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Project in Sustainable Energy: Extension of Residential Electricity Demand Model for the Case of Malta

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ABSTRACT

A lo largo del trabajo se analizan y adaptan diferentes modelos (software) que simulan la demanda energética de viviendas particulares. Estos modelos se basan en características de los electrodomésticos, elementos lumínicos y tecnologías que se favorecen de las energías renovables que se encuentran instaladas en la vivienda, además de patrones que estiman el comportamiento de los residentes. El objetivo es analizar y comparar varios escenarios en función de las características de cada modelo, todos ellos adaptados al caso de Malta

KEYWORDS

Residential model / Demand profile / Appliances / Lighting / Usage pattern

EXTENSION OF RESIDENTIAL ELECTRICITY DEMAND MODELS FOR THE CASE OF MALTA

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EXTENSION OF RESIDENTIAL ELECTRICITY DEMAND MODELS FOR THE CASE OF MALTA

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Declaration

No portion of the work referred to in the dissertation has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Signature of Student

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Abstract

In order to keep within the 2 ºC world temperature increase set in the Paris Agreement and thus avoid irreversible climate change, the world is undergoing a transition, and low carbon technologies are becoming more and more important. In a context where almost seventeen percent of the total carbon dioxide emissions in the world are emitted by households, energy efficiency can provide an important contribution to reduce the amount of carbon emissions.

The purpose of this dissertation is to analyse and understand the main sources of electricity consumption in the case of the Maltese households and the impact of the emerging technologies towards a low carbon economy. This is achieved using different available residential load profile models applied to the case of Malta. In particular, models developed by different universities such as EDPG (Electricity Demand Profile Generator by University of Strathclyde), ALPG (Artificial Load Profile Generator by University of Twente), and CREST (Centre for Renewable Energy Systems by Loughborough University) were researched. However, the last model was not used due to lack of time.

The EDPG model was applied to study the differences in energy demand requirements by various localities and households. The determination of appropriate energy demand profiles for a key pre-requisite for the implementation of protocols favouring smart readiness and other initiatives aiming towards a low carbon economy.

The ALPG model was adapted to study the impact of the emerging technologies such as solar photovoltaics and charging for electric vehicles on the energy demand profile.

Using a combination of statistical data of households in localities, actual energy consumption of electrical equipment and calibration, it was possible to generate typical energy consumption profiles for the different households. The impact of introducing PV to generate green electricity and charge electric vehicles were also analysed.

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A

ALPG: Artificial Load Profile Generator.

C

CO_2: Carbon dioxide.

CREST: Centre for Renewable Energy Systems Technology.

CSV: Comma Separated Value.

CFL: Compact Fluorescent Lamp.

D

DSM: Demand Side Management.

DECC: Department of Energy and Climate Change.

E

EFDB: Emission Factor Database.

EU: European Union.

EV: Electric Vehicle.

E: Electricity supply.

EDPG: Electricity Demand Profile Generator.

G

Gt: Gigatons.

GHG: Greenhouse Gas.

GLS: General Lighting Service.

I

IPCC: Intergovernmental Panel on Climate Change.

L

LV: Low voltage.

LED: Light Emitting Diode.

O

OLTC: On Load Tap Changer.

P

PV: Photovoltaics.

PCD: Planning, Control, and Design of energy systems.

PPM: Prediction by Partial Matching.

PHEVs: Plug-in Hybrid Electric Vehicle.

PAR: Parabolic Aluminized Reflector.

R

RLP: Residential Load Profile.

T

TCRE: Transient Climate Response to cumulative carbon Emissions.

TV: Television.

T: Transport.

TUS: Time Use Survey.

U

UNFCCC: United Nations Framework Convention on Climate Change.

UK: United Kingdom.

V

V2G: Vehicle-to-Grid.

Chapter 1: Introduction

Since 1850-1900, global temperatures have risen by approximately 0.8 ºC as stated by the International Panel on Climate Change (IPCC, 2006) [1]. This leads to a significant increase in the occurrence of climate disasters, both in terms of their severity and frequency.

The Paris Agreement of December [2] 2015 sets a limit on the world temperature rise of 2 ºC if one is to avoid irreversible climate change. Furthermore, it recommends not to exceed 1.5 ºC. To avoid reaching that critical level, the current amount of emitted carbon cannot be sustained and must be reduced. Hence, the limited amount of carbon that the atmosphere of the earth can absorb to reach the 2 ºC target, also called carbon budget, has been established as 1.170 gigatons (Gt) of carbon dioxide (CO_2). It has a massive impact mainly on industrial companies and nations. If the carbon budget threshold is exceeded, drastic consequences such as extinction of species, wildfires, increased severity of heat waves and storms, and coastal inundation might occur [3].

According to IPCC's Report "Global Warming of 1.5 ºC" [3], no more than 420 Gt of CO_2 can be absorbed by the atmosphere from end 2017. If current emissions are mantained, the 1.5 ºC warming target is expected to be reached in less than seven years from now. Furthermore, the 2 ºC threshold, approximately 1,170 Gt CO_2, would be used up in around25 years, these rates are followed in IPCC's presentation and shown in Table 1. Accordingto IPCC research, the CO_2 emissions must be reduced to zero between 2020 and 2040 to increase the probability of limiting global warming to 1.5 ºC.

Table 1. Assessed carbon budget and its uncertainties [3].

Additional Warming since 2006–2015 [°C]*(1)	Approximate Warming since 1850–1900 [°C]*(1)	Remaining Carbon Budget (Excluding Additional Earth System Feedbacks*(5)) [$GtCO_2$ from 1.1.2018]*(2)			Key Uncertainties and Variations*(4)					
		Percentiles of TCRE *(3)			Earth System Feedbacks *(5)	Non-CO_2 scenario variation *(6)	Non-CO_2 forcing and response uncertainty	TCRE distribution uncertainty *(7)	Historical temperature uncertainty *(1)	Recent emissions uncertainty *(8)
		33rd	*50th*	*67th*	*[$GtCO_2$]*	*[$GtCO_2$]*	*[$GtCO_2$]*	*[$GtCO_2$]*	*[$GtCO_2$]*	*[$GtCO_2$]*
0.3		290	160	80						
0.4		530	350	230						
0.5		770	530	380						
0.53	**~1.5°C**	**840**	**580**	**420**	Budgets on the left are reduced by about −100 on centennial time scales	±250	−400 to +200	+100 to +200	±250	±20
0.6		1010	710	530						
0.63		1080	770	570						
0.7		1240	900	680						
0.78		1440	1040	800						
0.8		1480	1080	830						
0.9		1720	1260	980						
1		1960	1450	1130						
1.03	**~2°C**	2030	1500	1170						
1.1		2200	1630	1280						
1.13		2270	1690	1320						
1.2		2440	1820	1430						

1.1. Directives

The European Union (EU) has also been active to mitigate climate change. It has been developing climate policies, targets, and activities to tackle that alarming situation since the late 1990s, pioneering the action and being a global leader in the field. It has issued numerous directives, as follows:

1.1.1. The EU Renewable Energy Directive (EU) 2018/2001

The Directive of the European Parliament and of the Council of 11 December 2018 (EU) 2018/2001 encourages the use of renewable technologies to reduce greenhouse gases (GHG) emissions to comply with the commitment under the 2015 Paris Agreement and the Union 2030 energy and climate framework. The latter objective is to reduce emissions by more than 40 % of 1990 levels by the year 2030.

Reducing energy consumption, incentives for the expansion and use of public transport, escalating technological improvements, using energy efficient technologies and renewable energies in the electricity sector, energy efficiency measures in the heating and cooling sector as well as the transport sector are some measures for decreasing the GHG emissions.[4].

1.1.2. The Energy Performance of Buildings Directive (EU) 2018/844 and The Energy Performance of Buildings Directive (EU) 2010/31/EU

The Directive of the European Parliament and of the Council of 30 May 2018 (EU) 2018/844 establishes targets to cut GHG emissions by minimum 40 % by 2030, compared to 1990 levels, to enhance Europe's sustainability and energy security [5].

This directive has updated the previous one 2010/31/EU and the aim remains the same. Specifically, to reduce the 40 % energy consumption share of buildings [6]. Moreover, the new update requires that all new and renovated buildings must provide a minimum level of energy independence and charging points for electric cars. In addition, new and renovated building need to have a minimum level of smart readiness in their energy operations. The main indicators for smart readiness can be summarised as follows [7]:

1. High energy efficiency measures in the building.
2. High share of renewable energy systems installed on site.
3. The availability of energy storage systems in the building.
4. The demand response capacity of the building to balance the grid supply and the generated renewable energy together with the stored energy.
5. Significantly sustainable and clean energy sources for cooling and heating technologies.
6. The appropriate usage of smart metering and controls.
7. Making use of any available dynamic energy tariffs.
8. The use or possible use of a micro-grid and/or smart grid.
9. The use of electromobility to commute to the building.

Such requirements demand appropriate research in the area of energy storage and matching the demand, while reducing dependency on the national grid. However, this can only be achieved if one has a true and reliable source of data that can define the energy load profile for the building under consideration. The whole process of matching load, demandand storage is dependent on the energy load profile or in other words, the amount, and thetime during which that energy is required to be consumed. This is the topic for this project.

1.1.3. The Energy Efficiency Directive (EU) 2018/2002

Energy demand moderation and efficiency in energy generation, transmission, distribution and end-use are included in The Energy Efficiency Directive (EU) 2018/2002. This directive forms the third pillar of the energy directives. It is focused on improving energy efficiency throughout the full chain to achieve good air quality, offset GHG emissions and reduce households' and companies' energy costs. In essence, it aims to improve citizens' quality and increase sustainability [8].

1.2. Low carbon technologies and their application to households

The main method to reduce the carbon footprint is to adopt renewable energy technologies for different purposes, such as the ones identified in Table 2.

Table 2. Renewable energy technologies [9].

Source	Form
Solar energy	Solar thermal, solar PV
Biomass energy	Woody fuels, non-woody fuels
Wind energy	Mechanical types, electrical types
Mini and micro hydro	A mass water fall, current flow of water
Geothermal	Hot water

Table 3 shows few main end-uses, activities, and processes where the emerging technologies can be applied.

Table 3. Applications of renewable technologies [9].

Energy source/technology	Productive end-uses and commercial activities
Solar	Lighting, water pumping, radio, TV, battery charging, refrigerators, cookers, dryers, cold stores for vegetables and fruits, water desalination, heaters, baking, etc.
Wind	Pumping water, grinding and provision for power for small industries
Hydro	Lighting, battery charging, food processing, irrigation, heating, cooling, cooking, etc.
Biomass	Sugar processing, food processing, water pumping, domestic use, power machinery, weaving, harvesting, sowing, etc.
Kerosene	Lighting, ignition fires, cooking, etc.
Dry cell batteries	Lighting, small appliances
Diesel	Water pumping, irrigation, lighting, food processing, electricity generation, battery charging, etc.
Animal and human power	Transport, land preparation for farming, food preparation (threshing)

Climate change is commonly associated with industry, but households are also GHG emitters. The issue is that the household energy consumption is difficult to restrict, and no legal institution can control it. In addition, household members often prefer cheaper appliances rather than greener ones.

Almost 17 % of the total carbon dioxide emissions in the world are emitted by households [10. Therefore, research to surpass data protection issues and to allow improvement in tracking all the energy flows can be carried out. Appliances, the average size of the households, lighting, the energy efficiency measures implemented, and the heating/cooling systems used, water heating and mechanical ventilation all determine each dwelling's energy consumption.

Dwellings can adopt different low carbon technologies in order to reduce their electricity consumption and GHG emissions such as electric vehicles (EVs), energy service contracts, low carbon heating, solar photovoltaic (PV) panels, and battery storage. These replacements guarantee a higher sustainability, lower carbon emissions and air pollution as well as the reduction of energy bills. In particular, energy storage needs to be introduced on a large scale to offset the negative impact of solar photovoltaic electricity generation on the grid (causing over-voltage during the day) and to reduce the peak loads on the electricity utility during the night (by using the stored energy from the batteries), besides other issues, as discussed below. However, battery storage is still not affordable for every household due to the high investment required.

As mentioned above, the emerging technologies present an important impact in the households' energy consumption, as well as the GHG emissions. Table 4 presents the impact of EV, PV, vehicle-to-grid (V2G), electricity supply (E) and transport (T) in the CO_2 emissions and electricity consumption of a household (HH).

Table 4. Household electricity demand and CO2 emissions for different scenarios in Riga, Latvia [11].

Electricity demand					
	Reference, kWh/day	HH+PV	HH+EV	HH+PV+EV	HH+PV+EV+V2G
Summer day	15.4	−41%	+117%	+76%	+62%
Winter day	12.1	−4%	+109%	+105%	+107%
CO_2 emissions					
	Reference, kg_{CO2}/day	HH+PV	HH+EV	HH+PV+EV	HH+PV+EV+V2G
Summer day	6.1 (E) + 9.7 (T) = 15.8	−41%	−56%	−79%	+87%
Winter day	4.8 (E) + 9.7 (T) = 14.5	−4%	+3%	+1%	−2%

1.3. The low voltage network.

The LV network is the end part of the electric power distribution network which accommodates the majority of the consumers. It includes the circuit between the distribution transformers, which provides the low voltage power, and the electricity meters to end customers. The electric current can travel through overhead or underground power lines, or their mixture. A simple scheme of a LV network showing different forms of consumers is shown in Figure 1.

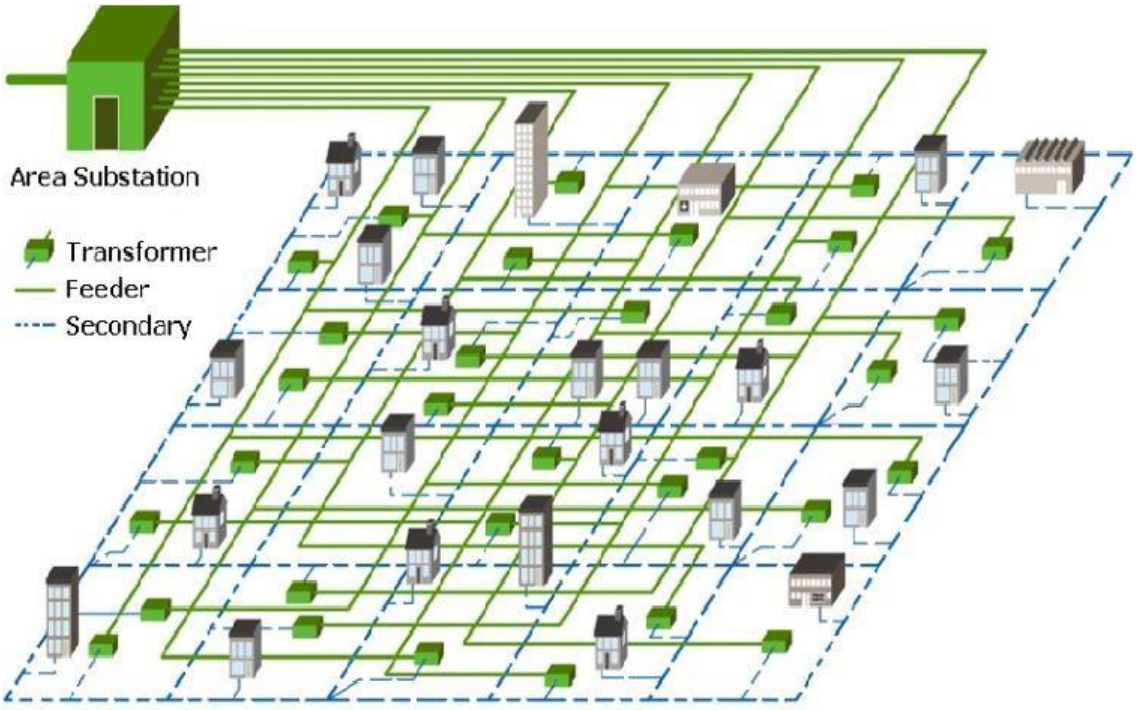

Figure 1. Low voltage network [12].

The constantly increasing usage of the low carbon technologies has raised several technical issues in LV networks. All these problems need to be deeply studied before the amounts become unsustainable. The most common issues are presented in the following sections.

1.3.1. Peak demand

The highest electrical power demand occurring on an electrical grid over a specified time period, also called peak demand, has to be handled and reduced, in order to not overload the system. The low carbon technologies could alleviate this problem if they generate renewable energy during the peak demand however excess generation and new demands such as charging of electric vehicles can compound the issue. If the peak load continues increasing in an area, then this could eventually lead to an increase in the infrastructural expenditure such upgrading of power lines or replacing transformers at the substation.

1.3.2. Voltage drop

The voltage drop issue is the energy dissipation due to the impedance of circuits' contacts, connectors, and mainly cables and lines. The current flow through passive elements leads to the decrease of electrical potential along the way leading to voltage levels which fall outside of the allowed range. The length of the circuit directly affects the drop. Voltage drop generally occurs when the overall demand on a particular sub-station is high, due to concurrent demand from multiple consumers. Once again, the use of renewables that generate electricity can support the grid in stabilizing this issue. However, renewables can also cause a new problem, as explained in the next sub-section.

1.3.3. Reverse power flow

Reverse power flow occurs throughout periods with low demand but high generation of renewable electrical energy at the consumers' side (for example, PV power injection). This causes over-voltages at the ends of the feeders and reduces the grid's power quality. These over-voltages are the principal issue limiting the distribution network's PV hosting capacity.

To tackle reverse power flow consequences, few solutions have been proposed such as grid reinforcement, transformers equipped with on load tap changers (OLTCs). The first method is effective, but its implementation requires a high investment. The second one automatically regulates the voltage at the substation mitigating over-voltages however the continuous regulation affects the lifetime of the OLTC. Alternative solutions include the introduction of consumer energy storage and reactive power management from the grid connected inverters. However, the effectiveness of reactive power management in PV inverters is low resistive nature of the feeders [13]. Active power control is more effective, but it leads to curtailment of renewable energy.

1.3.4. Overloads

The distribution network's over-current and over-voltage limits restrict the amount of renewable energy that can be connected. As the renewable energy production grows, so does the overload danger. In the case of a distribution transformer, continuous overload causes degradation of its lifetime.

The solutions to that issue are classified in two methods, hard curtailment methods and soft curtailment methods. For the first one, if an extreme case occurs, all renewable energy production units of a determined part of the grid are disconnected remotely. For the soft-curtailment case, the production will be cut just enough to avoid the overload [14]. Another approach is the introduction of energy storage in conjunction with renewable energy systems to avoid curtailment.

1.4. Aim of the project

The aim of this dissertation is the generation of load profiles through published demand models applied for the case of Malta. The determination of appropriate energy demand profiles form a key pre-requisite for the implementation of protocols favouring smart readiness and other initiatives aiming towards a low carbon economy.

The specific objectives of the project are:

1. Examine the main characteristics and output of published electrical load profile models.
2. Evaluate and compare the salient features of selected residential electrical load profile models.
3. Apply selected models to the case of Malta using relevant residential energy use trends.
4. Analyse and compare the generated profiles.

1.5. Dissertation layout

The full dissertation consists of six chapters. The general background of the dissertation introducing the topic, purpose, and relevance is presented in Chapter 1. Chapter 2 emphasizes on the structure, characteristics and methodology used to create reliable load profiles. This is followed by an introduction and description of the selected models in Chapter 3. Chapter 4 clarifies how the models will be adapted to generate profiles applicable to Malta. It also describes how they will be tested. Chapter 5 includes the outcomes and analysis of the modelling that have been carried out throughout the dissertation, discussing the obtained profiles and their potential used as a basis for future studies. Chapter 6 presents the conclusions on the results achieved. Furthermore, the reliability of the results is evaluated and recommendations for future research are suggested.

Chapter 2: Literature Review

This chapter will provide a general background and show that the consumer demand is changing due to Directives and introduction of low carbon technologies.

2.1. Main modelling issues

During the last decades, it has been believed that the number of occupants in each house, their socio-economic circumstances as well as the household type are factors that do not have a strong impact in the residential load demand. Hence, the residential load demand could be easily foreseen [15]. More recent smart meters' measurements have shown that residential profiles are neither easy to model nor predictable because the use of electric-powered devices such as those used for space heating and cooling, water heating and lighting depends on the individual lifestyles and schedules. Moreover, modern societies handle an ever-increasing number of electronic and electric plug-in devices such as TV, kitchen appliances, smartphones, and laptops, besides others. This family personality not only means that there are peaks and troughs in the power consumption profile when turning on/off the devices, but there is a high level of variability over time, principally for time resolutions of fifteen minutes or less.

Moreover, in recent decades, due to the increasing importance of electro-mobility, the surge of the Earth's population to ten billion humans, the increase in dependency on electric devices, the surge of new social conditions such as working from home, and the use of the distributed energy resources (PV, energy storage, EV, etc.), the residential load profile has been drastically altered [16], [15]. Therefore, a deep understanding of these profiles and their modelling is needed to be able to comprehend and foresee these changes.

2.2. Residential electrical load profiles

First of all, the concept "residential load profile model" has to be clarified. The word, "residential", refers to the private accommodation of households consisting of one or more persons. The overall electricity consumption of the various appliances and electrical equipment in the household is named as "electrical load". "Profile" is the variation that represents the significant attributes of the load over time. Finally, "model" refers to a representation that can predict the behaviour given the required input information.

[15] says that "residential load profile model" is a formal system that can replicate the total electricity consumption of the major loads in a single/multiple private/non-commercial residence. The residence has to be occupied by a minimum of one person during a portion of the calendar year. Input data variables characterize households, occupants, and their behaviour in terms of lifestyles and schedules.

A valid residential electric load profile model must have the following characteristics:

A. Load consumption model, which has to represent the electricity usage pattern of the various electric-powered devices within the household/community.
B. Occupancy model to simulate the behaviour, and timetables of the households' individuals.
C. Household type division in order to differentiate between the different categories of dwellings according to the inhabitants' lifestyles and number.

As expected, every characteristic is impossible to represent completely. Therefore, modelling approaches have to be carried out following a methodology, defining statistical approaches and the time resolution according to the purposes of the model.

2.2.1. Load categories

The electricity use pattern in a single household is dependent upon the occupants' activities, the range of electrical appliances and their usage. Mainly, the total consumption of a residential building is generated by the electric-powered appliances, these are generally categorised by the activity, for example cooking, heating/cooling, or lighting.

Figure 2 shows the annual overall household consumption shared between the different loads for a Maltese villa household.

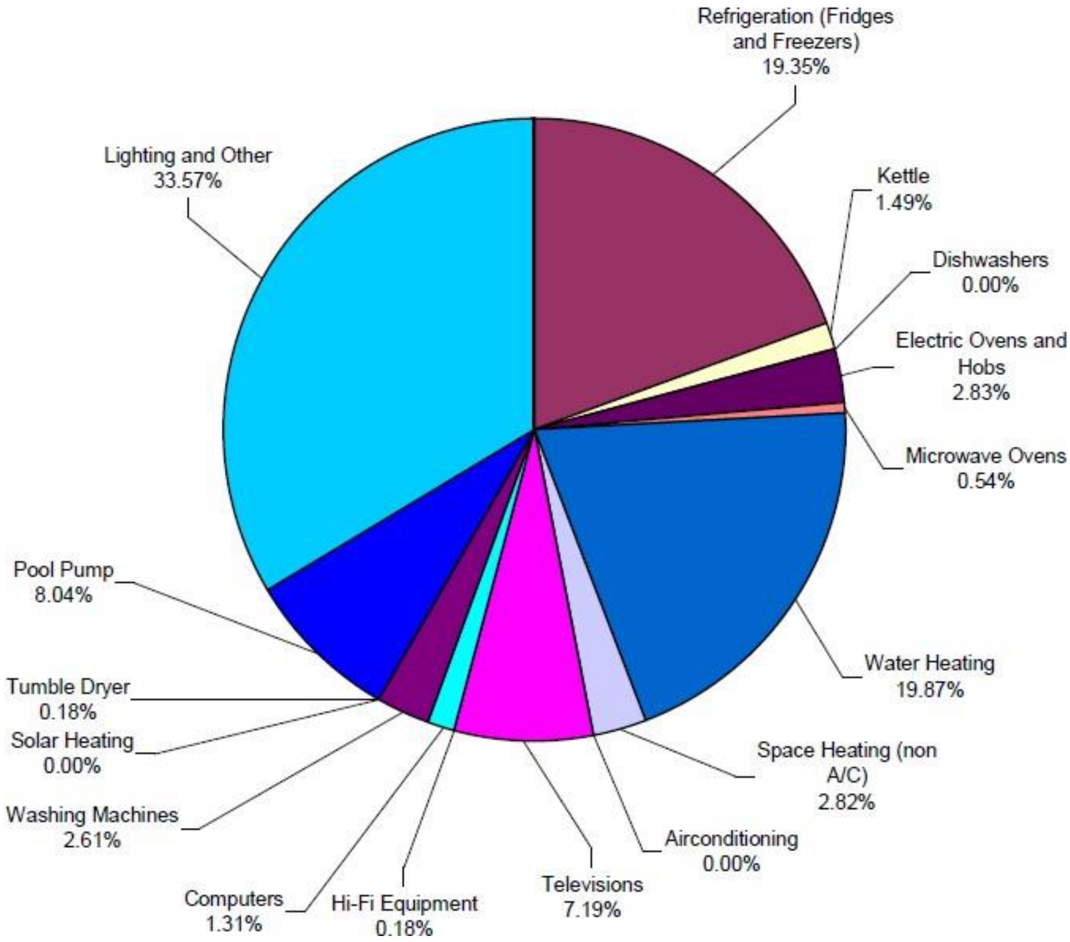

Figure 2. Energy consumption share for a Maltese villa [39].

