INSTITUTO TECNOLÓGICO DE COSTA RICA
ESCUELA DE QUÍMICA
CARRERA DE INGENIERÍA AMBIENTAL

Final Graduation Project to qualify for the University Degree of Environmental Engineering

"Development of a modelling tool for simulating electricity demand and on site Photovoltaics power production in high time resolution: Applications in Costa Rica."

"Desarrollo de una herramienta de modelado con tiempo en alta resolución para simular la demanda energética y la producción de energía fotovoltaica in situ: Aplicaciones en Costa Rica."

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"Development of a modelling tool for simulating electricity demand and on site PV power production in high time resolution: Applications in Costa Rica."

Report presented to the School of Chemistry of the Instituto Tecnológico de Costa Rica as a partial requirement to qualify for the title with University Degree of Environmental Engineer.

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LIST OF ACRONYMS AND ABBREVIATIONS

CFL	Compact Fluorescent Light
CNFL	Compañia Nacional de Fuerza y Luz
EESC	Energy Efficient and Smart City
GGE	Green Gas Emissions
GLS	General Lighting Service
ICE	Instituto Nacional de Energía
LED	Lighting Emitting Diode
LIA	Lighting Industry Association
PAR	Parabolic Aluminized Reflector
SPD	Surge Protection Devices
TUS	Time Use Survey

LIST OF SYMBOLS

AC	Alternating Current
CO_2	Carbon Dioxide
DC	Direct Current
GWh	Giga Watt per hour
KWh	Kilo Watt per hour
Min	Minutes
M^2	Square meters
MWh	Mega Watt per hour
OEF	On-site Energy Fraction
OEM	On-site Energy Matching
PV	Photovoltaics

ABSTRACT

Nowadays strategies towards more energy-efficient systems imply the integration and application of urban energy analysis tools, in order to support the sustainable energy systems. In intermittent solar power systems, the tools which couple energy modelling to assess the matching energy indexes require especial research into the comprehensive analysis between the demand and the production involving minimal source of error.

A significant source of error is attributed to the coarser time step resolutions used in the simulations; consequently, this also affects the matching indexes results. Solar energy production and domestic energy demand minute resolution models were created in order to identify the impact of time-step.

The generated PV on-site production model was developed with data from the research group Energy Efficient and Smart Cities (EESC) of the Technische Universität München. Relevant data needed for the model, such as irradiance and incident global radiation, were obtained using the software Meteonorm. The statistic computations of the high-resolution model of domestic electricity demand developed by the Centre for Renewable Energy Systems Technology of Loughborough University were used and modified in order to create the demand model that adequately represents energy demand in Costa Rica.

The matching error was more noticeable in partially cloudy sky conditions; the error was 39,18% for the month in study. In one case scenario, it was shown that daily resolution profiles conduce to the assumption that all the PV power produced is used to cover the house demand, although the 1-minute resolution results indicate that only 39% could be used with this purpose. Overall, it was found that the coarser resolutions average the existing demand and generation profiles spikes into much more continuous and flatter profiles, leading to an inaccurate representation of the general demand profile.

Keywords: High resolution, time step, electricity demand model, PV on-site power production, matching energy indexes.

RESUMEN

Con el fin de apoyar los sistemas de energía sostenibles hoy en día las estrategias hacia sistemas más eficientes implican la integración y aplicación de herramientas de análisis de energía urbana. En los sistemas intermitentes de energía solar, las herramientas de modelado que acoplan la simulación de sistemas energéticos para evaluar los índices de concordancia de energía, requieren de una investigación especial en el análisis global entre la demanda y la producción involucrando fuentes de error mínimas.

Una fuente de error importante, es la resolución de la frecuencia temporal aplicada en las simulaciones; por consiguiente, los resultados de los índices coincidentes de energía se ven afectados. Se crearon modelos de demanda eléctrica doméstica y producción energética solar con resolución fina de 1-minuto para identificar el impacto de la frecuencia temporal.

El modelo de producción de energía fotovoltaica generada in-situ fue desarrollado con los datos del grupo de investigación Energy Efficient and Smart Cities (EESC) de la Universidad Técnica de Múnich. Se utilizó el software Meteonorm para obtener la irradiación incidente y la radiación global. Se utilizaron los cálculos estadísticos del modelo de demanda domestica energética desarrollados por el Centro de Renewable Energy Systems Tecnología de la Universidad de Loughborough logrando representar adecuadamente la demanda de energética en Costa Rica.

El error de coincidencia fue más notable en las condiciones de cielo parcialmente nublado, el error fue 39,18% para el mes en estudio. En uno de los casos en estudio, se demostró que el perfil con resolución diaria conduce a la suposición de utilización total de electricidad generada por los paneles para cubrir la demanda domestica. Sin embargo, los resultados con resolución de 1 minuto indican que sólo el 39% podría ser utilizado. En general, se encontró que las resoluciones más gruesas promedian los picos en los perfiles de demanda y la generación de electricidad, en perfiles mucho más continuos y más planos, lo que conduce a una representación inexacta del perfil global.

Palabras claves: Alta resolución, frecuencia temporal, modelo de consumo eléctrico residencial, producción de energía solar in situ, índices de energía.

1. INTRODUCTION

Costa Rica enjoys abundant renewable energy resources; the country aims to become the first developing country to have 100% renewable electricity. This will require the replacement of distributed diesel generators used as back-up source. This can be accomplished with renewable-based energy systems that support sustainable and socially just forms of urbanizations that can provide solutions to the challenges of meeting the rapid increase in energy demand in urban areas, as well as the future demand. To accomplish this, it is necessary to identify the dynamics of transition that suits different scenarios.

The potential transition to decentralized renewable energy systems, such as photovoltaics, has been receiving an increasing analysis with the aim of taking advantage of the identified potential since the share of solar power is largely underrepresented in the country's electricity mix (Weigl, 2014). This technology, which is based on the use of the power of the sun, produces a low-carbon and sustainable form of energy. PVs not only can considerably reduce the emissions of greenhouse gases but also diversify the energy mix, which can, in turn, increase energy security, improve supply reliability, protect regional areas from energy price fluctuation and reduce adverse environmental impacts (Alvarado 2014).

A growing adoption of intermittent solar power in the energy systems requires research into the comprehensive analysis of the matching capability between the demand and the production. The matching capability can be analysed in different time resolutions using energy matching indexes, such as the on-site energy fraction index (OEF) which asses how much demand can be covered by the on-site energy generation and the on-site energy matching index (OEM) which indicates how much on-site generation can be consumed in the system rather than being exported or wasted. However, there is still a significant lack of research for the comprehensive analysis of the error in on-site matching results caused by different time resolutions (Cao, 2014).

Therefore, a model in high time resolution that involves the analysis of PV modules on site production and adequately represents the domestic electricity demand, will lead to a better understanding of the consequences of integration of the PV technology; on large, medium and small scale for the local energy balance. The use of high-resolution can eliminate the inaccuracy of the averaging effect, which leads to a significant improvement in energy efficiency by identifying flaws in simulations and decreasing the error (Molar, 2015). Also, the economic analysis, the financing and after-sales service, is taken into account in the benefits it has within.

In this study a model of PV energy production and a model of domestic energy demand were created in high-resolution. Minute measured data, collected from houses and PVs systems, was used for the validation and calibration of the models. Subsequently, the energy matching indexes were calculated and the correspondent matching error.

1.1. OBJECTIVES

1.1.1. General Objective

Identify the impacts of time resolution in simulations of PV power production and energy demand of dwellings.

1.1.2. Specific Objectives

- Simulate electricity demand and on-site PV power production in high time resolution.
- Evaluate the matching energy capability between the created profiles of energy demand and production on-site.
- Compare the matching results of coarser and finest resolution, assessing the matching errors.

2. LITERATURE REVIEW

2.1. ENERGY SCENARIO OF COSTA RICA

In recent years the structure of national energy consumption has shown a similar pattern, marked by a high dependence of hydrocarbons (72%). In 2013 the total final energy use was 153,040 terajoules, breaking down this consumption (Figure 2.1) it can be observed that the transport sector is the major consumer of energy and generator of emissions (Blanco, 2014).

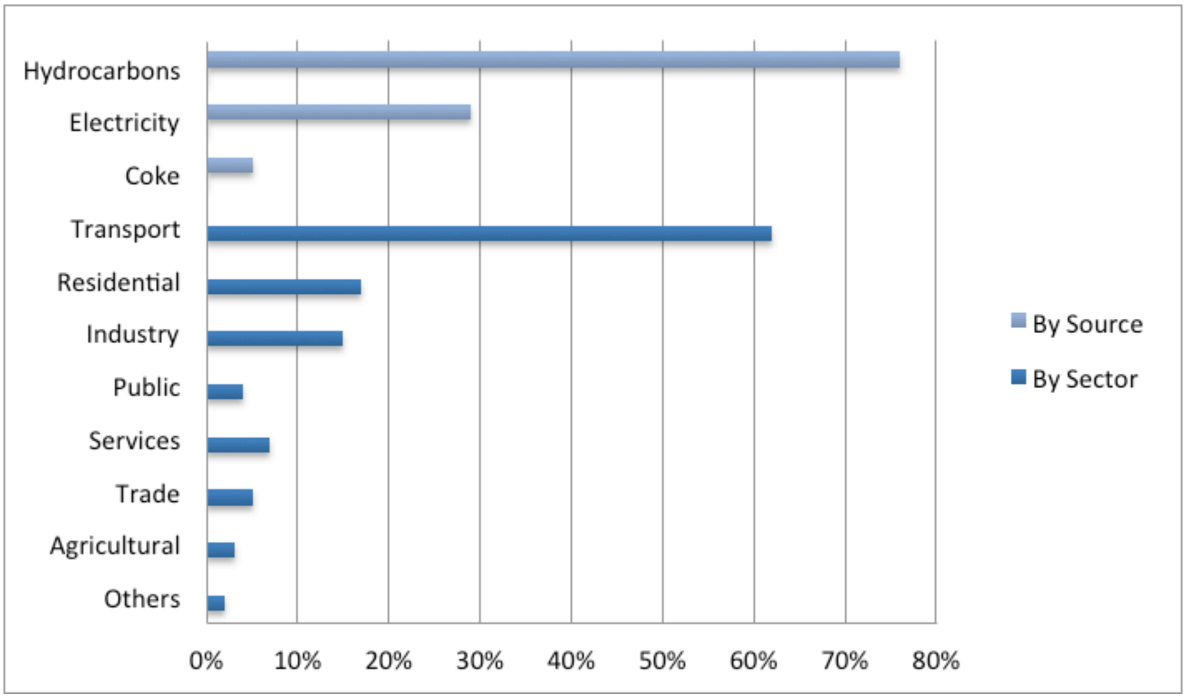

Figure 2.1. Total secondary energy consumption structure of the year 2013. (DSE, 2014).

However, there was a growth in the use of bunker in the electricity sector. Production grew by 44.1% between 2012 and 2013 also, 9.1% of the total sales of hydrocarbons at a national level correspond to the energy sector (Recope, 2013). This dependence could continue to grow, due to the impacts of climate variability and change on hydrological patterns and thus the availability of the flows that feed hydroelectric reservoirs. An example of this correspond to the Arenal reservoir, the most important in the country, who recorded in 2013 one of the lowest reservoirs in the past seven years (Blanco, 2014).

Before 2007, electricity demand increased on average 5% per year (ICE, 2012). As shown in Table 2.1, in 2013 the electricity demand increased only 0.9%, although electricity generation from bunker and diesel grew by 44.1%. This had an impact on pollution: in 2012 this activity generated only 8% of electricity, but it was responsible for the 72% of emissions of greenhouse gases associated with power generation (ICE, 2012).

Table 2.1. Environmental indicators of Costa Rica,

	2009	2010	2011	2012	2013
Electricity %	25.3	25.6	25.6	25.8	26
Energy Consumption Growth %	-1.3	3	1,4	3,6	1
Secondary Energy Consumtion (TJ)	118.094	120.480	122.049	125.619	126.177
Secondary Energy Consumtion Growth %	-1,7	2	1,3	2,9	0,4
Hidrocarbons	72,2	72,2	72,4	72,2	71,9
Biomass %	0,03	0,03	0,03	0,03	0,03

(Estado de la Nacion, 2014).

2.1.1. Electricity generation

The country's electricity generation capacity reached an installed capacity of 2,731 MW at 2014. Of the total, 78% corresponds to own plants operated by the two national energy companies of Costa Rica (which the Spanish abbreviations are ICE and CNFL). A 16% corresponds to plants contracted by private generators, 4% corresponds to four national cooperatives and the remaining 2% corresponds to two local distribution companies (Alvarado, 2014).

While private generation has played an important role in the development of the capacity of installed electricity, the percentage of participation reached its maximum limit. The conditions under which they could maintain or expand are part of a debate that is currently unresolved (Alvarado, 2014).

In 2013, a decrease of 5.3% was reported in hydroelectric generation, in order to maintain the reliability of the system, it was necessary to produce 1,196 GWh by burning bunker, 11.8% of the total electricity generated in that year (ICE, 2013). This not only increased the dependence on fossil fuels, but also resulted in higher prices for end consumers and higher emissions. It should be noted that, despite the problems of generation, electricity coverage in 2013 reached 99,4% of the territory, and is estimated that only 7,973 households have no access to public nationwide network (ICE, 2013).

The generation of clean energy has shown wide variations in recent years. During 2013, the system produced an effective total of 10,136 GWh, of which 67,6% came from hydroelectric plants, 14,9% from geothermal plants, 11,8% from thermal plants, 4,8% wind plants, 0,9% bagasse sugarcane and 0,01% solar energy (ICE, 2013).

The scenario changed in 2015, the respective generation can be seen in Figure 2.2. Hydropower still is the mayor source of renewable production but the percentages of wind power production and solar grew. Opposite, it can be seen that there was a decrease in the percentage of thermal energy production (Ministerio de Ambiente y Energía, 2015).

