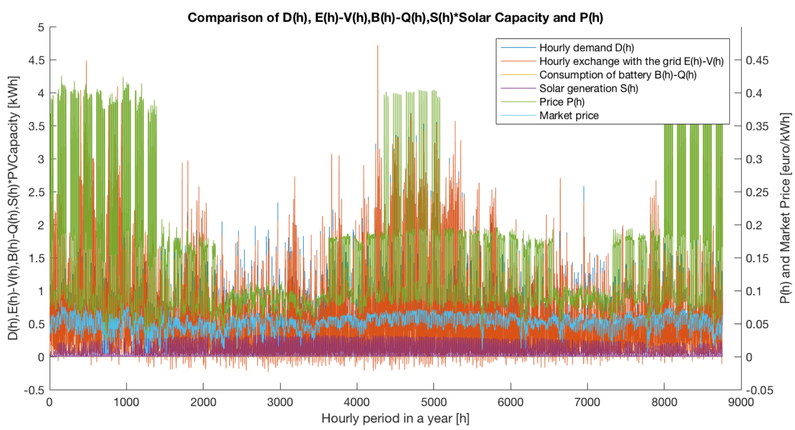

Figure 50 Comparison of demand, solar generation, household´s exchange with the network, and electricity prices under three types of tariff schemes (Three-period Tariff)

6.1.2 Comparison of the seasonal changes under the three-period tariff

Figure 51, Figure 52 and Figure 53 present the demand, solar generation and household-network exchange under the three-period tariff in three random days in winter (January 21st Thursday-24th Saturday), spring (May 1st-3rd) and summer (July 23rd Thursday-26th Saturday). Since there is no battery in the optimized solution, the demand and consumption from the network highly overlaps and the surplus are sold to the grid. As proved in the figure, installation of solar panels can slightly reduce the consumption from network during 9 am-18 pm. However, the optimized installed PV capacity is only 0,35, as a result, households seldom sell solar generated electricity to the grid.

However, whether the three-period tariff is helpful to reduce the pressure of grid network or to recover the network cost remains uncertain: one the one hand the households can reduce their consumption in peak hours. On the other hand, the household will also pay less during peak hours while still using the network to sell the surplus.

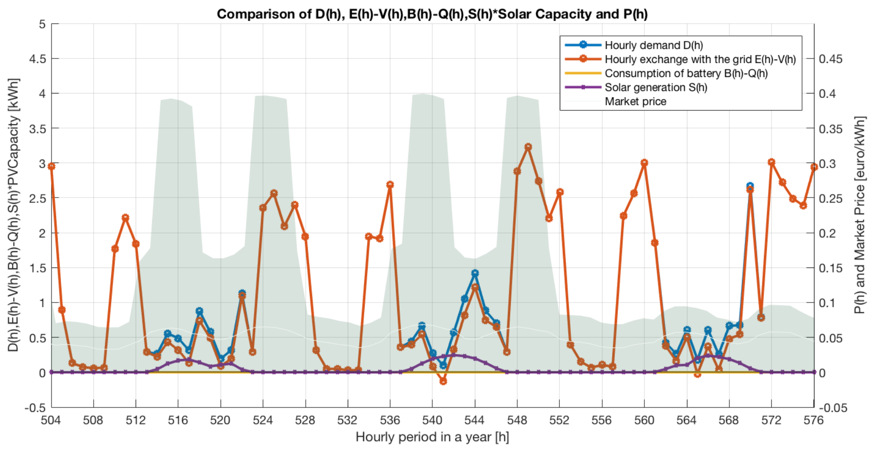

Figure 51 Comparison of demand, solar generation, household´s exchange with the network, and electricity prices under three three-period tariff on three random days in January

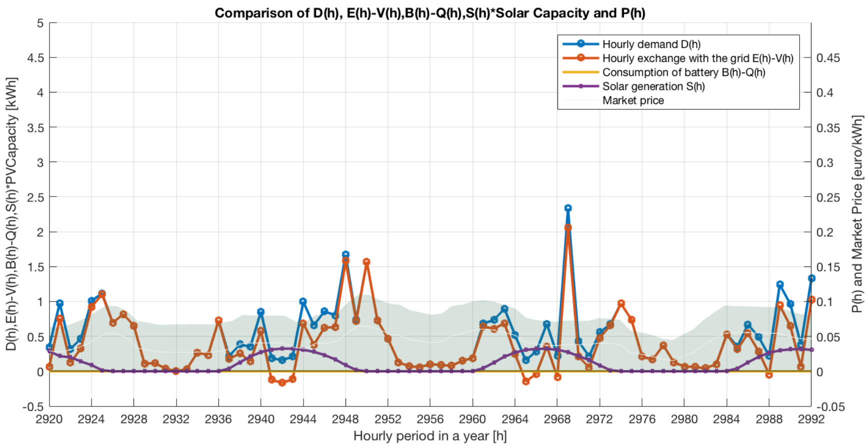

Figure 52 Comparison of demand, solar generation, household´s exchange with the network, and electricity prices under three three-period tariff on three random days in May

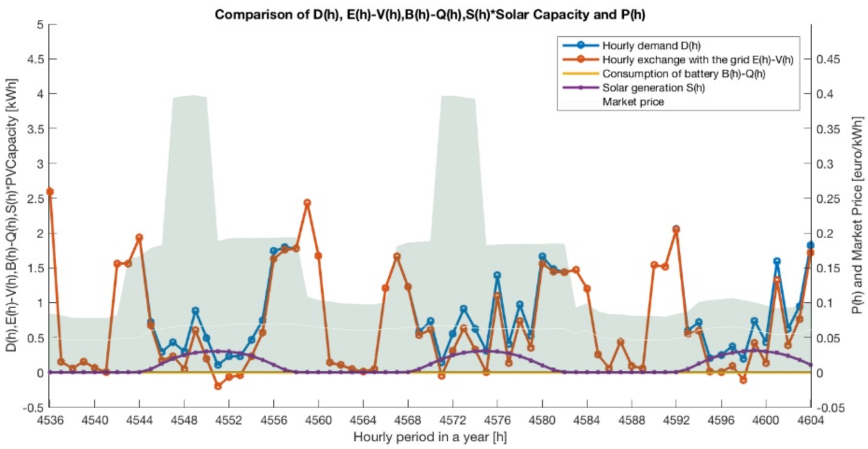

Figure 53 Comparison of demand, solar generation, household´s exchange with the network, and electricity prices under three three-period tariff on three random days in July

6.2 Future scenario analysis/sensitivity analysis

The former section provided an analysis on the business as usual case and compared the household's expenditure under the three tariffs. However, with the continuous decrease in PV/battery prices, the status quo is challenged by many uncertainties and an exploration for the future trends is important for all stakeholders.

From the perspective of households and other investors, a future analysis is required to guide their investment decisions. On the one hand, the downward trend of PV/battery prices provides the households more opportunities to benefit from the new technologies. However, the installation of PV or battery is a long-term decision with a large initial amount. Households, on the other hand, are exposed to risks of destresses and losses due to a lack of knowledge and inappropriate investments. Therefore, a future analysis is essential to provide an overview of profitability and to act as a guide for best combination. Only with the above-mentioned information, can the households and other investors make decisions more rationally.

From the perspective of regulators, the design of tariffs is a highly complex task and their future implications should be evaluated in advance. Pérez-arriaga (2013) addressed several ratemaking principles for tariff design, including sufficiency (cost recovery), economic efficiency, equity, transparency, simplicity, stability and consistency with the regulatory framework. Apparently, the principles all require that regulators or tariff designers cautiously evaluate the future performances of the tariffs beforehand.

However, Pérez-arriaga (2013) also pointed out the difficulty of meeting all the above-mentioned principles simultaneously and revealed the fact that all the tariffs are a compromise between trade-offs. Therefore, this work bears the above-mentioned principles in mind and evaluate the future performances of the tariffs in three steps:

1. Compare the influences of the three tariff schemes, including comparing the total expenditure and corresponding combination of PV and batteries.

2. Dynamic aspects for the future challenges: long-term effect, able to promote new and right technology.
3. Behavior difference (explore better incentives to support a more sustainable environment)

6.2.1 Scenario building

The future exploration aims to discover the changes of optimal combination with different scenarios of PV/battery prices. Previous works preferred to apply prediction of prices over years as an input to discover the future. By doing that, Yoza, et al. (2014) achieved a prediction of installation of PV capacity over the years 2013-2030. However, applying price predictions has many drawbacks. The large modeling horizon requires very complex models and large computation times. Besides, the quality of their results is highly dependent on the accuracy of the prediction. Once their prediction differs from the reality, the results loss the guiding value. To overcome the drawbacks, this project applied scenarios of PV/battery prices instead of price predictions over time. The reason is that the prices are the most direct variable that determines the behavior of the consumer. By excluding subjective predictions, this project can return objective conclusions that are more accurate and sound. Various sources of predictions for PV/battery price changes can be complements to this project. The objective results in this study, together with updated predictions, can ensure a sufficient accuracy for stakeholders' judgments.

To discover the future trends, PV/battery prices are assumed to decrease from the current prices to a percentage of the present level. The scenarios are presented in Table 13 and 100 scenarios can be formulated in total.

Table 13 Scenario building

Anuity of solar panels per watt (decrases to percentage compared with present value)

Percentage	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%
Present anuity=234,7	235	211	188	164	141	117	94	70	47	23

Anuity of batteries per watt (decrases to percentage compared with present value)

Percentage	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%
Present anuity=176,3	176	159	141	123	106	88	71	53	35	18

The three tariff schemes are tested under the above-mentioned scenarios and the results are presented and compared in terms of expenditures, installed PV capacities and battery capacities. The comparison of the expenditures aims to discover the profitability for households and the comparison of PV/battery capacities aims to discuss the potential effects on PV/battery promotion.

6.2.2 Comparison of the influences of three tariff schemes

Many costs incur during the developing, publicizing and implementing of a new tariff scheme. To avoid these losses, the effectiveness should be checked beforehand: whether the new tariff sends the right economic signals to each customers and can make effective changes.

This chapter focuses on qualitatively comparing the performances of the three schemes. Given the consumption of appliances unchanged, the optimal combination and the expenditure are simulated in all the scenarios under the three tariffs. The comparisons are conducted in three aspects: total expenditure and corresponding optimal sizes of PVs and batteries.

To better illustrate the comparison, tables in this chapter are marked in colors indicating the preferences. Green stands for the best (largest savings and highest installation), yellow stands for the second best, and red stands for the worst.

6.2.2.1 <u>**Analysis of the minimum yearly expenditure**</u>

The minimum expenditures under the three tariff schemes are presented in Table 14, Table 15 and Table 16. In rows different prices of solar panels are studied and different prices of batteries are presented in columns. 100% corresponds to today’s price calculated in Section 6.2.1. The values in the tables are the simulation results in the corresponding scenarios.