2.2.1.1. Electric-powered appliances

Appliances, in this case, refers to any individual domestic electricity load, except for lighting. For example, dehumidifiers, electric kettle, television, and in general electric-powered devices. Table 5 shows an example of appliance list within a household and uses a house zone categorisation, however other categorisations are possible for example according to the current occupants' activities (cooking, heating/cooling, etc.). The categorisation is generally used to model the likelihood of the appliances being used at the same time.

Table 5. List of household appliances [18].

House zone	Appliance
Kitchen	Washing machine Dishwasher Electric cooktop Kettle Electric oven Micro-wave Coffee machine Toaster Waffle iron Fridge
Bedroom	Radio Laptop Telephone charger
Bathroom	Electric heater Shaver Hair dryer Sauna stove
Living room	Television Stereo/Hi-Fi
Cleaning tools	Iron Vacuum cleaner

At the beginning of a run, a model usually populates each dwelling with appliances. This can be done using statistical ownership data [19]. Generally, statistical data is also used to configure the average annual energy demand and related power consumption attributes of each device, including common use cycles or steady-state demand. These parameters are used to generate each appliances load profile. Then, by aggregating them all together, the total appliances consumption profile is determined.

The usage pattern of an electric device is based on the occupancy pattern coupled with the activity that takes place. Certainly, more than one occupant may use multiple equipment at the same time, so the sharing of such equipment must be considered. Furthermore, as shown in Figure 3, the use of appliances might be increased non-linearly in accordance with the number of inhabitants.

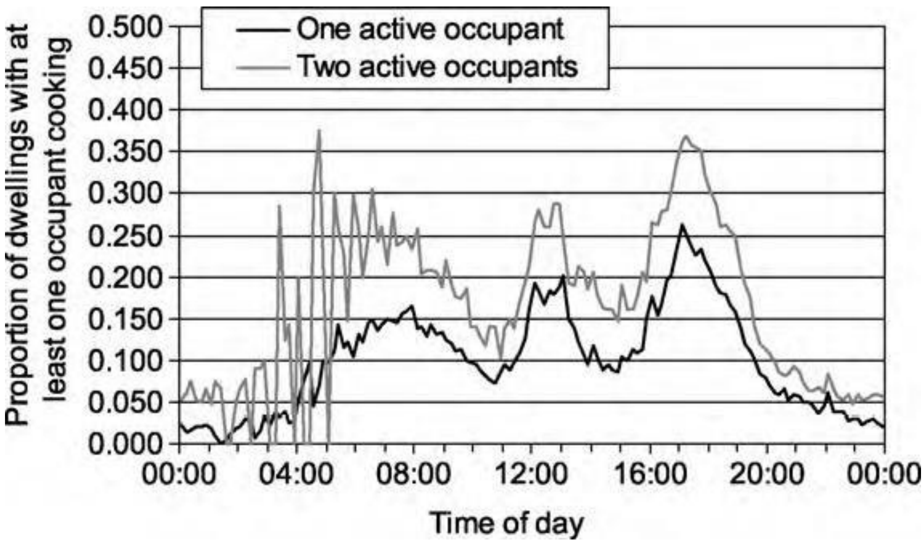

Figure 3. General household sharing of appliances for a UK study [19].

Generally, each electronic device is characterised by two different states, on or off. The latter should consider the standby mode, in that state an appliance consume power even thoughit is not being used. The turned-on events of some electronic devices are largely affected by occupancy patterns, although there are some appliances that can be programmed to activate or deactivate by themselves. In addition, some equipment's demand changes throughout the seasons, such as heating and cooling equipment.

Despite some electric devices, such as a laptop, which has constant power requirements when in operation, few other appliances should be expressed in terms of time varying demands. For example, the washing machine cycle goes through different stages with different power requirements. However, this can only be represented by high time resolution models. Unfortunately, such detailed appliance demand data is not generally available [19].

Furthermore, the electric loads can be grouped by controllability [20]. Uncontrollable appliances usage, and therefore their consumption, is highly influenced by the active occupancy, for example the cooking appliances. On the other hand, controllable devices refer basically to time-shiftable devices, also known as deferrable devices, which are able to provide timetable flexibility for demand response. For example, the cooling equipment (freezer or refrigerator) is less sensitive to people's activities and, moreover, on the occupancy levels. This can help to reduce the peak demand and generally leads on the reduction in electricity bill payments [21]. Dishwashers, tumble dryers, washing machines and water heaters are within this group.

2.2.1.2. Lighting consumption

The lighting consumption is defined as the aggregated consumption of each lighting unit (one or more bulbs connected to a single switch) within a household. It depends on the electric lighting usage, which is highly influenced by the outdoor irradiance and the layout of the dwelling coupled with the household residents' behaviour. The main issue is to represent the specific lighting technology, its rated power, and on the number of light bulbs installed as it varies from one residence to another due to human selection as Figure 4 shows.

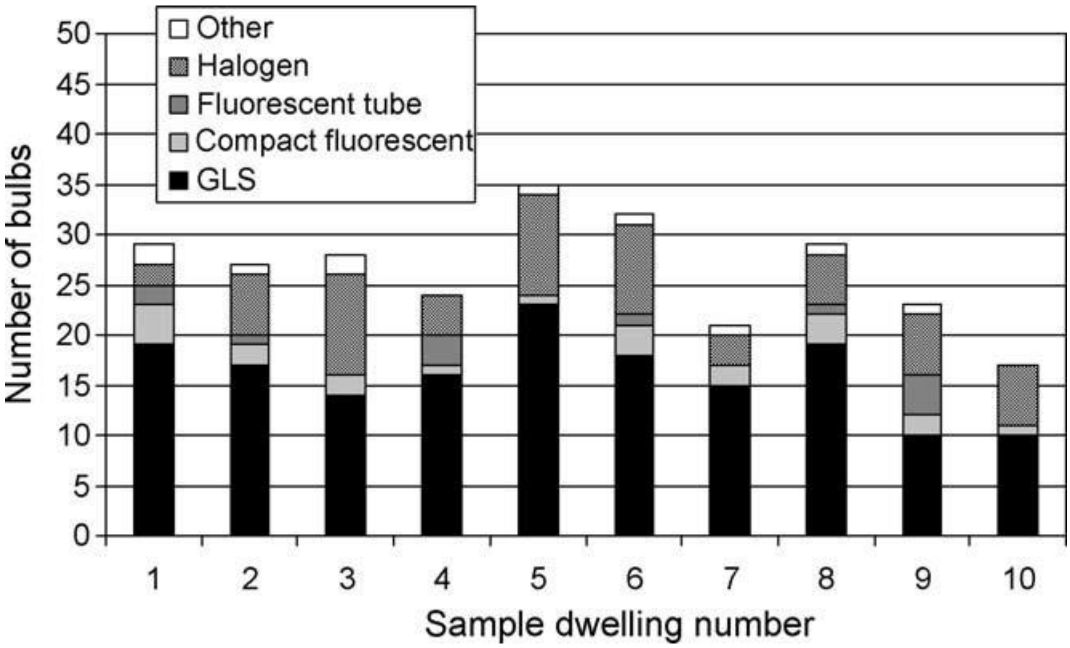

Figure 4. Allocation of lighting unit types in different dwellings [19].

The number of switched-on units and duration are defined by the behaviour of the inhabitants and, normally, the use of lighting is restricted to at least one active inhabitant within the dwelling. However, as long as there are at least two active inhabitants, the sharing of lights, also known as "co-use", is likely to occur by virtue of spending time in the same room. Moreover, some lighting units are utilized more than others such as the ones installed in living spaces and kitchens. [22].

As mentioned, the lighting usage is generally determined by the outdoor irradiance conditions but there are also rooms without windows, cellars, etc., the lighting units installed in these places are not affected by the irradiance levels.

Distributions, relative use weightings, and probabilities are often used to represent these characteristics [23], Figure 5 shows an example of an installed lighting rating and relative use in a dwelling.

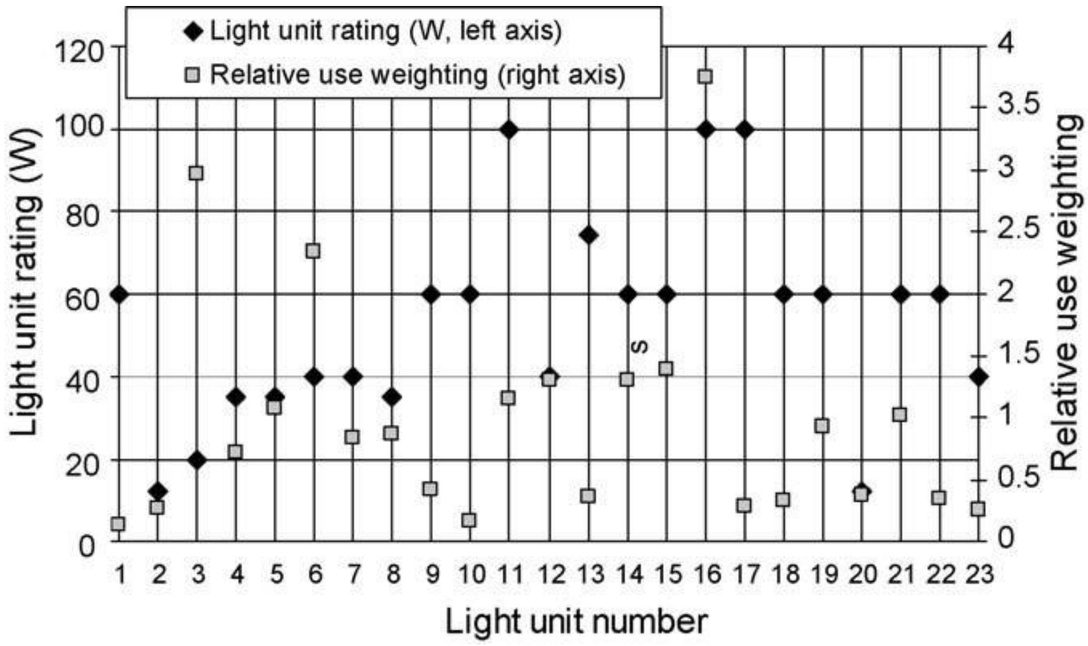

Figure 5. Installed lighting unit rating and relative use within a dwelling for UK dwellings [19].

2.2.2. Occupancy pattern

As mentioned, electric appliances' usage patterns are related to the electric activities of the inhabitants. Therefore, an occupancy pattern model becomes essential. The use of electrical appliances in a household is related to the number of people whose state is active. Active occupancy refers to the people who are indoor and awake; it is represented within each household as an integer which changes during the day. Its representation allows generation of electricity demand data with detailed profiles throughout the day. In addition, it supplies a basis for establishing time-related electricity consumption modelling within and between households. [19].

Generally, the individual's occupancy pattern has two different states: out of home or at home. The latter can also be divided in active occupancy or inactive occupancy (e.g. sleeping). Figure 6 shows an example of dwelling active occupancy profile. In the example, there are three different occupants within the household, they wake up between 6:00 and 8:00 AM and few hours later some of them leave the household to do their daily activities such as working. However, there is one active occupant throughout the day within the dwelling until they all go to sleep at 10:00 PM.

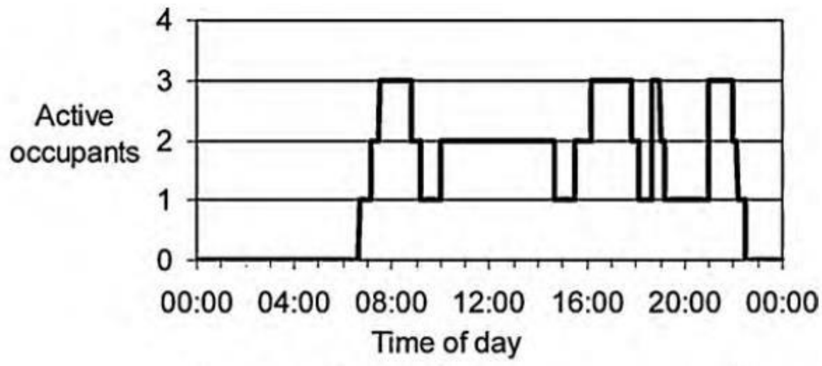

Figure 6. Household active occupancy profile [19].

2.2.3. Types of households

As mentioned above, different socio-spatial factors have a large impact in the households' overall electricity consumption. For example, lower income households are likely to have less appliances, big apartments require higher heating/cooling electricity demand, senior families usually spend more time at home, etcetera. In general, these are factors that affect their nation's consumption profile. Then, it is possible to relate specific measures to the main groups and to address the appropriate attributes to each group [24]. A categorisation of households according to number of members and the gender of the heading person is represented in Table 6.

Table 6. Sample distribution of different types of households [25].

Family members (No.)	Female-headed households		Male-headed households	
	No.	%	No.	%
1-2	67	44	17	9
3-4	56	37	97	49
5-6	23	16	73	35
7-10	4	2	13	8
Total	150	100	200	100

2.2.4. Applications of residential load profiles

Every model itself or its output is developed to have various applications, often more than one. Nevertheless, these profiles can be split up into three different subcategories: planning, control, and design of energy systems (PCD), demand side management (DSM), and residential load profiles (RLP). [15].

2.2.4.1. Planning, control, and design of energy systems

The main purpose is the development of energy systems, distribution networks and the local energy efficiency strategy belonging to this subcategory. This type of research aims tohelp grid planners use various technologies to build a grid that minimizes power consumption by the evaluation of worst-case scenarios regarding voltage drop, short-circuit currents and equipment's loading capacity [26].

2.2.4.2. Demand side management

Demand side management systems focus on how to reduce/change dwelling electricity consumption by implementing emerging technologies, or how to shift loads over time of day, to improve demand with generation capacities [27]. As mentioned above, this optimization is facilitated by the installation of smart appliances, e.g. refrigerators, washing machines, or time-programmed room heaters. Nowadays, there are algorithms available for some devices that allow them to turn on/off on demand, or algorithms that pre-arrange their usage when particular conditions are accomplished or within specific time periods of the day [15].

2.2.4.3. Residential load profiles

These models are created to forecast and analyse the different sources of the demand response of a household/community of households, focusing on the main issues within the LV networks, as well as the renewable energies integration in the context of low carbon technology uptake.

2.2.5. Modelling approaches

As mentioned, the inhabitant's behaviour has a large impact in the usage of the appliances and, therefore, in the household consumption profile. To represent that, every model takes a particular approach. The methodology, the time resolution and the statistical approach are the fundamental approaches which determine the end-use of the model. A categorization according to the main features is presented in Table 7.

Table 7. Model categorisation summary. Information extracted from [15].

Categories	Subcategories
Methodologies	Bottom-up models Top-down models Hybrid models
Sampling rate	Low resolution models. Middle resolution models. High resolution models.
Statistical approach	Markov chain techniques. Probabilistic techniques. Monte Carlo techniques.

2.2.5.1. Methodologies

Nowadays, we can differentiate between bottom-up, top-down and hybrid models. The categorisation is based on the procedure utilised to obtain the electricity demand profile of the dwelling. [15].

2.2.5.1.1. Bottom-up models

These models take the electricity consumption of each appliance within a dwelling, the occupancy pattern of the individuals, and their associated use of appliances into account to calculate each household's electricity consumption. They aggregate them together to generate the overall dwelling electricity demand.

In accordance with the end-use of the model, its input parameters may require some house characteristics such as layout or size, weather conditions, and heating/cooling characteristics. They can also represent different device usage patterns and low carbon technologies. The latter is to determine the impact of individual households to the electricity consumption curve. They can also be used for utility-level demand forecasting. From there, they can extrapolate the individual dwelling electricity demand to a higher level (community/village/city/region/country). In order to accomplish this extrapolation, a weight is assigned on each household/group of households.

The most commonly used procedure, step by step, to generate a bottom-up model is as follows [15], [28]:

1. Decide the end-use devices within the dwelling/s as well as the model's micro-variables.
2. Establish the human activity patterns from real data, applied to the households' appliances.
3. Create the load curves of each household electric-powered device for a determined time period.
4. Add these profiles of with every single or multiple dwelling, note that the period is the same of the third step.

Generally, bottom-up methodologies present three major advantages: they do not necessarily need to use historical electricity demand data to determine the electricity requirements of the community, they are suitable for studying technologies, policy decisions and energy optimisation methods on the dwelling load curves, and they generate very detailed results [28]. On the other hand, they have heavier computational demands because of the model's complexity and detail, and as input, they need activity occupancy patterns, the households' appliances ownership and information aboutthe use of electric devices at different time slots.

2.2.5.1.2. Top-down models

On the other hand, top-down models assign the electricity consumption estimation to the building's attributes. They compute complex random inference between stochastic variables [29], also known as stochastic predictors, commonly based on time series analysis, and macro variables to foresee the dwelling electricity demand profile and use them to couple the electricity consumption and the predictors themselves. The structural attributes of the households, the historical consumption data, the different characteristics of the occupants (number, age, gender, income, etc.) and their behaviour, the total community electricity consumption, and the weather conditions are some of the most used macro variables. Occupants' age is usually used to proxy the period of time occupants spend indoors and therefore the probability of electricity consumption. These models are normally developed for a utility-level demand forecasting.

As a result, their calculation strength is not as high as the bottom-up models [15], [28]. Top-down models calculation process are generally as follows:

1. Gather historical electricity datasets with the most suitable sampling rates.
2. Identify the macro variables that will characterise the model.
3. Categorise the macro variables within different combinations. For example, according to household type.
4. Determine the most suitable stochastic predictors to be used by performing time series analysis on the historical data.
5. Couple the macro variable categories with the stochastic predictors to generate the load curve of the household/s for a specific period of time.

If bottom-up and top-down models are compared, top-down models present two main advantages: no information about a single appliance is required and they are less complex as they do not utilise the usage pattern of every appliance. Hence, they are not as computationally demanding as the bottom-up models in terms of computation. Their main disadvantages are they usehistorical data about dwellings electricity consumption, and the time resolution is often large (between fifteen minutes and one hour). This leads to loss of information because only some statistical standards can be achieved. The top-down model is very suitable for simulating transformer, storage size, and power distribution network loading. The modelis also suitable for analysing demand response.

2.2.5.1.3. Hybrid models

Hybrid models combine methodologies and characteristics used in both, top-down and bottom-up models. Occupancy models, consumption load curves, electrical appliance usage, lighting usage, natural ventilation and hot water demand are some of the elements included in bottom-up models. Top-down models contribute building archetypes to characterize groups of buildings and their demand profiles.

The most commonly used procedure, step by step, to generate a hybrid model is explained in the next section [15]:

1. Indicate the macro and micro variables that the model will use.
2. Apply the bottom-up procedure steps from 1 to 3 to the micro variables.
3. Apply the top-down procedure steps from 1 to 4 to the macro variables.
4. Aggregate the macro and micro variables to generate load curves for a household/group of households in a determined period of time from one day to few years.

Hybrid models are developed to carry out demand side management efforts like demand forecasting by the use of smart meters. Thus, a variable set of techniques and input data will be required by the model in accordance with its purpose. Hence, the characteristics highly vary from one model to another. At the end, it is impossible to come up with a list of pros and cons as each model uses different elements.

2.2.5.2. Time resolution

A series of different challenges are presented by the time resolution of the available datasets. Most of them are used to generate models with a time resolution similar to or lower than that of the data sets. Therefore, smart home and demand side management applications require datasets with resolutions over 1 minute, sometimes even with 1 second granularity.

Generally, this feature defines the output's data time step and therefore the output's level of detail. Although the time resolution of the input data is not usually the same, the output's resolution has to be. Models with high sampling rates display far more state changes than the low-resolution models. The different models are usually classified in three different subcategories: low resolution models, middle resolution models and high-resolution models. [15].

2.2.5.2.1. Low resolution models

The sampling rate of these models is higher than fifteen minutes. General features such as studying the influence of the energy prices, modelling the end-use electricity of a region, or modelling the electricity load curve of a household/s are commonly represented with this data granularity.

2.2.5.2.2. Middle resolution model

They use time resolutions between fifteen minutes and one minute. Such models are not very numerous, and their general purpose is the study of the individual residential load profiles of individual households.

2.2.5.2.3. High resolution models

These models are characterised by having a time resolution over one minute. Such models are usually built with data of household electrical devices and smart meters' measurements of the power supply.

2.2.5.3. Statistical techniques

This characteristic establish the statistical approach used by the model to solve its uncertainties with representative data clustered functions/distributions, and provide useful information about demand patterns of costumers, annual consumption of households/communities, appliances' operation time, etcetera [23]. Three different approaches are enumerated in the following section [15]:

2.2.5.3.1. Markov chains

Markov chains are commonly used to simulate the behaviour of the appliances. The model is able to assume that the behaviour (activation/deactivation) of the device is related to the operation of other devices. For example, for a house with a washing machine and a tumble dryer, the dryer will only be utilized after the end of the washing machine's cycle whereas the use of the hob does not imply the usage of the vacuum.

In fact, all models use a combination of residents' usage patterns and devices' load curves to simulate household electrical load. Usually, these types of models define an initial state, which evolves to the following states depending on the transition probability. The conversion probability is generated using a pseudo-random number distributed uniformly. As it is compared with the cumulative distribution of the state transitions, it determines the transition to occur.

2.2.5.3.2. Probabilistic models

These models are called prediction by partial matching (PPM). Normally, they use general statistical methods such as conditional demand analysis, cumulative probability functions, probability distributions and Gaussians sums to model the load curves of entire households. They are commonly used to determine the device usage and the duration. In addition, they are used to create the occupancy pattern of the dwellings.

2.2.5.3.3. Monte Carlo models

PPM and/or Markov-Chains approaches are often combined with Monte Carlo methods. These procedures usually determine which devices are used and, for how long devices with uncertain usage periods, for example light bulbs, are used for. Less frequently, they are used to develop customer profiles, to represent indoor-lighting electricity usage and to create activity-specific occupancy profiles.

2.2.6. Assumed rates

Generally, each appliance is assigned an annual demand in kWh/year. Most of the needed data can be obtained through surveys or data sheets; it is also valid to use data from the different appliances available in the market. Frondel et al. [30] estimates a dataset, based on Germany, determining the consumption rates of households by requesting detailed information on electricity prices, bills, monthly fixed fees, and electricity consumption in the billing periods. The dataset gathers information on the appliances that are present in a householdand its consumption.

2.2.7. Combination with thermal models

Nowadays, the widespread electrification of heat supply, by replacing gas boilers with heat pumps, in the residential sector is foreseen to pose a significant challenge to the distribution network management due to the wide nature of these loads. The cost of reinforcing the installed power networks to absorb the heat pumps' load and other emerging technologies can be substantial. In low-voltage networks, this task is particularly difficult. Conventional low voltage (LV) network design methods are not well adapted to such type of load.

High resolution models of residential heat demand are being created in the way that they can provide basis for upcoming low-carbon network research. They are usually developed on the same occupancy pattern as the one used in the electric model and they generate, at the level of the individual household, randomised end-use energy demand data with high resolution that usually have a significant impact in the resulting profile.

The main novelty of the model lies in its integrated structure, which can appropriately correlate the time of the thermal and electrical output variables. Thermal models usually integrates a building thermal model, a solar thermal collector model, hot water consumption, timer and thermostat managements, and gas boilers. However, it is greatly affected by outdoor temperature. McKenna et al. [31] implemented a “low-level” thermal model, it is shown in Figure 7.

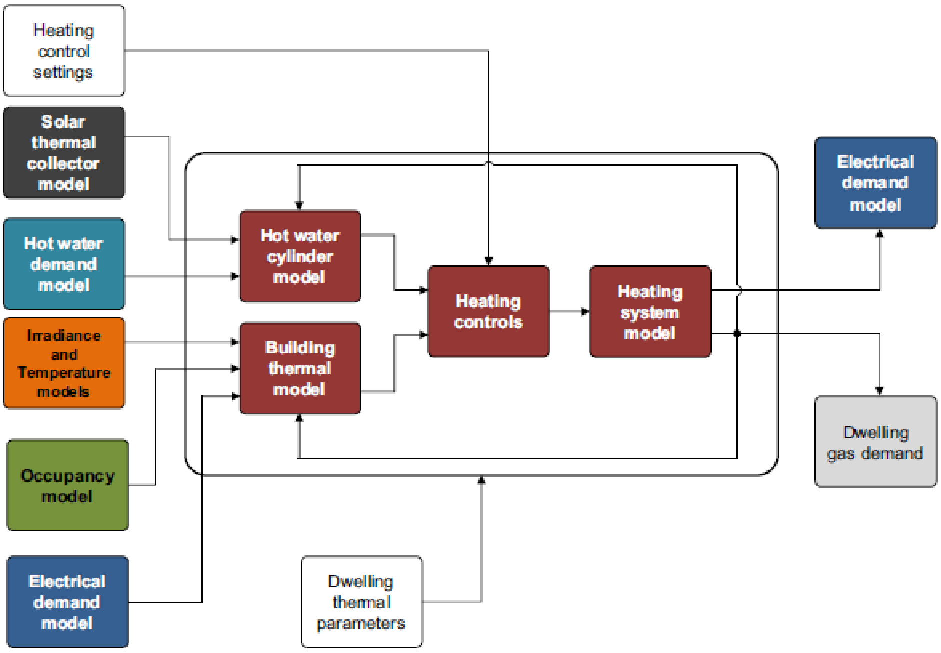

Figure 7. Structure of a thermal demand model [31].