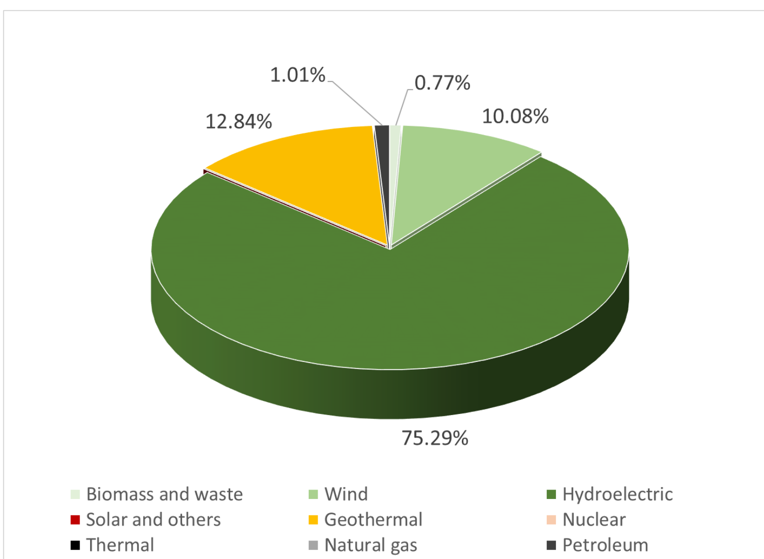

Figure 2.2 Costa Rica´s energy generation in 2015. (Ministerio de Ambiente y Energía, 2015).

2.1.2. Renewable Energy Potential Use

Although the country has identified a renewable energy potential of 9,051 MW, the effective power was exploited until 2012 (the most recent estimate available) and it corresponded to 2,147 MW, which is less than 25% of the local energy potential (see Table 2.2). The biggest contribution is electricity was generated by hydropower (1,768 MW), followed by geothermal (195 MW) and wind (144 MW) (Estado de la Nación, 2014).

Table 2.2. Energetic Local Potential of the year 2012. (ICE, 2014).

Energy Source	Identify Potential (MW)	Installed Capacity (MW)	% Installed
Hydropower	7.034	1.768	25
Geothermal	875	195	22
Wind Power	894	144	16
Biomass	122	38	31
Solar	126	2	1
Total	9.051	2.147	24

*The identify potential was obtained by the sum of different projects and it includes the capacity installed

*The installed capacity is the existence effective potential to December 2012

While hydropower generation remains predominant, climate change and other factors could make it necessary to develop new policies and programs to take more clean sources and thus, reduce the vulnerability of the system during the dry season (ICE, 2015).

Nonetheless, in 2015 from the total energy generation, 98.99% corresponded to renewable energy sources and only 1.0% corresponded to non-renewable energy sources (ICE, 2015).

2.1.2.1. Solar power potential: Irradiation data

Different studies and irradiation maps show the enormous potential of solar energy in the country, it was stated an average irradiation range of 1650-2200 kWh/m^2/year (Weigl, 2014). The mountain chain in the centre of Costa Rica and the two oceans heavily influenced the weather and divide the country in five main weather sections: North Pacific, Northern Zone, Central Valley, Central Pacific and Caribbean (Weigl, 2014).

2.1.3. Greenhouse Gas Emissions (GGE)

As mentioned previously, although the energy sector has a high weight in carbon footprint, actions to reduce its impact are limited and insufficient. In this area, the most recent concern comes from the increased use of hydrocarbons to produce electricity.

In 2013, ICE published an inventory of greenhouse gases of the National Electric System, using data from 2012 as shown in Figure 2.3. Thus, in the year studied, hydroelectric production supplied 72% of energy and generated only 16% of emissions; in the case of geothermal proportions were 14% and 11%, respectively, while wind sources contributed 5% of electricity without generating pollution directly (only indirect emissions produced during the construction and installation of the generators). The opposite happened with thermal plants, production supplied 8% of energy, but these were responsible for 72% of greenhouse gas emissions in this sector. The study also indicates that in 2012 the total emissions of the national electricity system were 777,000 tons of carbon, with an average of 77 tonnes/GWh (Montero, 2013).

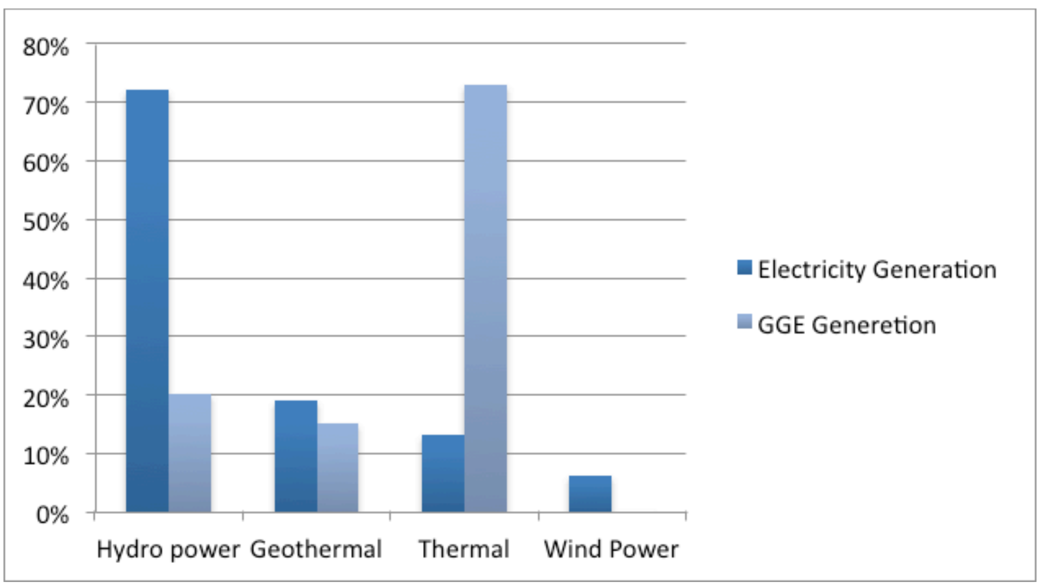

Figure 2.3. National Electric System Contributions of the year 2012. (Estado de la Nación, 2014).

In 2014, the total emissions of the National Electric System were 1.073.528 ton, 9.9% less compared with the previous year. This is contributed to the renewable energy matrix increase such as the growth of wind projects for energy generation, which have not any impact in the GEI emissions. Hydroelectric systems only produced 7.8% of the total emissions (Estado de la Nación, 2014).

2.1.4. Energy demand

Energy demand and the greenhouse emissions that it generates represent a large proportion of the ecological footprint of Costa Rica (about 31.1%) and it is considered the main factor driving the growth of it. The postponement of political decision jeopardizes the sustainability of the sector, especially the lack of clarity and consensus on the path to be followed to meet the challenges in this area (Estado de la Nación, 2014).

Various studies expect vast increase of the electricity demand in the upcoming years. In Figure 2.4, its shown the development of the Costa Rican net electricity generation since 1980 and projections of three different scenarios from 2014 to 2024 (Weigl, 2014).

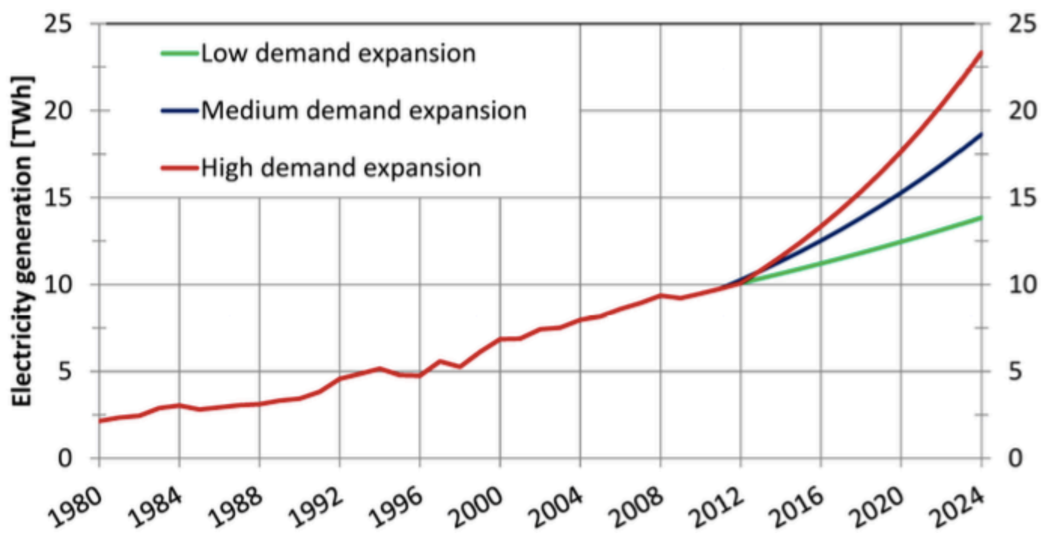

Figure 2.4. History and forecast of the net electricity generation. (Weigl, 2014).

In 2014, as shown in Figure 2.5 the mayor consumption of electricity was made by the residential sector, in which 39% of the electricity consume correspond to this sector. Because of not counting with a widely spread gas network, the heat demand has to be covered with electric energy. As well, electric boilers are used for the heat for cooking, warm water for showers and washing machines.

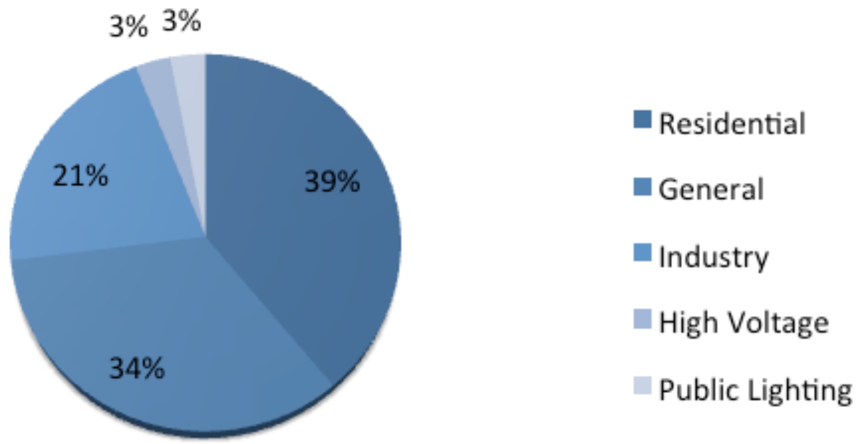

Figure 2.5. Different sectors share of electricity consumption in the year 2014. (ICE, 2014).

2.2. DWELLING ENERGY DEMAND

Energy use in the residential sector is defined as the energy consumed by households, excluding transportation uses. Energy use in this sector includes energy for equipment and appliances that provide heating, cooling, lighting, cooking, cleaning, drying, hot water, washing, entertainment and other household demands (Dennehy & Howley, 2013). The appliances can be categorized as flexible and non-flexible, and this division depends on the way users controls them. As shown in Table 2.3, there are two types of control: under direct user control like lighting, or under indirect user control which refers to appliances that are installed, configured and therefore operated autonomous like the fridge (Fischer et al., 2015).

Table 2.3. Categorization of appliances based on the demand share in Europe. (Fischer et al., 2015).

Appliance	**Electricity demand share (%)**
Under direct user control	
Office Equipment	14.5
Entertainment	13.3
Laundry and drying	13.1
Lighting	11.1
Cooking	10.1
Dish Washing	5.9
Under indirect user control	
Fridge	12.0
Pumps	7.4
Freezer	5.3
Other	7.4

"Income and energy prices affect the way energy is consumed in the residential sector. However, residential energy use also is affected by various other factors, such as location, building and household characteristics, weather, type and efficiency of equipment, energy access, availability of energy sources, and energy-related policies. As a result, the type and amount of energy use by households can vary widely within and across regions and countries." (U.S. Energy Information Administration, 2013)

2.2.1. Modelling household energy demand

Comprehensive models, that predict or simulate energy demand, are some of the significant tools necessary to use in city transformation plans and energy use national plans. As well, it enables the analysis of different aspects of urban energy demand and allows having a notion of the behaviour of the energy flow in this area. Besides, the models provide an insight of possible consequences regarding new energy policy initiatives (Mohammadi, De Vries and Schaefer, 2013). Nowadays, the top-down and bottom-up techniques are commonly used to estimate residential energy demand, as shown in Figure 2.6, the approaches of the models contrast between each other.

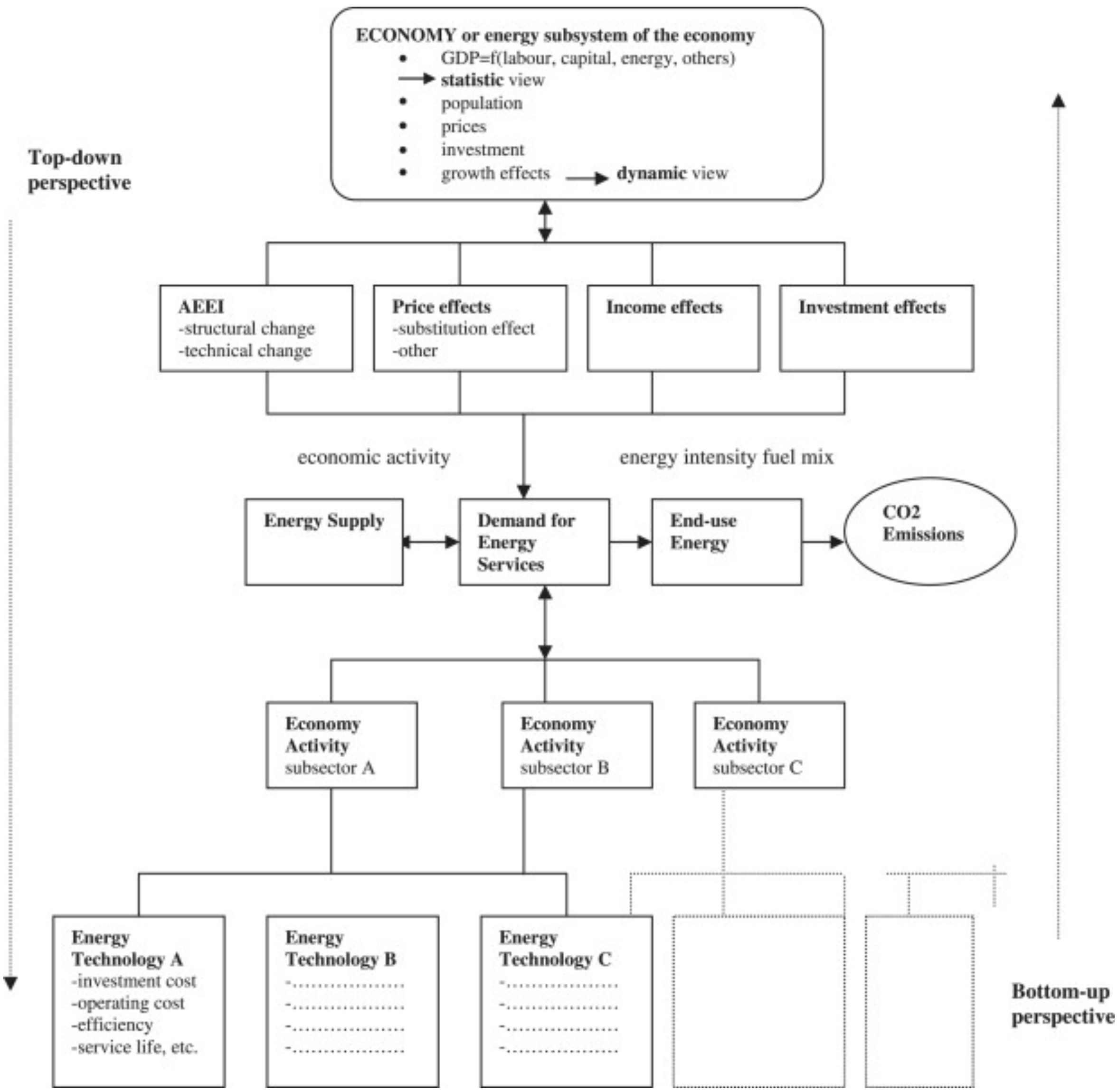

Figure 2.6. Top-down and Bottom-up model perspectives. (Kavig, et al 2010).