Table 14 Minimum expenditures with 2.0A under different PV/battery prices

Expenditure [€/year]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	311	416	450	447	447	447	447	447	447	447
PV 20%	527	632	666	663	663	663	663	663	663	663
PV 30%	705	770	809	824	841	824	824	824	824	824
PV 40%	759	851	890	925	955	959	959	959	959	959
PV 50%	813	936	959	994	1029	1031	1031	1031	1031	1031
PV 60%	867	972	1002	1037	1063	1068	1068	1068	1068	1068
PV 70%	921	1002	1037	1073	1096	1096	1096	1096	1096	1096
PV 80%	971	1033	1068	1103	1117	1117	1117	1117	1117	1117
PV 90%	1014	1060	1096	1125	1134	1134	1134	1134	1134	1134
PV 100%	1054	1085	1120	1145	1146	1146	1146	1146	1146	1146

Table 15 Minimum expenditures with 2.0DHA under different PV/battery prices

Expenditure [€/year]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	232	289	312	312	312	312	312	312	312	312
PV 20%	448	504	528	528	528	528	528	528	528	528
PV 30%	600	632	667	702	706	690	690	690	690	690
PV 40%	652	714	748	783	814	832	825	825	825	825
PV 50%	688	777	810	845	880	899	899	899	899	899
PV 60%	737	818	849	884	917	938	938	938	938	938
PV 70%	777	851	881	916	947	968	968	968	968	968
PV 80%	805	879	908	943	978	990	992	992	992	992
PV 90%	821	897	932	967	995	1012	1012	1012	1012	1012
PV 100%	829	918	953	988	1015	1028	1028	1028	1028	1028

Table 16 Minimum expenditures with the three-period tariff schemes under different PV/battery prices

Expenditure [€/year]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	234	331	384	403	403	403	403	403	403	403
PV 20%	449	546	600	619	619	619	619	619	619	619
PV 30%	568	666	722	757	763	763	763	763	763	763
PV 40%	622	729	805	838	873	871	871	871	871	871
PV 50%	676	783	869	899	935	940	940	940	940	940
PV 60%	723	829	902	937	973	977	977	977	977	977
PV 70%	760	866	934	969	1003	1003	1003	1003	1003	1003
PV 80%	788	897	961	996	1024	1024	1024	1024	1024	1024
PV 90%	800	919	984	1019	1039	1039	1039	1039	1039	1039
PV 100%	800	927	1003	1038	1049	1049	1049	1049	1049	1049

As can be seen from the colors, the household can achieve a minimum spending with 2.0 DHA in almost all the scenarios. On the contrary, the household has to pay the most with 2.0A tariff. Compared with the expenditure under 2.0 DHA, the expenditure under 2.0A is around €100 more and the difference increases with the PV/battery prices decreases. Currently, the expenditure under the three-period tariff is similar with the expenditure under 2.0 DHA at present. Interestingly, the difference between the expenditures under the two tariff schemes is broader when the PV prices decreases (in vertical direction) and is minor with battery prices decreases (in horizontal direction). Consequently, it can be expected that for rational households with the designed consumption pattern, their preference might be 2.0DHA>Three-period>2.0A.

There are two reasons that may explain the reason. One reason is that the household´s demand is more distributed in the off-peak hours than the aggregated demand. This is mainly due to the use of heating and air-conditioning at night. As a result, the two time-varying tariffs are more profitable than the flat one. Another reason is related with the solar panel generation. Under 2.0DHA and the three-period tariff schemes, the solar-generating hours are categorized as peak-hours with high retail prices. That is to say, the solar generation can compensate expensive consumption and thus leading to less expenditures.

To sum up, the three-period tariff will not decrease the expenditure dramatically: it is easier to be accepted by the households. Stable expenditure, not increase much from the current level, but cannot be helpful to reduce the costs.

6.2.2.2 <u>Analysis of the corresponding optimal size of solar panels</u>

The corresponding installed PV capacities to minimize the expenditures are presented in Table 17, Table 18 and Table 19.

Table 17 Optimal size of PV installations with 2.0A under different PV/battery prices

PV Capacity [kW]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2
PV 20%	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2
PV 30%	2,3	3,5	3,5	5,8	6,9	5,8	5,8	5,8	5,8	5,8
PV 40%	2,3	3,5	3,5	3,5	4,6	5,8	5,8	5,8	5,8	5,8
PV 50%	2,3	2,3	2,1	2,1	2,1	1,9	1,9	1,9	1,9	1,9
PV 60%	2,3	1,9	1,6	1,6	1,4	1,3	1,3	1,3	1,3	1,3
PV 70%	2,2	1,4	1,4	1,4	1,0	1,0	1,0	1,0	1,0	1,0
PV 80%	2,0	1,2	1,2	1,2	0,8	0,8	0,8	0,8	0,8	0,8
PV 90%	1,8	1,1	1,1	0,9	0,6	0,6	0,6	0,6	0,6	0,6
PV 100%	1,1	1,0	1,0	0,8	0,4	0,4	0,4	0,4	0,4	0,4

Table 18 Optimal size of PV installations with 2.0DHA under different PV/battery prices

PV Capacity [kW]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2
PV 20%	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2
PV 30%	5,8	3,5	3,5	3,5	4,6	5,8	5,8	5,8	5,8	5,8
PV 40%	3,5	3,5	3,5	3,5	4,6	4,6	5,8	5,8	5,8	5,8
PV 50%	2,3	2,0	1,9	1,9	1,9	2,0	2,0	2,0	2,0	2,0
PV 60%	1,9	1,5	1,5	1,5	1,4	1,4	1,4	1,4	1,4	1,4
PV 70%	1,5	1,3	1,2	1,2	1,2	1,1	1,1	1,1	1,1	1,1
PV 80%	0,9	1,1	1,1	1,1	1,1	1,0	0,9	0,9	0,9	0,9
PV 90%	0,5	1,0	1,0	1,0	0,9	0,8	0,8	0,8	0,8	0,8
PV 100%	0,3	0,8	0,8	0,8	0,8	0,6	0,6	0,6	0,6	0,6

Table 19 Optimal size of PV installations with three-period scheme under different PV/battery prices

PV Capacity [kW]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2
PV 20%	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2	9,2
PV 30%	2,3	3,5	3,5	3,5	4,6	4,6	4,6	4,6	4,6	4,6
PV 40%	2,3	2,3	3,5	3,5	3,5	4,6	4,6	4,6	4,6	4,6
PV 50%	2,3	2,2	2,0	1,9	1,9	1,9	1,9	1,9	1,9	1,9
PV 60%	1,8	1,8	1,5	1,5	1,5	1,3	1,3	1,3	1,3	1,3
PV 70%	1,4	1,5	1,2	1,2	1,0	1,0	1,0	1,0	1,0	1,0
PV 80%	0,9	1,1	1,1	1,1	0,8	0,8	0,8	0,8	0,8	0,8
PV 90%	0,0	0,7	0,9	0,9	0,5	0,5	0,5	0,5	0,5	0,5
PV 100%	0,0	0,0	0,5	0,5	0,4	0,4	0,4	0,4	0,4	0,4

As can be seen from the tables, three clusters of the scenarios can be identified based on the colors: (1) PV less than 20% of the current price; (2) PV costs more than 20% of the current price and batteries cost less or equal than 40% of the current price; (3) PV costs more than 30% of the current price and batteries cost more than 40% of the current price.

In cluster 1 (the above part of the tables), the installation of solar panels are the maximum and the same under the three schemes. However, this region is unreliable in the near future.

In cluster 2 (bottom right part of the tables), the PV installation under 2.0A outperforms the other two schemes. When the price of PV is high, the optimized PV installation is smaller under the three-period scheme.

In cluster 3 (bottom left part of the tables), the installation under 2.0DHA is larger than the amounts under the other schemes. In that region, the PV capacities are almost the same under 2.0A and the three-period scheme. Compared with the other two clusters, this cluster indicates the changes of prices from the current prices and it is more representative for the near future.

To sum up, it might be concluded that 2.0 DHA plays the strongest role in encouraging installation of solar panels in recent years. However, it should be noted that the conclusions are drawn from the ranking of the three schemes instead of the absolute values. For each scenario, the absolute values of installed capacity are similar under all the tariff schemes.

6.2.2.3 Analysis of the corresponding optimal size of batteries

The corresponding installed PV capacities to minimize the expenditures are presented in Table 20, Table 21 and Table 22.

Table 20 Optimal size of battery with 2.0A under different PV/battery prices

BA Capacity [kWh]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	10	4	1	0	0	0	0	0	0	0
PV 20%	10	4	1	0	0	0	0	0	0	0
PV 30%	7	3	2	0	0	0	0	0	0	0
PV 40%	7	3	2	2	1	0	0	0	0	0
PV 50%	7	7	2	2	2	0	0	0	0	0
PV 60%	7	3	2	2	1	0	0	0	0	0
PV 70%	7	2	2	2	0	0	0	0	0	0
PV 80%	7	2	2	2	0	0	0	0	0	0
PV 90%	7	2	2	1	0	0	0	0	0	0
PV 100%	3	2	2	1	0	0	0	0	0	0

Table 21 Optimal size of battery installations with 2.0DHA under different PV/battery prices

BA Capacity [kWh]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	6	2	1	0	0	0	0	0	0	0
PV 20%	6	2	1	0	0	0	0	0	0	0
PV 30%	5	2	2	2	1	0	0	0	0	0
PV 40%	6	3	2	2	1	1	0	0	0	0
PV 50%	7	3	2	2	2	0	0	0	0	0
PV 60%	7	3	2	2	1	0	0	0	0	0
PV 70%	7	3	2	2	1	0	0	0	0	0
PV 80%	7	3	2	2	2	1	0	0	0	0
PV 90%	7	2	2	2	1	0	0	0	0	0
PV 100%	7	2	2	2	1	0	0	0	0	0

Table 22 Optimal size of battery with three-period scheme under different PV/battery prices

BA Capacity [kWh]	BA 10%	BA 20%	BA 30%	BA 40%	BA 50%	BA 60%	BA 70%	BA 80%	BA 90%	BA 100%
PV 10%	7	5	3	1	0	0	0	0	0	0
PV 20%	7	5	3	1	0	0	0	0	0	0
PV 30%	7	4	2	2	0	0	0	0	0	0
PV 40%	7	6	3	2	2	0	0	0	0	0
PV 50%	7	6	3	2	2	0	0	0	0	0
PV 60%	7	6	2	2	2	0	0	0	0	0
PV 70%	7	6	2	2	0	0	0	0	0	0
PV 80%	8	6	2	2	0	0	0	0	0	0
PV 90%	10	6	2	2	0	0	0	0	0	0
PV 100%	10	6	2	2	0	0	0	0	0	0

The result indicates that the installation of the battery is not profitable at present or in the near future. As can be seen in all the tables, the optimized installation capacities remain zero until the price of batteries decreases to 50% of the current level. Hence, the main obstacle of promoting batteries is the high price in recent year.

When the price of batteries further decreases from 50% from the present value, the three-period tariff shows advantages in encouraging households investing in batteries. The advantage is extremely clear when the battery price decreases to 20% of the present level. At that time, the optimal battery installation is around 6 kW under the three-period tariff, while it is 3 kW under 2.0A and 2.0DHA tariff schemes. Compared with the designed capacity of the present available products (ranging from 1.94 to 14.4 kW, shown in Table 11), the optimized capacity is much smaller than the producers' designs.

It should also be noted that there are both complement and substitution effects between the batteries and the solar panels when the price of batteries is less than 50% of the present level. To be more specific, the cross elasticity between PV price and battery installation can be positive or negative on occasion. Given a certain level of battery price, the optimal battery capacity can either increase or decrease when the PV price decreases.

To sum up, batteries are not profitable for the household until their prices are reduced to 50% from the current level. Among the three tariff schemes, the three-period tariff shows advantages especially when the price of batteries is less than 30%. Meanwhile, households should be conservative when selecting batteries for the optimal battery size is quite small and might decrease when PV price decreases.

6.2.3 Dynamic trends for the future challenges

To ensure the stability, sufficiency, economic efficiency of the tariff scheme, an exploration of the future dynamic aspect is also an essential procedure. Particular attentions should be paid to the future households' interchange with the network and the coordinated installation of PV and batteries.