2.2.8. Published reference profiles

Table 8 shows a categorisation of some published models indicating the publication year, the time resolution, the application, and the modelling techniques applied. The most common methodology is the bottom-down at the time of the research. This is likely to change due to the increase of smart meters utilisation and demand side management. Within the referenced models, the time granularity varies between one second and one hour, the latter is the most used time resolution.

Table 8. Model categorisation [15].

Authors	Year	Sampling Rate	Application	Modelling Techniques
Bottom-up modes				
Train et al. [57]	1984	1 hour	RLP	PPM
Walker et al. [56]	1985	15 minutes	PCD, RLP	PPM, MChain
Yao et al. [54]	2005	1 hour	DSM, RLP	PPM
Melody Stokes [48]	2005	1 minute	PCD, RLP	PPM
Paatero et al. [52]	2006	1 hour	DSM, PCD, RLP	MChain, PPM
Armstrong et al. [7]	2009	5 minutes	DSM	MChain, PPM
Richardson et al. [46]	2010	1 minute	RLP	PPM, MChain
Dickert et al. [17]	2010	30 s	DSM, PCD	PPM
Ren et al. [45]	2012	1 hour	DSM, PCD, RLP	PPM
Gruber et al. [24]	2012	1 minute	DSM	MChain, PPM
Shao et al. [47]	2013	1 hour	DSM	PPM, MCarlo
Muratori et al. [39]	2013	10 minutes	RLP	MChain, MCarlo, PPM
Bajada et al. [8]	2013	1 minute	DSM	MChain
Ortiz et al. [42]	2014	1 hour	RLP	PPM
Alzate et al. [3]	2014	15 minutes	DSM	MChain
Collin et al. [16]	2014	10 minutes	DSM, PCD	MChain
Fischer et al. [19]	2015	10 s	DSM, REL	PPM
Gao et al. [55]	2016	8.5 minutes	DSM	PPM
Marszal-Pomianowska et al. [35]	2016	1 minute	DSM, PCD	PPM
McKenna et al. [5], [36]	2016	1 minute	RLP, DMS,	PPM
Gottwalt et al. [22]	2018	1 hour	DMS	MChain, PPM
Top-down modes				
Capasso et al. [14]	1994	15 minutes	DSM, RLP	MCarlo, PPM
Widen et al. [53]	2009	1 hour	RLP	PPM
McLoughlin et al. [37]	2010	30 minutes	RLP	MChain
Bucher et al. [13]	2012	1 minute	RLP	PPM
Labeeuw et al. [32]	2013	1 hour	RLP	MChain, MCarlo, PPM
Ge et al. [20]	2016	1 hour	PCD	PPM
Anvari et al. [87]	2020	2 seconds	DSM, RLP	PPM
Hybrid modes				
Bartels et al. [10]	1992	1 hour	DSM	NMCPS
Ardakanian et al. [6]	2011	1 minute	PCD, RLP	MChain
Johnson et al. [27]	2014	1 s	RLP	MChain, PPM
Neue et al. [41]	2016	1 minute	DSM	MChain, MCarlo

In addition, there are models that are commonly used in the commercial area with the purpose of simulate-based planning, design, and optimization of energy systems for buildings and districts. Furthermore, these models include new energy production technologies as well as thermal models. As commercial models, they provide easy tools for energy and data management. Polysun is an example of a commercial model.

2.3. Summary

This chapter has presented a general overview about residential electricity load profile models and focused into the main characteristics such as the considered loads and their categorisation, the value of the occupancy pattern, and the household clustering to represent occupants' behaviour. Furthermore, the main applications and methodologies were detailed and the combination with thermal models was considered. Chapter 2 is closed by considering various published residential load profile models.

Chapter 3: Considered load models

This chapter introduces the selected electricity demand models, explains how they operate, their input data requirements and the generated profiles.

3.1. Study models

Within the published and referenced models, three are selected to be analysed and applied for the case of Malta. First of all, a deep understanding of them has to be carried out. The selected models are the Electricity Demand Profile Generator (EDPG) [32], the Artificial Load Profile Generator (ALPG) [33], and the Centre for Renewable Energy Systems Technology (CREST) model [34]. The models are developed by the University of Strathclyde, UK, the University of Twente, the Netherlands, and Loughborough University, UK, respectively.

3.2. EDPG model

This tool was developed to generate the electricity demand profile of a whole community. It is designed to provide quick and accurate results and also shows profiles for particular households within the community. It provides demand data with a resolution of one hour. Nevertheless, the profile generator can be developed even more to generate data at higherresolution, up to a five minute time step.

3.2.1. Load profile calculation process

The calculation process starts with the identification of the inputs required by the model, i.e. the community census demographic results and the annual electricity consumption. After coupling them with the household occupancy patterns, the distribution of the load and the calibration the simulation is ready to start. The whole calculation process is shown in the flow-chart represented in Figure 8 and overviewed in the following section; the main points will be detailed:

1. The tool identifies the name of appliance, the number of times per day that it is in use, and the probability of its use during the particular period.
2. The appliances' usage pattern is randomised in order to obtain a stochastic demandprofile, the stochastic process is detailed below.
3. The lighting consumption profile is obtained according to the lighting usage pattern, the number of light units installed and their power rating.
4. Aggregating both profiles to generate each dwelling's consumption profile.
5. The community consumption profile is obtained by multiplying each single profile per the number of households within the type and summing them together.
6. The resulting profile is calibrated to generate an output profile in consonance with the statistical data.
7. The electricity demand profile is plotted.

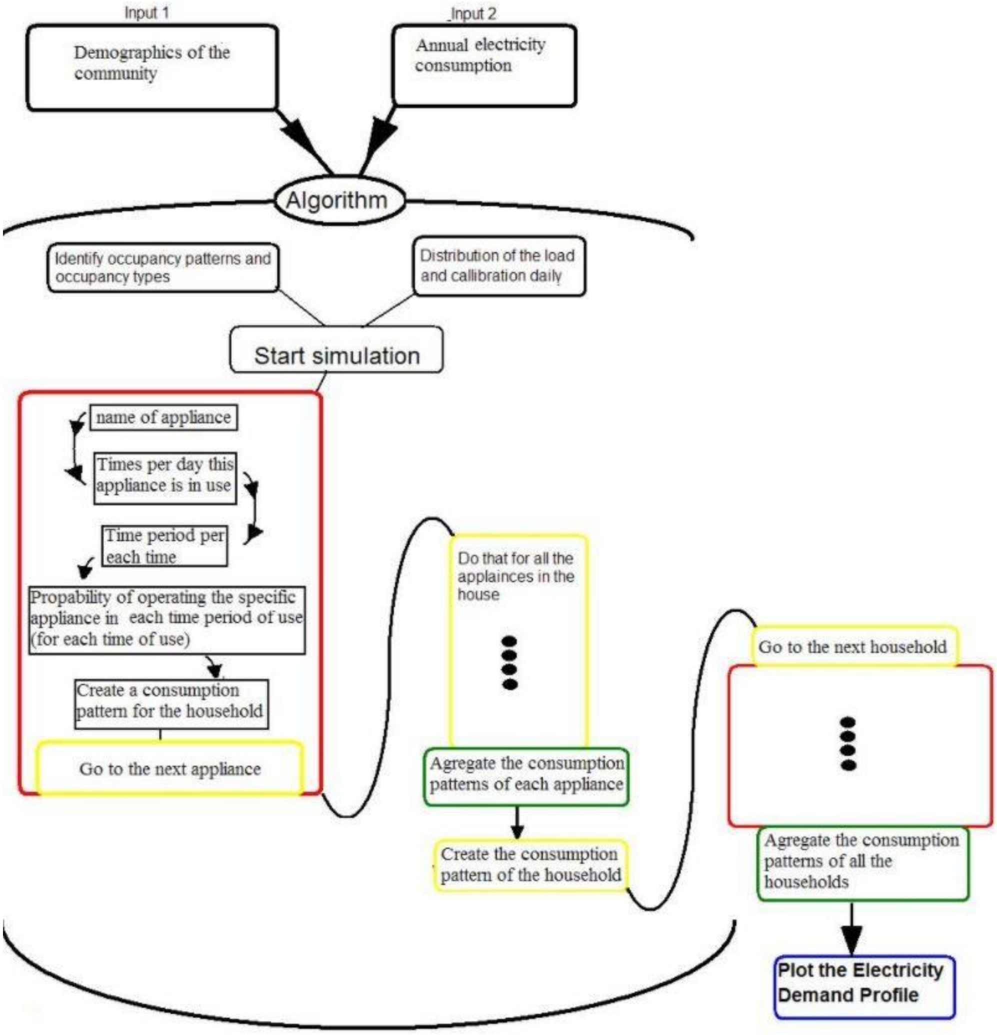

Figure 8. EDPG model calculation process [35].

3.2.1.1. Appliance profile generation

Every appliance has an assigned consumption per capita, in this case per person, in kWh/day and a number of times of usage per day. Both are then used to determine the number of households that use each appliance within a time period. This process is randomised to obtain a stochastic output as will be explained.

The randomised number of households using a determined appliance is multiplied by its consumption. Then, the profile is created just by aggregating all the appliances' demand.

3.2.1.1.1. Randomisation process

As explained below, each appliance usage is determined by the probability of use within the time period. To randomise the output, these probabilities are accumulated with defined cut off points and they are assigned a random tag, as shown in Table 9. For example, Hob first usage is shared between four different time slots, the likelihood of being used in the first period is 0.1, the second 0.2, third 0.6 and the final one 0.1.

Table 9. Randomisation process of the hob.

CUT OFF	Hob 1	
	Cut off	Random Tag
	0,00	1
	0,10	2
	0,30	3
	0,90	4

For n dwellings within the same household type, different samples are created. Each sample is represented by a random number bounded between zero and one. These samples are compared to the cut off points to determinate their random tag. Then, random tags are counted to generate number of households that are supposed to use the appliance within the respective time slot. Table 10 shows the resulting probabilities for the case of the hob. This process is applied to the appliances that are likely to be used once within two or more time periods.

Table 10. Resulting probabilities for the case of the hob.

PROBABILITY	Generated	Target
1	0,0	0,1
2	0,1	0,2
3	0,2	0,6
4	0,0	0,1
5		
6		
7		

3.2.1.2. Lighting profile generation

As discussed in the Literature Review, the lighting usage is highly influenced by the occupancy pattern. Therefore, to generate the lighting profile, the model identifies the input daily time intervals of lighting usage, for winter and summer seasons, and then the consumption of the lighting units installed within the dwelling.

The number of light bulbs per dwelling and the average energy rating per bulb in Wh/h set the electricity lighting requirements for a single dwelling. Subsequently, the tool multiplies the resulting value by the number of households within a household type and aggregates all together to produce the lighting consumption profile. For the case of the Table 11 the calculation process and data are as follows.

$$P_T = N_{LB} * P_{LB} * N_H \ (1)$$

$$P_T = 10 * 15 \ \frac{Wh}{h} * 234 * \frac{1 \ kW}{1000 \ W} = 35.10 \ \frac{kWh}{h}$$

P_T: Lighting consumption.

N_{LB}: Number of light bulbs.

P_{LB}: Energy rating per light bulb.

N_H: Number of households.

Table 11. Example of lighting usage pattern.

Time	Lighting		Lighting	
	Winter	Summer	Winter	Summer
00:00 - 01:00				
01:00 - 02:00				
02:00 - 03:00				
03:00 - 04:00				
04:00 - 05:00				
05:00 - 06:00				
06:00 - 07:00				
07:00 - 08:00	on		35.10	
08:00 - 09:00	on		35.10	
09:00 - 10:00				
10:00 - 11:00				
11:00 - 12:00				
12:00 - 13:00				
13:00 - 14:00				
14:00 - 15:00				
15:00 - 16:00				
16:00 - 17:00				
17:00 - 18:00				
18:00 - 19:00	on		35.10	
19:00 - 20:00	on		35.10	
20:00 - 21:00	on	on	35.10	35.10
21:00 - 22:00	on	on	35.10	35.10
22:00 - 23:00	on	on	35.10	35.10
23:00 - 24:00	on	on	35.10	35.10

3.2.1.3. Calibration process

The purpose of a residential profile generator is to represent community according to its statistics. The calibration process aims to accomplish this by use of a calibration process. A load normalisation summary (Table 12 shows one example scenario of the summary) is built using the calculated community demand data and the annual community electricity consumption entered initially. These normalised values represent the time slot one-percentage consumption data out of the daily total, according to household type.

Table 12. Normalisation of daily electricity consumption based on household type excluding lighting load.

Household Type	Single Adult	Single Pensioner	Two Adults	Two adults with Children	Two Pensioners	Two adults a with Pensioner(s)	Three Adults
00:00 - 01:00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
01:00 - 02:00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
02:00 - 03:00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
03:00 - 04:00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
04:00 - 05:00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
05:00 - 06:00	0.02	0.01	0.02	0.01	0.01	0.01	0.02
06:00 - 07:00	0.03	0.03	0.03	0.03	0.03	0.03	0.04
07:00 - 08:00	0.06	0.04	0.06	0.03	0.04	0.04	0.06
08:00 - 09:00	0.03	0.03	0.03	0.03	0.03	0.03	0.01
09:00 - 10:00	0.01	0.05	0.01	0.01	0.05	0.04	0.01
10:00 - 11:00	0.01	0.06	0.01	0.01	0.05	0.03	0.02
11:00 - 12:00	0.01	0.06	0.01	0.01	0.06	0.02	0.01
12:00 - 13:00	0.01	0.04	0.01	0.01	0.03	0.03	0.03
13:00 - 14:00	0.01	0.03	0.01	0.10	0.02	0.08	0.01
14:00 - 15:00	0.01	0.08	0.01	0.10	0.08	0.11	0.01
15:00 - 16:00	0.01	0.07	0.01	0.04	0.06	0.05	0.01
16:00 - 17:00	0.01	0.07	0.01	0.05	0.06	0.06	0.01
17:00 - 18:00	0.02	0.07	0.05	0.07	0.06	0.06	0.01
18:00 - 19:00	0.08	0.08	0.11	0.10	0.09	0.09	0.08
19:00 - 20:00	0.18	0.05	0.14	0.08	0.07	0.09	0.19
20:00 - 21:00	0.12	0.07	0.11	0.09	0.10	0.07	0.12
21:00 - 22:00	0.14	0.07	0.12	0.05	0.09	0.05	0.12
22:00 - 23:00	0.10	0.01	0.11	0.05	0.01	0.03	0.10
23:00 - 24:00	0.07	0.01	0.06	0.05	0.01	0.03	0.06

Then, calibrated profiles are obtained by multiplying the time slot normalised value by the total consumption during the day. The latter is determined using Equation 2.

$$E_{DS} = \frac{E_{TS}}{E_T} * \frac{E_C}{N} \quad (2)$$

E_{DS}: Daily consumption according to season.

E_T: Total annual electricity demand.

E_{TS}: Total electricity demand according to season.

E_C: Total annual community consumption.

N: Number of days within the season.

Subsequently, the daily consumption according to season is applied to the normalisation value getting, as a result, the required total calibrated consumption during the day.

In this process the spring/autumn consumption is calculated using the average, winter, and summer daily consumption to adjust the output in accordance with the statistics.

3.2.2. Input data

As input data, the model requires (a) the annual electricity demand in kWh/year, (b) the census demographic results applied to the different types of households, both limited to the community, and (c) the ownership of the listed appliances within each household expressed as a percentage.

The model is developed, by default, including the household types that are shown in Table 13. However, characteristics such as occupancy times and the usage patterns of the appliances can be changed to generate a diverse household stock.

Table 13. Household types and occupants' lifestyles [32].

Household Type	Unoccupancy times	Other Assumptions
Single adult	09:00 to 18:00 on weekdays	1. Occupied by a full time working adult 2. The average daily consumption of every appliance will be distributed through out the day into two main periods, 6:00 till 9:00 and 18:00 till 01:00.
Single Pensioner Adult	occupied all the time	1. Most loads are distributed through out the day in a random way and only what is related to cooking has a specified period (for lunch and dinner).
Two adults	09:00 to 18:00 on weekdays	1. Usage pattern is similar to one adult household
Two adults with children	09:00 to 13:00 on weekdays	1. One member has a full time job 2. The second adult holds a part time job in the morning in order to take care of the children after school
Two pensioners	occupied all the time	1. Usage pattern is similar to one pensioner household
Two adults at least 1 pensoner	occupied all the time	1. The head of the household has a full time job and the second adult has a part time job in the afternoon session 2. However, the house is always occupied by at least one person (pensioner).
Three adults or more	13:00 to 18:00 on weekdays	1. Two of the house members have a full time job 2. The third one has a part time job in the afternoon session.

In order to generate the load profile, the appliances ownership has to be introduced. Table 14 includes the listed appliances within the model including their categorisation. Each one of them has a fixable daily average consumption in kWh/day used to represent their power requirements. The average consumption per capita represents the demand per occupant, the average number of residents used is 3.3.

Table 14. Appliances' categorization [32].

Category	Appliance	Average consumption per capita (kWh/day)	Average consumption per household (kWh/day)	Ownership level (%)	
		National	National	National	Community
Cooking Appliances	Electric hob	0.03	0.10	37	14
	Electric oven	0.42	1.39	56	35
	Microwave Oven	0.02	0.06	74	57
Cold Appliances	Refrigerator	0.25	0.82	53	100
	Freezer	0.42	1.39	55	100
Brown Goods	TVModemSettopbox	0.12	0.39	97	100
	ElectricalWaterHeater	0.67	2.21	75	99
Wet Appliances	Dishwasher	0.02	0.06	16	15
	Washing Mashine	0.09	0.28	88	97
	Tumble Driers	0.58	1.92	49	22
Miscellaneous	Electric Kettle	0.07	0.24	5	100
	Computers/Laptops	0.02	0.07	80	67
	Iron	0.01	0.04	100	100
	Dehumidifier	0.84	2.76	100	100

The usage pattern has to be set, as shown in Table 15, according to the inhabitants' lifestyles and the appliances included in the model. Each appliance is established to be used a number of times per day according to the household type. The likelihood of an appliance to be used during a time slot is determined by a probability. As can be noticed, the accumulated probability during one usage period has to add to unity. This probability represents the proportion of the community that is likely to use the appliance within that time slot.

Table 15. Appliances usage pattern.

TIME	Hob	Oven	Microwave Oven	Refrigerator	Freezer	Television	Video Recorder
00:00 - 01:00				1	1		
01:00 - 02:00				1	1		
02:00 - 03:00				1	1		
03:00 - 04:00				1	1		
04:00 - 05:00				1	1		
05:00 - 06:00	0.1		0.1	1	1		
06:00 - 07:00	0.2		0.2	1	1		
07:00 - 08:00	0.6		0.6	1	1		
08:00 - 09:00	0.1		0.1	1	1		
09:00 - 10:00				1	1		
10:00 - 11:00				1	1		
11:00 - 12:00				1	1		
12:00 - 13:00				1	1		
13:00 - 14:00				1	1		
14:00 - 15:00				1	1		
15:00 - 16:00				1	1		
16:00 - 17:00				1	1		
17:00 - 18:00	0.05	0.05	0.05	1	1		
18:00 - 19:00	0.2	0.2	0.2	1	1	1	
19:00 - 20:00	0.5	0.5	0.5	1	1	1	
20:00 - 21:00	0.15	0.15	0.15	1	1	1	
21:00 - 22:00	0.1	0.1	0.1	1	1	1	0.3
22:00 - 23:00				1	1	1	0.4
23:00 - 24:00				1	1	1	0.3

The lighting profile is usually generated in accordance with the occupancy pattern and the outdoor irradiance. Unfortunately, an outdoor irradiance input is not included in the model. Therefore, a lighting usage estimation has to be introduced in a table according to the time slot, similar to the appliances usage pattern but introducing the total single household consumption during the slot. As mentioned above, the rate of this demand is obtained by multiplying the number of light bulbs installed within the dwelling by the average energy rating per light unit in watts. Both values can be established.

3.2.3. Output data

Various daily electricity consumption profiles are generated, gathered in tables, and represented by charts. These demand profiles are categorised by season (winter, summer, spring/autumn, or all year) and type of household (between household types or the total with lighting). For example, Table 16 and Figure 9 shows an example of output. As mentioned above, the time resolution by default is one hour.

Table 16. Daily electricity demand according to type of household including lighting load for winter.

Household Type	Single Adult	Single Pensioner	Two Adults	Two adults with Children	Two Pensioners	Two adults a with Pensioner(s)	Three Adults
00:00 - 01:00	0.03	0.03	0.06	0.10	0.06	0.10	0.09
01:00 - 02:00	0.03	0.03	0.06	0.10	0.06	0.10	0.09
02:00 - 03:00	0.03	0.03	0.06	0.10	0.06	0.10	0.09
03:00 - 04:00	0.03	0.03	0.06	0.10	0.06	0.10	0.09
04:00 - 05:00	0.03	0.03	0.06	0.10	0.06	0.10	0.09
05:00 - 06:00	0.05	0.03	0.10	0.10	0.06	0.10	0.17
06:00 - 07:00	0.09	0.09	0.18	0.29	0.19	0.28	0.30
07:00 - 08:00	0.30	0.24	0.48	0.62	0.36	0.64	0.83
08:00 - 09:00	0.21	0.21	0.28	0.60	0.29	0.58	0.43
09:00 - 10:00	0.03	0.26	0.06	0.10	0.42	0.65	0.09
10:00 - 11:00	0.03	0.16	0.06	0.10	0.32	0.23	0.20
11:00 - 12:00	0.03	0.17	0.06	0.10	0.35	0.16	0.09
12:00 - 13:00	0.03	0.11	0.06	0.10	0.21	0.31	0.24
13:00 - 14:00	0.03	0.09	0.06	0.84	0.15	0.73	0.09
14:00 - 15:00	0.03	0.22	0.06	0.85	0.50	0.94	0.09
15:00 - 16:00	0.03	0.20	0.06	0.37	0.40	0.42	0.09
16:00 - 17:00	0.03	0.32	0.06	0.76	0.50	0.89	0.09
17:00 - 18:00	0.05	0.33	0.25	0.95	0.49	0.87	0.09
18:00 - 19:00	0.36	0.35	0.76	1.20	0.67	1.11	1.00
19:00 - 20:00	0.64	0.27	0.90	1.05	0.56	1.09	1.85
20:00 - 21:00	0.46	0.32	0.75	1.10	0.76	0.92	1.33
21:00 - 22:00	0.51	0.32	0.81	0.78	0.71	0.73	1.31
22:00 - 23:00	0.41	0.16	0.75	0.75	0.19	0.63	1.16
23:00 - 24:00	0.31	0.16	0.49	0.77	0.19	0.61	0.78
Max	3.81	4.19	6.58	11.90	7.66	12.36	10.74

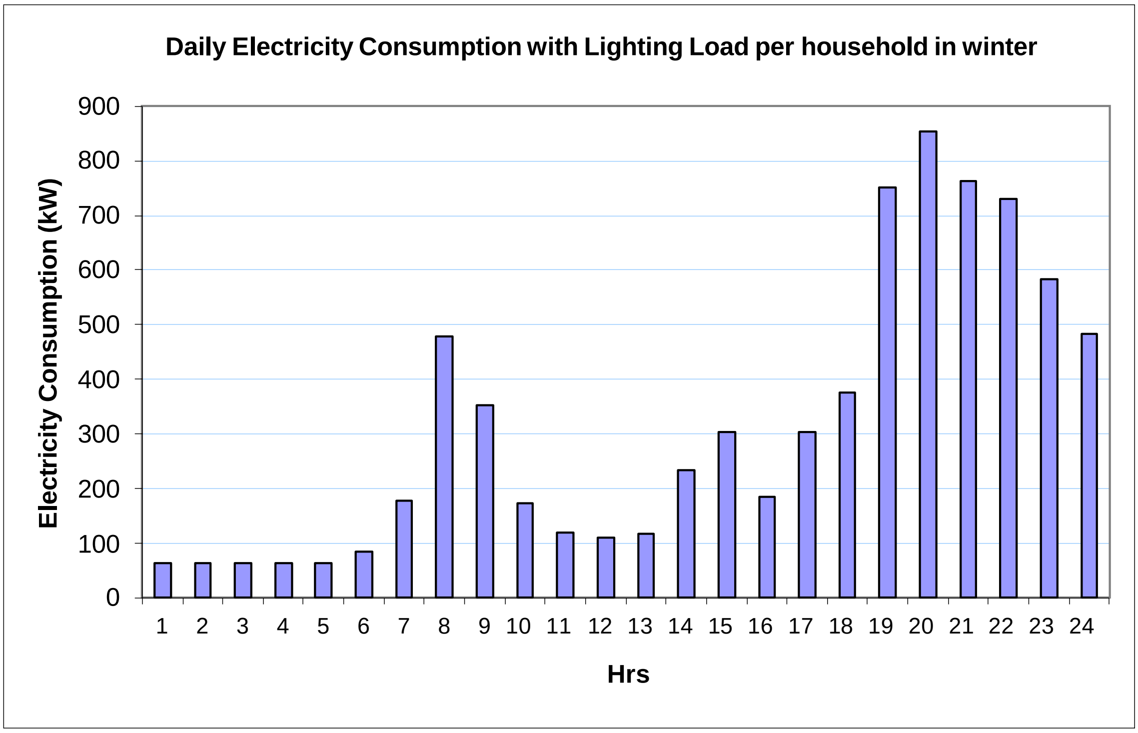

Figure 9. Daily electricity demand according to type of household including lighting load for winter. Example of result of EDPG model.