2.2.1.1. Top-down modelling

The top-down modelling approach is also known as a statistical modelling that works at the aggregated and macro level (Mohammadi, De Vries and Schaefer, 2013). The main objective is to create energy profiles with the same statistical properties by a decomposition of measured data. In this way, patterns of energy use on different time scales, can be establish for a specific region or sector. This approach is normally use in investigation of diverse interrelationships and the influence factors between the energy sector and other aspects such as weather conditions, social factors, demographic behaviour, economic factors, etc. (Molar, 2015). This kind of models don't rely on individual physical factors that can influence energy demand, instead, the model relies on past energy-economy interactions and place the emphasis on the macroeconomic trends and relationships observed in the past (Kavig, et al 2010). Thus, a significant disadvantage of this type of model is that there is no information about the components of the extracted profiles (Cheng, Jambagi and Kramer, 2014).

2.2.1.2. Bottom-up modelling

Bottom-up modelling are built up from empirical data on a hierarchy of disaggregated components, it approaches work at the micro level. The model characterizes the energy system with great technological detail, focusing it with technical and economic information (Fortes et al., 2014) (Kavgic et al., 2010).

The components are combined according to their individual contribution on the energy usage, therefore are useful in terms of calculating the impact on CO_2 emission reduction as a consequence of an action to improve energy efficiency (Kavgic et al., 2010).

The key advantage of bottom-up modelling lies in the randomly determined process for the generation of detailed individual load profiles; nonetheless this implies the accurate modelling of human behaviour, which is one of the main difficulties (Molar, 2015).

On the other hand, this type of modelling neglects realistic microeconomic framework and interactions among energy system and the rest of the economy (Fortes et al., 2014).

Besides, they need extensive data bases of empirical data from each component in order to adequately complete the apportionment and the description of each one (Kavgic et al., 2010).

2.3. BOTTOM-UP MODEL OF THE CENTRE FOR RENEWABLE ENERGY SYSTEMS TECHNOLOGY OF LOUGHBOROUGH UNIVERSITY

The main purposed of this model is to adequately represent the variability of individual dwelling demands, in order to model the operation of local distribution networks. Also, the aims consider modelling and quantify the potential impacts and benefits of low-carbon measures (Richardson et al., 2010).

At first instance the common appliances of a dwelling are identified and these appliances are used as the basic block of the model (see Table 2.4).

Table 2.4 Block set of appliances used in the model

Appliance category	Appliance type
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

Then, to effectively represent time-correlated appliance use, the model describes the appliances by their mean total annual energy demand and associated power characteristics. They are configured using statistics data and are based on measurements of power consumption. The most relevant factors for the appliance demand configurations are:

- Mean power factor
- Base cycles/year (n)
- Calibrated cycles/year (n) using a factor of 1
- Mean cycle length (min)
- Mean cycle power (W)
- Standby Power (W)
- Delay restart after cycle (min)
- Mean cycle energy demand (kWh)
- Time running in a year (min)
- Time not running in a year (min)
- Minutes in year when event can start (min)

- Mean time between starts events given occupancy (min)
- Lambda (min^{-1})
- Average activity probability
- Total energy (kWh/year)
    - Energy used when on (kWh/year)
    - Energy used on standby (kWh/year)
- Active occupancy Dependent

As well, for each appliance the model assigns the average activity probability and the proportion of time when starts (in the using) can occur, due to the respective occupancy given profile (which is assigned randomly). Consequently, with all this data, the overall average energy demand per dwelling can be calculated. Since, the configuration depends on the user input data, the results varies according to this (Richardson et al., 2010).

To every appliance that is included in the model by the user, a respective profile is assigned to it. As well, an additional profile of active occupancy dependent is assigned, to categorize the appliances that are linked to an activity-taking place. This, at the same time is simulated stochastically.

2.3.1. Occupancy

The number of people, which is a requirement of the user to input the model (from 1 to 5), determined the appliance energy demand. Appliances that include steady-state consumption or typical use cycles are included in the configuration. On the other hand, to determine the appliances that demand energy when the people are awake, the model to reflect the natural behaviour of the people uses an integer that varies throughout the day. The data for this was obtained from a Time Use Survey (TUS), which is a comprehensive survey of how people spend their time in United Kingdom (Richardson et al., 2010).

Since the number of people in the house is directly correlated with the appliance use (using the mechanisms mentioned above), the sharing of appliances is present in the model. This means, that multiple occupants of the house can use a same appliance simultaneously. This, can be projected in a lightly increase or in a non-linearly increased (Richardson et al., 2010).

2.3.2. Switch on events

The model works with two sets of data: weekday data and weekend data. Each set represent different characteristics since the behaviour of the inhabitants differs significantly. Then, for each set it is assigned the time of the day in which the activity profile occurs plus the number of active occupants at that current time step (due to appliances that depend on daily activity profiles that may only start if there is active occupancy in the residing). With this features established by the model, the activity probability to occur is determined (Richardson et al., 2010).

Once the activity probability is calculated, the switch-on probability can be determined by using a calibration scalar. Each appliance has a calibration scalar; the purpose of this is asserting the mean annual consumption of the appliance (Richardson et al., 2010).

Later, the result obtained is compared to a random number between zero and one. If the probability is more than the random number, then a switch-on event occurs (Richardson et al., 2010).

2.3.3. Lighting model

The model uses as component a previous develop lighting model, which is configured to provide data at 1-minute resolution. According to Richardson et al. (2009), for determining the use of electric lighting is necessary to analyse the human perception of the natural lighting correlated with the number of inhabitants in the house and the share lighting that can occur.

The model uses statics from The Lighting Industry Association (LIA) of United Kingdom, to randomly populate each dwelling with a different but representative set of lightings, according to their database. LIA is the largest trade association in Europe, it provides a wide range of services such as data advice, technical support, and laboratory testing's services (LIA, 2015).

The model has 100 sets of different probabilities, with different numbers, types and power ratings. This set of lights can have variations from a single light bulb to multiple bulbs operated from a single switch; also the bulb types are arranged arbitrarily and every single one has the respective power consumption. As well, some sets are more used frequently than others due to occupancy in the different rooms of the dwelling (Richardson et al., 2009).

The technology category of each unit is picked as one of either: incandescent general lighting service (GLS), low energy compact fluorescent (CFL), fluorescent tube, halogen, lighting emitting diode (LED) and parabolic aluminized reflector (PAR).

The model cannot generalize in typical grouping configurations but, the power consumption is arranged in a way that randomly group of lower power bulbs will switch on with a single switch; due to the fact that this a common scenario in households. And, the allocation and distribution per dwelling of the lighting sets differs each time the model runs (Richardson et al., 2009).

Each household has an irradiance limit, which defines the natural lighting level below which occupants will consider using lighting and vice versa. This means that the current irradiance level is compared at each time step with the established limit; this also allows to determinate the duration of the switch-on. Furthermore, a filter, explain below, is used due to the fact that occupants may not respond immediately to low lights levels.

Because some units will be used more than others, a fixed weight is allocated to each unit in the start of the simulation. This happens with the purpose of indicating how much power is used in comparison with other units. In Figure 2.6 it can be appreciated an example of how the weighting functions (Richardson et al., 2009). The distribution is formed from a natural logarithmic curve. "Each unit in every dwelling is assigned a scalar value from this distribution by picking a random number between 0 and 1 and picking the relative usage weight from the curve. Each unit is assigned a value at the start of the simulation and this remains constant throughout the run. In practical terms, a frequently used lighting unit, such as one installed in a kitchen, would have a higher use weighting (towards the left of the graph), compared to an infrequently used unit, such as a cellar light (towards the right)" (Richardson et al., 2009).

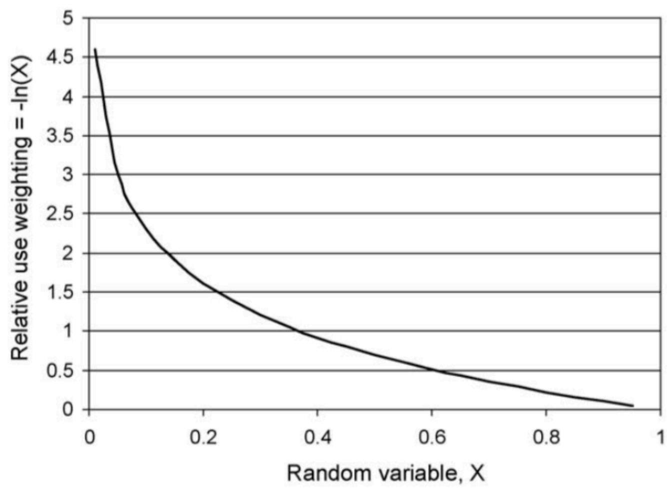

Figure 2.6. Natural logarithmic curve used to estimate relative weightings. (Richardson et al., 2009).

2.4. PV POWER PRODUCTION

The substitution of conventional fossil-fuelled power generation for renewable energy resources has been increasing throughout the years. Among renewable energy resources, due to the identified potential, the fastest growing resource with the highest power has been solar photovoltaic cells (Jordehi, 2016).

2.4.1. Generalities and components

PV cell is the main component of the system; it functions as a semiconductor, with a maximized absorbing surface (Falvo & Capparella, 2015).

A PV module is form by several PV cells, which can be connected in series and/or in parallel to form a PV panel. A PV array may be composed of one or a couple of PV panels (Jordehi, 2016). Concurring to the power produced, a PV system can involve one or more generators.

Another main component is the inverter, which can be equipped with a high or low frequency transformer. The inverter is in charge of converting a DC (direct current) into an AC (alternating current), due to their functions: DC is for electricity consumption meanwhile AC is for household appliances energy demand. As well, as shown in Figure 2.7, other components are: storage systems, grounding systems, protection devices against over current in the DC and AC side, Surge Protection Devices (SPD), and interface systems to the grid (Falvo & Capparella, 2015).

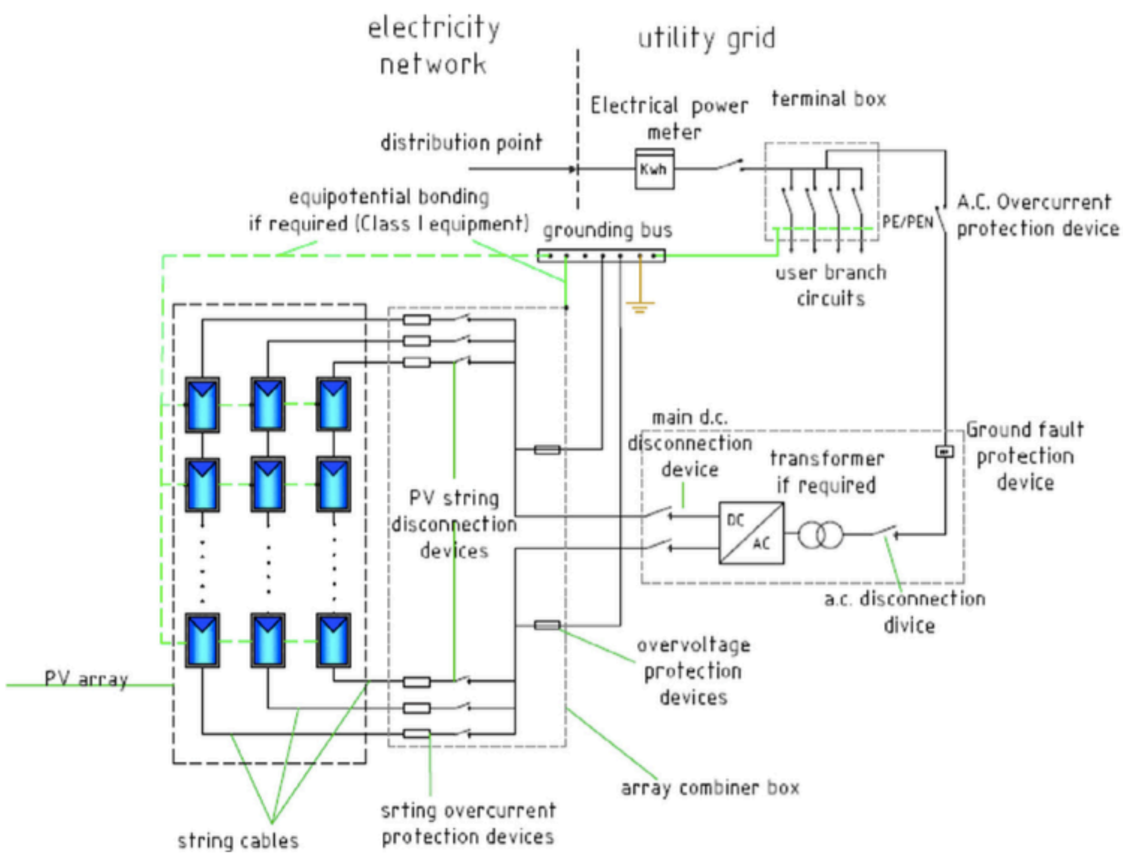

Figure 2.7. Typical PV system layouts with one array. (Falvo & Capparella, 2015).

2.4.2. Categories

PV may work as large-scale centralized power plants or as smaller-scale distributed generation units PV systems, also they can be categorized by the relation to the grid: stand-alone and grid-connected (Falvo & Capparella, 2015; Jordehi, 2016).

Stand alone or also known, as off-grid systems are not connected to the electricity national grid. They are usually designed to provide electricity for low power domestic loads (2-3kW per dwelling). Normally batteries are use in the off-grid systems since it allows the energy storage of the polar power produce that wasn't consumed nonetheless, it cannot be expected that the PVs provide power for all the loads (Gonzalez-Prida and Raman, 2015).