The 'Duck Curve Effect' can explain the underlying reason. The current electricity grid is not designed to cope with large volumes of solar energy exports reversing back into the grid. Household's solar generation is concentrated during specific periods, which usually ranges from 8 am to 7 pm in Spain. On the one hand, the generation from demand side is helpful to release the peak demand in the daytime. On the other hand, the nature of the generation may result in the 'Duck Curve Effect': a concave in electricity demand and prices over the given time. The anticipated Duck Curve Effect in California is presented in Figure 53 and Figure 54 from the California grid operator. It should be noted that the concave in the demand is not helpful in releasing the peak demand in the evening. In other words, solar generations are not helpful in reducing the required investments in electricity sector to cover the peak of the demand. Nevertheless, the amount of other electricity resources required in the middle of the day decreases significantly and sharper ramps are required in the shoulders between 4 pm and 8 pm. Even worse, the wholesale price during the daytime hours might even be negative as predicted by the California grid operator (as shown in Figure 54). To cope with this, technologies with rapid start-up and fast-ramping capabilities have to be used to take the place of other cheaper base loads. This effect might eventually lead to overcapacity, increasing electricity prices in certain hours and lower social welfare.

Luckily, batteries in households have the potential to reduce the reversing day loads and offset evening peak loads. However, whether the installation of batteries can be helpful remains to be checked. For all stakeholders, a better understand of the changes in residential demand is helpful in risk avoidance and investment optimization.

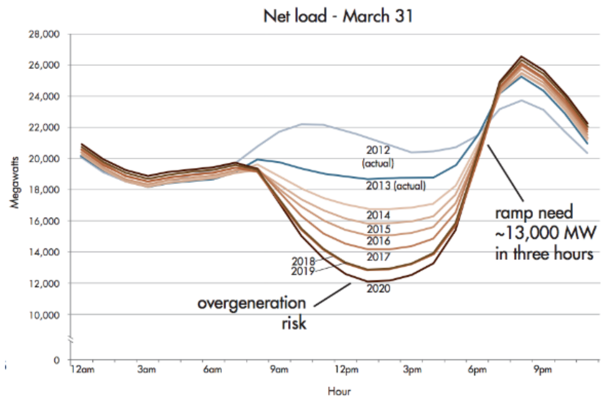

Figure 54 The Duck Curve Effect of large volume of solar power generation on the network (Fares, 2015)

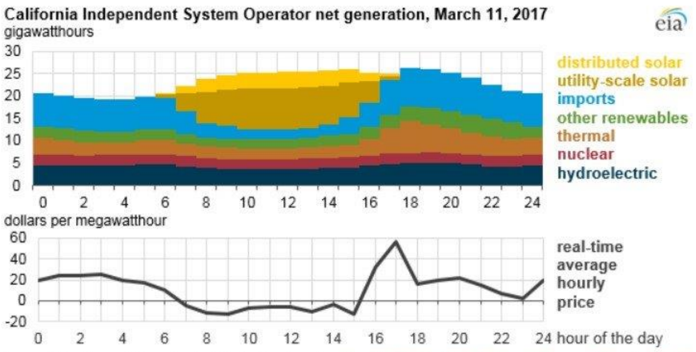

Figure 55 Rising solar generation in California coincides with negative wholesale electricity prices (Source: U.S. Energy Information Administration)

6.2.3.1 **Future trends of the combination: Coordinated installation of PV and batteries**

(1) Analysis of the sensitivity of savings with the PV/battery prices

Figure 56, Figure 57 and Figure 58 present how the maximum saving changes when different PV/battery prices decreases. The savings are calculated as the difference between the business as usual expenditure and the future expenditure with optimal combination. Notably, the annuity of the solar panels and batteries are 234,7 €/kW and 173,6 €/kW respectively. Since the annuities are similar, the difference in slops is not considered as a consequence of reduction in investment costs.

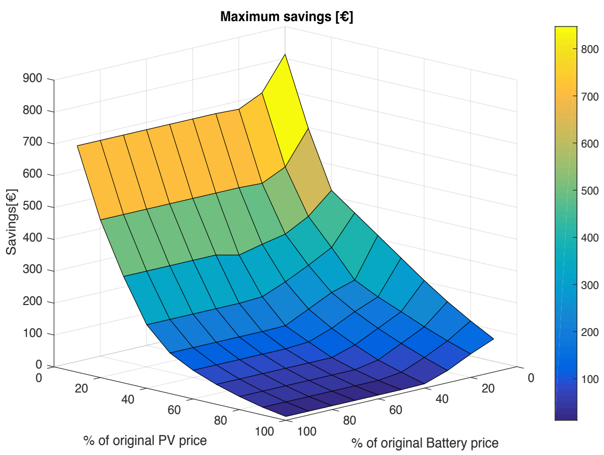

Figure 56 Maximum saving with 2.0A under different PV/battery prices

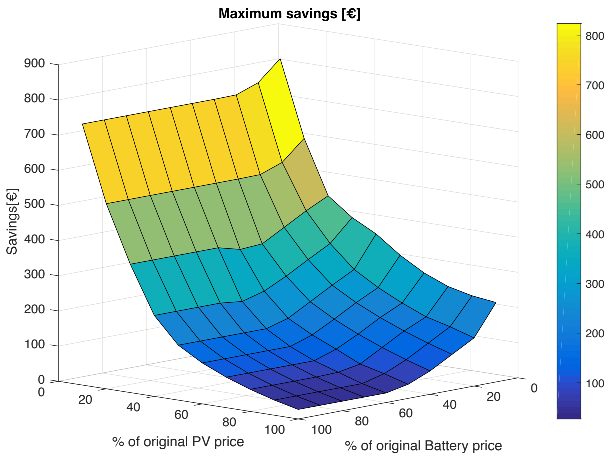

Figure 57 Maximum saving with 2.0DHA under different PV/battery prices

Figure 58 Maximum saving with three-period tariff scheme under different PV/battery prices

As can be seen in all the three figures, the increase of savings is more sensitive to the PV price. For a given PV price, the savings are similar irrespective to battery price changes. Hence, the consumers may easily be attracted by installing solar panels but might not install batteries even if their prices decrease. As a result, there might be a risk of reluctance in battery installation.

(2) Analysis of the break points for PV installations

Figure 56, Figure 57 and Figure 58 present how the optimal size of solar panels changes when different PV/battery prices decreases. By plotting the data into a 3-D graph, the break points for the optimal sizes can be identified clearly.

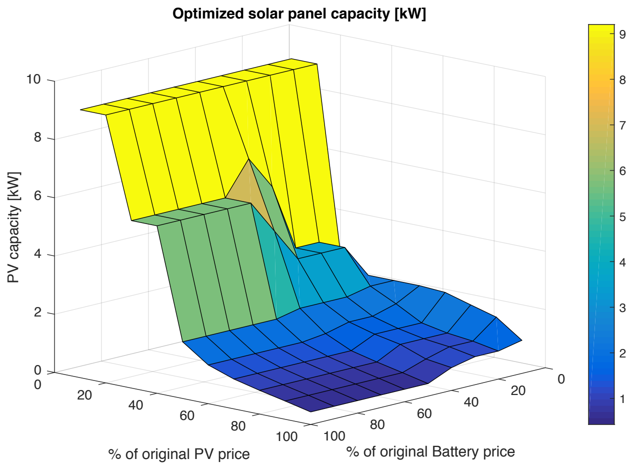

Figure 59 Optimal size of PV installations with 2.0A under different PV/battery prices

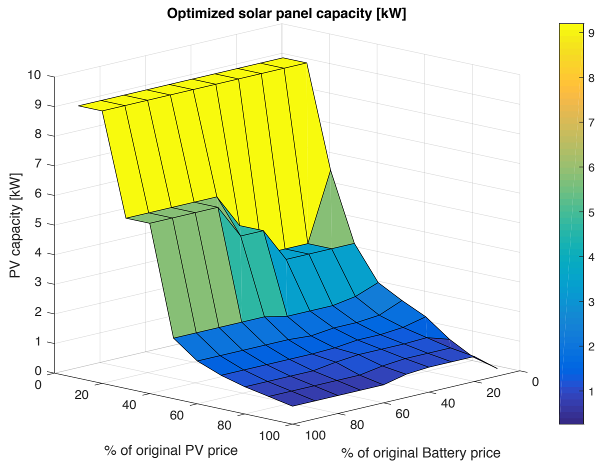

Figure 60 Optimal size of PV installations with 2.0DHA under different PV/battery prices

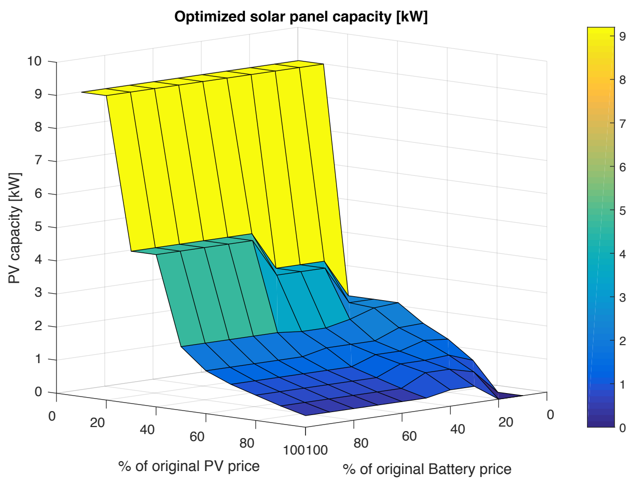

Figure 61 Optimal size of PV installations with three-period scheme under different PV/battery prices

As can be seen in the figures, there are two break points for the optimal size of solar panels, which are 40% and 20% of the present level. Before the PV price decreases to 40%, the optimal size of the solar panels increases gradually. However, when the PV prices are lower than 40%, the optimal size of the solar panels increases dramatically. The existence of the break points can be explained by the design of contracted capacity standards. With the PV prices decrease, it becomes more profitable for the household to expand the contracted capacity and install larger solar panels. In other words, the contracted capacity is determined by the installed solar capacity instead of peak demand.

The figure also indicates the risk of overcapacity of PV for the household. On the one hand, the solar capacity increases dramatically when the PV price decreases to 40%. On the other hand, the optimal solar size also decreases with the price for battery decreases. Hence, the household will suffer not only the low price due to the duck curve effect, but also the substitution of batteries.

(3) <u>Analysis of the break points for battery installations</u>

Figure 62, Figure 63 and Figure 64 present how the optimal size of the battery changes when different PV/battery prices decreases.