3.2.4. Assumptions

The assumptions of this method are as follows:

1. Percentage share of type of households in the year of the demographic and consumption results is the same as identified in the model.
2. All hobs and ovens considered are electric powered.
3. No appliance is left on standby.
4. Each dwelling only has one of each appliance listed.
5. The specific schedules are assumed for each household type.
6. Spring and autumn average daily consumption is assumed to be the same.

3.2.5. Limitations

The limitations of such a study are the following:

1. The number of households is equal to the number of buildings within the community.
2. The appliances listed, including lighting, are the only electric consumption devices within every household.

3. Each appliance is used a determined number of times per day, every day.
4. The number of light bulbs within a household is the same for all the households of the same type.
5. The energy rating per bulb is constant and the same for all bulbs, and all bulbs are assumed to be switched-on during the occupancy period.
6. Model does not differ between weekend days and weekdays.

3.3. ALPG model

The ALPG model was developed using Python, a general open-source programming language, where load curves are generated for active and reactive power with one-minute time granularity. Unfortunately, the output should only be used as input for different control and optimization algorithms. It also generates heat demand profiles by the simulation of thermostat setpoints, hot water usage and ventilation.

3.3.1. Load profile calculation process

The program runs by executing "*profilegenerator*.py". First of all, parameters for households, person, devices, etc. are chosen by using different fixable probability distributions. [36]. This likelihood determines the availability within dwellings of some devices such as dryers and appliances such as dishwashers and tumble dryers, in accordance with the household type. A truncated Gaussian distribution is used to choose the annual power demand for some uncontrollable load categories and annual consumption for households (Table 17). The average consumption value constitutes the category's mean power demand depending on the household type as well as the number of adults and children. Both values, the number of adults and the number of children, are generated using a bounded uniform distribution. Finally, for the employed occupants, a Gaussian distribution determines the driving distance to work.

Table 17. Annual consumption according to number of occupants assumed by the model [36].

Name	Annual consumption	Persons (Adults)
SingleWorker	1610 - 2410 kWh	1 (1)
DualWorker	2660 - 4060 kWh	2 (2)
FamilyDualWorker	3460 - 7060 kWh	3 - 6 (2)
FamilySingleWorker	3460 - 7060 kWh	3 - 6 (2)
FamilySingleParent	2600 - 6200 kWh	2 - 5 (1)
DualRetired	2660 - 4060 kWh	2 (2)
SingleRetired	1610 - 2410 kWh	1 (1)

Using a simple behavioural model, the occupancy profile is generated using mean times for scenarios that shift the state of a person occupant to active, inactive, or away. The model uses a truncated Gaussian distribution to determinate the exact times for inhabitants. Activities such as home working, washing days and sporting activities are also chosen.

After establishing the persons and the individual households, the dwellings listed are shuffled and allocated to a physical household. Then, the low carbon technologies are spread between the different households. The orientation of the dwelling is selected using a truncated Gaussian distribution. Meanwhile, PV and induction cooking are randomly distributed. Later, the quantity of battery storage devices is assigned. Finally, the largest commute distance is used to distribute the PHEVs and EVs.

At this point, the simulation process starts according to the flow-chart shown in Figure 10. Note that every dwelling is simulated individually and reflected in the output file. Habitants' lifestyles are simulated first in order to obtain their occupancy profile. Then, the activity event exact times are randomized.

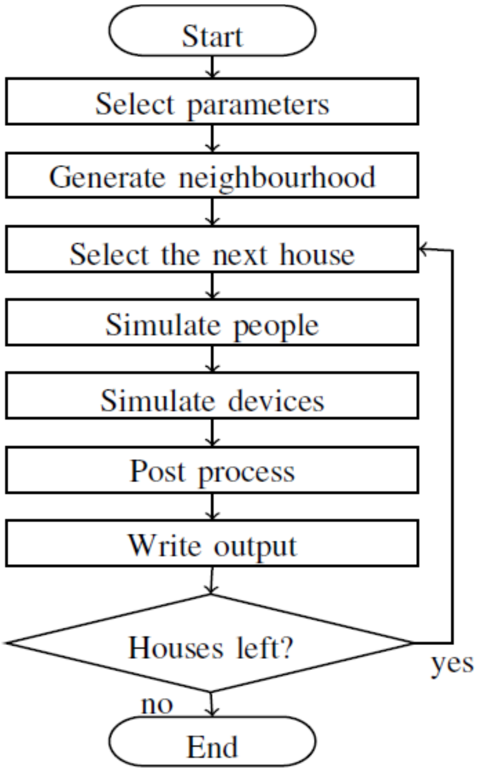

Figure 10. ALPG simulation process [36].

At first, the individual refrigerators and freezers are simulated. Later, according to the inhabitants, the electronic equipment is activated using a probability function, this can only happen if there is at least one active person. Once a device is turned on, its power consumption's weight is randomly selected between 0.7 and 1.3, the mentioned value corresponds to the weight for its power consumption. This value is used to scale, as explained below, the electricity demand to match the annual power demand. If the house is empty, any electronic device is left on.

Finally, the static load curves are calibrated. The annual consumption of the category is reflected by rescaling the lighting, standby and electronics profiles. The same procedure is applied to every category for addressing a reliable reactive power curve.

3.3.2. Input data

The two following inputs must be gathered in Excel files. These inputs are the Global horizontal irradiation in J/cm^2 (one-hour timebase), and active and reactive power of the dishwasher and washing machine cycle (both on a one-minute timebase).

Besides, a configuration file named "*config.py*" is also available and can be changed. In this file the following parameters can be fixed: the output folder, the number of days to simulate and the start day, the geographical location, the penetration in percentages as well as the characteristics of the listed emerging technologies, the power consumption in watts of the different devices, the household randomization by the predictability of inhabitants, and the household stock in the neighbourhood.

The tool takes the following dwelling types into account: household single worker, household single jobless, household single part time, household couple, household dual worker, household family dual parent, household family dual worker, household family single parent, household dual retired, and household single retired.

3.3.3. Output data

Output is formed by two main sections: The inflexible section and the flexible section. The first one is represented by comma separated values (csv) files that represents the average power demand in watts according to household, with a one-minute resolution. The rows constitute the time slots in ever-increasing disposition and each column constitute a single dwelling in ever-increasing sequence. Likewise, reactive power in *var* is gathered in another csv file. Furthermore, negative values indicate power injection into the existing low voltage network [36].

The flexible appliances are divided in general flexibility classes, as follows:

- Time shiftable: for example dishwashers, dryers and washing machines. As mentioned above, real data from measurements is used to generate the static demand profile in watts. The resulting profile is represented in time periods with their respective start times and end times in seconds.

- Buffer-time shiftable: for example electric vehicles. The flexibility is specified as the time shiftable class with the electricity demand in watt-hours.
- Buffer: for example hot water buffer or a battery. The maximum amount of power consumption or production level is indicated, as well as the capacity in watt-hours.
- Curtailable: for example photovoltaic solar energy. This class specifies a fixed consumption or production profile and the quantity of power that can be curtailed.

3.3.4. Manner of use

The command window included in Windows is used to run the ALPG model, "*profilegenerator.py*" has to be executed with three different configuration flags.

1. "-c" flag must be followed by the path to the configuration file. Note that "*.py*" has to be excluded.
2. The output directory must be introduced after the "-o" flag.
3. "--force" is used to force the output directory to be cleared.

Therefore, executing the model with the configuration file "*configs/example.py*" and clearing and writing the results into "*output/results*" is done as follows.

profilegenerator.py -c example -o results --force

3.3.5. Assumptions

For the purpose of this project, this model provide sufficient parameters which can be changed to reflect all the conditions for the different scenarios. Therefore, no limiting assumptions were found to be taken.

3.3.6. Limitations

The limitations of such a study are the following:

1. The number of households is equal to the number of buildings within the community.
2. The appliances listed, including lighting, are the only electric consumption devices within every household.
3. In order to run the model, packages such as Python and Astral have to be installed.
4. Generation of output takes a long time.
5. The tool is aimed to simulate up to a hundred households.
6. Requires knowledge in Python programming.
7. Requires an optimisation tool to manage the output, or an explicative file to understand it.

3.4. CREST model

This model is an integrated thermoelectric demand model based on a bottom-up activity-based structure. It uses random programming techniques to represent the diversity of houses. It produces high resolution (one-minute timebase) data output, based on reduced-order thermoelectric networks to represent thermodynamics. This model was developed as free open-source software to promote transparency and further research. Its thermal model includes domestic hot water consumption, gas boilers and thermostat and time controls towards the electrification of heating.

3.4.1. Load profile calculation process

As a bottom-up model, this model firstly populates each dwelling with appliances. Each appliance can be represented by On/Off state as well as standby and they have an assigned consumption. The likelihood of an electronic device being turned on is determined by the current active inhabitants, on the appliance type, and whether it is a weekday or weekend and corrected by a calibration scalar, used to give a particular consumption over various simulations. Then, if the result is over a randomised number, the appliance is switched-on. This process is repeated for all the appliances during every time interval and shown in Figure 11. Once all the appliance's energy requirements are simulated, the model aggregates them obtaining their energy profile.

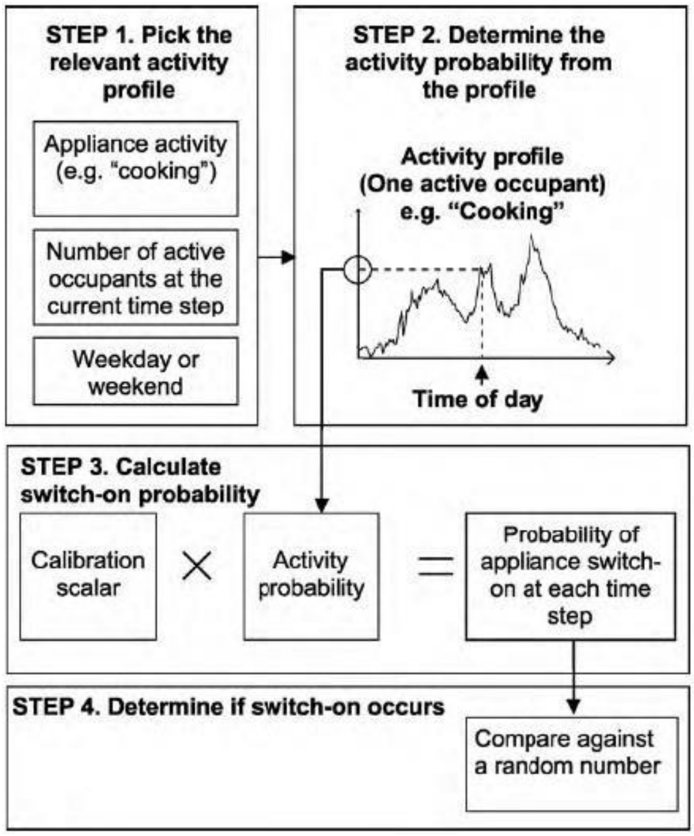

Figure 11. CREST's switch on calculation process for appliances [19].

In addition, a power factor is used to represent the average value over the time resolution. For resistive heating appliances the value is at unity, 0.9 is used for electronic entertainment appliances and 0.8 for cooling and washing type appliances.

In the case of lighting, each household has a different irradiance threshold chosen by a normal distribution with a mean of 60 W/m^2 and a standard deviation of 10 W/m^2. Furthermore, it includes a filter to make illuminance variations soft (for example in the case of passing clouds) [22].

A normal distribution determines the number of lighting units within each dwelling. The same statistics is used to select the technology installed between General Lighting Service (GLS), Compact Fluorescent Lamp (CFL), halogen, fluorescent tube, or other types such as Light Emitting Diode (LED) or Parabolic Aluminized Reflector (PAR). Their power rating is randomly selected between a selection from the most common types. [22].

The switch on process starts comparing the irradiance level with the household's irradiance threshold. Then, the weighting of each light unit is considered. This value is obtained with a random number and Figure 12.

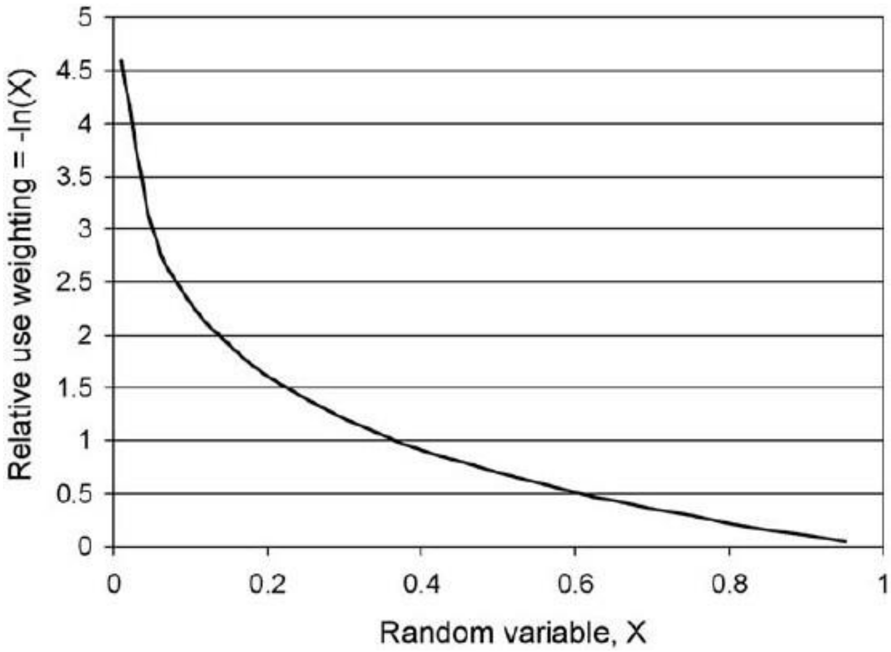

Figure 12. Light units weighting calculation [22].

Later, the effective occupancy is taken into consideration according to the number of active occupants, as shown in Figure 13.

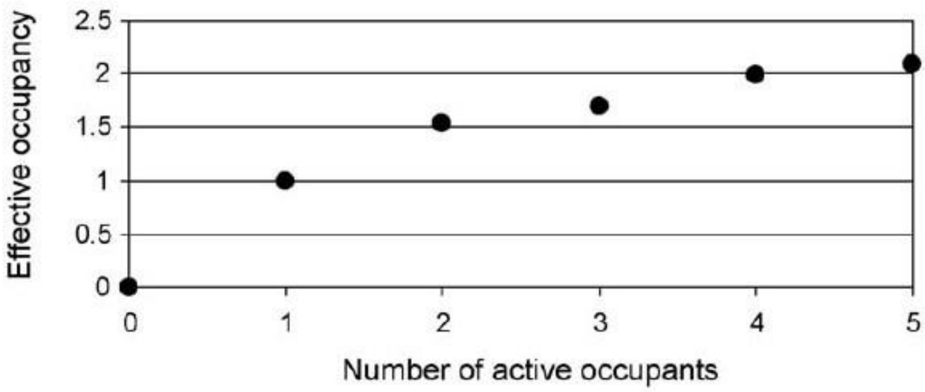

Figure 13. Effective occupancy curve [22].

In addition, for five percent of the time intervals some light units are switched on to represent the existence of rooms without windows. The duration of each switch on event is picked randomly according to the curve shown in Figure 14.

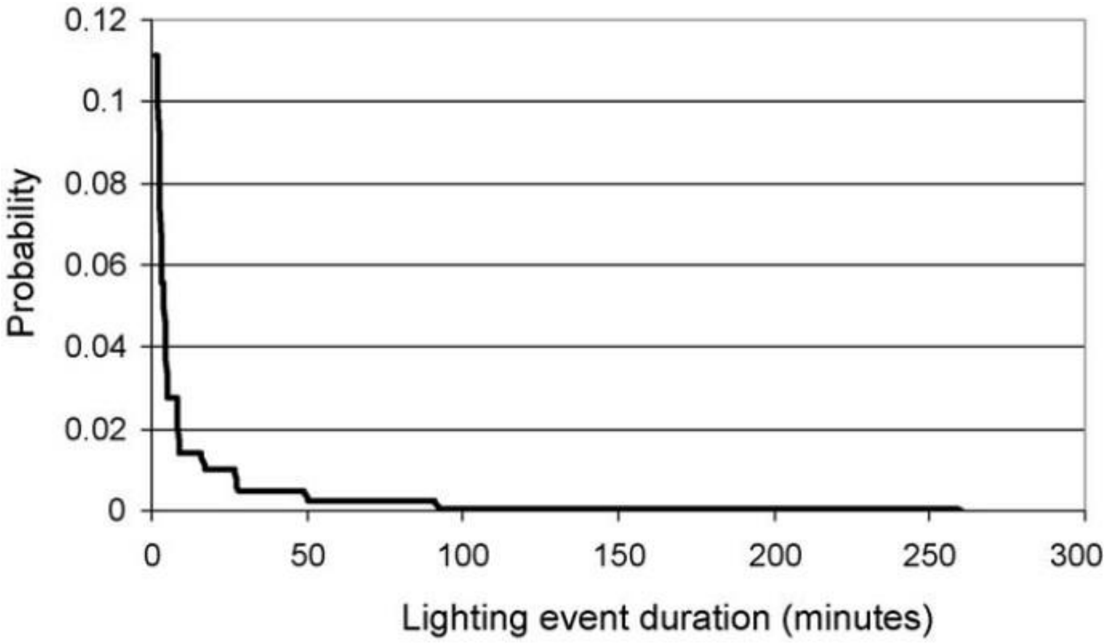

Figure 14. duration of switch on events [22].

Finally, to give a particular overall energy demand in accordance with the statistics over a few simulations, the calibration scalar is considered.

3.4.2. Input data.

Starting with the appliance's model, the daily activity profile is required to generate the active occupancy pattern, including whether it is a weekday or weekend. Time Use Survey (TUS) is included in the model and sets the base to simulate the behaviour of the occupants. Also statistical ownership data form the UK Department of Energy and Climate Change (DECC) is taken to populate each household's electric devices. The model's appliances list is shown in Table 18. Furthermore, each appliance has an assigned consumption in kWh/year according to the statistics gathered in a UK's survey published in 2006.

Table 18. List of appliances.

Cold	Chest freezer
	Fridge freezer
	Refrigerator
	Upright freezer
Consumer Electronics + ICT	Answer machine
	Cassette / CD Player
	Clock
	Cordless telephone
	Hi-Fi
	Iron
	Vacuum
	Fax
	Personal computer
	Printer
	TV 1
	TV 2
	TV 3
	VCR / DVD
	TV Receiver box
Cooking	Hob
	Oven
	Microwave
	Kettle
	Small cooking (group)
Wet	Dish washer
	Tumble dryer
	Washing machine
	Washer dryer
Water heating	DESWH
	E-INST
	Electric shower
Electric Space Heating	Storage heaters
	Other electric space heating

In order to generate the lighting model, the model requires the outdoor irradiance level, to set the likelihood of the light units being switched-on, and the calibration scalar to correct the model's output.

The thermal model uses an external temperature model, and the heating control settings have to be predefined. However, the mentioned irradiance model, the occupancy transition probabilities and the activity profiles are also utilised to define the output.

3.4.3. Output data

A daily profile is generated with one-minute time resolution. All the output data is gathered in three different Excel worksheets and express the overall power consumption according to the household: daily totals, disaggregated and aggregated. In the first case each row represents one dwelling, whereas in the others each row represents a one-minuteinterval. In both cases, each dwelling is referenced by an index.

Principally, the active occupancy, the lighting demand, the appliance demand, and the PV output are shown. However, as mentioned above, this model also includes a heat demand model to obtain the domestic hot water consumption and the solar thermal collector heat gains. The low order building thermal model generates the thermal energy required by the water and space heating as well as the gas demand in the case it is installed. Furthermore, it can determine the operating times of the installed space heaters.

3.4.4. Assumptions

The only limitation that was identified up to the time of writing the dissertation was that if there are no inhabitants within the dwelling or they are sleeping, the model assumes that every light is switched off.

3.4.5. Limitations

The limitations of such a study are the following:

1. The number of households is equal to the number of buildings within the community.
2. Although there are a lot of appliances included within the model, there was no facility to include others.
3. The model requires large datasets as inputs for the active occupancy pattern and consumption rating.
4. The model can populate each household with up to thirty-three devices.

3.5. General features

Table 19 shows the models' general features according to the characteristics discussed in the Literature Review.

Table 19. Models' general features.

Feature	**EDPG**	**ALPG**	**CREST**
Application	RLP	RLP, DSM	RLP, DSM
Methodology	Top-down	Bottom-up	Bottom-up
Resolution	Low (1 hour)	High (1 min)	High (1 min)
Statistical approach	Not included	Probabilistic models	Probabilistic models
Thermal model	Not included	Included	Included

3.6. Summary

The profile generation process, its inputs and outputs, assumptions, and limitations included within each model were presented in this chapter. As a conclusion, according to the features presented in Chapter 2, ALPG and CREST model are included within the bottom-up approach matched with a high-resolution output while EDPG modelbelongs to the top-down category and includes a low-resolution output.

Chapter 4: Methodology

This chapter presents the changes that the models require to adapt them for various scenarios referring to Malta, together with the sources of the utilised data.

The aim of this research is to generate energy consumption profiles for a mix of Maltese dwellings through the use and adaptation of published models. The consumption profiles are to be extended to represent the Maltese scenario. In order to accomplish this, every model has to consider the lifestyles and the schedules of Maltese households as well as the typical appliances and their consumption. Depending on the capability of the particular model, emerging technologies and their characteristics can be used to generate the alternate profiles and allow the analysis of their resulting impact. Only two of the three identified models will be studied, namely the EDPG model and ALPG model. Unfortunately, theCREST model will not be simulated due to lack of time.Moreover, as the electricity consumption analysis is the main purpose of the dissertation, thermal models will not be studied in detail.

4.1. Measured data

Both identified models require knowledge of the electricity consumption rates of the considered household appliances. In order to reflect typical use in the Maltese scenario, an energy meter was used to log the operating profile at high resolution. The monitored appliances are listed in Table 20. The consumption data was measured for different time periods depending on the type and usage pattern of the particular appliance, as indicated in Table 20.

Table 20. Measurements durations.

Appliance	Measurement duration	Average hours/day usage
Iron	30 min	30 min
Oven	30 min	30 min
Dehumidifier	1 day 8 h 30 min 56 s	8 hours
Electric water heater	2 days	7.29 hours
Laptop	30 min	6.14 hours
Refrigerator	2 days	24 hours
TV-modem-set top box	30 min	9.57 hours
Washing machine	7 hours	1 hour 30 min
Tumble dryer	2 h 40 min	3 hours

The Fluke 1732 Power Measurement Logger shown in Figure 15 has been used to measure and log the data at intervals of one minute.

Figure 15. Fluke 1732 Three Phase Power Measurement Logger [37].

In order to analyse the logged data, the Fluke Energy Analyze Plus 3.6. software was used. Analysis tools to facilitate the gaining of insights into the measured data are provided by this application. The software allows analysis of data through the use of cursors/markers and different graphic charts (e.g. RMS power, V, A, THD, etc.) of either individual variables or selected trend lines. For this work, the active power and energy profiles were extracted.

The appliance consumption was expressed as an hourly consumption rate. For the appliances where the measurement duration is longer than one hour, the hourly consumption was determined by dividing the cumulative active energy consumption within a cycle of usage by the time period of this cycle. For example, Figure 16 shows the cumulative active power demand of the dehumidifier where the constant parts represent the periods when it was idle. The average hourly demand rate for the active hour is taken as the difference between the high and the low cursor energy values, which amounts to
0.23 kWh. The average consumption for the dehumidifier is taken as 0.23 kWh/h.