The grid-connected systems comprehend of a series of installations which are normally connected to large independent grids, typically public (Falvo & Capparella, 2015). If the consumption is fully covered by the PVs due to the fact that the inverters function in a bidirectional way, the excess can be fed back to the utility grid. On the other hand, batteries aren't commonly used since the local grid is considered as the back up power source (Gonzalez-Prida and Raman, 2015).

2.4.3. Power production

The magnitude of electricity produced from PV relies directly on intensity of sunlight; therefore, the penetration of PV depends on incident solar radiation (often referrer as global radiation). The total incident solar radiation on a tilted surface involves beam, diffuse and reflected radiation power output (Shivashankar et al., 2016).

The beam radiation comes directly from the sun, without having been dispersed in the atmosphere. On the other hand, the diffuse radiation has been dispersed in multiple ways over the atmosphere. The reflected radiation is the solar radiation reflected from terrain and surrounding surfaces (Duffie & Beckman, 2013).

Likewise, the PV power output is mainly affected by changes in weather conditions like rainfall and movements of the clouds. Consequently, the output fluctuates daily, hourly, per minute and even per second (Shivashankar et al., 2016).

2.4.4. Simulations of PV power production

The use of simulation methods in the study of solar processes is a relatively recent development. They are constructed based on different assumptions, input data and level of details. The simulations have the advantage of being relatively quick and inexpensive and can produce information on effect of design variable changes on system performance. The simulations can give the same results, as can physical experiments due to the numerical experiments that are included in order to solve the combinations of algebraic and differential equations that represent the physical behaviour of the system in study (Duffie & Beckman, 2013).

It is possible to compute what is possible to measure, therefore integrated performance over appropriate time period and information on process dynamics can be obtained There can be programs that represent the performance of specific types of systems, in which the aim is to simplify computations by combining algebraically different equations of the components of the system. Also another type of program is the one that have a general purpose and are more flexible than the ones mention above. The difference is that the equations representing components are not combined algebraically; instead they are kept separate to be solved simultaneously (Duffie & Beckman, 2013).

2.5. QUANTITATIVE INDICATORS

Quantitative indicators can be used as assessment tools, that might be useful for different target audiences such as: Building designers and owners, community designers and urban planners, grid operators at a local distribution level and grid operators at a national or regional level. These indicators are suitable for the targets mentioned before, due to the fact that they can be used to describe the load matching (how the local energy generation compares with the load or vice versa) and grid interaction conditions (energy exchange between the building and a power grid including peak powers delivered) (Candanedo et al., 2011).

Grid indicators with very high temporal resolution may help in assessing and design the operation limits of the grid such as voltage regulations in the case of high penetration rates of PV, as well they help to manage national grids and to performed analysis of penetration of renewable in the electric power system increments. On the other hand, a low temporal resolution is useful to assess the general impact of low consumption buildings in the grid (Candanedo et al., 2011).

There is a limit of usage of these indices, regard of the advanced renewable energy systems evolved with various energy forms and conversions. For example, some indices only focus in electrical energy, they don't focus on the matching analysis of heating or cooling. Therefore they neglect factors such as electrically driven ground source heat pump, or solar thermally driven absorption frostier; although they considered the effect of an excess renewable electricity-hot water recharging strategy (Cao, Hasan, & Sirén, 2013).

3. METHODOLOGY

In this section a brief description of the modelling process will be described, as well as the methodology used to obtain the results generated during the development of this project.

3.1. DOMESTIC ENERGY DEMAND MODEL

A series of modifications, incorporation of data, and new computational mathematical algorithms were performed using as a resource the statistics, technology data, lighting model and equations of the bottom-up model developed by the Centre for Renewable Energy Systems Technology of Loughborough University. The main purpose of this model is to adequately represent the variability of individual dwelling demands, in order to model the operation of local distribution networks. Also, the aims consider modelling and quantify the potential impacts and benefits of low-carbon measures (Richardson et al., 2010).

3.1.1. Occupancy

The TUS of United Kingdom involves many thousands of 1 day diaries recorded at a 10-minute resolution. This represented a barrier to certainly prove the similarities with Costa Rican behaviour, since there are not studies of this kind available. The TUS model results were compared with national data from Costa Rica and obtained from a survey made in the country by the entity called Ministerio del Ambiente y Energía in the year 2006 (Carazo, Ramírez, & Alvarado, 2006).

Nonetheless, the aim is to simulate daily profiles, which the basis adapts commonly to most of the worldwide population: high-energy consumption during the day and low-energy demand during the night, high peaks in the morning, and at noon, significant peaks at the cooking hours, etc. So, the comparisons made were based on results, which at the same time were based in these aspects.

Besides, the TUS results were used to directly link the different activities performed during the day and night and the respective appliances involved in the different times of the whole day (every minute). Therefore, a stochastic simulation is linked to the probability of the appliance used at certain time of the day.

3.1.2. Lighting model

The outline structure of the model comprehends the outdoor irradiance data series, which indicate that all the dwellings experience the same irradiance. However, the original sample irradiance database set of twelve days (one day per month) of 1-minute resolution was changed with national data. The irradiance used per month understands a minute day average for the respective months and uses an inclination angle of the roof of 15 °.

The irradiance data was obtained using the software Meteonorm in which the mechanisms of using this software are explained further in the next section.

A noteworthy fact is that the occupancy model is not seasonal; this means that the behaviour of the people according to the weather is not taken into account in the model. However, the seasonal effect is taken into account, which comprehends the natural daylight conditions.

3.1.3. Programming

The model sample available creates synthetic data with a temporal resolution of 1-minute, it expresses results of one day, imitating it to one day's period. So, in order to draw significant conclusions about the electricity demand new scripts were done to have monthly and annual consumption profiles.

3.1.3.1. Annual averages

The used model can only provide 24-hour demand profiles. So, as a first step, the computation of the algorithms was based on the principles of this factor and derivatives. Then, the algorithm to estimate the power demand average over a year expressed in one day iterates through the number of occupants (from 1 to 5), in each iteration a new set of data is created; hence results for each set of dwelling occupants are obtained.

In the model, an iteration thorough the weekdays and weekends occur. Using a loop, the information for each month can be processed, making averages in the process. Consequently, for each week of the month five loops occur operating the data sets of the weekdays and two loops occur using the data of the weekends. This is computed in order to contemplate both scenarios of the week. When the loop is finished, the current value is divided by the number of samples in order to have the average of the weeks of the month.

The algorithm is made in a way that the process is continuously repeated for each month of the year. Consequently, the data is stored and added successively from January to December, having averages through the year at the end of the process.

As well, the program determines the corresponding month in which the maximum demand occurs. It also determines that this occurs in a weekend or a weekday and gives the value which is expressed in Watts.

3.1.3.2. Monthly averages

In order to obtain specific results for each month, the model described above is modified. The principles are the same, with the exception that for simplicity the loops are used exclusively with the configurations of the month chosen respectably.

3.1.4. Validation of the model

The validation of the model allows more formal statistical comparisons between the measured and synthetic data.

For validating the model, the main source of real data was provided by the company Enertiva, leader in Central America in the market for solar energy and cogeneration. They provide data of two different households, in different time steps: monthly energy consumption, daily, hourly and one-minute resolution.

Through the software Engage Efergy, the company has direct access to the energy demand of the houses. Each house has a feed cable which is connected in the breaker panel; in here a CT sensor is clipped. The CT sensor functions as a transmitter, sending real-time data to the software hub, which is connected to the user internet router via. The data is obtained per month, and real time step data of 1-minute of each day, is gathered and can be stored through the software. The company has few houses using this program since it is a pilot project to gather more information.

The Mann-Whitney U was performed as a complementary tool for the validation process. The test is a non-parametric test, used as an alternative to the independence sample t-test. The test compares two population samples, to find out whereas they are equal or not. In other words, it allows drawing different conclusions regarding if there are differences in medians between the evaluated groups (Statistics Solutions, 2016).

The sample sizes must be equal, and the median is calculated to perform the test. This test does not assume any assumptions related to the distribution, but it considers the randomness of the sample drawn from the data sets, the independence within the samples (as well as mutual independence) and an ordinal measurement (Statistics Solutions, 2016).

3.1.4.1. First House

As shown in Figure 3.1, the house is located in Sabanilla Montes de Oca, Costa Rica. It was constructed in 1991 and comprehends an area of 180 m^2. The inhabitants are a woman and a man. Other relevant data used to run the model is listed below:

- Type of water heating: electric
- Type of Kitchen: electric
- Size of the Fridge: medium size
- A/C in the house: no
- Type of Lighting: fluorescent
- Drying cloths machine in the house: yes

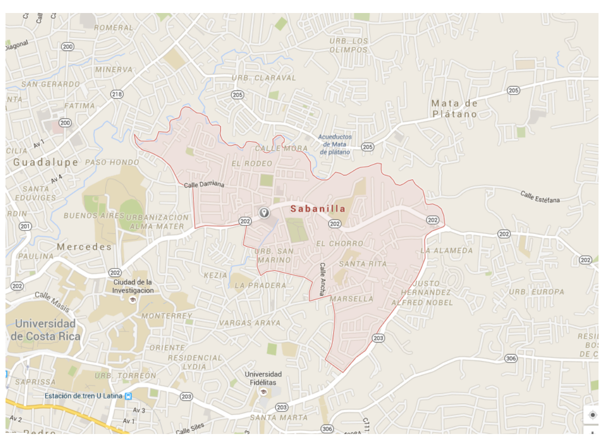

Figure 3.1. Localization of the house in study with the coordinates 9.944842, -84.034901 (Google Maps, 2015).

3.1.4.2. Second House

As shown in Figure 3.2, the house is located in Residential in Bello Horizonte de Escazú, Costa Rica. The house was constructed in 1994 and comprehends an area of 400 m^2. The inhabitants are four women and a man. Other relevant data used to run the model is listed below:

- Type of water heating: thermo solar
- Type of Kitchen: electric
- Size of the Fridge: 1,25 ft^2
- A/C in the house: no
- Type of Lighting: incandescent
- Drying cloths machine in the house: no

Figure 3.2. Localization of the house in study with the coordinates 9.919044, -84.126521 (Google Maps, 2015).

3.2. PV POWER PRODUCTION ON-SITE MODEL

The research group Energy Efficiency and Smart Cities (EESS) of the Technische Universität München provided the following equations that were used in the computation of the model.

$$Equation\ 1. \qquad Ppv = A_c\, G_T\, \eta_{pv}\eta_{inv}(1\text{-}C_{loss})$$

Where,

Ppv: Output from PV module (W)

A_c : Total PV array area (m^2)

G_T: Incident solar irradiance on PV (W/m^2)

η_{pv}: PV module efficiency (in maximum power point conditions)

η_{inv}: DC to AC conversion efficiency

C_{loss}: Performance losses due to soiling, shading, wiring and aging

Equation 2 $\eta_{pv} = \eta_{ref}$ *(1-$\beta\left(T_C - T_{C,ref}\right) + \gamma \log\left(\frac{G_T}{G_{T,ref}}\right)$)

Where,

η_{pv}: PV module efficiency (in maximum power point conditions)

η_{ref} : PV module efficiency

β: PV module temperature coefficient of power

T_C: PV cell temperature (°C)

$T_{C,ref}$: PV cell temperature when η_{ref} is measured (°C)

G_T: Incident solar irradiance on PV (W/m^2)

$G_{T,ref}$: Incident solar irradiance on PV when η_{ref} is measured (W/m^2)

γ: PV module solar irradiance coefficient of power---assume 0.12 for silicon solar cells.

Equation 3. $T_C = T_a + \left(\frac{G_T}{G_{T,NOCT}}\right) * \left(\frac{9{,}5}{5{,}7+3{,}8V_w}\right) * \left(T_{NOCT} - T_{a,NOCT}\right) * \left(1-\frac{\eta_{ref}}{\mathrm{t}\alpha}\right)$

Where,

T_C: PV cell temperature (°C)

T_a: Ambient air temperature (°C)

G_T: Incident solar irradiance on PV (W/m^2)

$G_{T,NOCT}$: Incident solar irradiance on PV when $NOCT$ is measured (W/m^2)

V_w: Wind speed (m/s)

T_{NOCT}: Normal operation cell temperature (℃)

$T_{a,NOCT}$: Ambien air temperature when $NOCT$ is measured (℃)

η_{ref} :PV module efficiency

tα: Transmittance and absorbance product

NOCT: normal operating cell temperature

Table 3.1 Categorization of the equations and values for standard PV test

User input/manufacturer data	Extracted from Meteonorm Software
A_c	G_T
β	T_a
η_{inv}	V_w
η_{ref}	
T_{NOCT}	
Possible values of roof inclination = 15°, 20°, 25° and 30°.	
Values assume for standard PV test	
$T_{C,ref}$=25 ℃	
$G_{T,ref}$= 1000 W/m^2	
$G_{T,NOCT}$=800 W/m^2	
$T_{a,NOCT}$ = 20 ℃	
tα= 0.9	

3.2.1. Weather data

It is critical to have high-resolution weather profiles for the generation of high-resolution electrical generation data from PV. Through the Meteonorm Software, this data could be obtained. This software contains worldwide weather data: comprehends 8325 weather stations, 1325 meteorological stations with irradiation measurements, five geostationary satellites and 30 years of experience. Thus, many climate parameters can be obtained, such as irradiation, direct radiation, temperature, wind velocity, etc.

The Meteonorm software works with monthly, hourly and minute time step resolution. It manages irradiation historical data from 1991-2010 and for other weather parameter the period is from 2000-2009.

The steps for using the Meteonorm software and the specifications used are the following:

1. Definition of the Location

   The location selected was Fabio Baudrit weather station, which is located in Alajuela, Costa Rica. This weather has an altitude of 840 meters above sea level, latitude of 10.017 °N and longitude of -84.267 °E.

2. Specifications of the location and specific parameters

   In here, the azimuth and inclination angle were modified: the azimuth angle assigned was 0° and the different inclination angles used were: 15°, 20°, 25° and 30°.

3. Definition of the time parameters and advanced settings

   The period of radiation chosen in this section comprehends 1991-2010 and the period temperature comprehends 2000-2009. As well, in this section the ration model corresponds to the minute model by Aguilar & Collares-Pereira. The chosen diffuse radiation; temperature, tilt radiation and the time system models were the ones assigned by default thought the software.

4. Designation of the output format

   The output format chosen was the standard one.

By last, downloadable results as a file in the specific format were obtained. Due to the different inclination angles, different runs of the software were performed obtaining four different sets of data. Notably, the runs of the model with different angles were performed with the aim to cover all the possible inclinations that a PV can have on the roofs of houses.