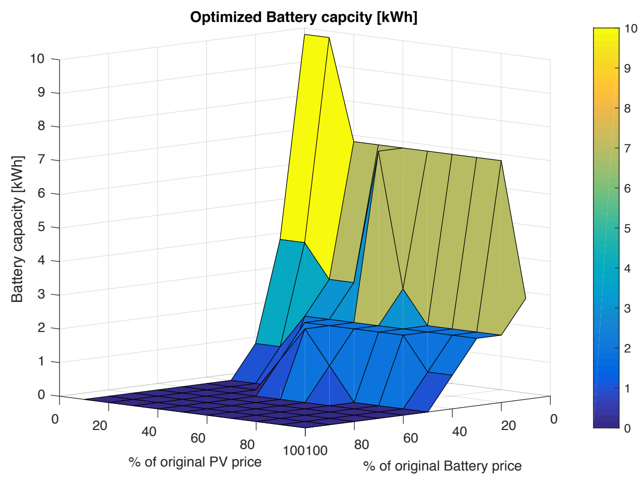

Figure 62 Optimal size of battery with 2.0A under different PV/battery prices

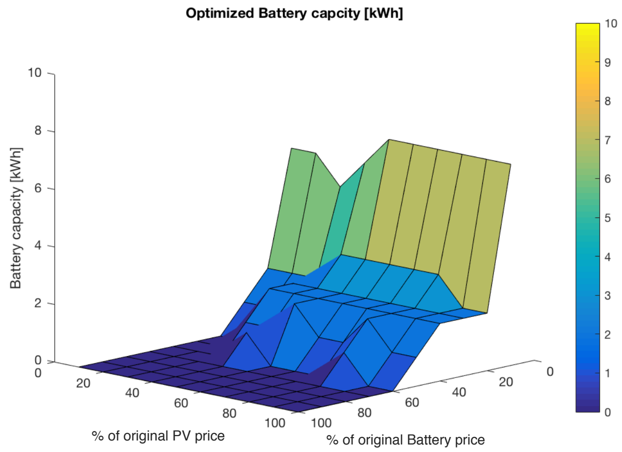

Figure 63 Optimal size of battery with 2.0DHA under different PV/battery prices

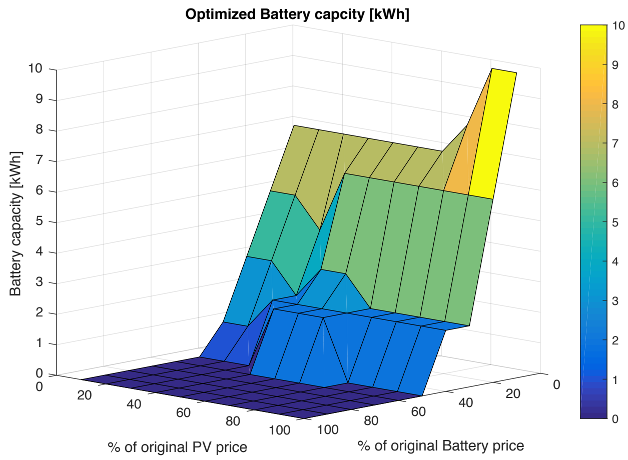

Figure 64 Optimal size of battery with three-period scheme under different PV/battery prices

As can be seen in the figures, there are two break points for batteries: 40% - 50% and 10%. The second break point under the three period tariff is around 20% and it is larger than those in 2.0A and 2.0 DHA.

As discussed in the above two aspects, batteries are essential in the future. Households can for sure take advantages of the future benefits and their investment can complement the battery investments. Of all the three tariffs, batteries are not profitable at present. When prices decrease to 60-70% of the present level, batteries become attractive. When the batteries are profitable, the three-period shows advantages in installing bigger batteries. The encouragement is especially significant when the battery price is decreased to 20% of the current level.

6.2.3.2 The future interchange with the network

It is interesting to investigate the changes of the electricity interchange with the network on breaking points and discover the plausible challenges in the future.

As discussed in the former section, there are certain break points for the installations of PVs and batteries in the household. The break points for the solar panel are 40% of the present level. There are two break points for batteries, which are around 40% - 50% and 10%. It should be noted that the second break point is 20%, which is larger than these in 2.0A and 2.0 DHA. Consequently, there are four break points for the combination:

Break points for the whole combination

Break points	PV price (% of the current level)	Battery price (% of the current level)	Description
1	>40%	>50%	Gradual increase in PV, no battery
2	<40%	>50%	Boom in PV, no battery
3	>40%	<50%	Gradual increase in PV, with battery
4	<40%	<50%	Boom in PV, with battery

In this section, two typical weeks in winter, spring and summer are presented under the scenarios to illustrate the interchange with the network.

Break point 1: PV =50% and BA =60%

When the price of solar panels decreases, the installation of PV increases gradually in that region. In this specific scenario, the optimal sizes of the solar panels are the same (around 2kW) under the three tariff schemes and it is not profitable for the household to install batteries. The solar generation surplus equals the solar generation minus the demand and the household will sell its solar generation surplus to the grid.

The interchanges between the household and the grid are presented in Figure 65, Figure 66, and Figure 67. Since there are no batteries installed and the installed capacity of solar panels is similar, the interchanges are similar in the three tariff schemes. Therefore, only the figures of the three period tariff are presented.

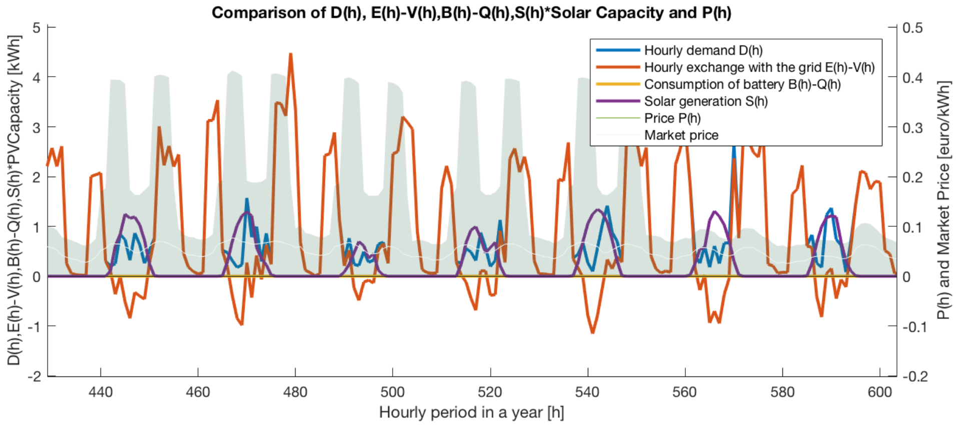

Figure 65 The interchanges between the household and the network under three-period in winter (PV 50%, BA 60%)

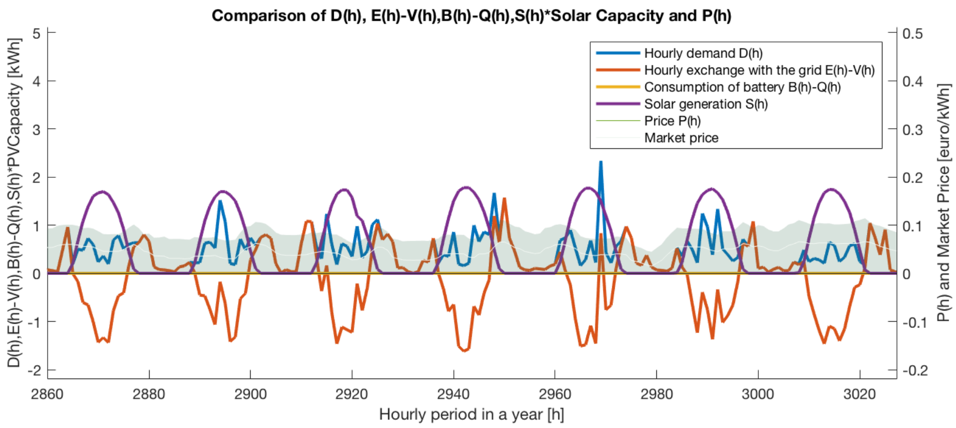

Figure 66 The interchanges between the household and the network under three-period in spring (PV 50%, BA 60%)

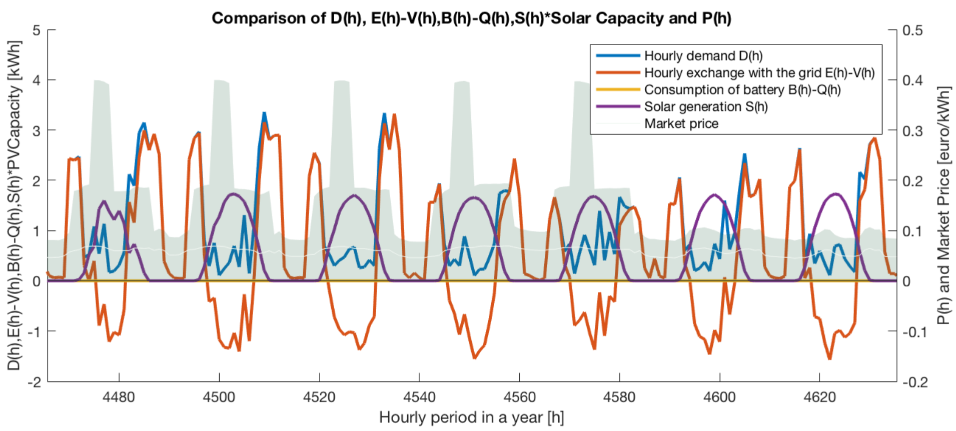

Figure 67 The interchanges between the household and the network under three-period in summer (PV 50%, BA 60%)

In terms of the exported surplus to the grid, the household will sell around 1kW to 2kW electricity to the grid when the price of solar panels is 50% of the current level. Influenced by the seasonality of solar intensity, the household´s generation surplus is larger in spring and summer than in winter.

In terms of the ramp in the interchange, it can be seen that the installation of solar panels will lead to large ramps all the year round. During the sunrise and the sunset, the household´s demand from the grid will experience an increase or decrease of around 3 kW in one hour. The ramp will be extremely large in winter and summer due to the usage of heating and air-conditioning.

Break point 2: PV =40% and BA =60%

In this scenario, the price of batteries remains at 60% of current prices while the price of solar panels decreases. As in line with the former scenario, it is not profitable for the household to install batteries either. The household will sell the surplus of solar generation to the grid. However, as there is a boom in PV installation, the household will seldom consume in the daytime and will sell a large amount of electricity to the grid. As can be expected, the duck curve effect will occur in Spain if that PV boom actually takes place. The interchanges between the household and the grid are presented in Figure 68, Figure 69, and Figure 70.

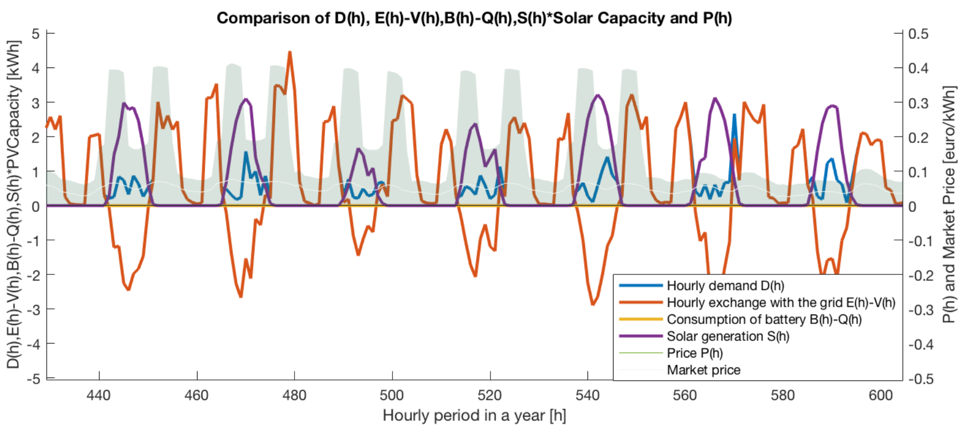

Figure 68 The interchanges between the household and the network under three-period in winter (PV 40%, BA 60%)

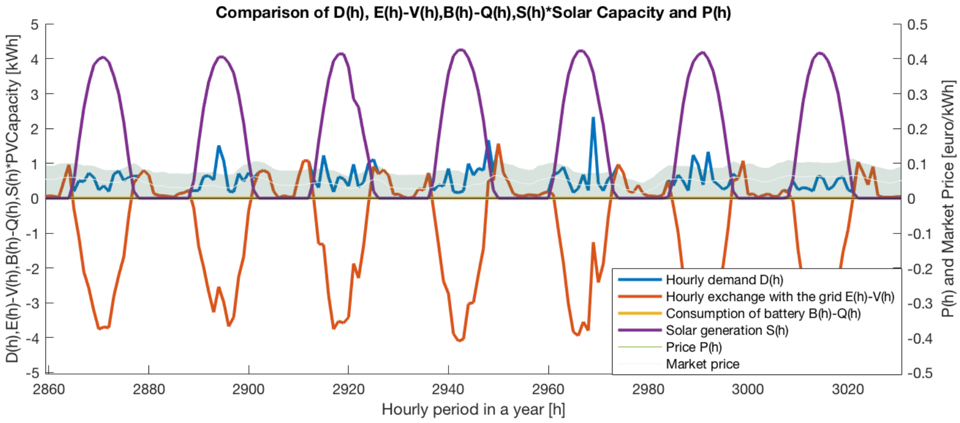

Figure 69 The interchanges between the household and the network under three-period in spring (PV 40%, BA 60%)