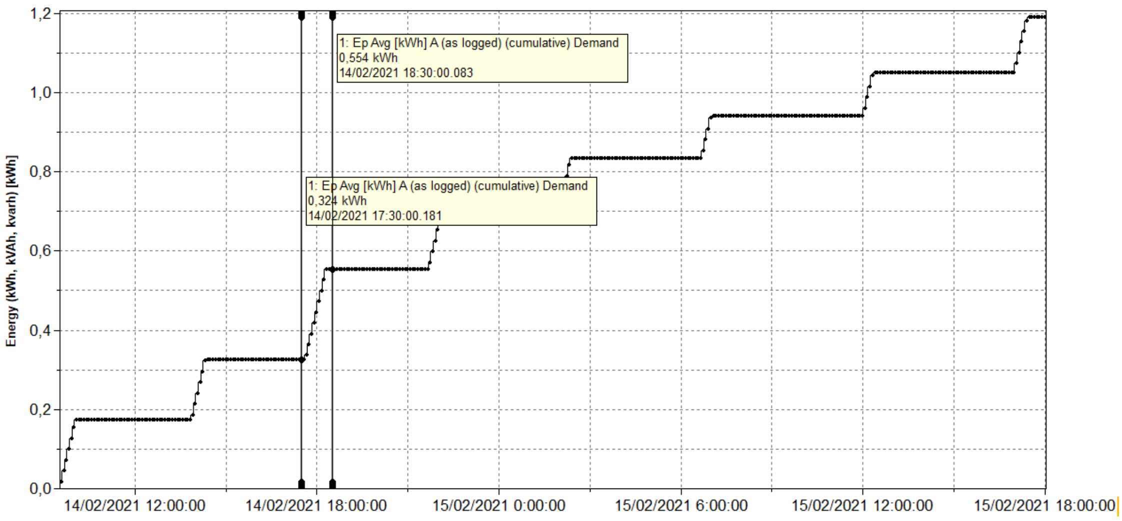

Figure 16. Cumulative consumption of the dehumidifier.

In the case of the laptop and the TV-modem-set top box, it is assumed that their consumption is constant during their operation and equal to the average consumption within the measurement time period.

Table 21 indicates the resulting consumption rates of each appliance once this procedure was applied.

Table 21. Appliances' consumption rates.

Appliance	Average hourly consumption (kWh/h)
Iron	0.148
Oven	0.929
Dehumidifier	0.23
Electric water heater	0.553
Laptop	0.014
Refrigerator	0.034
TV-modem-set top box	0.097
Washing machine	0.189
Tumble dryer	0.64

4.2. EDPG model

This model was used to generate the electricity demand profiles for selected zones in Malta. The area of St Julian's in Malta was used to represent a city while Xewkija in Gozo was used to represent a village. The particular areas were chosen as the required information were available in the NSO Census 2011 [38]. The model was used to generate a base profile and then to study the impact of the greener lighting technologies where theinstalled light units are changed from halogen to LED.

The required inputs by this tool are the zone annual electricity demand, the census demographic results, the appliances ownership level together with their consumption and usage patterns. In addition, the lighting usage pattern, the number of bulbs installed within each household and their power rating are required. The extraction of this data and its conversion for input to the model is described in the next sections.

4.2.1. Household stock and annual electricity demand

To determine the household stock of the settlement, the census demographic results of the region were used. The available dataset was reported by the National Statistics Office

(NSO) in its 2011 report *[38]*. Due to lack of more recent data, the percentage share of type of households identified in the report is used as input to the model.

Both models used for this work considered a number of household types. In particular, the EDPG model includes the households listed in Table 22.

Table 22. Household types assumed by the model and their categorisation by size and status of the reference person.

Model Household type	Status	Size
Single Adult	Employed	1
Single pensioner	Retired	
Two adults	Employed	2
Two pensioners	Retired	
Two adult with children	-	4, 5, 6+
Two adult with pensioner	Retired	3
Three adult	Employed	

In order to segregate the households into the considered types, the following procedure was used to determine the household stock for one-, two-, and three-person households.

The numbers of employed and retired persons according to the household type were collected for Malta and are shown in the first two columns of Table 23. These data were used to establish the employed and retired percentage distributions as shown in the last two columns. It is assumed that the reference person of every household within each household in Malta is employed or retired. Then, each percentage is applied to Table 24 which includes information about the number of households within St Julian's and Xewkija depending on household size. As a result, the number of households related to household type is obtained.

Table 23. Percentage of employed and retired reference person within Malta according to household type. Information extracted from NSO Census 2011 [38].

Household type	Employed	Retired	Employed (%)	Retired (%)
One-person, under 30	1,881	0	58.68	41.32
One-person, aged 30-64	10,377	2,070		
One-person, aged 64 and over	373	6,825		
Two adults, no dependent children - both under 65	13,135	3,496	44.77	55.23
Two adults, no dependent children - at least one aged 65 and over	1,513	14,577		
Other households without dependent children	12,049	9,794	55.16	99.44

Table 24. Private households according to household size and region. Information extracted from NSO Census 2011 [38].

Household size	St Julian's	Xewkija
1	1,099	286
2	1,082	278
3	613	219
4	461	231
5	141	92
6 or more	52	42
Total	3,448	1,148

The sum of the households included in the four, five, and six or more household size within each region was assumed to be the number of two adults with one or more children household type.

As a result, the number of households and their type within each community is set as shown in Table 25.

Table 25. Household stock EDGP model.

Household type	St Julian's	Xewkija
Single Adult	645	168
Single Pensioner	454	118
Two Adults	484	124
Two Pensioners	598	154
Two Adult With Children	654	365
Two Adult With Pensioner	275	98
Three Adult	338	121

In addition to the household stock, the EDPG model requires the zone's annual electricity demand. This information was not directly available. It was established from the energy consumption survey [39] showing the consumption for different types of Maltese dwellings. These are classified as apartments, maisonettes, terraced houses, and villas. The extracted daily and corresponding annual average consumption data are shown in Table 26.

Table 26. Average consumption according to dwelling type. Information extracted from [39].

Consumption	Apartments	Maisonettes	Terraced Houses	Villas
Daily Average (kWh/day)	9.48	10.76	11.02	12.72
Annual Average (kWh/year)	4,073	3,927	4,022	4,643

Since no additional data was available, the model households listed in Table 25 were assumed to be linked to the dwelling categories in Table26 according to household size. One- and two-persons households were assumed to live in Apartments, three-person households in Maisonettes, four- and five-person households in Terraced Houses and finally, six and more person households in Villas. Taking this assumption and considering the average annual consumption and the number of respective households, the annual electricity consumption is obtained and shown in Table 27.

Table 27. Annual electricity consumption according to region.

Consumption	St Julian's	Xewkija
Total annual consumption in kWh/year	12,554,802	4,256,619

4.2.2. Considered appliances in households

Each of the considered models uses a different list of appliances. The ones considered for the EDPG model are listed in Table 28.

Table 28. Household appliances considered in the EDPG model.

Category	Appliance
Kitchen appliances	Electric hob
	Electric oven
	Microwave oven
Cold appliances	Refrigerator
	Freezer
Wet appliances	Electrical water heater
	Dishwasher
	Washing machine
	Tumble dryer
Miscellaneous	TV-modem-set top box
	Electric kettle
	Computers/laptops
	Iron
	Dehumidifier

Therefore, only the most utilised appliances can be considered. The identified appliances listed in Table 29. Their ownership level in Malta are also specified in the survey and are shown in Table 30. Unfortunately, not all the appliances listed in the model are included in the survey, thereby an ownership level of one hundred percent was assumed for the last three appliances included in Table 29.

Table 29. Appliances ownership. Information extracted from [39].

Appliance	Ownership (%)
Electric oven	34.43
Electric hob	13.59
Microwave oven	56.87
Dishwasher	14.89
Fridge	100.00
Freezer	100.00
Electric water heater	90.50
Computer/Laptop	66.45
Television	99.01
Washing machine	96.42
Tumble dryer	21.12
Electric kettle	100.00
Iron	100.00
Dehumidifier	100.00

4.2.2.1. Appliance's usage pattern

The appliance's usage pattern will depend on the active occupancy pattern and, therefore, on the lifestyles of the inhabitants. As described in Chapter 3, the model represents the pattern by a number of usage times in fixed one-hour intervals per day. The set number of usage intervals for each household type were based on the following assumed profiles and are shown in Table 30.

- Adults working on a full-time basis: wake up at 7:00 a.m., have lunch at work, return home at 5:00 pm to watch TV and have dinner afterwards.
- Pensioners loads are distributed randomly throughout the day. Cooking appliances have a specified period that corresponds to breakfast, lunch, and dinner.

- Children assumed to go to school after having breakfast at 7:00 am, return from school around 2:00 pm, in the evening they use the entertainment devices.

The electrical water heater is considered to operate during six hours to provide hot water for two-persons households and during nine hours within three-persons dwellings. The dehumidifier is assumed to be cycling throughout the day operating for one hour and switching off for two, alternately.

Table 30. Number of usage intervals using one-hour resolution.

Appliance	Single Adult	Single Pensioner	Two Adult	Two Adult Children	Two Pensioner	Two Adult Pensioner	Three Adult
Hob	2	3	2	3	3	3	3
Oven	1	1	1	1	1	1	1
Microwave	2	3	2	3	3	3	3
Refrigerator	24	24	24	24	24	24	24
Freezer	24	24	24	24	24	24	24
Tv-modem-set top box	8	8	9	12	9	9	12
Electrical water heater	6	6	6	9	6	9	9
Dishwasher	1	1	1	1	1	1	1
Washing machine	1	1	1	2	1	1	2
Tumble dryer	1	1	1	2	1	1	2
Kettle	3	2	4	4	3	5	5
Computers	6	2	8	10	3	8	10
Iron	1	1	1	1	1	1	1
Dehumidifier	8	8	8	8	8	8	8

4.2.2.2. Assumed rates

Each appliance has an assigned power rating, the survey [39] also records the daily average energy ratings in relation to the building type (apartments, maisonettes, terraced houses, villas and all the households combined). Assuming that the consumption rates can also be applied to the year of publication, this consumption according to the combined households will be the energy requirements of the model appliances. These rates are collected in Table 31.

Table 31. Daily consumption rates. Information extracted from [39].

Appliance	Average consumption (kWh/day)
Fridges and Freezers	2.42
Electric oven and hob	0.19
Microwave oven	0.06
Dishwasher	0.03
Kettle	0.12
Electric water heater	2.67
Computer/Laptop	0.43
Television	0.98
Washing machine	0.26
Tumble dryer	0.03

The appliances consumption rates used in the model were obtained from both the measured and collected data. Firstly, the measured data was used for the appliances considered in the measurement exercise. Then, the consumption of the remaining appliances was set according to the survey's ratings. It is important to note that the model assumes the daily consumption of the appliances equal for every household type. Despite this, the hours/day usage assumed is different as it depends on the household type, size, etcetera. To calculate the appliances' daily consumption, the average between all the usage patterns within each household type is taken. The resulting consumption according to the appliance is shown in Table 32. Note that the model requires the daily average consumption in kWh/day.

Table 32. Assumed consumption rates.

Appliance	**Consumption (kWh/day)**	**Hours/day usage**	**Consumption (kWh/h)**
Electric oven	0.465	0.5	0.929
Electric hob	0.190	-	-
Microwave oven	1.200	-	-
Dishwasher	0.060	-	-
Fridge	0.816	24	0.034
Freezer	1.604	-	-
Electric water heater	4.029	7.29	0.553
Computer/Laptop	0.086	6.14	0.014
Washing machine	0.284	1.5	0.189
Tumble dryer	1.919	3	0.640
TV-Modem-Set top Box	0.928	9.57	0.097
Electric kettle	0.240	0.1	2.400
Iron	0.074	0.5	0.148
Dehumidifier	1.840	8	0.230

4.2.3. Lighting

For the case of lighting load the data required is principally the lighting usage pattern, the number of bulbs per household, and their average power rating. First of all, the lighting usage pattern was assumed in accordance with the household type considering the outdoor irradiance levels in summer and winter. Table 33 shows an example for the single adult household type.

Table 33. Lighting usage pattern for single adult household type.

Time	Lighting	
	Winter	Summer
00:00 - 01:00		on
01:00 - 02:00		
02:00 - 03:00		
03:00 - 04:00		
04:00 - 05:00		
05:00 - 06:00		
06:00 - 07:00	on	
07:00 - 08:00	on	
08:00 - 09:00		
09:00 - 10:00		
10:00 - 11:00		
11:00 - 12:00		
12:00 - 13:00		
13:00 - 14:00		
14:00 - 15:00		
15:00 - 16:00		
16:00 - 17:00		
17:00 - 18:00		
18:00 - 19:00	on	
19:00 - 20:00	on	
20:00 - 21:00	on	on
21:00 - 22:00	on	on
22:00 - 23:00	on	on
23:00 - 24:00	on	on

The light unit stock is chosen between the different types of light bulbs available in the market. General Lighting Service (GLS), Compact Fluorescent Lamp (CFL), fluorescent tube, halogen, Light Emitting Diode (LED), Parabolic Aluminized Reflector (PAR), and incandescent are the most common types.

As mentioned in Chapter 3, one limitation of the EDPG model is that every household type has the same number of light units installed within each dwelling. Moreover, the model considers that during lighting usage every light unit is switched on throughout the time period, thereby the number of light units that are switched on according to household number of occupants was considered. One-, two-, three-, and four-person households were assumed to have an average of two, four, six, and eight light units installed, respectively.

Each lighting unit has a changeable consumption during the utilisation period. Therefore, for models without statistical approach that cannot represent this variation, a constant power rating has to be assumed. Besides, the average consumption depends on the required illuminance level, as shown in Table 34.

Table 34. Power according to bulb and illuminance level [40].

Type of bulb	200-300 Lumen	300-500 Lumen	500-700 Lumen	700-1000 Lumen	1000-1250 Lumen	1250-2000 Lumen
Incandescent	25-30 Watt	40 Watt	60 Watt	75 Watt	120 Watt	150-250 Watt
Halogen	18-25 Watt	35 Watt	50 Watt	65 Watt	100 Watt	125 Watt
CFL	5-6 Watt	8 Watt	11 Watt	15 Watt	20 Watt	20-33 Watt
LED	2-4 Watt	3-5 Watt	5-7 Watt	8-10 Watt	10-13 Watt	13-20 Watt

The sixty-watt incandescent light bulb was the most commonly installed, thereby it was assumed that the required brightness is between five hundred and seven hundred lumen as per Table 34. Thus, the corresponding power rating for the halogen, CFL, and LED bulbs will be 50 W, 11 W, and 6 W, respectively.

To compare between the village and city consumption, as there are no available statistics about the bulbs installed within Maltese dwellings, an equal share of the light bulbs stock within the community is assumed. Therefore, the average between every bulb's power rating will be used in accordance with the 500-700 lumen brightness, the resulting power rating is 32 W.

4.2.4. Limitations

The limitations of such a study are the following:

1. The date of the NSO Final Report dated 2011 was used.
2. The total consumption of the settlements was estimated as this data was not available.
3. The measurements were taken throughout a short time period, thereby no seasonal variation was considered.
4. The appliances' usage pattern was mostly assumed.
5. The number and type of light bulbs installed within the community dwellings were assumed due to lack of available information.

4.3. ALPG model

The ALPG model can incorporate different emerging technologies such as electric vehicle charging (EV), solar photovoltaics (PV), battery storage system and heat pumping technologies. The effect of these greener appliances will be examined by carrying out simulations with and without these technologies.

As mentioned in Chapter 3, this model requires two different types of inputs. The first type consists of excel file inputs representing the solar irradiation and the active and reactive power requirements for dishwashers and washing machines. The second type of input consists of characteristics of emerging technologies, consumption rates of the remaining appliances and the household stock. They are gathered in the configuration Python file.

4.3.1. Excel file inputs

The global horizontal solar irradiation in J/cm^2 with hourly resolution was provided by the Institute for Sustainable Energy at the University of Malta. Two profile examples are shown in Figures 17 and 18 with the horizontal axis showing the time in hours, the scale resolution has been set to represent a day.

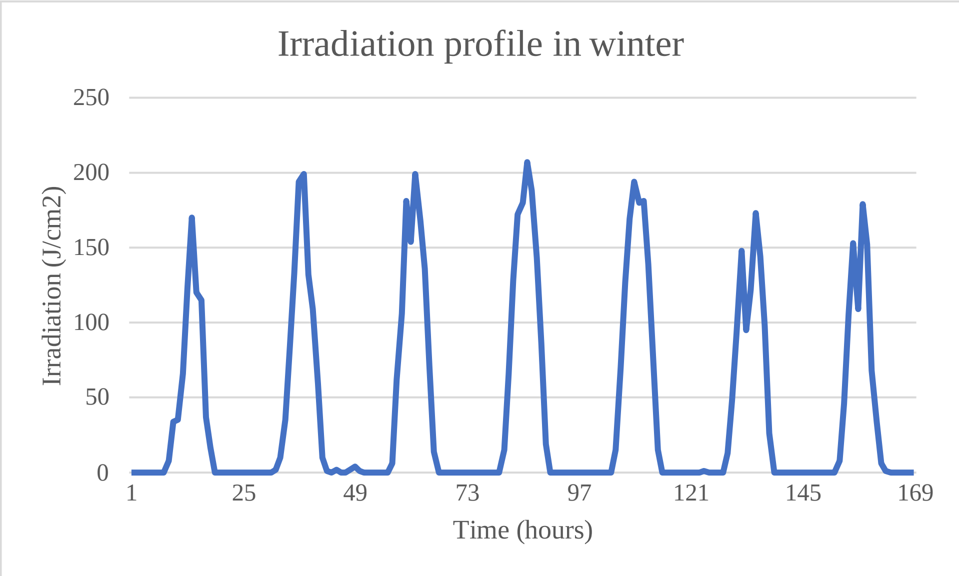

Figure 17. Global horizontal irradiation profile for a week during winter.

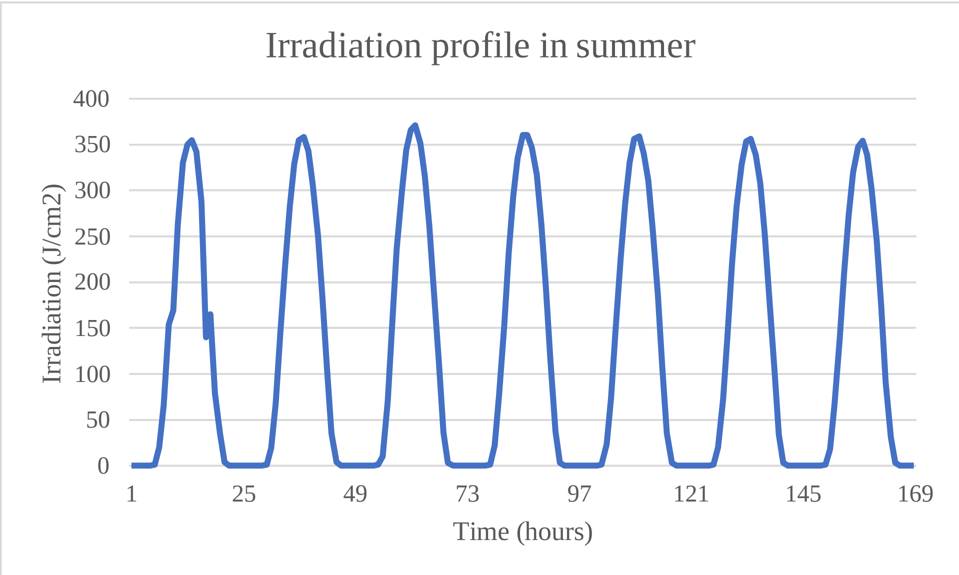

Figure 18. Global horizontal irradiation profile for a week during summer.

The default power profile was kept for the dishwasher as the consumption of such appliance was not monitored. On the other hand, data was available for the washing machine consumption with a thirty-second resolution. The measured data was exported to Excel csv file and transformed to one-minute resolution as required by the model by calculating the average between two consecutives thirty-second power samples. Both profiles are shown in Figures 19 and 20.

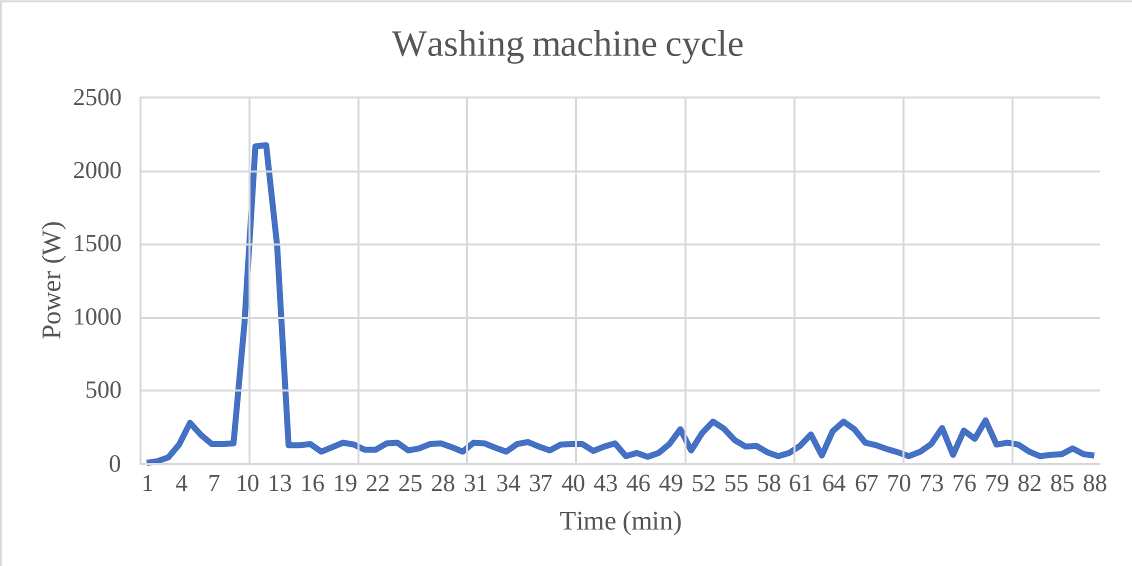

Figure 19. Washing machine cycle active power profile.

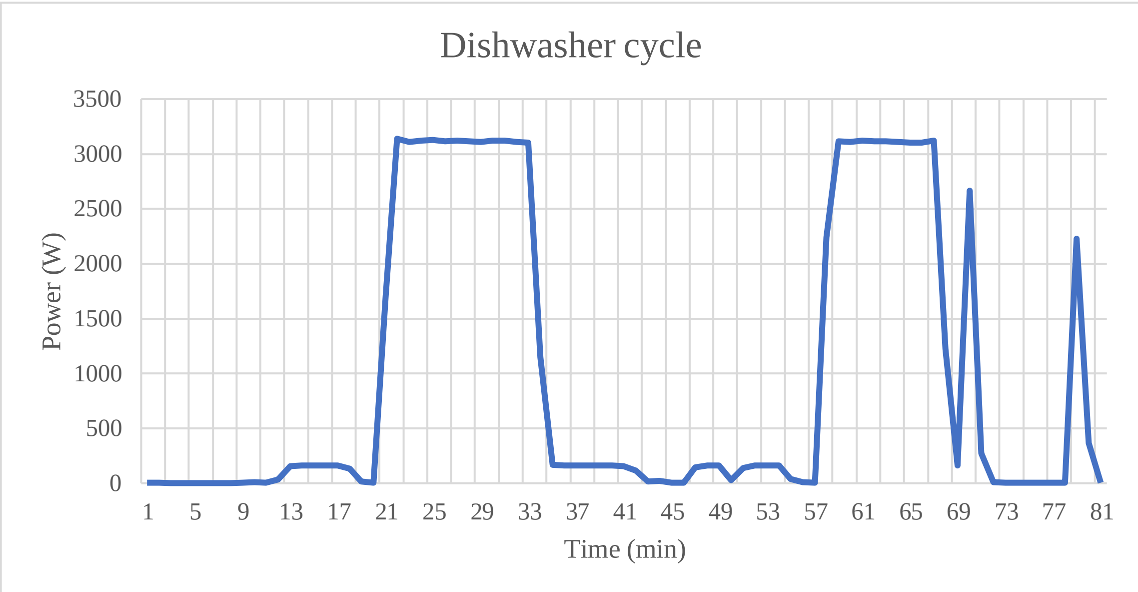

Figure 20. Dishwasher cycle active power profile.

4.3.2. Configuration file

The configuration file 'config.py' needs to be adapted to reflect the geographical location of the country. This was set to Malta as shown in Figure 21.

```python
location = Location()
location.solar_depression = 'civil'
location.latitude = 35.917973
location.longitude = 14.409943
location.timezone = 'Europe/Malta'
location.elevation = 0
```

Figure 21. Malta's geographical parameters.

Then, data for a week will be generated according to the season. The third weeks of March, June, September, and December 2021 were selected to represent spring, summer, autumn, and winter, respectively. For example, for the case of summer, the parameters were configured as shown in Figures 22 and 23.

```python
numDays = 7                                  # number of days
startDay = 31+28+31+30+31+12                 # Initial day
```

Figure 22. Simulated week configuration for summer.

```python
numDays = 7                                            # number of days
startDay = 31+28+31+30+31+30+31+31+30+31+30+11         # Initial day
```

Figure 23. Simulated week configuration for winter.