3.2.2. Validation of the model

For validating the model, the main source of real data was provided by the company Enertiva, leader in Central America in the market for solar energy and cogeneration.

They have a pilot program (for various installed systems) that consists in: monitoring the installed systems, performing the adequate maintenance of the installed PV systems, having a better detection of problems, identifying improvement potentials and also, they aim to collect real-time data of the PV power production on-site for further analysis.

The PV systems are equipped with the monitoring devices of Enlighten, this system is integrated in the micro inverters of Enphase Energy. It consists of an online monitoring tool that captures daily electricity generation of each module (see Figure 3.3). The micro inverters are directly connected using a networking hub, therefore real time and module level performance is accomplished. The envoy of the software allows bi-directional communication, this means that the data performance from the micro inverters to the Web and at the same time carries the system updates from the Web to the micro inverters (Enphase Energy, 2016).

The data is collected in multiple time step resolutions: daily, hourly, and 5-minute. There are multiple choices and types in which a report can be downloaded: report of the site energy production, site recent power production, per module one-day energy production, per module one-month energy production, monthly energy production report, grid profile settings report, yearly energy production report and multiple year energy report.

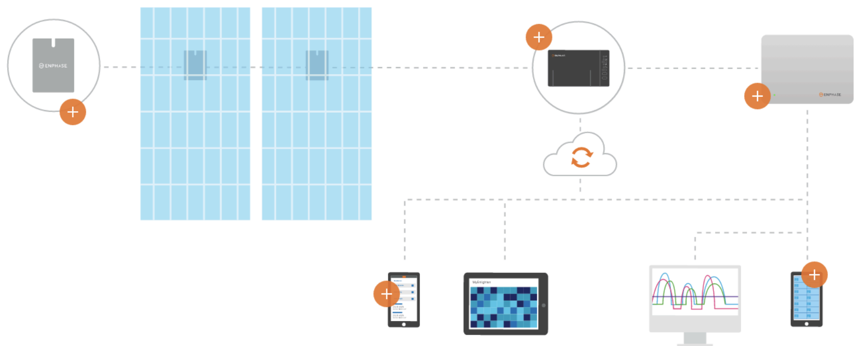

Figure 3.3 Diagram of the Enphase working system. (Enphase Energy, 2016).

For the validation analyses, the computed program was run introducing input data of three different systems; the input data corresponded to actual characteristics of measured data from the provided PV systems. The systems used had 6, 17 and 28 micro inverters each. Daily, hourly and annual profiles were analysed and compared. For the minute data, the time step of 5-minutes given by the Enphase program was extrapolated into 1-minute by assuming same minute values for every 5 minutes.

For examining daily profiles, from the created model, a clear sky day, a cloudy sky day and a partially cloudy sky day conditions were elected for each comparison. From the created model graphs and the simulated PV power production of all months of the year, the selection was made first by choosing one random month of the real data set. Then the next step consists in analysing all the days of the selected month in the model. The aim of this step is to comprehend which pattern fits the desired characteristics of sky condition the most (see Appendix 1). Later, the comparison between both data sets could be visualized by interposing the curves of the computed data and the measured data.

As well, the Mann-Whitney U, previously mentioned above, was performed as complementary resource for the validation process.

3.3. ENERGY MATCHING INDEXES

The matching of the high-resolution energy demand and production can be quantified using two basic indexes: OEF and OEM. According to Cao (2014), the OEF (on-site energy fraction) refers to how much demand can be covered by on-site energy generation. The OEM (on-site energy matching) indicates how much on-site generation can be consumed in the system rather than being imported or dumped.

With the following equations, the energy matching can be calculated at any instantaneous time:

$$Equation\ 4 \qquad OEF = \frac{\int_{t_1}^{t_2} Min\,[G(t);\ L(t)]dt}{\int_{t_1}^{t_2} L(t)dt};\ 0 \leq OEF \leq 1$$

$$Equation\ 5 \qquad OEM = \frac{\int_{t_1}^{t_2} Min\,[G(t);\ L(t)]dt}{\int_{t_1}^{t_2} G(t)dt};\ 0 \leq OEM \leq 1$$

Where,

$G\ (t)$: PVs on-site generated power

$L\ (t)$: Electricity demand of the household

dt: is the differential time difference, which also can refer to the computational time step used in the simulation.

The starting and ending points of the time span are represented with the variables t_1 and t_2 respectively; therefore, by adjusting these variables and *dt*, the indices of a certain period can be calculated.

The exemplifications of the equations are shown in Figure 3.4. The intersection of the areas (section III) represents the numerators of the equations. This value to the total area of sections III and I represents OEF, meanwhile to the total of sections III and II represents OEM (Cao, 2014).

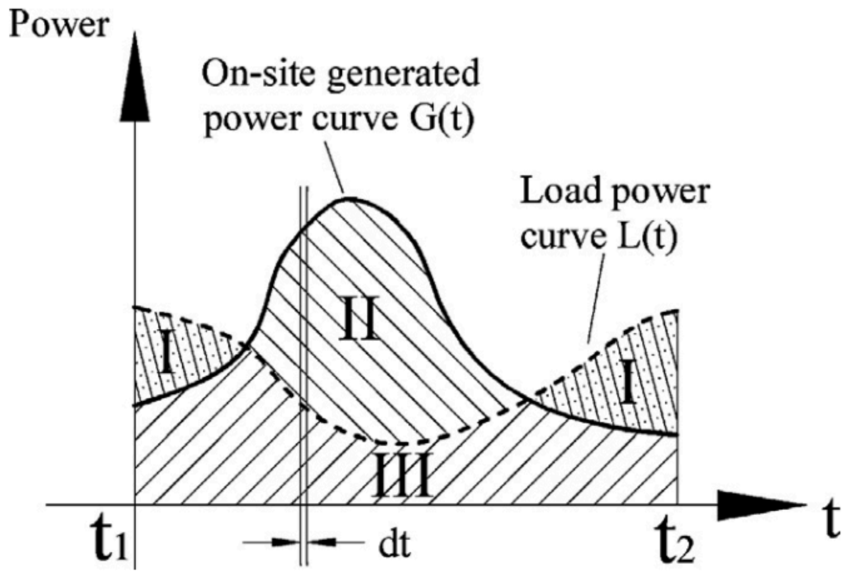

Figure 3.4. Matching indexes representation (Cao, 2014).

3.3.1. Error in the matching results

In order to express and compare the significant errors in the matching results caused by coarser resolution against finest resolution (of 1-minute), the error in energy matching can be calculated at any instantaneous time with the following equations (Cao & Sirén):

$$Equation\ 6 \qquad e_{OEF}[\%] = \frac{OEF|_{\Delta t} - OEF|_{1\ min}}{OEF|_{1\ min}} * 100$$

$$Equation\ 7 \qquad e_{OEM}[\%] = \frac{OEM|_{\Delta t} - OEM|_{1\ min}}{OEM|_{1\ min}} * 100$$

Where, $OEF|_{min}$ and $OEM|_{min}$ are the index values with 1-minute resolution. Meanwhile $OEF|_{\Delta t}$ and $OEM|_{\Delta t}$ refers to a coarser resolution, which in this case it was worked with 1-hour resolution results.

4. RESULTS AND DISCUSSION

Below are the results and the analysis of the proposed objectives. By comparing measured data with synthetic data obtained from the models, the validation of the PV power production and dwelling electricity consumption models could be performed. As well, the effect of the temporal resolution in the matching of electricity is analysed and visualized in three different time spans.

4.1. VALIDATING THE MODELLING TOOL: DWELLING ENERGY DEMAND

The measured data obtained from two different households is used comprehensively to validate the model by way of a broad comparison of the arithmetical characteristics of the synthetic and measured data. The model is computed in Visual Basics language (see Appendix 2). The simulation duration of each month takes approximately 20 minutes due to lack of support that this language has with the complexity of the data sets and statistical algorithms included the one the model has.

For the first house, the measured data comprehends months from May to September of the year 2015. This means that the runs of the model focus in these months exclusively. Each run has the same allocation of appliances, what differs is the month (see Annex 1). The results obtained are the followings:

Table 4.1. Data obtained from the simulation of the model and real data of the first house in study.

Month	Real Data (kWh)	Model Data (kWh)	Error %	Absolute error %
May	377	441,7	-17,2	17,2
June	353	399,6	-13,2	13,2
July	327	338,2	-3,4	3,4
August	336	316,2	5,9	5,9
September	373	376,7	-1,0	1,0
October	379	406,4	-7,2	7,2

As shown in Table 4.1, the biggest difference between the mean monthly-simulated data and the measured data is 17, 2%; meanwhile the smallest is 1%. The low differences show that the model has been calibrated appropriately and that the measured data is not atypical from the simulated data.

In Figure 4.1, it can be appreciated the data plotted side by side. By inspection, it can be seen that the match is not direct but the overall trend of electricity consumption is perceived.

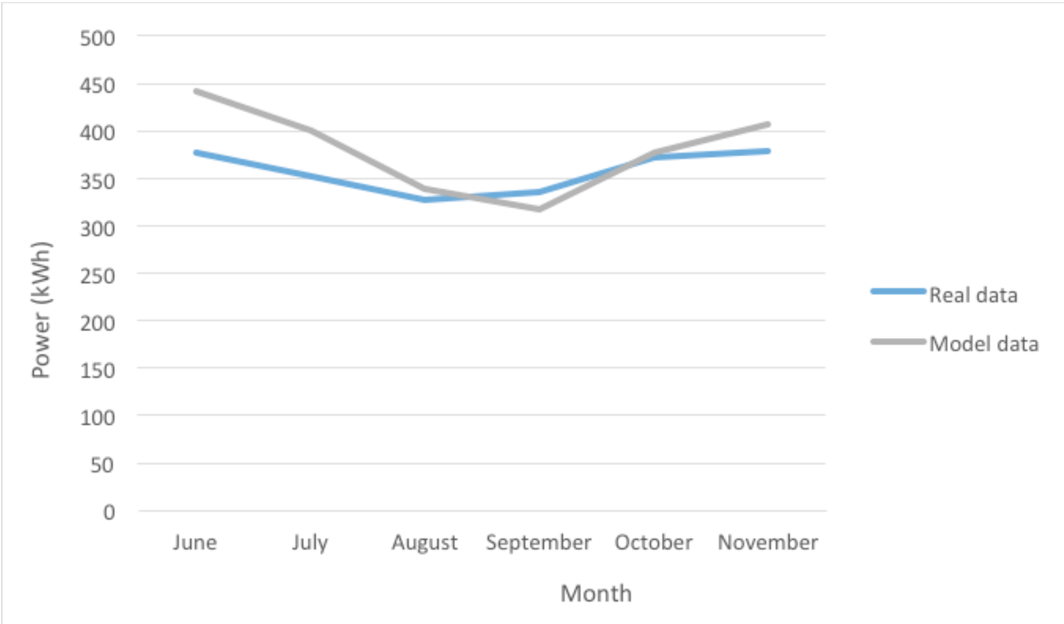

Figure 4.1. First house measured and model data annual profile.

Using the software MiniTab, a Mann-Whitney U test was run on to determine if there were differences in engagement score between the data median engagement score for real data (363) and synthetic data (388,15). The results express that the data is not statistically significantly different p = 0,3785, (p>0,05) with 95,47% archived confidence.

The variance in results is due to the stochastic approach that is used in the model, the results are different every time the model is run and as well as the behaviour of the residence of the dwellings (see Figure 4.2). Otherwise stated, individual events have a random start time and duration based on statistics particular to each load category that strongly influences the variations of results. As well, one of the major deficits of the model is that it does not represent the standby objects or always-consuming appliances like the refrigerator. Therefore, some minutes of the day no consumption of electricity is assigned.

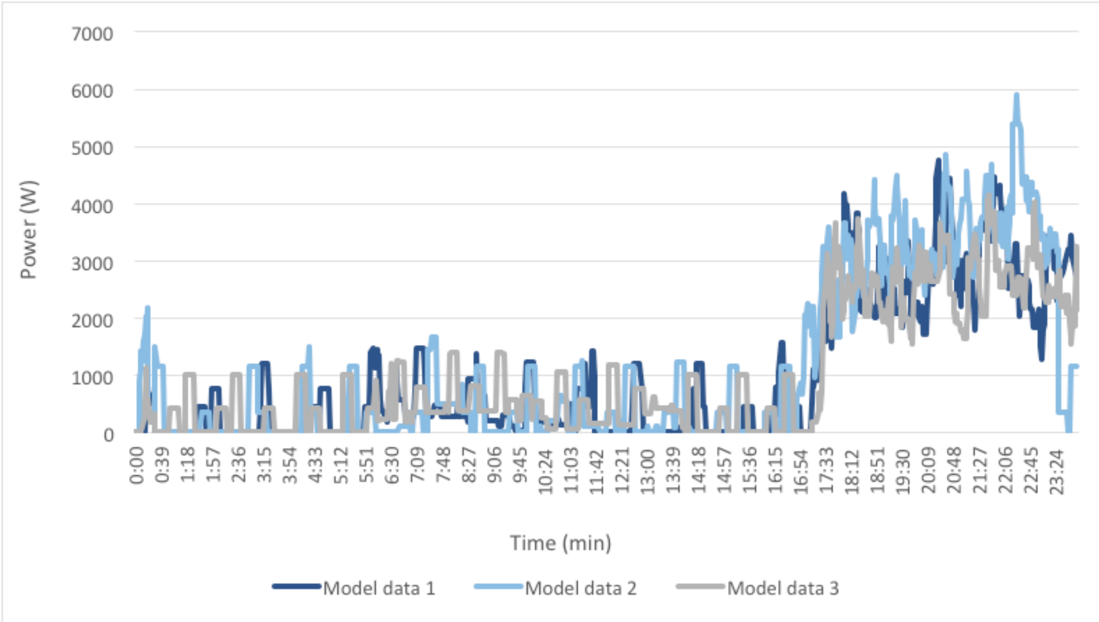

Figure 4.2. Different simulated daily profiles of a weekday of January.

For the second house, the measured data comprehends months from June to November of the year 2015. The results obtained are the followings:

Table 4.2. Data obtained from the simulation of the model and real data of the second house in study.

Month	Real Data (kWh)	Model Data (kWh)	Error %	Absolute error %
June	676	685,3	-1,3	1,3
July	836	756,7	9,5	9,5
August	875	810,3	7,4	7,4
September	976	1068,2	-9,4	9,4
October	921	902,6	2,0	2,0
November	858	807,6	5,9	5,9

The biggest difference between the mean monthly-simulated data and the measured data is 9,4 % meanwhile the smallest is 1,3%. These differences are significantly smaller than the first house, and on the other hand, the electricity consumption is bigger due to the amount of people and appliances (see Annex 1). Nevertheless, the overall trend of electricity consumption also matches (see Figure 4.3).