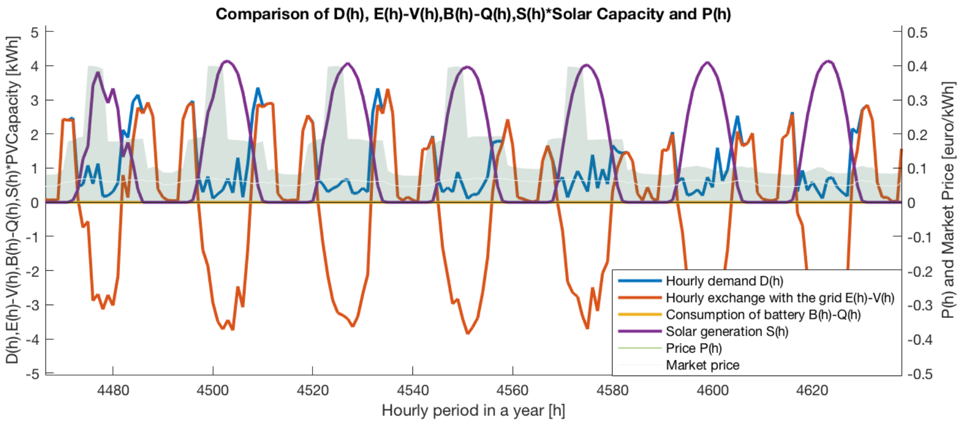

Figure 70 The interchanges between the household and the network under three-period in summer (PV 40%, BA 60%)

In terms of the exported surplus to the grid, the household´s export will increase to more than twice from the former scenario, reaching more than 4kW. In terms of the ramp in the interchange, the ramp will be larger than the former case due to the larger solar generation. During the sunset in summer and winter, the household interchange with the network can vary from -4 kW to 3 kW in a short period of time.

Break point 3: PV =50% and BA =40%

The above-mentioned two scenarios all proposed large challenges in terms of exporting and ramp requirements. Compared with the first scenario (PV 50%, BA 60%), the optimal size of the solar panels is the same (around 2kW) in this scenario while the optimal size of the battery increases from zero to 2 kW.

As discussed before, the installation of solar panels might lead to the 'Duck Curve Effect' and introduce difficulties mainly related to overcapacity in the daytime and large ramp during the sunset and the sunrise. By decreasing the price of batteries, the installation of batteries by the household is able to realize the effect.

When batteries are installed, the interchange between the household and the network will be different under the three tariffs due to the difference in the scheduling of batteries. Figure 71, Figure 72, and Figure 73 compare the interchanges between the network and the household under the three tariff schemes in winter, spring, and summer respectively.

The purple shaded area represents the original interchange without batteries (PV 50%, BA 60%). As shown in the figures, by introducing the batteries, the household´s surplus during the daytime is slightly reduced and the ramps during the sunrise and the sunset are reduced as well.

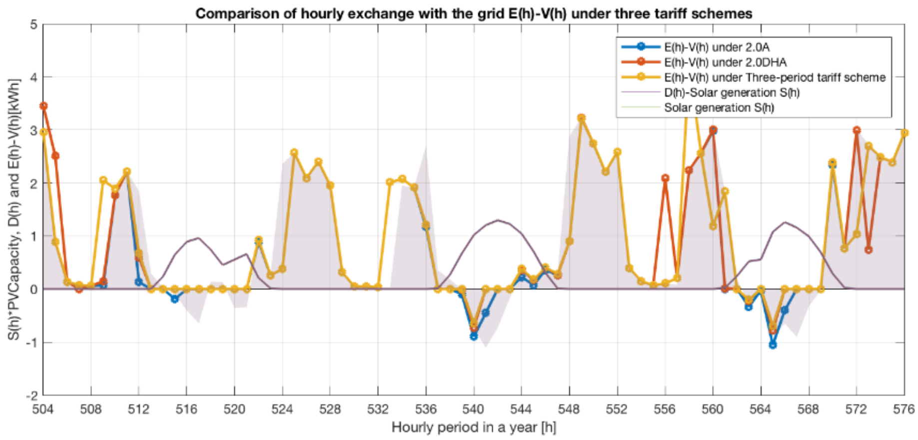

Figure 71 Comparison of the interchanges between the network and the household under the three tariff schemes in winter (PV 50%, BA 40%)

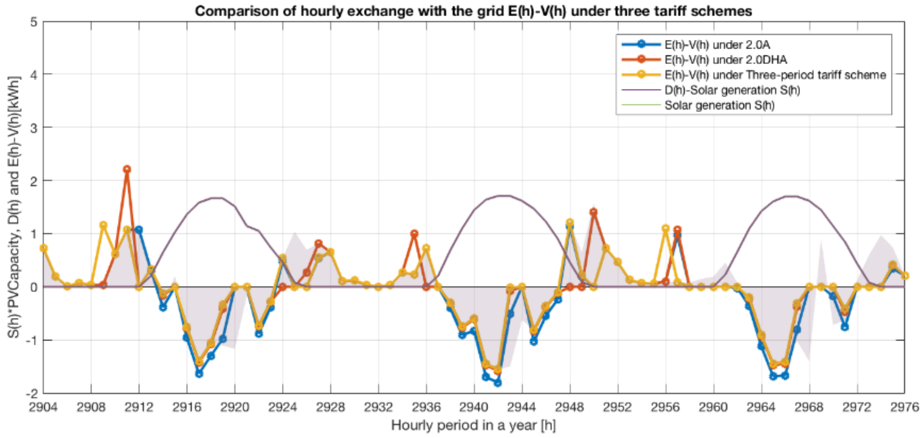

Figure 72 Comparison of the interchanges between the network and the household under the three tariff schemes in spring (PV 50%, BA 40%)

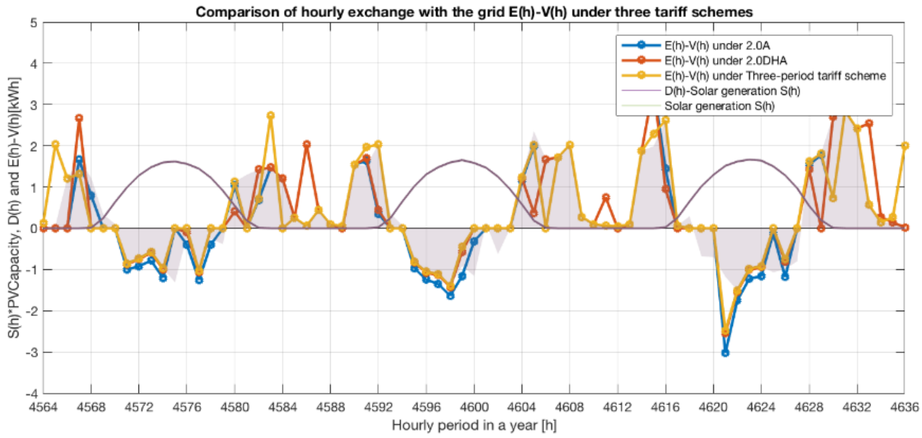

Figure 73 Comparison of the interchanges between the network and the household under the three tariff schemes in summer (PV 50%, BA 40%)

Break point 4: PV =40% and BA =40%

Compared with the scenario (PV 40%, BA 60%), the optimal size of the solar panels decreases from 4.6kW to 3.5kW while the optimal size of the battery increases from zero to 2 kW. Hence, in that range, the batteries and solar panels are substitutes instead of complements anymore.

Figure 74, Figure 75 and Figure 76 compares the interchange between the network and the household under the three tariff schemes in winter, spring, and summer respectively. The purple shaded area represents the original interchange when PV prices are 40% of current prices and BA prices are 60% of today's prices.

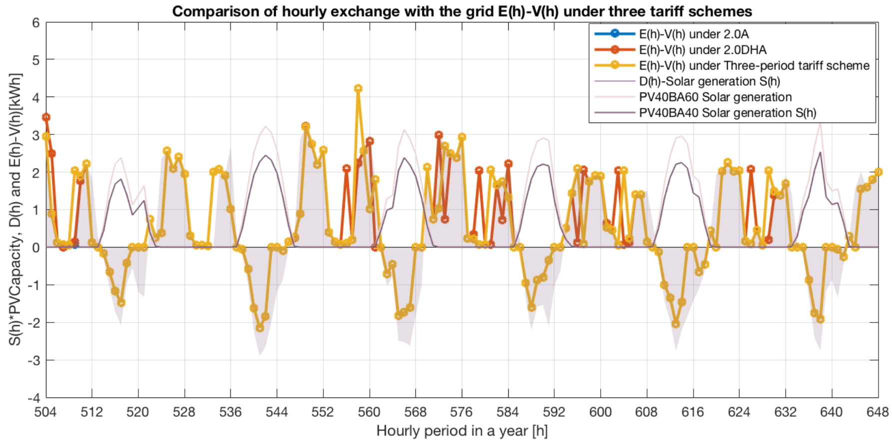

Figure 74 Comparison of the interchanges between the network and the household under the three tariff schemes in winter (PV 40%, BA 40%)

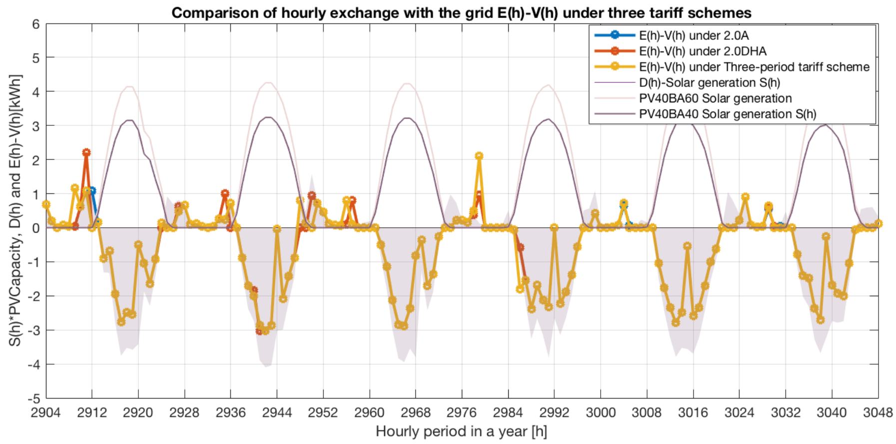

Figure 75 Comparison of the interchanges between the network and the household under the three tariff schemes in spring (PV 40%, BA 40%)

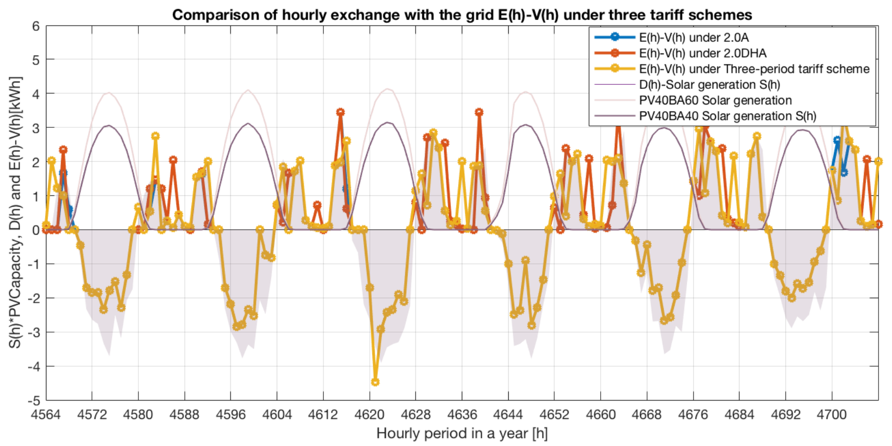

Figure 76 Comparison of the interchanges between the network and the household under the three tariff schemes in summer (PV 40%, BA 40%)

As can be seen in the figures, by introducing the batteries, the household´s surplus during the daytime is slightly reduced and the ramps during the sunrise and the sunset are reduced as well. The light purple line represents the solar generation in scenario 2 (PV 40%, BA 60%). It then indicates that installing the optimal combination before reaching the break point for batteries can result in overcapacity of solar panels if prices keep going down.