4.3.2.1. Renewable technologies

In this model, the impact of the emerging technologies was analysed. Therefore, four different scenarios were simulated. The base simulation was carried out with all the technologies penetration values set to zero. The second simulation included the PV related parameters shown in Figure 24. These were set according to data provided by the Institute for Sustainable Energy at the University of Malta. The *penetrationPV* value represents the percentage of households with this technology installed. A value of one hundred percent was assumed as the aim is to analyse PV effect in the household profile.

```
#PV
penetrationPV =         100
PVProductionPerYear =   242     #average kWh per m2 solar panel on annual basis
PVAngleMean =           30      #degrees, 0 is horizontal to earth surface
PVAngleSigma =          10      #degrees
PVAzimuthMean =         180     #degrees, 0 is north, 90 is east
PVAzimuthSigma =        90      #degrees
PVEfficiencyMin =       15      #% of theoretical max
PVEfficiencyMax =       20      #% of theoretical max
```

Figure 24. PV parameters.

The third simulation was focused on the electric vehicle (EV) impact. The EV parameters were left in default as these were considered adequate, whereas the penetration value of this technology was assumed again one hundred percent. Furthermore, in this case, the model requires the driving distances to work, a mean value of fifteen kilometres and a standard deviation of five kilometres were assumed given the small size of the island. All this data together is shown in Figure 25.

```
#EV
penetrationEV = 100
capacityEV =    42000   #Wh
powerEV =       7400    #W
```

Figure 25. EV parameters.

Finally, the fourth simulation was carried out with both mentioned low carbon technologies, PV and EV, in order to analyse the combination of such loads. The parameters were the same as determined above.

4.3.2.2. Considered appliances

The electrical appliances in the three categories considered for the model are shown in Table 35 together with their assumed power ratings. For the oven and large fridge electrical energy consumption, the data was obtained from the measured data analysed with the Fluke software. The average value of the logging interval was taken for the oven, while the maximum and minimum values for the large fridge were extracted as shown in Figure 27.

The small fridge consumption was assumed 30 Watts lower than that of the big one. The others appliances' consumption was established using available models in The Home Depot Market webpage [41].Table 35 shows the assumed power ratings.

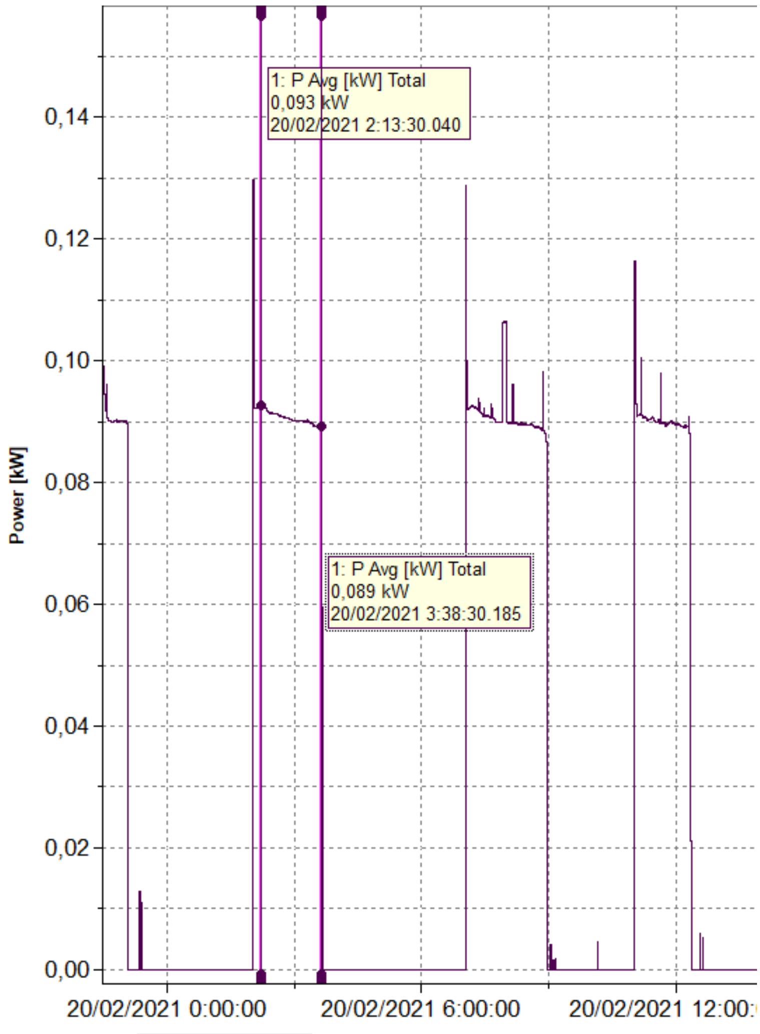

Figure 26. Fridge's active power profile.

Table 35. Appliances' consumption for ALPG model.

Category	Appliance	Power (W)
Kitchen	Oven	929
	Microwave	1000
	Stove ventilation	100
	Induction stove	1800
	Fridge big (max)	93
	Fridge big (min)	89
	Fridge small (max)	63
	Fridge small (min)	59
	Kettle	1500
White goods	Iron	1500
	Vacuum cleaner	1200
House	House ventilation	52

4.3.2.3. Household stock and randomization

The household randomization expresses the likelihood of the family leaving the dwelling as well as the chance of a person starting an activity considering whether it is a weekday or the weekend. These parameters were left at the default values, as shown in Figure 27, due to the difficulty of establishing a general pattern for Maltese households.

```
#Household randomization
#all values must be between 0-100
familyOutingChanceMin =            10  #percentage
familyOutingChanceMax =            20  #percentage
personWeekdayActivityChanceMin =   20  #percentage
personWeekdayActivityChanceMax =   30  #percentage
personWeekendActivityChanceMin =   20  #percentage
personWeekendActivityChanceMax =   30  #percentage
```

Figure 27. Household randomization.

Finally, as the tool is developed to simulate up to one hundred dwellings, the households stock had to be reduced to one hundred dwellings. This was done using the percentage of each household type within the community.

The household stock was determined by repeating the procedure already explained for the EDPG model but applied to the new list of household types. Table 36 shows the selected types as the chosen community fits within this types. Half of St Julian's three-person households were assumed to be of the Family Single Parent type, while the other half together with the households of larger size were taken to be part of Family Dual Worker type. Single and dual person households were divided between employed and retired categories. For the single person households, an unemployed category was also considered. This categorisation is shown in Table 35.

Table 36. Assumptions in the household type calculations according to data from NSO Census 2011 [38].

Household type	**Status**	**Household size**
Single worker	Employed	1
Single jobless	Unemployed	
Single retired	Retired	
Dual worker	Employed	2
Dual retired	Retired	
Family single parent	-	3
Family dual worker	-	3, 4, 5, 6+

Therefore, adding the unemployed data for the one- and two-person household type shown in Table 37, one can obtain the percentages shown in Table 38.

Table 37. Employed, retired, and unemployed reference persons according to household type. Information extracted from NSO Census 2011 [38].

Household type	Employed	Retired	Unemployed
One-person, under 30	1,881	0	499
One-person, aged 30-64	10,377	2,070	1,694
One-person, aged 64 and over	373	6,825	1
Two adults, no dependent children - both under 65	13,135	3,496	609
Two adults, no dependent children - at least one aged 65 and over	1,513	14,577	29

Table 38. Percentage of employed, retired and unemployed reference persons according to household size.

Household type	Employed (%)	Retired (%)	Unemployed (%)
One-person	53.25	37.50	9.25
Two-person	43.91	54.18	1.91

Table 39 shows the result of applying the identified number of households for each type for the EDPG's model to establish the distribution of the considered 100 household stock. As mentioned above, this limitation is due to the computational requirements of the model.

Table 39. ALPG model household stock for St Julian's.

Household type	St Julian's	% St Julian's
Household Single Worker	585	17
Household Single Jobless	102	3
Household Dual Worker	475	14
Household Family Dual Worker	961	28
Household Family Single Parent	307	9
Household Dual Retired	607	17
Household Single Retired	412	12

4.3.3. Limitations

The limitations of such a study are the following:

1. The date of the NSO Final Report dated on 2011 was used.
2. The measurements were taken throughout a short time period, thereby no seasonal variation was considered.
3. Certain parameters were left at default due to lack of information.

4.4. Comparison between models

Chapter 3 detailed the different features included within each selected model. A comparison between the two used models, EDPG and ALPG, was carried out. However, as each model was developed using a different methodology and, in general, they have different characteristics, one had to be adapted according to the other's features. The ALPG model was adapted as it is more detailed and easier to fix and the EDPG model was left withSt Julian's city settlement settings.

Both models were changed to simulate St Julian's zone during one day according to EDPG's output, for summer and winter seasons. The EDPG settings were the same as the ones explained above, whereas the ALPG model was fixed. As EDPG model does not include emerging technologies, all the penetration values of the ALPG configuration file were set to zero. Moreover, the simulated day had to be a weekday since the EDPG model does not differ between weekdays and weekend days. This day was assumed to be the first one after the start day established in Figure 22 for summer and in Figure 23 for winter. Unfortunately, ALPG's appliances cannot be changed since they have a particular behaviour represented in Python's code, thereby the listed appliances within each model was different.

4.4.1 Limitations

The limitations of such a study are the following:

1. ALPG's appliances are already defined, and they cannot be changed.

2. The EDPG model can be improved to generate up to five minutes time resolution output data. However, this is not enough to reach the ALPG model's one-minute resolution and was not done due to lack of time.

4.5. Summary

This chapter presented the methodology used to calculate or experimentally determine the energy consumption of a set of typical appliances. This was followed by a detailed description of the key settings for the two models to tailor-make them to the case of Malta, focusing on the sources of the required input data as well as their processing to obtain the necessary inputs that are used within the simulation process.

Chapter 5: Results and Discussion

5.1. Results and Discussion

This chapter presents the results generated by the EDPG and ALPG models described in Chapter 3. It examines and provides a comparison between the different profiles generated by the same model and similar profiles from both models.

5.2. The EDPG model

This model was set as described in Section 4.1. The differences in the consumption profiles between the main household types within localities were analysed. In order to focus on the active occupancy, some loads are explained following the generated profile for a single household in St Julian's which is shown in Figure 28. First of all, a general profile shown in Figure28 is detailed to describe the loads that characterize every dwelling.

In general, appliances that are operating throughout the day, such as the refrigerator and the freezer, consume electricity during every interval and represent the profile's base consumption. On the other hand, controllable appliances such as the electric water heater or the dehumidifier have a significant consumption and they operate within specific periods of time. The dehumidifier was scheduled to generate a load every three time slots starting from midnight to 1:00 am whereas the water heater load operates for three separate time slots depending on the household size. For one and two household sizes, the water heater operates from 4:00 am and from 1:00 pm whereas for the case of three or more household sizes it operates from 4:00 am and from 1:00 and 7:00 pm.

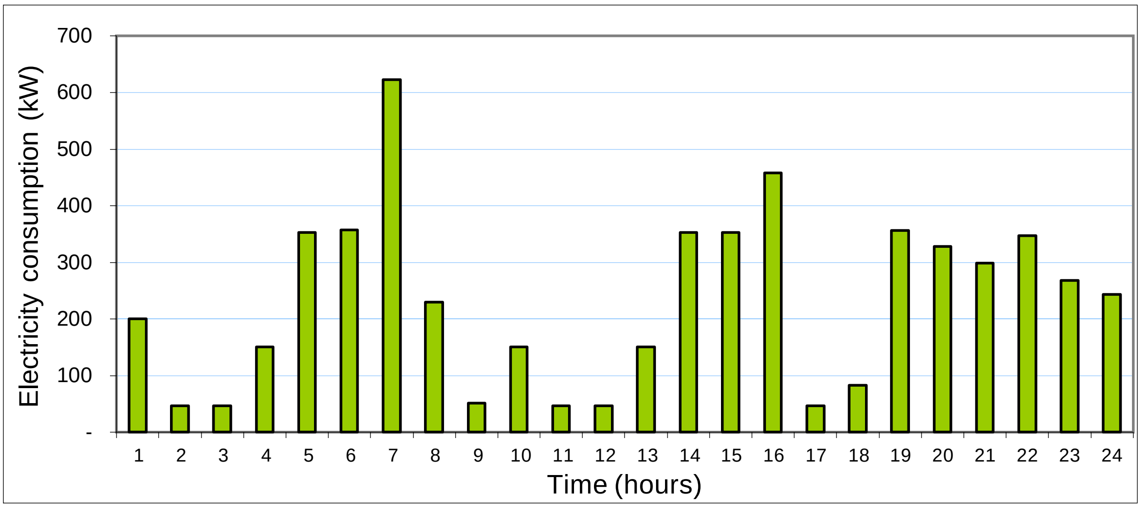

Figure 28. Example of a generated electricity consumption profile for the community.

5.2.1. Population scenario

In this scenario, as mentioned in Section 4.2., the zones of St Julian's and Xewkija were considered as the purpose is to study the demand of a city and a village. Such profiles are affected by the number of dwellings within each household type inside the studied community, although the appliances usage pattern was supposed to be similar in accordance with the household type throughout every simulation. The household types with less similar appliances usage, i.e. 'single worker', 'single pensioner', 'two workers with pensioner', and 'two workers with children', together with the complete zone are studied in detail below. The seasonal variation within this model is presented in the following section.

Figures 29 and 30 show the 'single worker' household daily average consumption for winter for both zones. Although both charts have the same profile throughout the day as the same appliances usage pattern was assumed for these two cases, the number of dwellings is different. Xewkija's profile has a peak demand lower than 180 kW while St Julian's peak reaches more than 600 kW. The characteristics 'single worker' profile are detailed below.

Generally, a significant increase in the dwelling consumption during the morning indicates the occupant's waking up time, in this case between 6:00 and8:00 am before leaving to work. Then, only controllable and continuously operating appliances generate a load until the occupant returns around 18:00. After that, various appliances are used until bedtime at midnight.

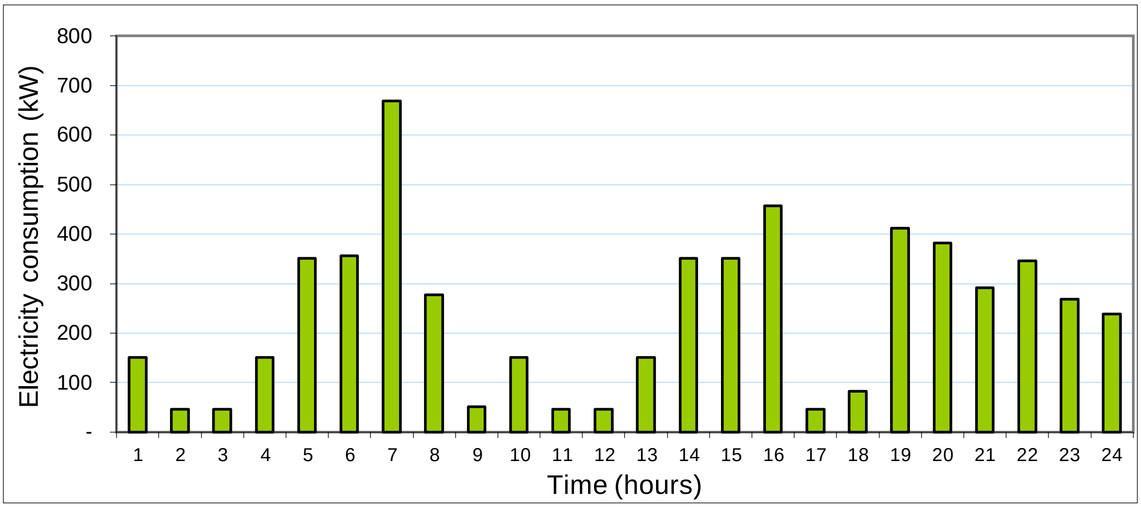

Figure 29. Single worker households daily average consumption for winter in St Julian's.

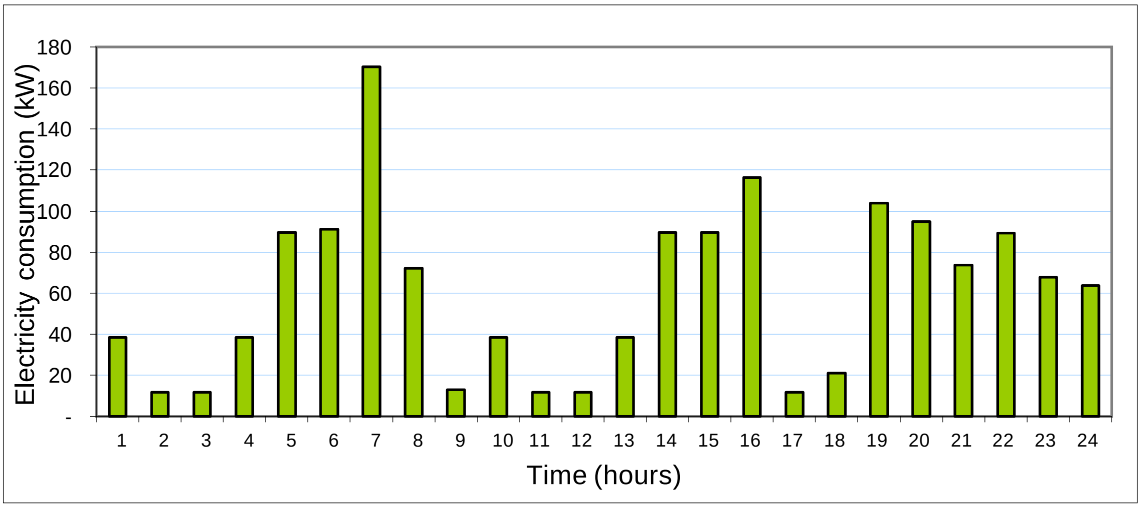

Figure 30. Single worker households daily average consumption for winter in Xewkija.

The 'single pensioner' profile shown in Figures 31 and 32 follows a pattern that shares the different loads randomly throughout the day, as the retired persons occupancy does not follow an exact pattern. However, as the 'single worker' case, the wake up and bedtimes are the same.

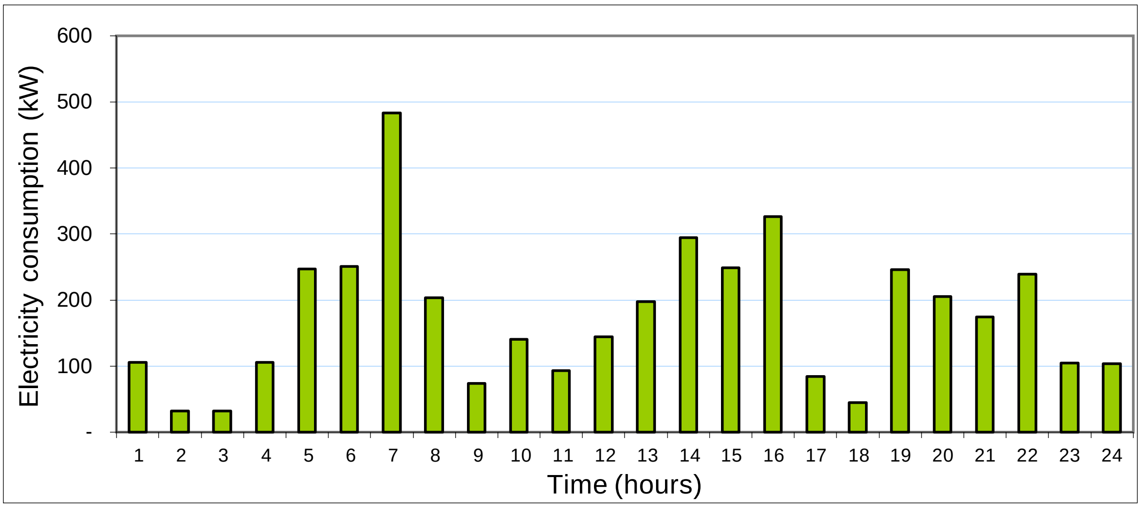

Figure 31. Single pensioner households daily average consumption for winter in St Julian's.

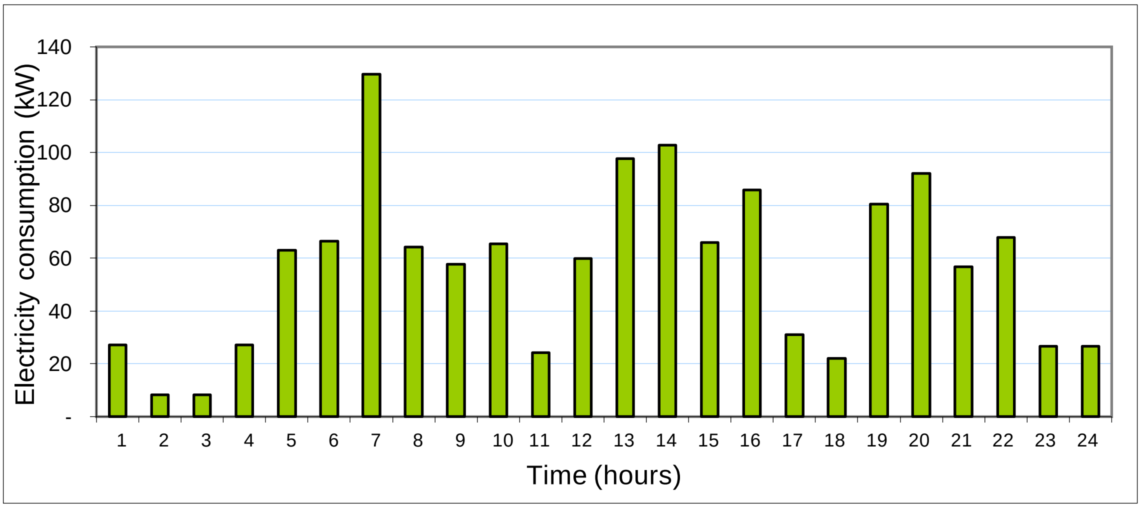

Figure 32. Single pensioner households daily average consumption for winter in Xewkija.

In the next case, the number of occupants increases to three. Hence, the overall electricity consumption for a single dwelling is higher. However, as there are 645 'single adult', 454 'single pensioner', and 275 'two workers with pensioner' dwellings within the locality, the daily average consumption taking all the latter type households is lower than for the othercases.

Figures 33 and 34 profiles are characterized by both worker and pensioner, profiles explained before. Therefore, the consumption peaks are shared between two different periods, the morning and the evening, when all the occupants are indoors and active.

Furthermore between 18:00 and 21:00, the appliances' load is mainly due to the high active occupancy level, coupled with the electrical water heater operation cycle leading to in a period with a high and constant consumption.

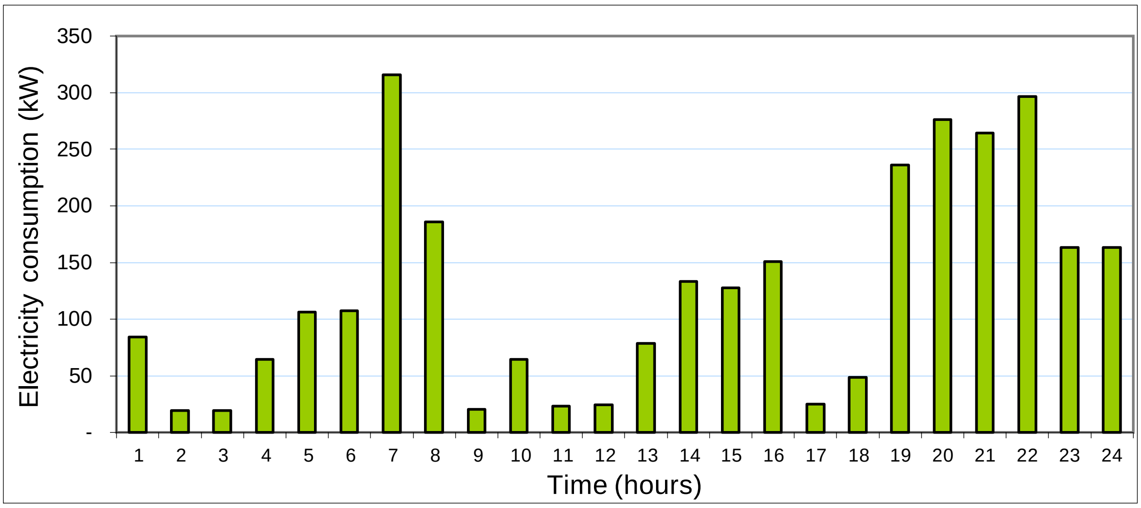

Figure 33. Households with Two Workers with pensioner. Daily average consumption for winter in St. Julian's.