Also, it has to be taken into account that there are more inhabitants in the second house; therefore, the consumption has more variables that might affect the unsystematic results in the model. The original statistic data of house occupancy comprehends many thousands of 1-day diaries recorded at a 10-minute resolution. This represented a barrier to certainly prove the similarities with Costa Rican behaviour, since there are not studies of this kind available. However, the overall trend involves similar patterns, which are represented in the obtained results.

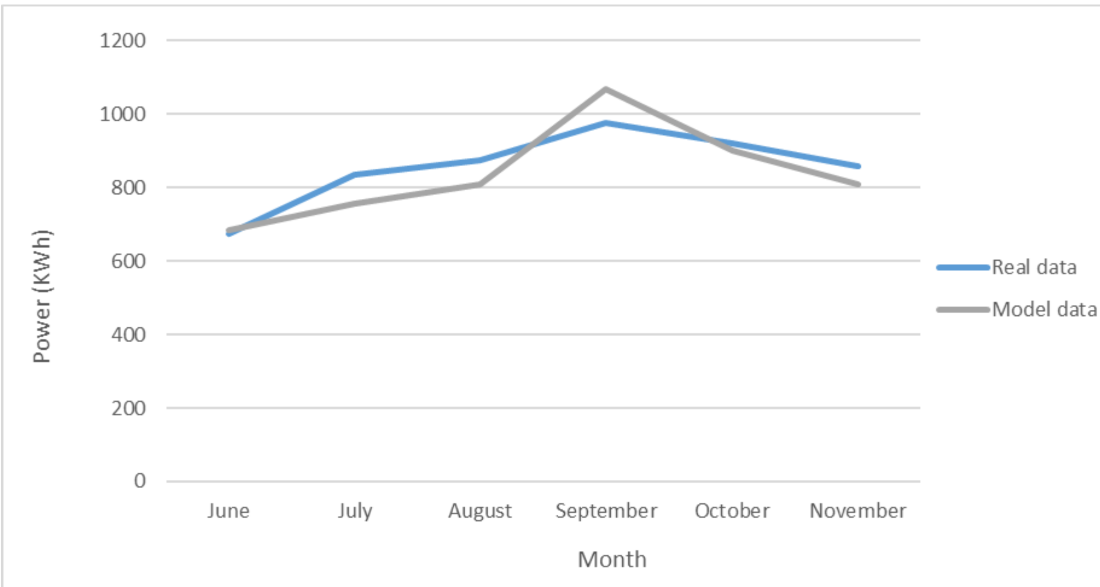

Figure 4.3. Second house measured and model data annual profile.

For the data sets, Mann-Whitney U test was also performed to determine if there were differences in engagement score between the data median engagement score for real data (866,5) and synthetic data (808,9). The results express that the data is not statistically significantly different p = 0,5752, (p>0,05) with 95,47% archived confidence.

Overall, variations in different load categories are attributed only to the differences in the total daily energy demand, as no specific behavioural differences such as seasonal dependent occupancy profiles or seasonal categories share are taken into account in the model.

One of the factors that considerable might affect the accuracy of monthly and yearly results are the irradiance profiles used. In the model, the irradiance profiles extracted from the Meteonorm software are only for 12 days, which means that an average irradiance for one day corresponds to the assign value for the simulation of the whole month. This implies the same lighting profiles for each day throughout the month, which has direct effects in the demand of electricity.

As well, the model seeks to emulate the variability of occupancy but it may be over-representing it with lower energy use, due to various factors that are not included in the model such as multitasking. Also another important factor not included but affects directly the energy demand is the energy aware. This last element depends strictly on the costumes of the occupants and their conscious of their energy use.

4.2. VALIDATION OF THE MODEL: PV ON SITE POWER GENERATION

The following tables (Table 4.4, 4.5 and 4.6) are meant to compare the simulated data with the annual measured data of three different PV systems. According to Molar, (2015) the common system losses comprehend a total of 7%: which 1% corresponds to shading, 2% to soiling losses due to dirt and other foreign matter on the surface of the PV module, and 2% to wiring. Besides the inverter efficiency is 98% so an additional loss of 2% is considered. This parameter can be changed in the computation of the model.

The input configuration in the model is shown in Table 4.3, all the variables in this table were maintained constant for the evaluated PV systems. However, the total PV array area was changed due to different quantity of micro inverters in each system. To estimate the total PV area of each system, it was assumed a value of 1.76 m^2 for each micro inverter, an azimuth angle of 0°-10° (this to indicate the software to calculate the results with a south orientation) and a standard tilt angle. Therefore, the first, second and third PV systems, that were evaluated, had a total array area of 10.5, 29.5 and 49 m^2 respectively.

The model's simulation process is fast and efficient (see Appendix 3), characteristics that make it practical. Once, the input variables are arranged: daily, monthly and yearly 1-minute data with respective and exemplify graphs are obtained in less than a minute.

Table 4.3. Values used in the simulation of the PV power generation on-site model.

User input/manufacturer data	Value
β	$0{,}004°C^{-1}$
η_{inv}	0,97
η_{ref}	0,15
T_{NOCT}	$50°C$

The first PV system of 6 micro inverters south orientated is located in Heredia, Costa Rica. The measured data from January and February correspond to the year 2016, meanwhile the rest of the months are from 2015. Depicted in Table 4.4, the months of June and July have the biggest percentage of error; meanwhile the month of March has the smallest one. These differences can also be appreciated in Figure 4.4.

Table 4.4. Data obtained and simulated of a system with 6 micro inverters.

Month (2015)	Real Data (kWh)	Model Data (kWh)	Error %	Absolute error %
January	240,724	266,112	-10,411	10,411
February	244,593	239,367	2,136	2,136
March	230,197	246,813	-7,218	7,218
April	227,693	245,540	-7,838	7,838
May	239,477	209,858	12,368	12,368
June	234,060	178,196	23,867	23,867
July	240,502	193,534	19,529	19,529
August	236,242	201,699	14,622	14,622
September	223,488	190,449	14,783	14,783
October	226,169	204,472	9,593	9,593
November	216,278	206,084	4,713	4,713
December	229,074	248,141	-8,323	8,323
Total	2547,773	2364,153	7,207	7,207

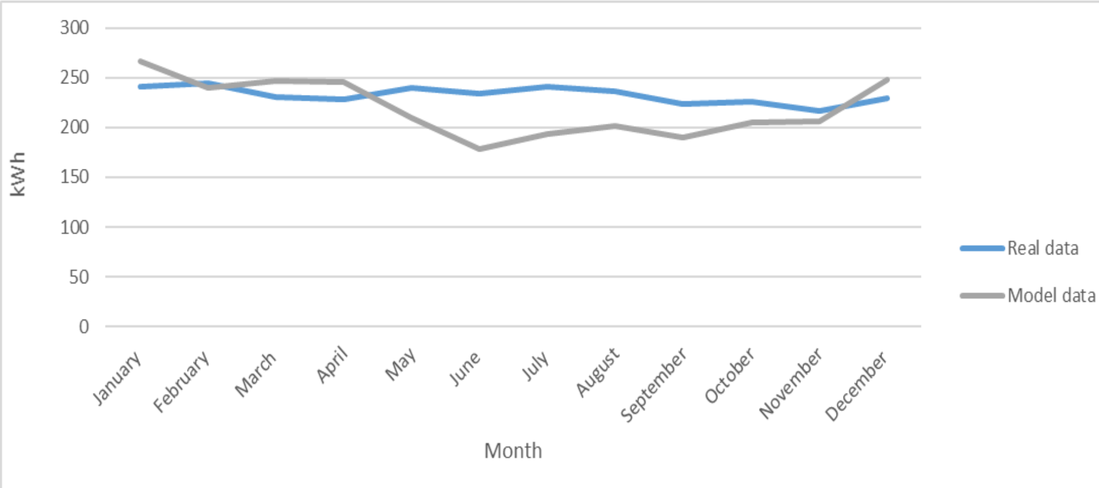

Figure 4.4. Annual energy produced by a PV installation of 6 micro inverters.

As well, the Mann-Whitney U test was run on to determine if there were differences in engagement score between the data. Median engagement scored for real data (232,129) and synthetic data (388,15). The two groups did not differ significantly, p = 0,3708 (p>0,05) with 95,36% archived confidence.

One of the problems to be emphasised is the wide fluctuation in the irradiance conditions in the Central Valley, even in just small distances of 20 kilometres. This is caused by the influence of local clouds and microclimates in the valley (Weigl, 2014). Thus, this represents a barrier in the modelling, due to the fact that high-resolution irradiance profiles are obtained from the meteorological station of Fabio Baudrit, which means that the locations are not the same. Even though the proximity of this station is close to the PV systems in study, the distance represents a barrier to the accuracy of the results modelled.

Nonetheless, because significant spatial differences in irradiance exist, it is crucial to determine the unique solar irradiance profile for each PV site to analyse the impact of high PV penetration. Hence, to exemplify how the model can simulate appropriately the PV penetration, two different sky conditions were analysed using minute data of the month of February; measured and synthetic (see Figure 4.5 and 4.6).

Therefore, it is proven the fact that even though the error percentages are relative big, overall the model can simulate appropriately different sky conditions.

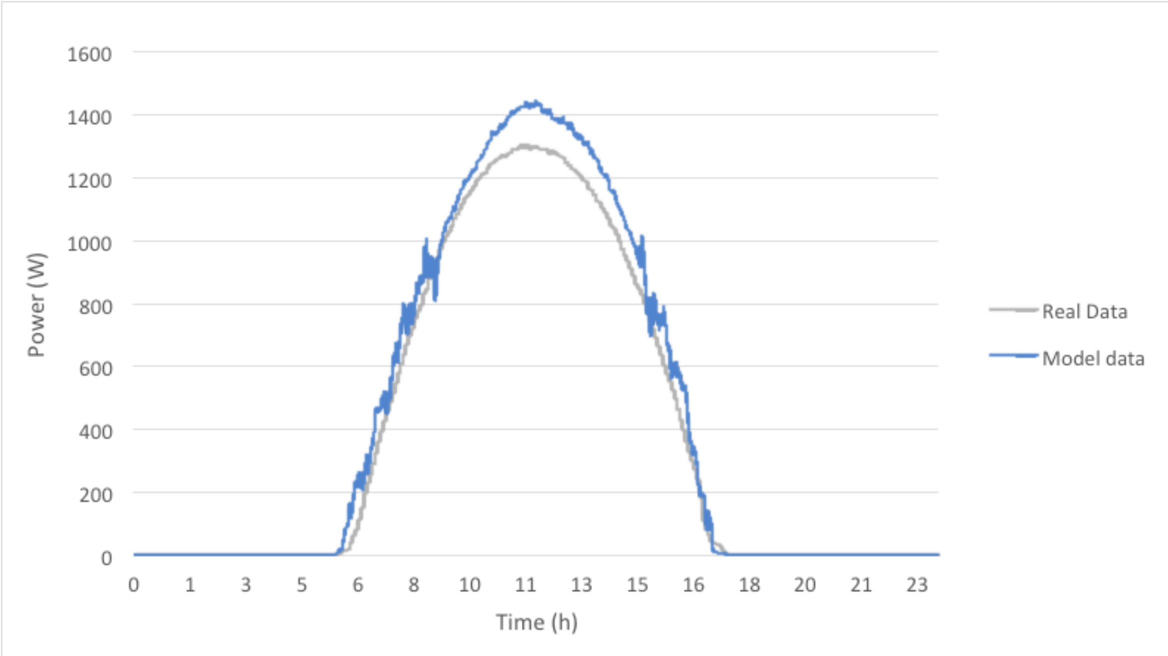

Figure 4.5. On-site electricity profile generated with clear sky conditions.

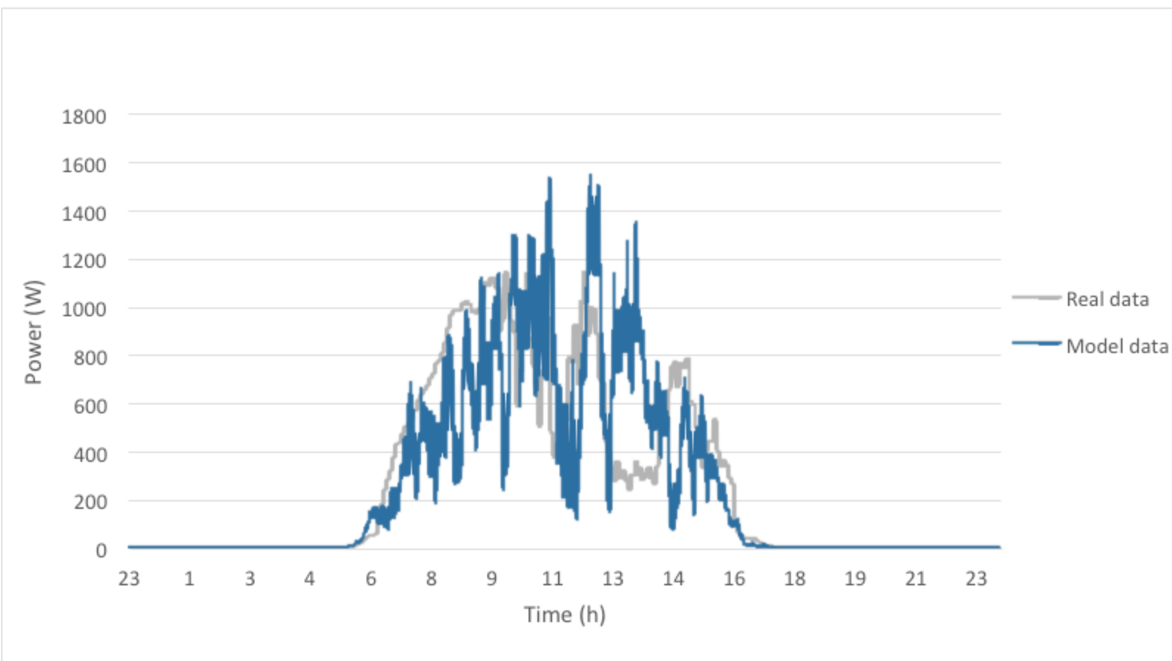

Figure 4.6. On-site electricity profile generated with cloudy sky conditions.

The different results according to sky conditions are because unshaded areas receive a high level of irradiance and cloudy areas receive a lower level of irradiance that depends on the optical depth of the cloud. Nonetheless, because atmospheric effects such as aerosol scattering unshaded areas do not necessarily receive 100% of clear sky irradiance. On the other hand, shaded areas can receive considerably more than zero irradiance due to considerable diffuse horizontal irradiance even on cloudy days (Nguyen et al., 2016).