To sum up, the installation of solar panels will lead to larger surplus exporting and larger ramp requirements. This is especially relevant in winter and summer due to the usage of heaters and air-conditioners. The case is extremely serious when the PV price decreases to the break point (40% of the current level).

6.3 Suggestions arisen from the future scenario analysis

As indicated in the former sections, the future performance of the three-period tariff is challenged by many uncertainties.

Firstly, the household's benefit is more sensitive to the decrease of PV prices rather than that of the batteries. As a result, households may be reluctant to install batteries even if their prices are reduced to a low level (40% of the current level).

Secondly, the batteries and the solar panels are substitutes in some price intervals. This substitution effect is especially significant when the prices of the batteries or the solar panels are around 40% of the current level. Consequently, as discussed in the former section, the sequence of reaching the break points matters and a too fast decrease in PV prices and gradual decrease in battery prices may lead to overcapacity of solar panels in the future.

Last but not the least, the installation of solar panels from the industrial and the residential side may lead to the 'duck curve effect', resulting in higher prices during the sunset and lower wholesale prices during the daytime.

Due to the above-discussed challenges, the peak-price hours in the three period tariff might be changed in the future and batteries may have more potential than the one they have at the moment. This section aims at exploring better incentives to support more sustainable future development. The targets of the incentives are listed as follows:

1) Allocate costs more effectively respecting the cost causality principle;

2) Ensure a coordinated and efficient installation of solar panels and batteries;
3) Provide more incentives for promoting batteries.

To achieve the above targets, the following suggestions are formulated.

Suggestion 1: Fully disclose the future risks related with existence of negative wholesale prices and reserve the rights to change the designed 'peak-periods'.

To help the households make more rational decisions as well as to avoid future complaints and conflicts, the regulator should fully disclose the future risks to the households. Meanwhile, due to the contribution of solar generation, the peak-periods may be different from the current ones. To recover the costs of the system, the regulator should monitor the change of the demand curve and make in time adjustments to the peak-periods.

Suggestion 2: Avoid is a bubble in the installation of solar PVs that will become unnecessary or excessive when batteries reach their tipping points.

The former section discussed the importance of reaching the break point of batteries before the boom of solar generation. To reach the battery's break point first, the following measures can be taken from two perspectives: limiting the installation of solar panels and promoting the installation of batteries.

Putting on stricter restriction on the size of solar installation can be a way to slow down the installation of solar panels. Currently, the solar installation should no no more than the contracted capacity and the contracted capacity is charged at a flat price per kilowatt. As can be seen in the figures in the former chapter, the installation at the break points of solar panels are influenced by the contracted capacity. When the price of batteries decreases, the batteries can shift some peak demands and reduce the contracted capacity required by the demand. Compared with the fixed price of the contracted capacity, it becomes more profitable for the household to reduce the contracted capacity and install less solar panels. Based on the results of the scenario analysis, the household should not install more than 2.3 kW of the solar panels. To provide more precise and accurate signal, the regulator can set a new restriction on the size of solar panels and limit the size of solar panels less than half the contracted capacity.

Suggestion 3: Provide incentives to speed up the installation of batteries

Based on the current simulation, the savings of the household are relatively insensitive to the price of batteries. Meanwhile, recall the current battery products in the market, the size of the batteries is beyond the optimal size for the typical household. As a result, the incentives provided are not enough for consumers to invest in batteries. Battery is a core technology for the future to deal with the intermittency of renewable generation and it is worthwhile to discuss how to promote the installation of batteries. Many actions can be taken to provide incentives:

Change of taxes

VAT (known as IVA in Spanish) is due on any supply of goods or services sold in Spain. The current general VAT rate is 21% (from 1st September 2012) but not everything is taxed with the full 21%. There are two lower rates of 10% and 4%. The 10% rate is payable on non-basic food products, some public infrastructure and cultural events. The 4% rate is payable on basic food, books and medicines (reference). Insurance, public educational, cultural and sporting services are exempt from the tax. Currently, the retail price of batteries includes the VAT charged at 21%. By reducing or removing the VAT from the retail price, the profitability of batteries can be increased.

Subsidies to lower the costs of batteries

To encourage the deployment of batteries, the government can also provide direct subsidies for battery products to lower the price. The subsidies can be provided to battery producers, retailers or households.

Another way to reduce the cost of batteries is to lower the financing cost of the households. The interest rate of loans on purchasing the batteries are estimated at 6%. By reducing the interest rate for the loan, the financial cost of the batteries is reduced.

Negative externalities should also be taken in account. The subsidies are ultimately collected through the electricity bills or from the state Budget. By providing the subsidies, the burden on the tariff deficit or the fiscal deficit is therefore exposed to a risk of exaggerating. Hence, the regulators have to cautiously monitor the changes.

CHAPTER7:

CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

The residential sector is expected to play an important role in the renewable integration. The case is especially true in Spain, a country that is rich in solar resources. Due to the world-wide regulatory support and reduction in photovoltaic/battery prices, the residential sector is more and more willing to manage their consumption from the grid and install distributed facilities. Driven by these facts, developing PV/battery expansion models has become a hot research topic and has attracted many efforts. However, the previous are either too rough or not suitable for the Spanish case. Therefore, a detailed PV/battery expansion model focusing on the Spain residential sector is essential for all the stakeholders in the Spanish electricity sector.

This Master Thesis is focused on developing a grid-connected photovoltaic battery optimization model that minimizes the annualized expenditure of Spanish households. Although the results are illustrated with a 5-room household in this paper, the model can be applied to any type of households.

The determination of the load curve for the household is crucial. A bottom-up stochastic load curve model is built to generate the load curve of the household given the information of location, temperature, appliances, and time-of use data. The load curve model shows advantages in modeling randomly usage and peak demand for a specific household.

The generated load curve, together with actual data about solar generation efficiency, retail prices and wholesale prices in the year 2015, are used as input for the grid-connected photovoltaic battery sizing optimization model. In terms of the retail prices, three types of tariff schemes are tested, including the current 2.0A/2.0DHA tariffs and a newly proposed three-period tariff.

The optimization model is built in GAMS with mix integer linear programming technique. Besides the business as usual scenario, a series of future scenarios are created to represent the reduction of PV/battery prices in the future. The future scenario analysis is not only a helpful guide for the households, but also a reliable tool for the regulators to test the performance of the tariff schemes and to discover the effective incentives.

The business as usual case indicates that:

- For the 5-room household with electrical heater and air conditioner, the expenditure under 2.0DHA and the three- period tariff are similar and are lower than that under 2.0A tariff.
- Batteries are not profitable for the household give the current prices and tariff schemes. Solar panels, on the other hand, have already been profitable theoretically. However, the optimal size and the corresponding savings are still very small. As a result, the tipping point of solar panels is not reached since the households might be reluctant to install solar panels.

The future scenarios analysis indicates that:

- Under all the price levels of PV/batteries, the household has to pay the least under 2.0DHA and the most under 2.0A. 2.0DHA tariff can play the strongest role in encouraging installation of solar panels in the recent years. Batteries are not profitable for the household until their prices are reduced to half of the current level. The three-period tariff shows advantages when the price of the battery is less than 30% of the current level.
- The households' expenditure is more sensitive to the price changes of PV than that of the batteries. There are certain break points for the prices of PV and batteries. The break point for solar panels comes at a price of 40% of the present level. There are two break points for batteries, which are around 40% - 50% and 10% of current prices.
- Analysis of interchange between the household and the grid under the break points for the whole combination indicates that the sequence of reaching the break points matters: a fast decrease in PV prices and a gradual decrease in battery prices may lead to overinvestment in PV panels and large ramp requirements for the electricity system.

Consequently, a series of suggestions are formulated:

- Fully disclosure of the future risks related with existence of negative wholesale prices and reserve the rights to change the designed 'peak-periods'.
- Avoid is a bubble in the installation of solar PVs that will become unnecessary or excessive when batteries reach their tipping points

- Providing incentives to speed up the installation of batteries, such as changing the taxes and providing subsidies.

7.2 Limitations and future work

As long as the prices of PV/batteries continue to decrease, the optimization model for sizing and scheduling of the PV/batteries will remain a focus for the households and other stakeholders. Considering the trade-off between accuracy and simplicity, there are two main limitations that should be noted.

Firstly, the thesis only presents modeling results for a 5-room household in Sevilla. Whether the conclusions hold for the other type of households in the regions remains to be checked.

Secondly, the thesis might be too optimistic in the minimization of the expenditure. The optimization works with the full ex-post information of prices and solar generation. Based on this information, the optimal scheduling of the battery is achieved. However, this full future information is unachievable ex-ante. Therefore, there is no perfect forecast for the future information or perfect smart devices to manage the operation of the devices based on the forecasts. As a result, the savings the household can generate are always overestimated in this thesis.

Several matters of interest arose to promote the project as well as to deal with its limitations.

Firstly, more work should be carried out to model more types of households. In fact, all types of households can be modelled with the proposed model given the appliance data. By enlarging the modelled sample, the work can provide more specific guides to all types of households and an overall consideration can provide the stakeholders sounder indications.

Secondly, forecasted data can be used to take the place of real past data. As mentioned above, the use of past data leads to overestimate of benefits. By applying forecasted data, the overestimate bias will be reduced.

Thirdly, more future scenario analysis should be done to take into account the changes of the electricity wholesale or retail prices. This thesis has already proved that the household's benefit is challenged by the 'Duck Curve Effect'. To better explore the profitability of the investments, the risks about the prices should not be neglected.