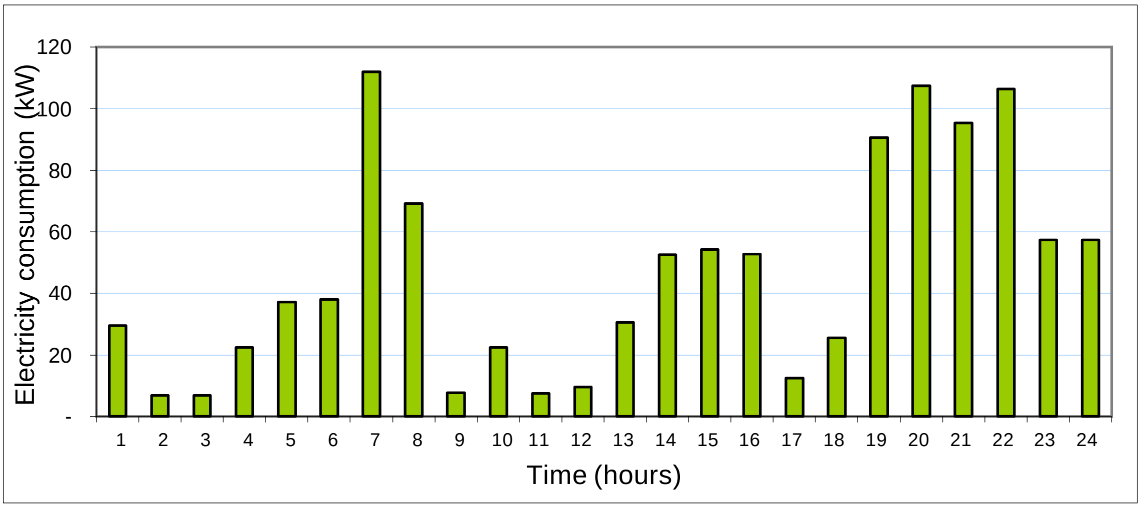

Figure 34. Households with Two Workers with pensioner. Daily average consumption for winter in Xewkija.

The 'two workers with children' household profiles introduce the children occupant. These persons wake up around 7:00 am, go to school and return at around 14:00, they spend the day indoors until their bedtime at 22:00.

Figures 35 and 36 are characterised by the high demand in the evening due to the number of appliances in use when both parents and the children are at home. The consumption throughout the day maintains a low level although the children return from school dueto the insignificant load compared to the same occupancy periods referred to above.

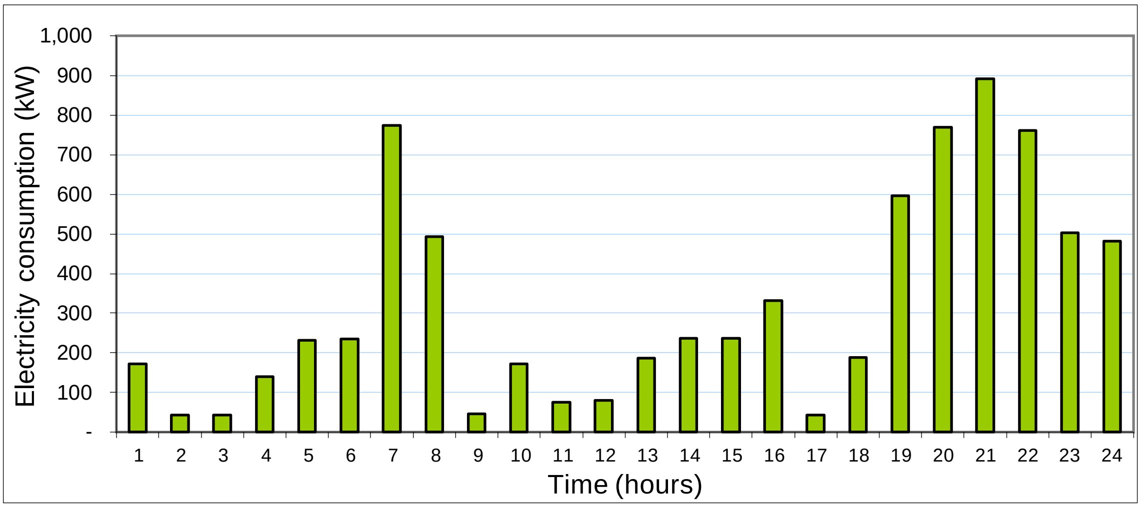

Figure 35. Households with Two Workers with children. Daily average consumption for winter in St. Julian's.

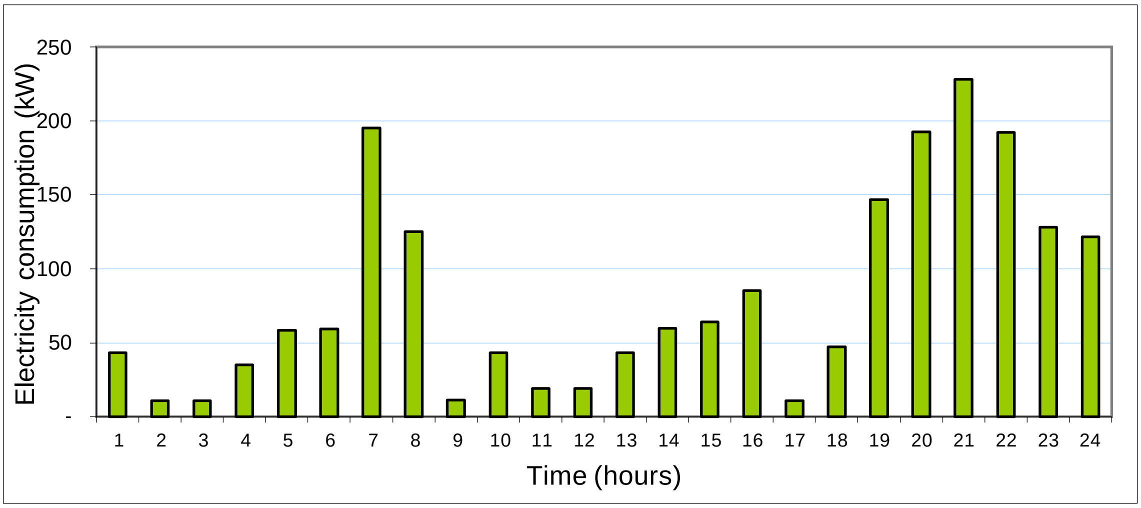

Figure 36. Households with Two Workers with children. Daily average consumption for winter in Xewkija.

Then, the daily average load profile for the complete localities was studied simulating the community for summer and winter seasons and shown in Figures 37 and 38 for St Julian's case and Figures 39 and 40 for Xewkija's case. The seasonal effect within this model concerns the lighting usage pattern, which will be discussed in the following section.

The figures show the generated average profile of all household types' profiles within the community. In general, the loads are spread between three different time periods throughout the day corresponding to the wake-up time, the afternoon's electrical water heater usage coupled with the dehumidifier operation and loads of used appliances used by pensioners or children, and the period from the time after return from work until bedtime.

Furthermore, there are three significant three peak demands, one in the morning and two in the evening. Such loads should be reduced as they affect the lifetime of LV network devices and trigger over-voltages and over-currents.

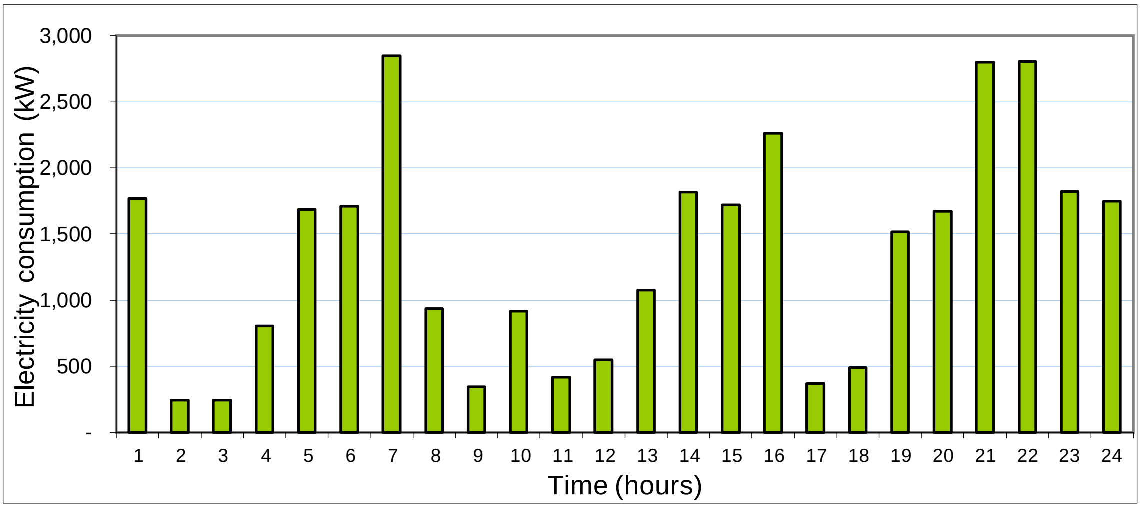

Figure 37. Total community daily average consumption for summer in St Julian's.

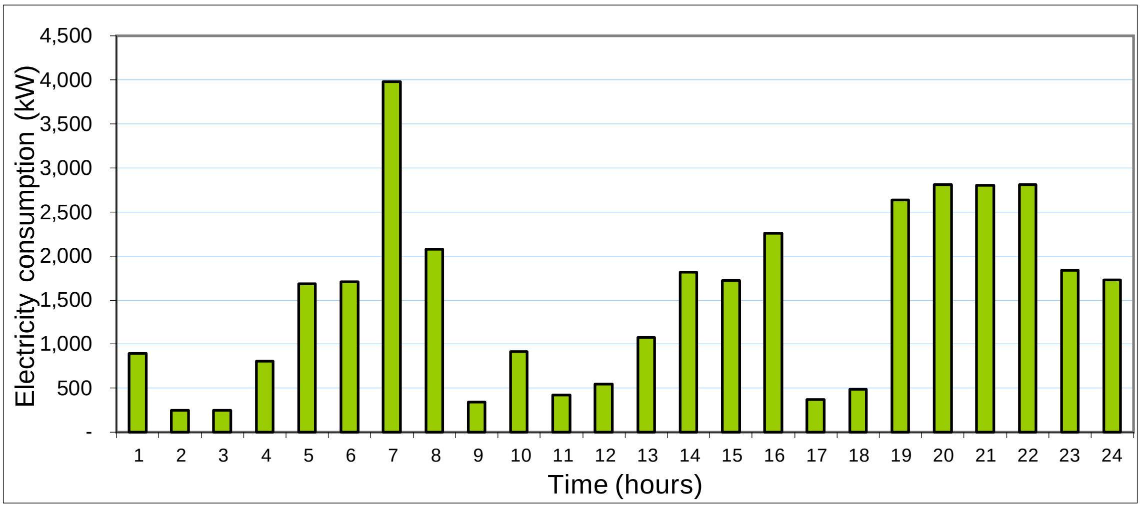

Figure 38. Total community daily average consumption for winter in St Julian's.

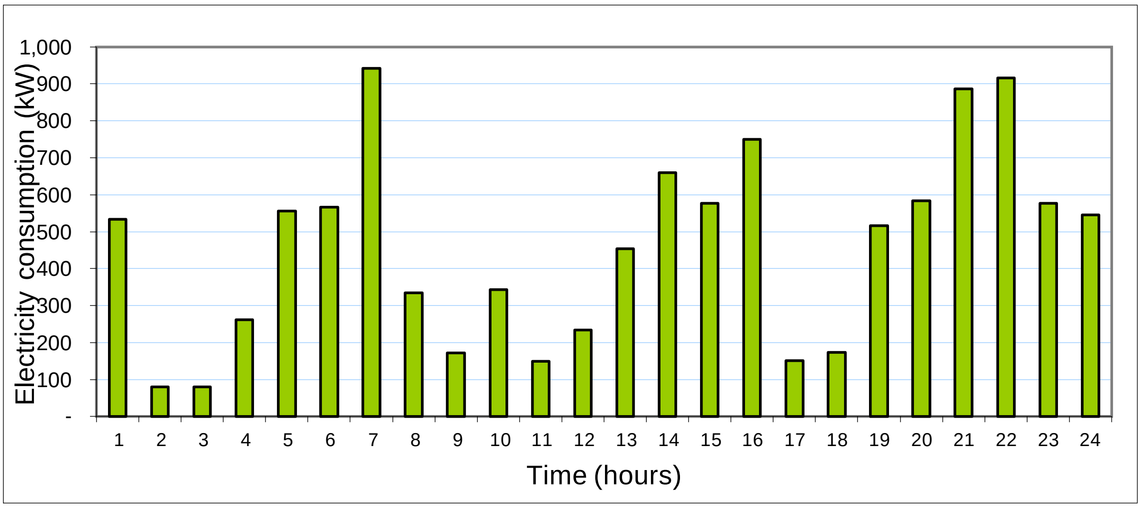

Figure 39. Total community daily average consumption for summer in Xewkija.

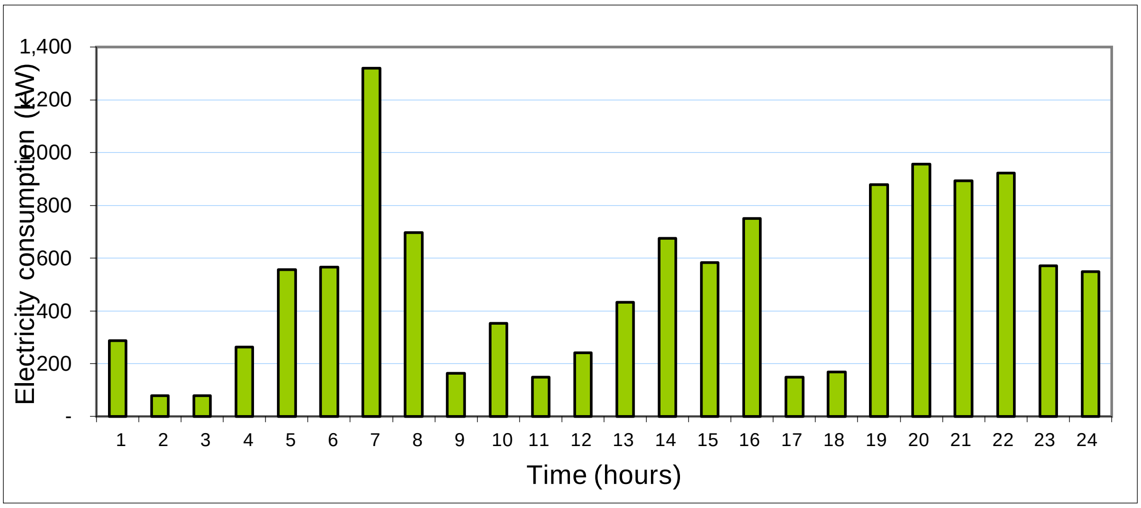

Figure 40. Total community daily average consumption for winter in Xewkija.

5.3. The ALPG model

The model allows study of the impact of emerging technologies such as photovoltaics, electric vehicles, and their combination. As a result, charts in accordance with technologies installed and season were plotted in this section. Due to the high amount of generated data for the one-minute resolution, one dwelling within the household type with the greatest number of dwellings inside the community, i.e. the 'family dual worker', is studied in more detail. However, every generated profile even for the same household can be different due to the stochastic nature of the model.

In order to facilitate the analysis, each category was plotted using the same scale. The plotted categories are household consumption, PV production, and the solar irradiance level. The PV production is shown, for households with PV installed, while the solar irradiance level was plotted for households without PV, to indicate the days throughout the week simulation period. This period is the same week according to the season considered.

First of all, the household consumption without any low carbon technology installed was simulated. The results are shown in Figure 41 and 42. As can be noticed, both profiles present a very different demand profile due to the stochastic nature of the model. In general, the spikes represent usage periods of the appliances. The size of the spikes is determined by the cumulated consumption of the operating appliances, thereby the highest ones are generated by high-consumption appliances such as the electric kettle, the iron, or the induction stove together with other appliances characterised by lower consumption rates. As shown in the figures, the consumption profile is always over zero due to the appliances left in stand-by and ever-operating appliances such as the refrigerator.

Focusing on the profile curve, the first daily variation indicates that the occupants wake up in the morning, they use some appliances such as the microwave and/or the TV and leave the dwelling to work or school. Then, they return in the early evening and are awake until midnight making use various included appliances. Nevertheless, appliances are used during the day, before the workers arrive, as children are active indoors.

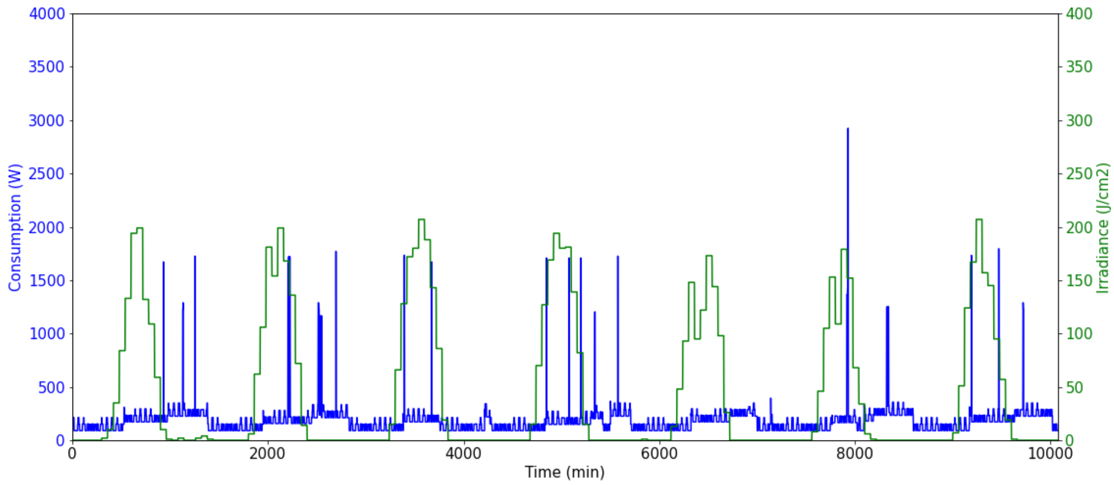

Figure 41. Family dual worker one-week consumption in winter.

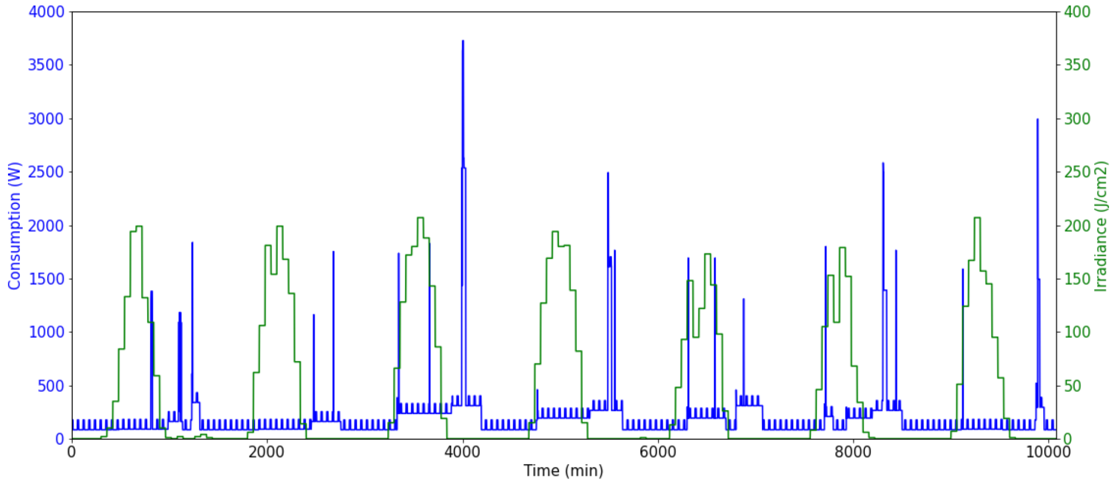

Figure 42. Family dual worker one-week consumption in summer.

In the second simulation, every household was assumed to own an EV which is charged at home. This load, as shown in Figures 43 and 44, is usually visible during the evening when the employed persons return from work and plug the electric vehicle. Therefore, as the figures show, after the sunset the household consumption shows a sustained increase during the charging period. This leads into an increase of the peak demand. Although both profiles are different, this emerging technology is not affected by the seasonal effect as the EV's load depends on its usage pattern and its characteristics such as the capacity, and the power rating.

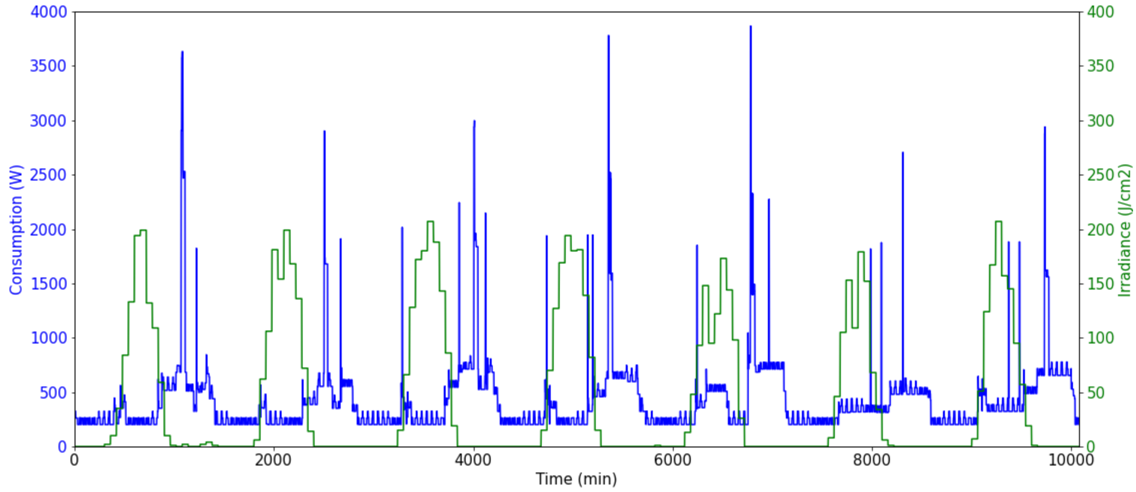

Figure 43. Family dual worker one-week consumption with EV in winter.

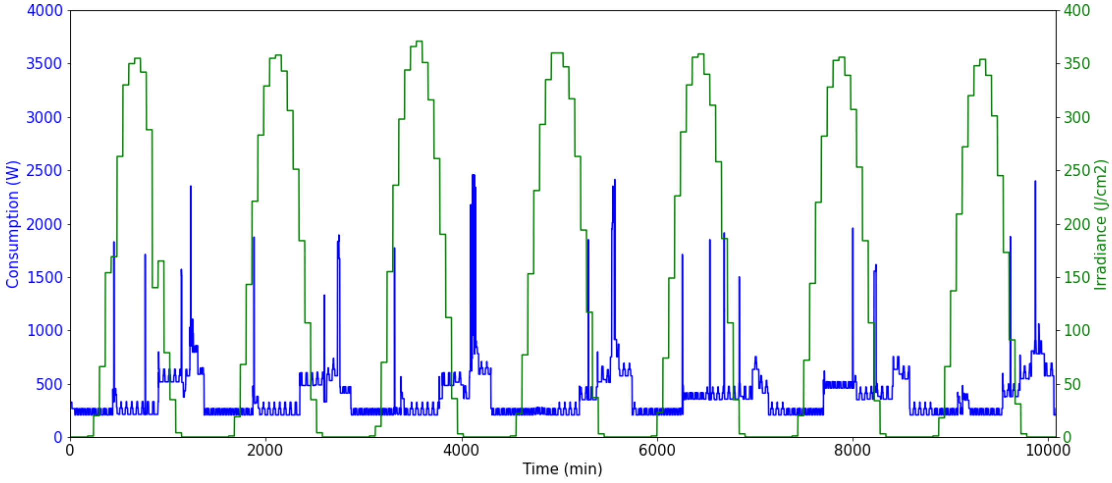

Figure 44. Family dual worker one-week consumption with EV in summer.

In Figures 45 and 46, the family dual worker household has a PV system installed. This should reduce the demand pattern due to PV power production. However, as no battery storage system was installed due to the high investment that it requires, the PV power production only affected during the exact period of generation. Figure 45 shows this feature, where during the production intervals the household consumption level is minimum and when the PV stops producing the household consumption increases rapidly. In the case of Figure 46, in spite of the higher PV production rates, the household consumption is seen to pick up before the end of the PV production. This reflects the longer hours of PV production which extend to late afternoon.

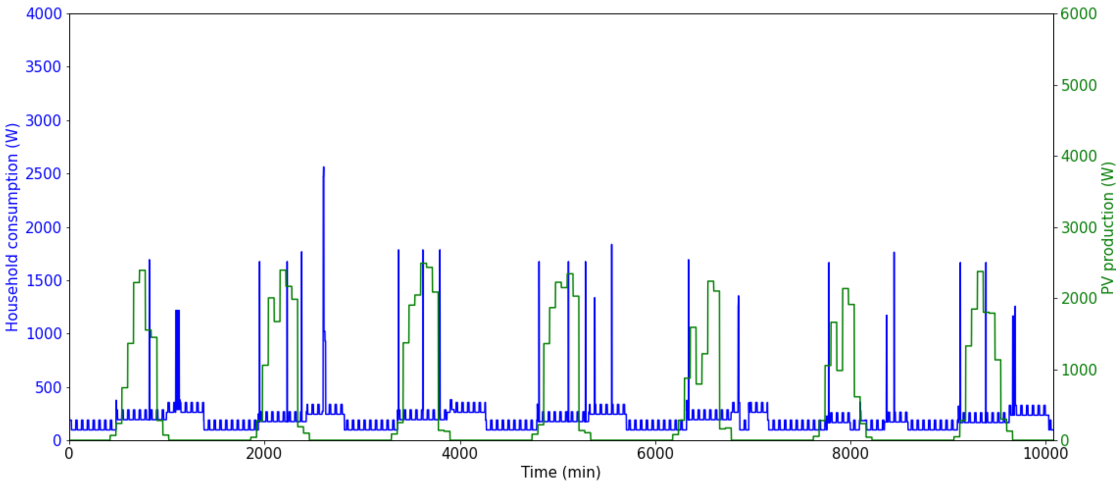

Figure 45. Family dual worker one-week consumption with PV in winter.