The second PV system is located in Puntarenas, Costa Rica. The PV system array consists of 9 micro inverters south orientated and 8 east orientated for a total of 17 micro inverters. The results are shown in Table 4.5.

Table 4.5. Data obtained and simulated of a system with 17 micro inverters.

Month	Real Data (kWh)	Model Data (kWh)	Error %	Absolute error %
January	669,201	736,441	-10,049	10,049
February	625,210	662,435	-5,954	5,954
March	699,507	683,031	2,354	2,354
April	585,904	679,518	-15,978	15,978
May	579,829	580,769	-0,162	0,162
June	531,239	493,148	7,170	7,170
July	547,116	535,594	2,106	2,106
August	592,960	558,189	5,864	5,864
September	581,476	527,056	9,359	9,359
October	621,800	565,864	8,996	8,996
November	598,184	570,325	4,657	4,657
December	649,005	686,717	-5,811	5,811
Total	6612,230	6542,655	1,052	1,052

It can be appreciated that the error percentage is significantly smaller in comparison to the previous system. In this case, the month with the biggest absolute error percentage corresponds to May and the following month has the smallest value. As well, the yearly total difference can be considered insignificant. In Figure 4.7, the similarities in the patterns of the data throughout the year can be appreciated.

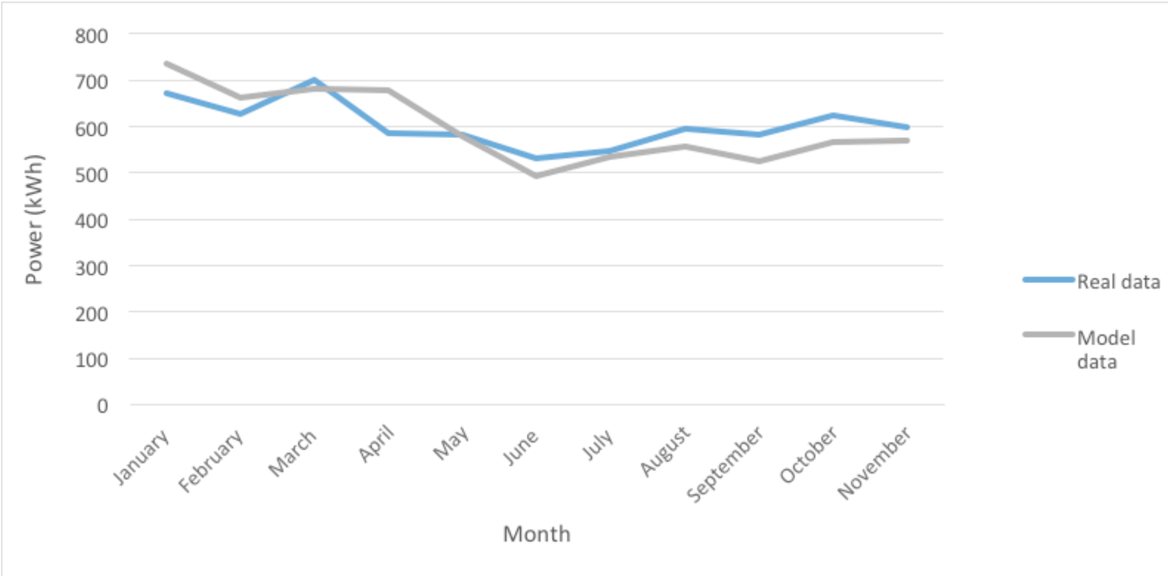

Figure 4.7. Annual energy produced by PV installation of 17 micro inverters.

The Mann-Whitney U test was run on to determine if there were differences in engagement score between the data. Median engagement score for real data (595,572) and synthetic data (575,547). It was proven that they are not statistically significantly different, p = 0,7075, (p>0,05) with 95,36% archived confidence.

Since the system has almost half of the micro inverters orientated to the east, in order to analyse the effect in Figure 4.8, it is shown a clear sky day profile of the month of February. Both measured data and simulated data belong to this month.

It is identified in Figure 4.8 that the highest peak of energy production is achieved in different times of the day. In the model data, the peak is shifted to the afternoon and the highest point is approximately at 12 a.m. meanwhile in the measured data the peak shifted to the morning with the highest point at 9 am approximately. According to Weigl (2014), the most profitable orientation is south due to the localization on the Northern Hemisphere of the Earth. Nevertheless, variations can occur, without causing mayor effects in the power output. In the months between April and September the sun has higher elevation angles starting from 90° with respect to the south, therefore PVs facing north in these months would be favour for this effect. On the other hand, at noontime in April and September the sun's elevation equals 90° (See Annex 3).

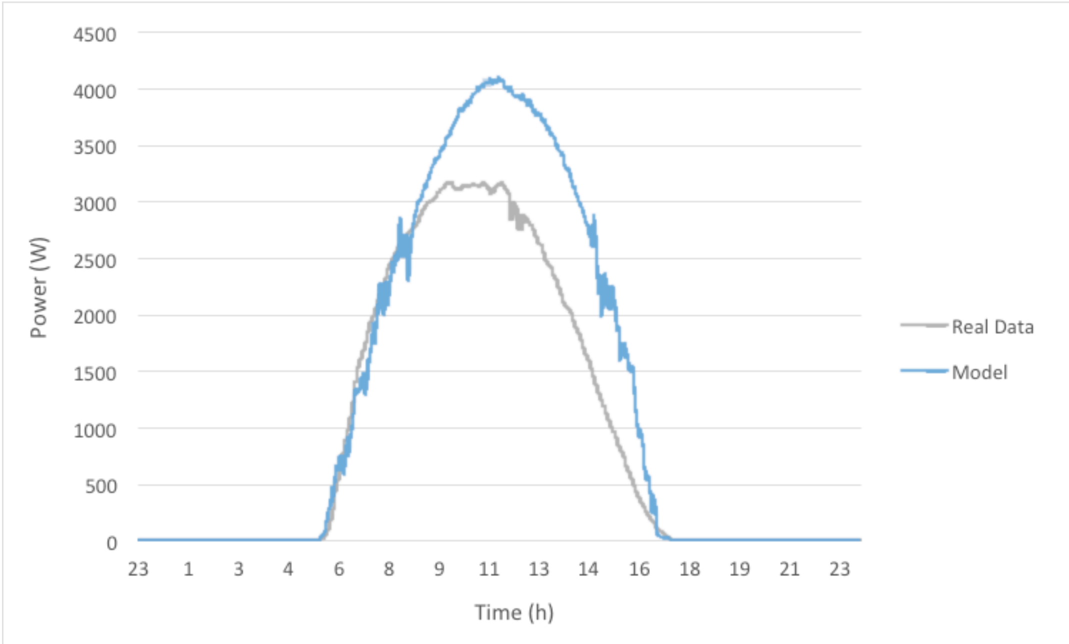

Figure 4.8. On-site electricity profile generated with clear sky conditions

The last PV system evaluated is located in San José, Costa Rica. The PV system array consists of 22 micro inverters south orientated and 6 west orientated for a total of 28 micro inverters. The results are shown in Table 4.6. From January to April the data is from 2016, the rest of the monthly data corresponds to the year 2015.

Table 4.6. Data obtained and simulated of a system with 28 micro inverters.

Month	Real Data (kWh)	Model Data (kWh)	Error %	Absolute error %
January	1069,113	1212,976	-13,456	13,456
February	1054,507	1091,070	-3,467	3,467
March	1122,753	1125,007	-0,201	0,201
April	1019,589	1119,206	-9,770	9,770
May	828,573	956,560	-15,447	15,447
June	729,022	812,243	-11,416	11,416
July	741,472	882,154	-18,973	18,973
August	842,333	919,370	-9,146	9,146
September	692,273	868,092	-25,397	25,397
October	825,076	932,012	-12,961	12,961
November	796,485	939,359	-17,938	17,938
December	949,001	1131,063	-19,184	19,184
Total	9601,084	10776,136	-12,239	12,239

In this case the month with the biggest absolute error percentage corresponds to September. March has the smallest value. In Figure 4.9, it can be appreciated the similarities in the patterns of the data throughout the year, and a noticeable gap of approximately 100 kWh from April to November.

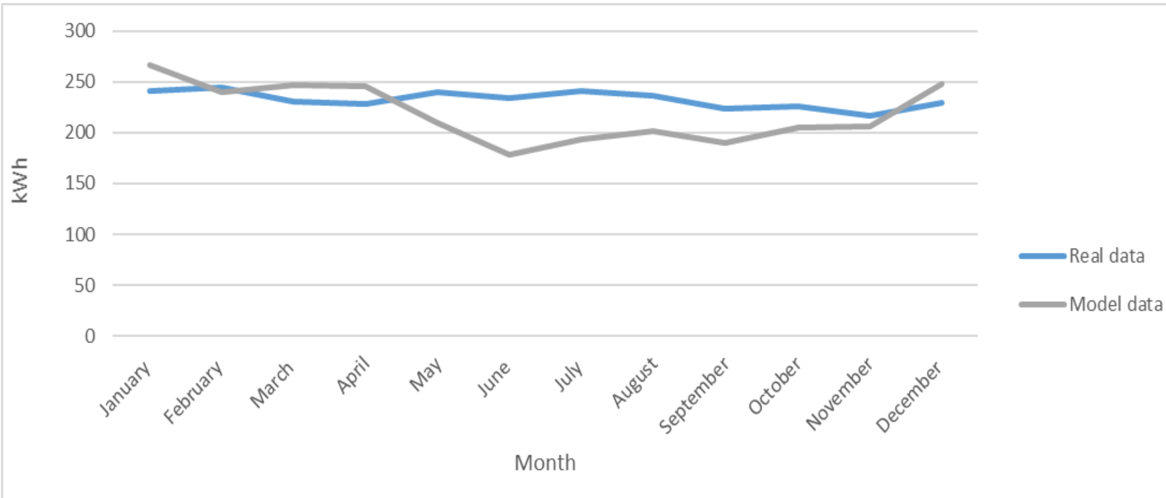

Figure 4.9. Annual energy produced by PV installation of 28 micro inverters.

Likewise, for the data sets, a Mann-Whitney U test was run on to determine if there were differences in engagement score between the data. Median engagement score for real data (835,453) and synthetic data (947,960). The results expressed that the groups are not statistically significantly different, p = 0,0606 with 95,36% archived confidence.

It should be noted that the ground area occupied by the PV system depends on its DC power rating; that is, PV systems with a higher rating are normally made up of more PV panels that cover a larger area. Thus, because its extension, these systems are more sensitive to the shading effect, some modules are more affected than others, making the power output not homogenous. Alternatively stated, it means that at a given time, clouds may shade some area while another part of the same array may be unshaded. Therefore, this factor also represents the reason of higher error percentages in the modelling process.

Attention should also be drawn to the fact that the output of a large PV system will not be interrupted immediately when a small cloud begins to pass over and gradually shades the array. Instead, there will be an averaging effect and the cloud-caused variation of the PV power output will be smooth rather than sharp.

On the other hand, for smaller areas, the time frame between maximum generation (clear sky) and low generation (which means that the array completely shaded by clouds) tends to be much shorter. The reason is that it takes less time for a cloud shadow to cover the entire array area. As well, the incident solar radiation from shadows caused by objects near the PV array plays an important role.

4.3. MATCHING INDEXES

In order to evaluate the impact of the time resolution on the matching of PV production and electricity demand data of the first house previously evaluated in section 4.1 and a south oriented PV system of approximately 11 m^2 was analysed. Three different sky conditions were evaluated: clear sky, partially cloudy sky and cloudy sky; to perceive the different scenarios on variable weather conditions fitting to the seasons of the year in Costa Rica. Daily profiles were taken from the month of March (see Figures 4.10, 4.11 and 4.12), which correspond to dry season and from the month of August (see Figures 4.13, 4.14 and 4.15), which correspond to the wet season.

It was not included in the analysis the effect of energy storage in the system. The battery is considered a buffer between the generation and the demand, this leads to a higher mismatch of the results which at the same time makes the energy matching comparison of different resolution effects less consequential.

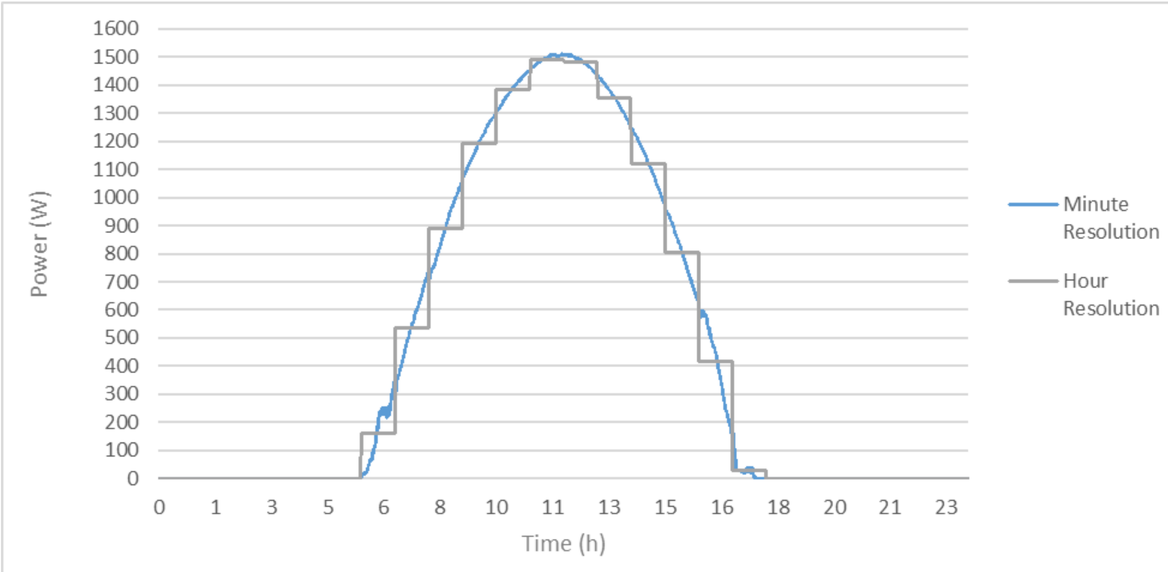

Figure 4.10. Dry season day with clear sky on-site electricity generation profile.