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ANNEX

A. MatLab code for load curve generation model

```
%%Step 1: Generation of random number for appliances
(Matrix A)
A =  rand(25,1440*365);   %1440=24*60; 25 for number of
appliances

%%Step 2: Matrix B, read probability table in excel
%Bilbao
%B1=xlsread('2.14 Bilbao(Bizkaia).xlsx',
'ApplianceProbability', 'H5:AE29');
%Sevilla
B1 = xlsread('3.13
Sevilla.xlsx','ApplianceProbability','H5:AE29');


for k=1:365
for j= 1:24
for i = 1:60
     B(:,1440*(k-1)+60*(j-1)+ i) = B1 (:,j);
end
end
end
%B = repelem (B1,1,60*365); %can be used to take the place
of the for loops in 2016 version

%%Step 3: Matrix C, 0/1 start-up decisions
C=(B>A);
%H=sum(C);
%Matrix H indicates the number of working appliances in
each minute


%%Step 4: Marix D, add working time per cycle
T = xlsread('3.13
Sevilla.xlsx','ApplianceProbability','G5:G29');
% Use loops to modify matix elements
for i = 1:25
             for j = 1:1440*365
                 for k = 1:T(i,1)
                     if C(i,j)>=1
                     D1(i,j+k-1) = 1;
                     end
                 end
```

```
            end
        end
D=D1(1:25,1:1440*365);
% Plot number of appliances
%N2=sum(D)
%Plot (N2)

%%Step 5: Matrix E, add nominal power
%P = xlsread('2.14
Bilbao(Bizkaia).xlsx','ApplianceProbability','E5:E29');
%Heating = xlsread ('2.14
Bilbao(Bizkaia).xlsx','Consumption','F3:F367')/(40*40.5*6/6
0)*1000*100;
%Cooling = xlsread ('2.14
Bilbao(Bizkaia).xlsx','Consumption','D3:D367')/(49*40.5*6/6
0)*1000*100;


P = xlsread('3.13
Sevilla.xlsx','ApplianceProbability','E5:E29');
Heating = xlsread ('3.13
Sevilla.xlsx','Consumption','F3:F367')/(40*40.5*6/60)*1000*
100;
Cooling = xlsread ('3.13
Sevilla.xlsx','Consumption','D3:D367')/(49*40.5*6/60)*1000*
100;


%E = D.*(repelem(P,1,1440*365));
for i = 1:1440*365
    P1(:,i) = P (:,1);
end


%Pheat = repelem (Heating',1,1440);
for i = 1:1440
    for j=1:365
    Pheat(1,i+(j-1)*1440) = Heating(j,1);
    end
end


%Pcool = repelem ((Cooling'),1,1440);
for i = 1:1440
    for j=1:365
    Pcool(1,i+(j-1)*1440) = Cooling(j,1);
    end
end
```

```
P1(1,:)=Pheat;
P1(2,:)=Pcool;
E = D.*(P1);

%%Step 6: Matrix F, sum of all loads
F=sum(E);
%plot(F);
% figure;
% plot(F,'LineWidth',1.5);
% title('Graph of 1-minute step demand curve');
% xlabel('Minutely period in a year');
% ylabel('Power [W]');
% set(gca,'XTick',[0:1440:525600]);
%% Plot loads of appliances
%figure;
%plot(E(1,:),'LineWidth',1.5); %Heating
%plot(E(3,:),'LineWidth',1.5); %Sanitary hot water
%plot(E(21,:),'LineWidth',1.5); %Microwave oven
%plot(E(24,:),'LineWidth',1.5); %Standby
%plot(E(5,:),'LineWidth',1.5); %Lighting
% title('Graph of 1-minute step demand curve of sanitary
hot water');
% xlabel('Minutely period in a year');
% ylabel('Power [W]');
% set(gca,'XTick',[0:1440:525600]);

%% 15-minute step
%for i=1:96*365
%   G15(i)=sum(F(((i-1)*15+1):(i*15)));
%end
%E15=G15/15;
%F15=repelem (E15,1,15);
%for j= 1:96*365
%for i = 1:15
 %   F15(:, 15*(j-1)+i) = E15 (:,j);
%end
%end
%figure;
%plot(F15);

%% 60-minute step
for i=1:24*365
    G60(i)=sum(F(((i-1)*60+1):(i*60)));
end
E60=G60/60;
%F60=repelem (E60,1,60);
```

```
for j= 1:24*365
for i = 1:60
    F60(:, 60*(j-1)+i) = E60 (:,j);
end
end
% figure;
% plot(F60,'LineWidth',1.5);
% title('Graph of 60-minute step demand curve');
% xlabel('Hourly period in a year');
% ylabel('Hourly demand [W]');
% %figure;
% %plot(F60);
% set(gca,'XTick',[0:1440:525600]);
%title('Graph of 60-minute step demand curve');
%xlabel('Hourly period in a year');
%ylabel('Hourly demand [W]');
```

B. MatLab code for connecting GAMS with MatLab

B.1 Parameter writing of GAMS code

```
%% Connection to GAMS
% SETS
file='sets.txt';
fid=fopen(file,'w');
% set time periods
letraTimePeriod='h';
[~,nombreTimePeriod] =
xlsread('HourlyPrice2015.xls','Workbook4','A2:A8761');
EscribirFicheroGAMS(fid,'SET',letraTimePeriod,nombreTimePeriod);

% Parameters
file='parametros.txt';
fid=fopen(file,'w');
%parameter de hourly demand
Nombre='d(h)';
nombreColumn1=nombreTimePeriod;
valorInputs_dh= E60/1000;
EscribirFicheroGAMS(fid,'PARAMETER',Nombre,nombreColumn1,valorIn
puts_dh);
%parameter de hourly solar efficiency
Nombre='s(h)';
nombreColumn1=nombreTimePeriod;
[valorInputs_sh] = xlsread('Zonal solar
efficiency.xlsx','Sheet1','F3:F8762');
EscribirFicheroGAMS(fid,'PARAMETER',Nombre,nombreColumn1,valorIn
puts_sh);
%Market price selling to the grid
Nombre='pv(h)';
nombreColumn1=nombreTimePeriod;
[valorInputs_pvh] =
xlsread('HourlyPrice2015.xls','Workbook4','D2:D8761');
EscribirFicheroGAMS(fid,'PARAMETER',Nombre,nombreColumn1,valorIn
puts_pvh);
%parameter de hourly price
Nombre='p(h)';
nombreColumn1=nombreTimePeriod;
%2.0 A Tariff, workbook4
% [valorInputs_ph] =
1.21*1.05113*xlsread('HourlyPrice2015.xls','Workbook4','B2:B8761
');
%2.0 DHA Tariff
[valorInputs_ph] =
1.21*1.05113*xlsread('HourlyPrice2015.xls','Workbook4','C2:C8761
');
%Tariff 3
% [valorInputs_ph] =
1.21*1.05113*xlsread('HourlyPrice2015.xls','Workbook4','H2:H8761
');
```

```
EscribirFicheroGAMS(fid,'PARAMETER',Nombre,nombreColumn1,valorIn
puts_ph);

%parameter period 1
Nombre='period1(h)';
nombreColumn1=nombreTimePeriod;
[valorInputs_period1] =
xlsread('HourlyPrice2015.xls','Workbook4','E2:E8761');
EscribirFicheroGAMS(fid,'PARAMETER',Nombre,nombreColumn1,valorIn
puts_period1);
%parameter period 1
Nombre='period2(h)';
nombreColumn1=nombreTimePeriod;
[valorInputs_period2] =
xlsread('HourlyPrice2015.xls','Workbook4','F2:F8761');
EscribirFicheroGAMS(fid,'PARAMETER',Nombre,nombreColumn1,valorIn
puts_period2);
%parameter period 1
Nombre='period3(h)';
nombreColumn1=nombreTimePeriod;
[valorInputs_period3] =
xlsread('HourlyPrice2015.xls','Workbook4','G2:G8761');
EscribirFicheroGAMS(fid,'PARAMETER',Nombre,nombreColumn1,valorIn
puts_period3);
```

B.2 Business as usual analysis of the three tariffs

```
file='parametros2.txt';
        fid=fopen(file,'w');
        Price_PV={num2str(234.7)};
        fprintf(fid,'%s \n','PARAMETERS');
            fprintf(fid,'%s \n',['Price_PV',' /']);
                fprintf(fid,'%s  \n',[Price_PV{1},'/']);
        %parameter de change of price for batteries
        Price_BA={num2str(176.3)};
        fprintf(fid,'%s \n','PARAMETERS');
            fprintf(fid,'%s \n',['Price_BA',' /']);
                fprintf(fid,'%s  \n',[Price_BA{1},'/']);

[fobjG, CPG, cost_withoutstorageG, PVCapacityG, wmaxG, qG, bG,
wG, eG, vG]=gams('MatLab_EXPENDITURE_all');
% [fobjG, CPG, cost_withoutstorageG, PVCapacityG, wmaxG, qG, bG,
wG, eG, vG]=gams('MatLab_EXPENDITURE_all_V2_tariff3');

%demand and solar generation
figure;
plot(1:8760,valorInputs_dh,'r',1:8760,PVCapacityG.val*valorInput
s_sh,'b');
%read e(h)
EH=zeros(8760,1);
a=size(eG.val);
for i=1:a(1)
EH(eG.val(i,1),1)=eG.val(i,2);
end
%read v(h)
VH=zeros(8760,1);
a=size(vG.val);
for i=1:a(1)
VH(vG.val(i,1),1)=vG.val(i,2);
end
%Compare e(h) and v(h)
figure;
plot(1:8760,EH,'r',1:8760,-VH,'b');
legend('Input from the grid e(h)','Output to the grid v(h)');
%read q(h)
QH=zeros(8760,1);
a=size(qG.val);
for i=1:a(1)
QH(qG.val(i,1),1)=qG.val(i,2);
end
%read b(h)
BH=zeros(8760,1);
a=size(bG.val);
for i=1:a(1)
BH(bG.val(i,1),1)=bG.val(i,2);
end
```

```
%compare q(h) and b(h)
figure;
plot(1:8760,QH,'r',1:8760,-BH,'b');
legend('Battery output q(h)','Battery input b(h)');
%Compare all
figure;
ind=1:8760;
[hAx,hLine1,hLine2] = plotyy(ind,[valorInputs_dh',EH-VH,BH-
QH,PVCapacityG.val*valorInputs_sh],ind,
[valorInputs_ph,valorInputs_pvh]);
title('Comparison of D(h), E(h)-V(h),B(h)-Q(h),S(h)*Solar
Capacity and P(h)');
ylim(hAx(1),[-5 5]);
ylim(hAx(2),[-0.1 0.3]);
xlabel('Hourly period in a year [h]');
ylabel(hAx(1),'D(h),E(h)-V(h),B(h)-Q(h),S(h)*PVCapacity [kWh]');
ylabel(hAx(2),'P(h) and Market Price [euro/kWh]');
legend('Hourly demand D(h)','Hourly exchange with the grid E(h)-
V(h)','Consumption of battery B(h)-Q(h)','Solar generation
S(h)','Price P(h)');
```