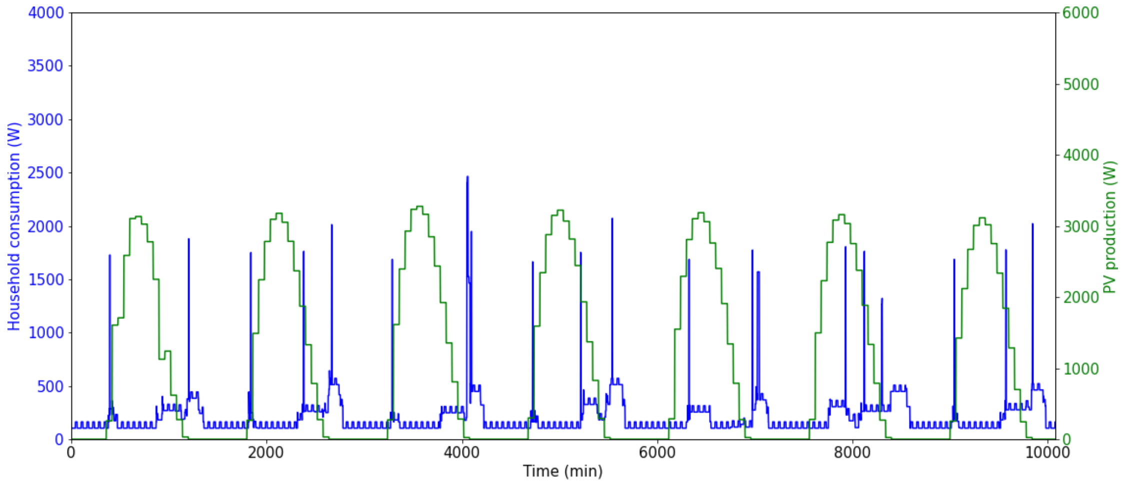

Figure 46. Family dual worker one-week consumption with PV in summer.

Finally, both EV and PV technologies were installed within the household. The impact of these loads on the dwelling consumption profile, as discussed above, is opposite. The EV, while operating, would increase the consumption whereas the PV, while producing, would decrease the consumption. Figures 47 and 48 show this scenario for winter, and summer seasons, respectively. In both Figures the effect of these two technologies, as discussed above, can be noticed. Although these technologies have the opposite effect in the consumption profile, Figures show that these loads are not distributed in the same time periods throughout the day. Therefore, the increase of the peak demand due to EV's load will still be a serious issue. Figure 47 clearly shows that the EV is not charged on all the days due to short working distances in Malta.

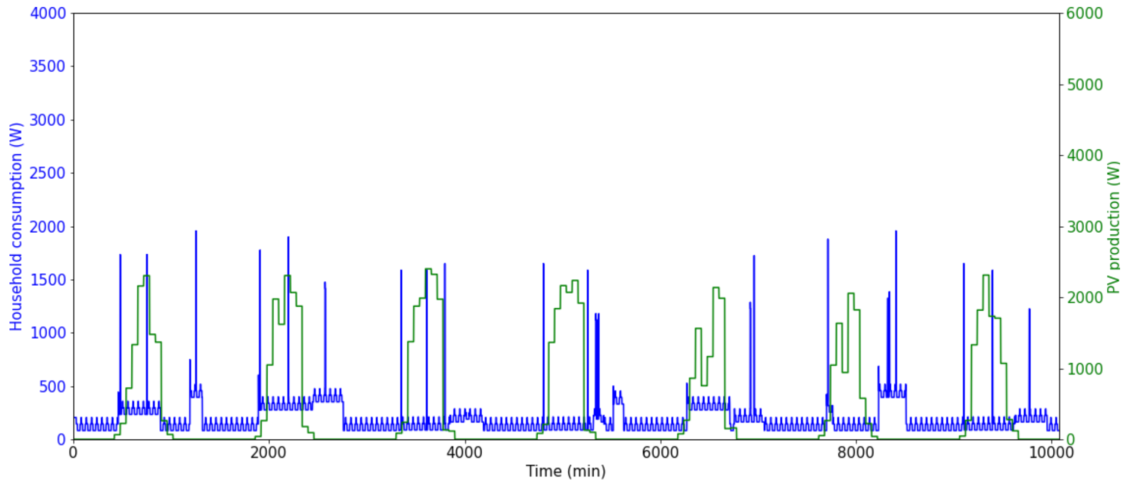

Figure 47. Family dual worker one-week consumption with PV and EV in winter.

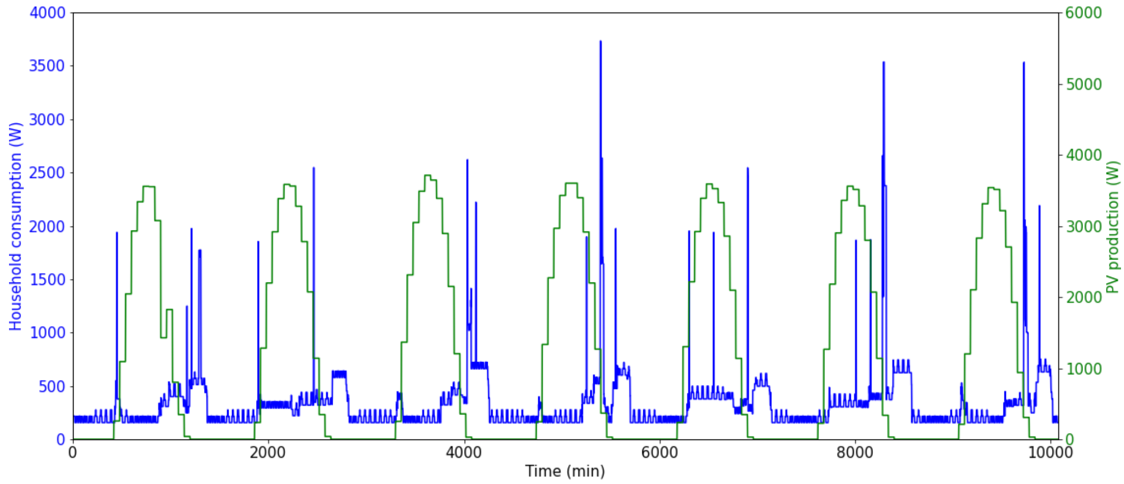

Figure 48. Family dual worker one-week consumption with PV and EV in summer.

5.4. Comparison between models

Both models are now compared keeping in mind the different usage pattern in use. The most striking difference is the output time granularity. The ALPG model profiles portray significantly more detail as the model includes a higher time resolution, hence appliances that are typically on for a short time but consume considerable power such as the electric kettle are represented. The one-hour resolution of the EDPG model masks such activity.

On the one hand, the EDPG's 'single worker' load profile shown in Figure 49 is determined by the occupant's working schedule. As the profile shows, the wake-up time is between 6:00 and 8:00 am, when the occupant cooks and leaves to work. Then, the occupant returns from work at around 18:00 and uses different appliances for cooking, washing, or entertainment. The profile is highly affected by the electrical water heater and the dehumidifier, as discussed above.

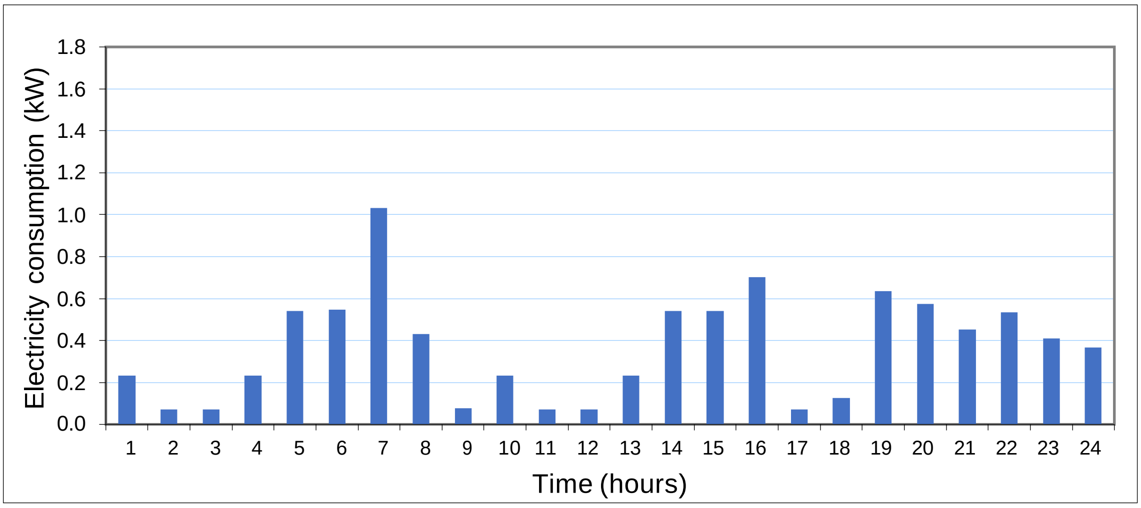

Figure 49. Single worker EDPG profile for winter.

On the other hand, ALPG's 'single worker' load profile, shown in Figure 50, presents a contrasting profile as the consumption varies principally during the last part of the day. Thus, the occupant leaves the dwelling after probably cooking due to the variations in the consumption pattern during the morning. Once the occupant returns from work, this is when the appliances such as the vacuum cleaner, the induction stove, or the microwave oven are used. Lighting units are used at the end of the day, from around 6:00 pm until around11:00 pm, when the inhabitant goes to bed.

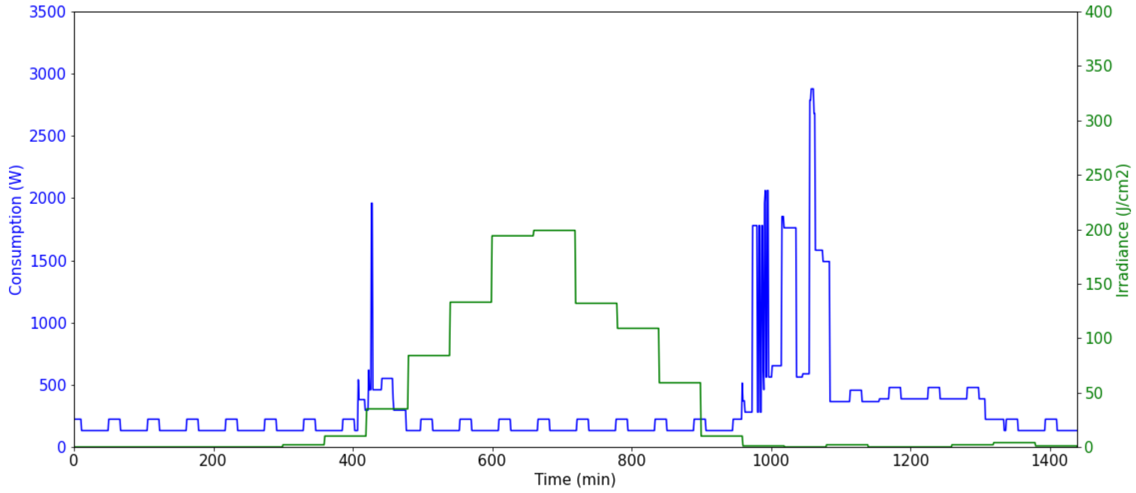

Figure 50. Single worker ALPG profile for winter.

ALPG's output load profile presented higher peak power due to the power ratings of the included appliances. In comparison, the EDPG model uses an hourly resolution hence its consumption rates are average values over this period. Nevertheless, the minimum demand of both profiles is slightly lower than 200 W which means that the refrigerator and freezer included in EDPG present similar loads compared to the fridge and the small fridge included in ALPG model.

Comparing Figures 49 and 51 the seasonal variations in the EDPG model profiles can be noticed. Table 40 presents the assumed lighting usage pattern for winter and summer seasons. The profiles' hourly consumption rates change during the intervals where the lighting usage pattern does not match due to season. Therefore, an increase in the household consumption in accordance with the number of bulbs installed in the dwelling and the bulb power rating occurs for summer, compared with winter, from midnight to 1:00 am, whereas from 6:00 to 8:00 am and in the evening the winter consumption is higher.

Table 40. Non-pensioner households lighting usage.

Time	Lighting	
	Winter	Summer
00:00 - 01:00		on
01:00 - 02:00		
02:00 - 03:00		
03:00 - 04:00		
04:00 - 05:00		
05:00 - 06:00		
06:00 - 07:00	on	
07:00 - 08:00	on	
08:00 - 09:00		
09:00 - 10:00		
10:00 - 11:00		
11:00 - 12:00		
12:00 - 13:00		
13:00 - 14:00		
14:00 - 15:00		
15:00 - 16:00		
16:00 - 17:00		
17:00 - 18:00		
18:00 - 19:00	on	
19:00 - 20:00	on	
20:00 - 21:00	on	on
21:00 - 22:00	on	on
22:00 - 23:00	on	on
23:00 - 24:00	on	on

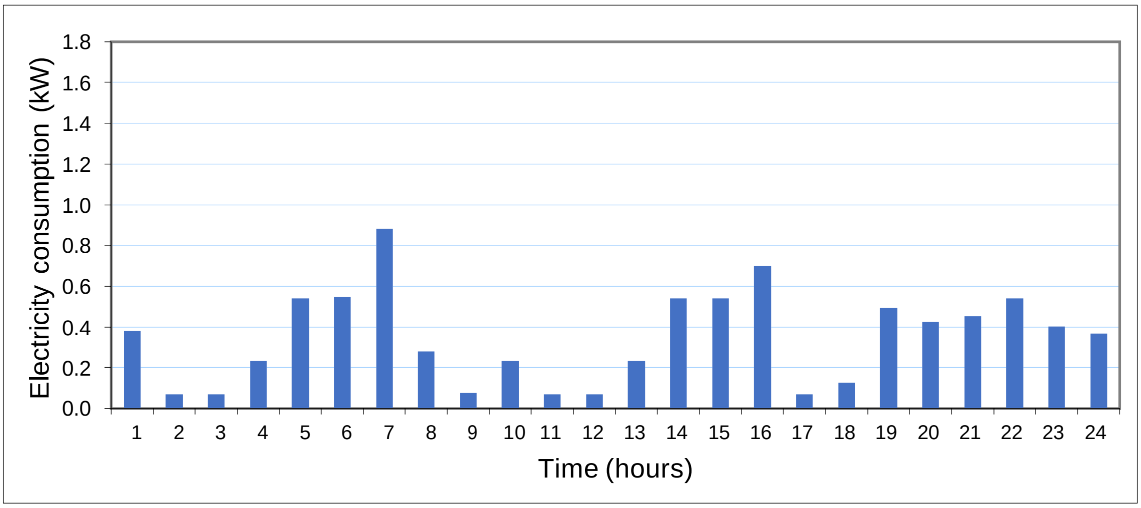

Figure 51. Single worker EDPG profile for summer.

The summer's ALPG model output shown in Figure 52 is slightly different from the winter's one. Ventilation is installed within the dwelling, therefore its load is included during this season. However, the active occupancy period in the evening is longer, although the bedtimes are similar.

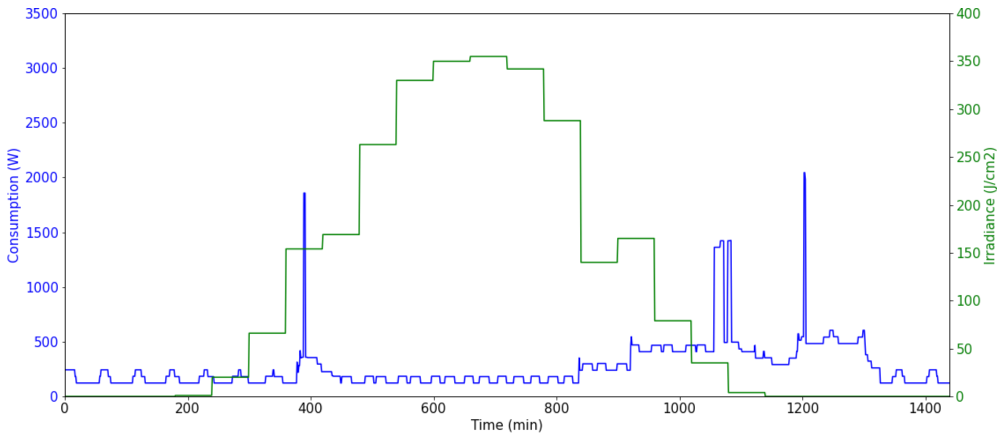

Figure 52. Single worker ALPG profile for summer.

The lighting usage pattern differs for the two models. The ALPG model also includes a ventilation load for summer. However, both profiles are lightly affected by the variations in lighting usage and, moreover in the ALPG case, due to the ventilation load. These variations will be even less significant as the greener lighting technologies are becoming more popular.

5.5. Summary

This chapter presented the results obtained throughout the dissertation, which are generated by the EDPG and ALPG models. The first model was used to discuss the contrast between different zones and lighting technologies, whereas the second was simulated to study the effect of PV and EV technologies on the dwelling load profile. At the end, a comparison between the output of these models was discussed.

Chapter 6: Conclusions and Recommendations

Chapter 6 outlines the summary conclusions based on the outcomes of the main results in accordance with the aim and objectives of the dissertation. It will also include some observation and recommendations towards future research.

6.1. Conclusions

Chapter 4 presented the results generated by EDPG and ALPG models. The results mainly discussed the installation of greener technologies and the difference between locality sizes regarding the electricity load consumption.

6.1.1. Locality consumption variations

The generated load profiles representing the selected zones were characterised by the same appliance's usage pattern according to household type. Therefore, the number of households within each type together with their total appliances' consumption profile have influenced the generated profile.

As a conclusion, the average dwelling load profile within the studied location was principally shared between three different time periods due to high active occupancy levels and high-consumption time shiftable appliances. Therefore, in order to equally share the load throughout the day, the controllable electronic devices operating times should be set during unoccupancy or non-active occupancy times, as the occupants schedules cannot be changed. This would reduce the peak demand hence the risk of overloads which leads into an increase in the lifetime of the electric equipment that is within the network.

6.1.2. Renewable technologies

Simulations considering PV and EV technologies were carried out using the ALPG model. The PV power production was driven by the available outdoors solar irradiance level, hence influenced and therefore by the household's orientation and the season. The net consumption levels were seen to be at the minimum level during the PV generation periods as shown in Figure 53.

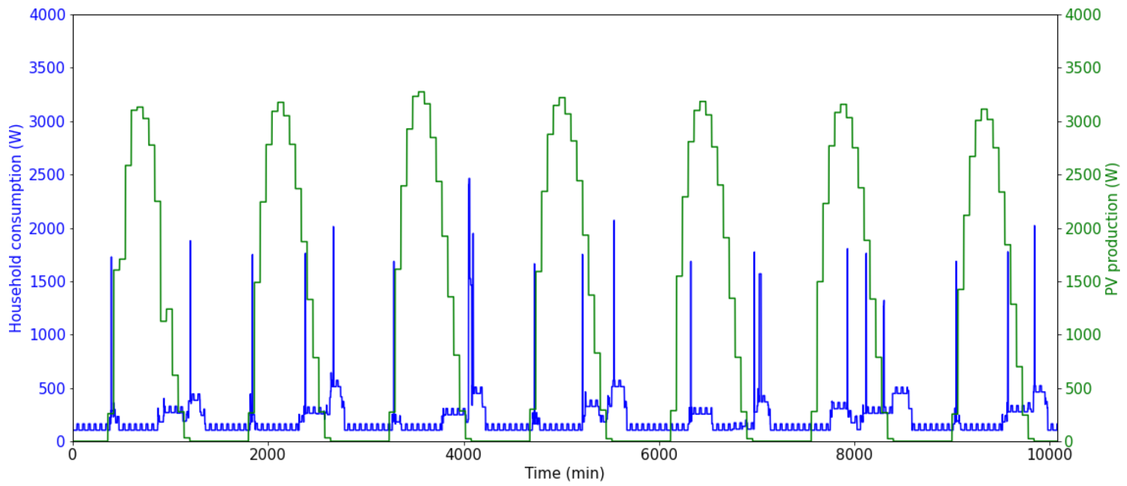

Figure 53. Household profile with installed PV technology.

However, this technology only generates power under sufficient irradiance levels, leading to a mismatch between the generated power and the household consumption. The coupling of this technology with battery storage systems is highly recommended as the energy can be stored for self-consumptions later in the day. The use of batteries presents the ability of reducing the peak loads on the power station after sunset, while at the same time support the longevity of battery lifetime, because they would undergo the expected cycling of charge/discharge periods. Furthermore, it would reduce the reverse power flow during high PV power injection and low demand periods.

On the other hand, the EV load increases the load on the power station, because it usually occurs in the evening. Normally, the charging period during the weekdays will be once the employed occupant returns from work as shown in Figure 54. Notwithstanding, if the grid introduce night-time tariffs, then charging of EV can occur at night when the electricity tariff is lower. This is turn favours a more efficient power station operation, because the difference between the base load at night and the higher energy demand during the day levels off. Thus making the power stations operate at better overall efficiency.

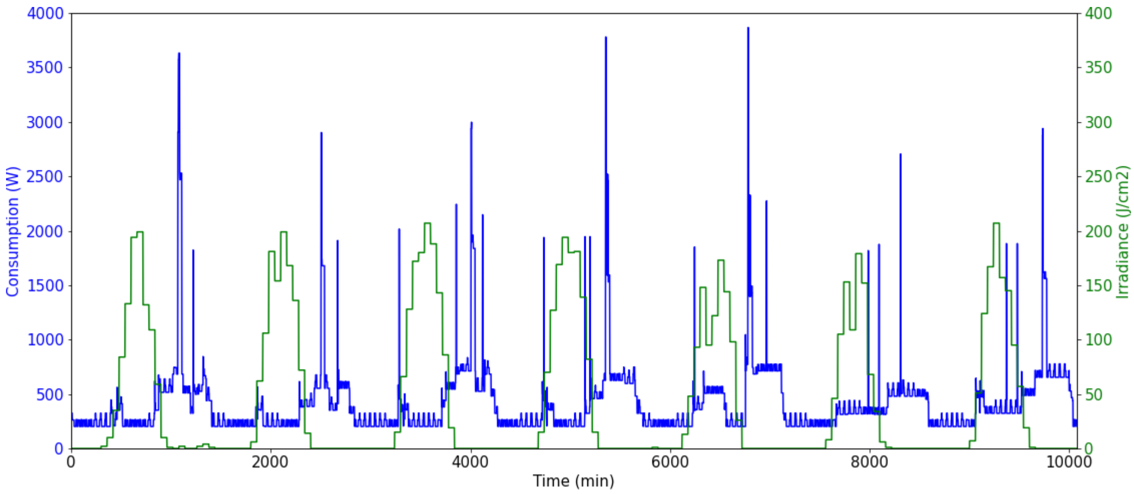

Figure 54. Household profile with installed EV technology.

If battery storage systems were installed within the household's network, as mentioned above, PV's production could be used to provide the EV's consumption reducing EV load, thus reducing the impact on the household load profile and the low voltage network. In this case, sizing of the battery system has to be carefully carried out to cater for both the evening load and the EV charging demand.

6.1.3. Model comparison

In general, higher time resolutions facilitate understanding of residential consumption profiles due to the relatively arbitrary use of appliances. Once can then justify the nature of the demands variations whereas, for the case of the longer time resolution demand, knowledge about the model is needed to interpret the output data. Furthermore, the EDPG model required a significant number of assumptions due to lack of information about Maltese dwellings. However, as the issue is the lack of information, this problem affects every top-down model. For these cases, bottom-up models with statistical approach such as ALPG or CREST are more suitable.

As a conclusion, EDPG model relies on data which might not be directly available thus requiring a number of assumptions. On the contrary, ALPG model requires less data as a statistical approach is included. Moreover, its output resolution facilitates the generated profile interpretation, making it more suitable for analytical purposes. However, both models have their application since the former can be used for loading scenarios of the low voltage network while the latter allows in depth analysis of the household demand with different appliance combinations.

6.2. Further studies and recommendations

This project has shown that the selected published models have a number of limitations and cannot represent all the scenarios. In particular, Malta lacks availability of information about people's lifestyles, population, energy consumptions trends and low carbon technologies. It is recommended that surveys are carried out finding answers to such frequently asked questions. The forthcoming National Census in 2021 should be able to answer some of these questions. Furthermore, it is recommended to use models such as CREST and Polysun to get more perspective on the impact of low carbon technologies and the households loading on low voltage networks.

6.3. Limitations

This dissertation was carried out with some difficulties due to COVID-19 pandemic and mandatory hospital quarantine. A number of suggestions that were first proposed could not be studied due to lack of time. However, the project succeeded in achieved the objectives proposed at the beginning in a satisfactory manner.

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