B.3 Future scenario analysis

```
%step=100/10;
step=10;
lowestPrice=10;
highestPrice=100;
numElements=(highestPrice-lowestPrice)/step+1;
m_PVCapacity=zeros(numElements,numElements);
m_BACapacity=zeros(numElements,numElements);
m_Savings=zeros(numElements,numElements);

vRows=zeros(numElements,1);
vColumns=zeros(numElements,1);

for i=lowestPrice:step:highestPrice
    R=(i-lowestPrice+step)/step;
    vRows(R)=i;

    for j=lowestPrice:step:highestPrice

        C=(j-lowestPrice+step)/step;
        vColumns(C)=j;

        file='parametros2.txt';
        fid=fopen(file,'w');
        Price_PV={num2str(i*234.7/100)};
        fprintf(fid,'%s \n','PARAMETERS');
            fprintf(fid,'%s \n',['Price_PV',' /']);
                fprintf(fid,'%s  \n',[Price_PV{1},'/']);
        %parameter de change of price for batteries
        Price_BA={num2str(j*176.3/100)};
        fprintf(fid,'%s \n','PARAMETERS');
            fprintf(fid,'%s \n',['Price_BA',' /']);
                fprintf(fid,'%s  \n',[Price_BA{1},'/']);

        %[fobjG, CPG, cost_withoutstorageG, PVCapacityG, wmaxG,
qG, bG, wG, eG, vG]=gams('MatLab_EXPENDITURE_all');
        [fobjG, CPG, cost_withoutstorageG, PVCapacityG, wmaxG,
qG, bG, wG, eG, vG]=gams('MatLab_EXPENDITURE_all_V2_tariff3');
        %PV capacity
        if isempty(PVCapacityG.val)
            PVCapacity=0;
        else
            PVCapacity=PVCapacityG.val;
        end

        m_PVCapacity(R,C)=PVCapacity;
```

```
text=['scenario_',num2str(i),'_',num2str(j),'.','PVCapacity=',nu
m2str(PVCapacity),';'];
        eval(text);
        %Battery capacity wmaxG
        if isempty(wmaxG.val)
            wmax=0;
        else
            wmax=wmaxG.val;
        end

        m_BACapacity(R,C)=wmax;

text=['scenario_',num2str(i),'_',num2str(j),'.','wmax=',num2str(
wmax),';'];
        eval(text);
        %Savings
        cost_original=cost_withoutstorageG.val;
        fobj=fobjG.val;
        m_Savings(R,C)=cost_original-fobj;

text=['scenario_',num2str(i),'_',num2str(j),'.','Savings=',num2s
tr(cost_original-fobj),';'];
        eval(text);

        text=['scenario_',num2str(i),'_',num2str(j)];
        eval(text);

    end
end
%read results from scenario structures
i=lowestPrice:step:highestPrice;
j=lowestPrice:step:highestPrice;
[ii,jj]=meshgrid(i,j);
figure;
surf(ii,jj,m_PVCapacity);
title('Optimized solar panel capacity [kW]');
ylabel('% of original PV price');
xlabel('% of original Battery price');
zlabel('PV capacity [kW]');
% shading interp

i=lowestPrice:step:highestPrice;
j=lowestPrice:step:highestPrice;
[ii,jj]=meshgrid(i,j);
figure;
surf(ii,jj,m_BACapacity);
title('Optimized Battery capcity [kWh]');
ylabel('% of original PV price');
xlabel('% of original Battery price');
```

```
zlabel('Battery capacity [kWh]');
%shading interp

i=lowestPrice:step:highestPrice;
j=lowestPrice:step:highestPrice;
[ii,jj]=meshgrid(i,j);
figure;
surf(ii,jj,m_Savings);
title('Maximum savings [€]');
ylabel('% of original PV price');
xlabel('% of original Battery price');
zlabel('Savings[€]');
% shading interp
```

C. GAMS code

C.1 GAMS code for tariff 2.0A and 2.0DHA

```
*$Title Short-term Models: Daily Usage of Storage Devices
*option solprint=on
*Statement of sets and indices
$set matout "'matsol.gdx', fobj, CP, cost_withoutstorage,
PVCapacity, wmax, q, b, w, e, v"
$include sets.txt
$include parametros.txt
$include parametros2.txt


PARAMETERS
*Contracted capacity
CP1             Contracted capacity 2.3 kW
/2.3/
CP2             Contracted capacity 3.45 kW
/3.45/
CP3             Contracted capcity 4.6 kW
/4.6/
CP4             Contracted capacity 5.75kW
/5.75/
CP5             Contracted capacity 6.9kW
/6.9/
CP6             Contracted capacity 8.05kW
/8.05/
CP7             Contracted capacity 9.2kW
/9.2/
*Properties of Batteries
rend          Efficiency of the storage device g [p.u.]
/ 0.95 /
w0            Initial storage level of storage device g [KWh]
/ 0 /
;


VARIABLES
fobj                  Value of objective function (Expenditure
with storage devices)
cost_withoutstorage   Expenditure without storage devices
CP                    Contracted Capacity [kW]
saving               Savings
bmax                  Maximum gross input power of battery [KW]
qmax                  Maximum gross output power of battery [KW]
;

*INTEGER VARIABLES
POSITIVE VARIABLES
PVCapacity            Solar Pannel Capaicity  [kW]

INTEGER VARIABLES
```

```
wmax                  Battery capacity [kWh]

POSITIVE VARIABLES
q(h)                 Power supply by storage device[KW]
b(h)                 Power consumed by the storage device when
storing electricity [KW]
w(h)                 Energy storage in the battery at the end of
p [kWh]
e(h)                 Direct feed-in from the network[kW]
v(h)                 Output to the network [kW]
;

BINARY VARIABLES
*Contracted capacity
scp1            Selection of contracted capacity 2.3 kW
scp2            Selection of contracted capacity 3.45 kW
scp3            Selection of contracted capacity 4.6 kW
scp4            Selection of contracted capacity 5.75 kW
scp5            Selection of contracted capacity 6.9 kW
scp6            Selection of contracted capacity 8.05 kW
scp7            Selection of contracted capacity 9.2 kW
;

EQUATIONS
E_SAVING                Savings
E_FOBJ                  Objective Function
E_WITHOUTSTORAGE        For comparison
E_CAPACITY              Contracted Capacity
E_SelectionCapacity     Selection of contracted capacity
E_DMND(h)               Meet the demand (net-metering reading)
E_MINE(h)               No injection to the network
E_MAXE(h)               Installed capacity no exceed contracted
capacity
E_MAXS                  No exceed contracted capacity
E_RSRVH(h)              Evolution of capacity with time period
E_WMAXT(h)              Maximum storage capacity
E_Qmax                  Correlation between capacity and qmax
E_Bmax                  Correlation between capacity and bmax
E_QMAXT(h)              Maximum output power of storage devices
E_BMAXT(h)              Maximum input power of storage devices
;

E_SAVING ..        saving=E=cost_withoutstorage-fobj;
E_FOBJ ..
                   fobj=E=SUM[h,p(h)*e(h)]+38.043426*CP-
0.93*SUM[h,pv(h)*v(h)]+Price_BA*wmax+PVCapacity*Price_PV;
E_WITHOUTSTORAGE ..
                   cost_withoutstorage =E=
SUM[h,p(h)*d(h)]+38.043426*5.75;
E_CAPACITY ..
```

```
CP=E=CP1*scp1+CP2*scp2+CP3*scp3+CP4*scp4+CP5*scp5+CP6*scp6+CP7*s
cp7;
E_SelectionCapacity ..
                  scp1+scp2+scp3+scp4+scp5+scp6+scp7 =E= 1;
E_DMND(h)..
                   e(h) =E= d(h)-(q(h)-b(h))-
s(h)*PVCapacity+v(h);
E_MINE (h) ..
                   e(h) =G=0;
E_MAXE (h) ..
                   e(h) =L=CP;
E_MAXS ..
                   PVCapacity =L=CP;
E_RSRVH(h) ..
                   w(h)  =E= w(h-1)$ [ORD(h) > 1] - q(h) + rend
* b(h);
E_WMAXT(h) ..
                   w(h) =L= wmax;

E_Qmax ..
                   qmax =E= 0.295*wmax+1.39;
E_Bmax ..
                   bmax =E= 0.295*wmax+1.39;
E_QMAXT(h) ..
                   q(h) =L= qmax;
E_BMAXT(h) ..
                   b(h) =L= bmax;



MODEL EXPENDITURE /all/;
SOLVE EXPENDITURE USING MIP MAXIMIZING SAVING;
execute_unload %matout%;
```

C.2 GAMS code for the three-period tariff

```
*$Title Short-term Models: Daily Usage of Storage Devices
*option solprint=on
*Statement of sets and indices
$set matout "'matsol.gdx', fobj, CP, cost_withoutstorage,
PVCapacity, wmax, q, b, w, e, v"
$include sets.txt
$include parametros.txt
$include parametros2.txt

PARAMETERS
*Contracted capacity
CP1             Contracted capacity 2.3 kW
/2.3/
CP2             Contracted capacity 3.45 kW
/3.45/
CP3             Contracted capcity 4.6 kW
/4.6/
CP4             Contracted capacity 5.75kW
/5.75/
CP5             Contracted capacity 6.9kW
/6.9/
CP6             Contracted capacity 8.05kW
/8.05/
CP7             Contracted capacity 9.2kW
/9.2/
*Properties of Batteries
rend          Efficiency of the storage device g [p.u.]
/ 0.95 /
w0            Initial storage level of storage device g [KWh]
/ 0 /
Pmax
/15/
;


VARIABLES
fobj                  Value of objective function (Expenditure
with storage devices)
cost_withoutstorage   Expenditure without storage devices
CP                    Contracted Capacity [kW]
saving               Savings
bmax                  Maximum gross input power of battery [KW]
qmax                  Maximum gross output power of battery [KW]
;
*
POSITIVE VARIABLES
PVCapacity            Solar Pannel Capaicity  [kW]

INTEGER VARIABLES
wmax                  Battery capacity [kWh]
```

```
POSITIVE VARIABLES
q(h)                Power supply by storage device[KW]
b(h)                Power consumed by the storage device when
storing electricity [KW]
w(h)                Energy storage in the battery at the end of
p [kWh]
e(h)                Direct feed-in from the network[kW]
v(h)                Output to the network [kW]
;

BINARY VARIABLES
*Contracted capacity
scp1           Selection of contracted capacity 2.3 kW
scp2           Selection of contracted capacity 3.45 kW
scp3           Selection of contracted capacity 4.6 kW
scp4           Selection of contracted capacity 5.75 kW
scp5           Selection of contracted capacity 6.9 kW
scp6           Selection of contracted capacity 8.05 kW
scp7           Selection of contracted capacity 9.2 kW
;

EQUATIONS
E_SAVING                Savings
E_FOBJ                  Objective Function
E_WITHOUTSTORAGE        For comparison
E_CAPACITY              Contracted Capacity
E_SelectionCapacity     Selection of contracted capacity
E_DMND(h)               Meet the demand (net-metering reading)
E_MAXV(h)               Maximum output to the network
E_MAXE(h)               Installed capacity no exceed contracted
capacity
E_MAXS                  No exceed contracted capacity
E_RSRVH(h)              Evolution of capacity with time period
E_WMAXT(h)              Maximum storage capacity
E_Qmax                  Correlation between capacity and qmax
E_Bmax                  Correlation between capacity and bmax
E_QMAXT(h)              Maximum output power of storage devices
E_BMAXT(h)              Maximum input power of storage devices
;

E_SAVING ..        saving=E=cost_withoutstorage-fobj;
E_FOBJ ..
                   fobj=E=(SUM[h,p(h)*e(h)]+38.043426*CP-
0.93*SUM[h,pv(h)*v(h)]+Price_BA*wmax+PVCapacity*Price_PV);
E_WITHOUTSTORAGE ..
                   cost_withoutstorage =E=
SUM[h,p(h)*d(h)]+38.043426*4.6;
E_CAPACITY ..

CP=E=CP1*scp1+CP2*scp2+CP3*scp3+CP4*scp4+CP5*scp5+CP6*scp6+CP7*s
cp7;
```

```
E_SelectionCapacity ..
                  scp1+scp2+scp3+scp4+scp5+scp6+scp7 =E= 1;
E_DMND(h)..
                   e(h) =E= d(h)-(q(h)-b(h))-
s(h)*PVCapacity+v(h);
E_MAXV (h) ..
                   v(h) =L=Pmax;
E_MAXE (h) ..
                   e(h)
=L=(period1(h)+period2(h))*CP+period3(h)*Pmax;
E_MAXS ..
                   PVCapacity =L=CP;
E_RSRVH(h) ..
                   w(h)  =E= w(h-1)$ [ORD(h) > 1] - q(h) + rend
* b(h);
E_WMAXT(h) ..
                   w(h) =L= wmax;
E_Qmax ..
                   qmax =E= 0.295*wmax+1.39;
E_Bmax ..
                   bmax =E= 0.295*wmax+1.39;
E_QMAXT(h) ..
                   q(h) =L= qmax;
E_BMAXT(h) ..
                   b(h) =L= bmax;

MODEL EXPENDITURE /all/;
SOLVE EXPENDITURE USING MIP MAXIMIZING SAVING;
execute_unload %matout%;
```