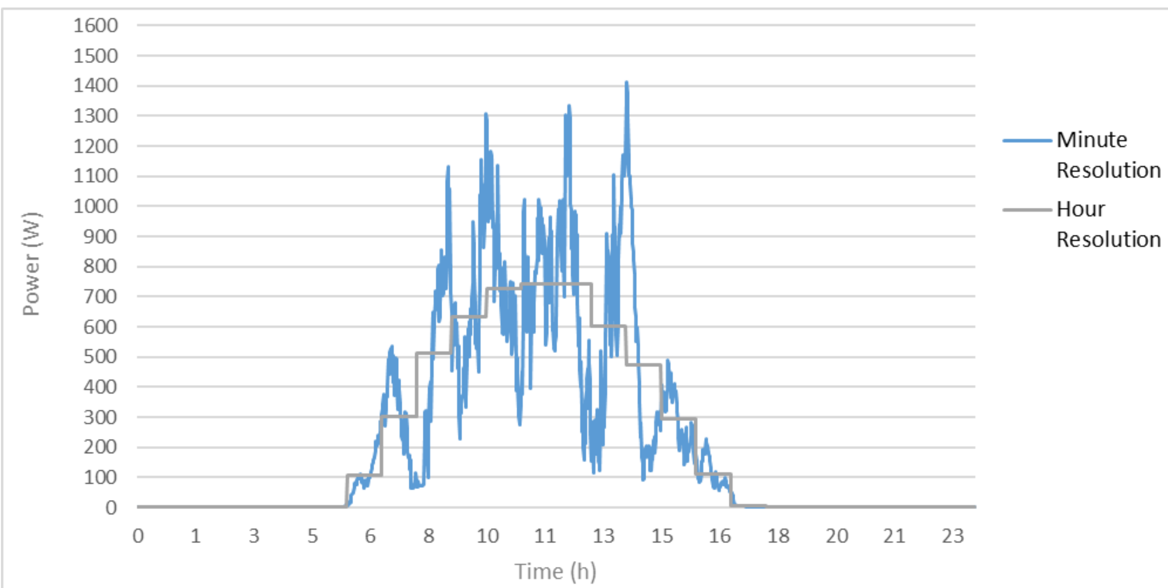

Figure 4.11. Dry season day with partially cloudy sky on-site electricity generation profile.

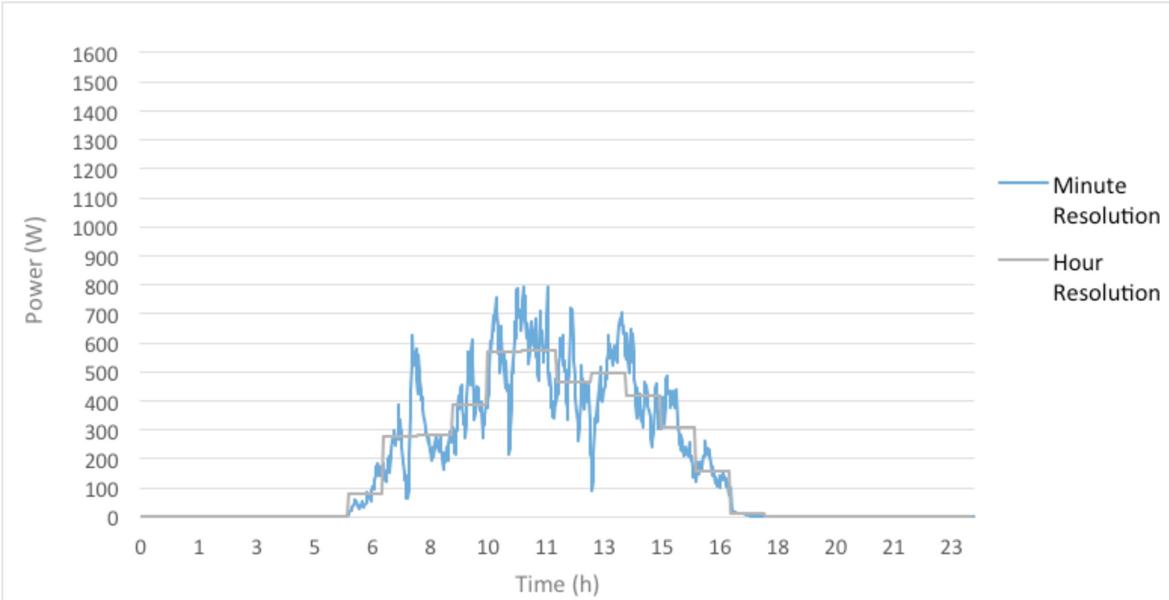

Figure 4.12. Dry season day with cloudy sky on-site electricity generation profile.

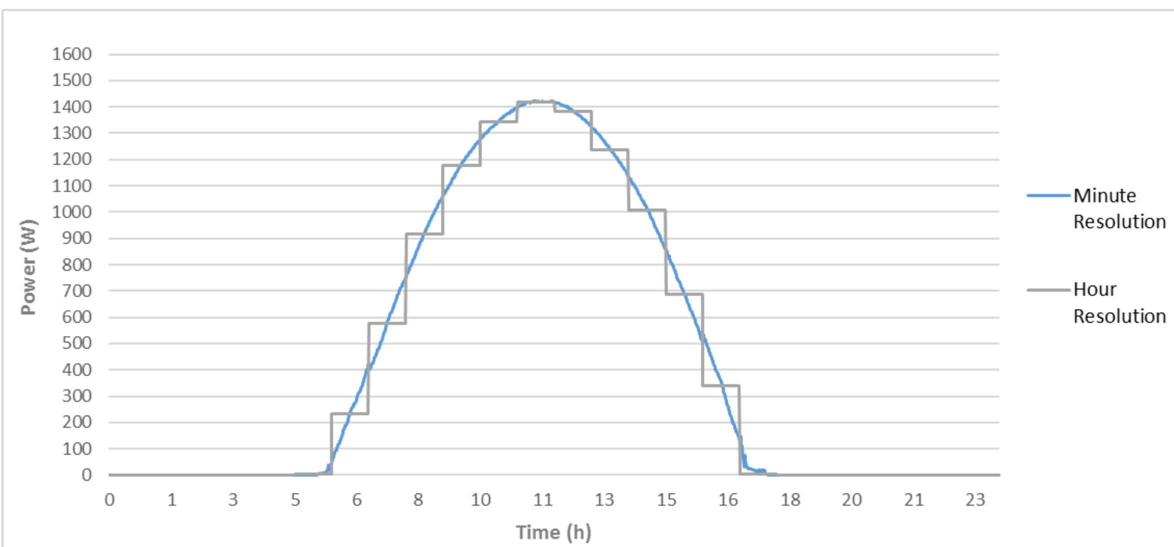

Figure 4.13. Wet season day with clear sky on-site electricity generation profile.

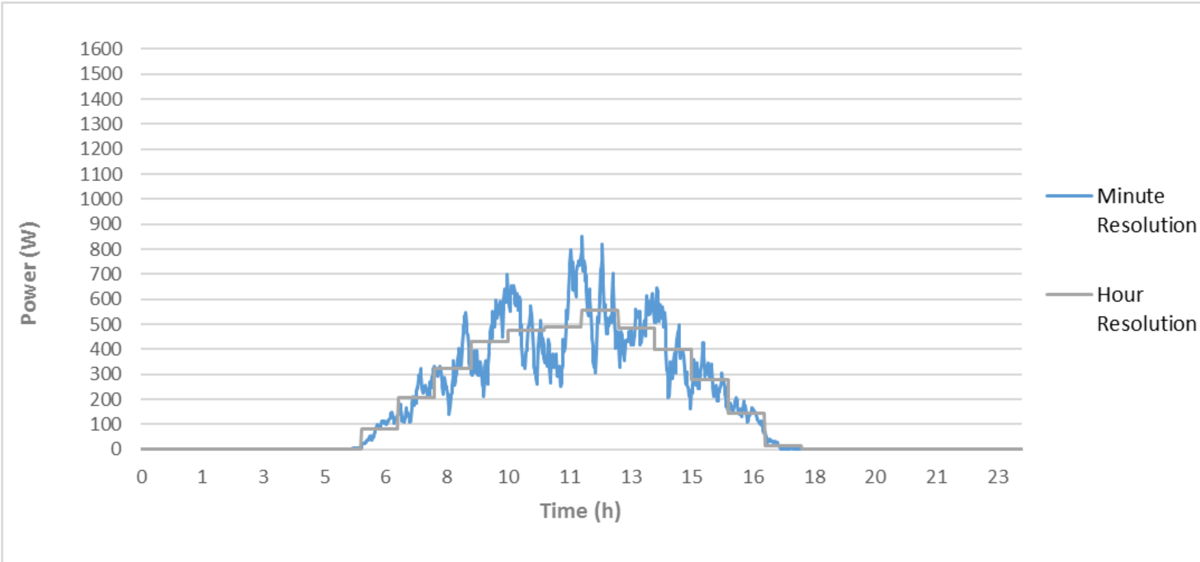

Figure 4.14. Wet season day with cloudy sky on-site generation profile.

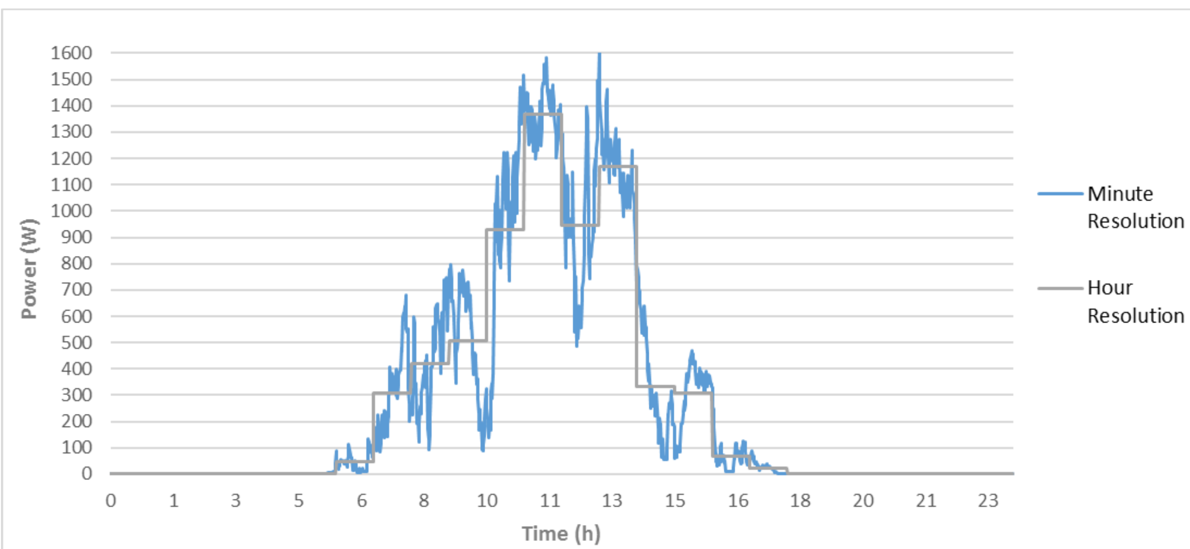

Figure 4.15. Wet season day with partially cloudy sky on-site generation profile.

It can be observed in Figures 4.10 and 4.13 the smoothness of the profiles. The slight averaging effect in clear sky conditions in comparison with the other sky conditions assured that the profiles are less sensitive to this.

On the other hand, a noticeable difference between the resolution profiles is shown in partially cloudy sky conditions (see Figures 4.11 and 4.14).

The averaging effect expressed by the hour resolution clearly differs from the minute resolution because the constant output power fluctuates provoked by the rapidly oscillation of the solar radiation intensity in a time scale ranging from several minutes to a few seconds (Cao & Sirén, 2014). Therefore, the impact of coarser resolution is bigger when sky conditions are partially cloudy or cloudy as well (see Figures 4.12 and 4.15).

It can be appreciated that the season does not have a major impact in the PV power production. Consequently, the solar production fluctuates only slightly through the year. Therefore, data exclusively from the month of March was used to effectuate further analysis.

The error in the matching was calculated to consider it in the matching results triggered by different resolutions. The results are shown in Table 4.7.

Table 4.7. eOEM and eOEF error results in different sky conditions of the month of March.

Clear sky		Partially cloudy sky		Cloudy sky	
e_{OEF}	e_{OEM}	e_{OEF}	e_{OEM}	e_{OEF}	e_{OEM}
10,32%	10,20%	39,18%	39,02%	37,86%	37,70%

The mean error, in all the scenarios, shows the overestimation of the amount of electricity demand that can be covered by the PVs and the consumption of energy produced. The stronger impact occurs for partially cloudy sky conditions where both e_{OEF} and e_{OEM} are bigger.

According to Cao and Sirén (2014), the maximum value of the error at one simulation time-step is dependent on the proportion of the peak duration to the simulation time step and on the proportion of the generated power to the base load.

Likewise, the error is correlated to the frequency of the distribution of the long spikes within 24 hours. This means, that the more frequently the spikes are, then the larger the error is likely to be (Cao & Sirén, 2014). It is evident in Figures 4.11 and 4.14 that the partially cloudy sky conditions profiles are the ones with the more quantity-distributed spikes along the hours. That is why the biggest error is present here.

To carry out the energy analysis, a random daily energy profile of the month of March was chosen from the energy demand model. The results show the shape of the demand (L(t)) and the PV on site power production curve (G(t)) of the same month, and the interconnections, as observed in Figures 4.16, 4.17 and 4.18.

The most noticeable mismatch between G(t) and L(t) occurs in the profile with more intermittent variations that correspond to the partially cloudy sky profile (see Figure 4.17). In here, it is clearly exposed the discrepancy between consumption and demand peaks on hourly resolution.

Also, the different curves at different time steps demonstrate the effect at one-hour step resolution and how it does not take into account the effects of events with shorter duration. In other words, the 1-minute resolution curves take into account the intermittent and fluctuated long spikes, which can be interrelated as peaks in demand and supply. Instead, the coarser resolutions average these spikes into much more continuous and flatter profiles leading to an inaccurate representation of the profiles.

It can be noticed the intermittent spikes of up to 8kW peak-load in the demand curves. For the PV power production, a peak-load of 15 kW is observed for clear sky, 14 kW for partially cloudy and 8 kW for cloudy sky conditions. However, the peak loads do not match in any scenario; in other words, the production peaks do not meet the demand peaks. Even though the generation unit with larger capacity covers the instantaneous demand peaks, the poor self-consumption of an oversized generation unit leads to the unreasonable cost of the energy system.

As well, mismatches between the generation and demand represent a risk for the electrical grid if the unit is with a grid feed-in option. There is a potentially increase in the probability of a destabilising the voltage and capacity limitations of the grid. Therefore, the instantaneous matching of the production and demand aims and prevent this situation (Cao & Sirén, 2014).

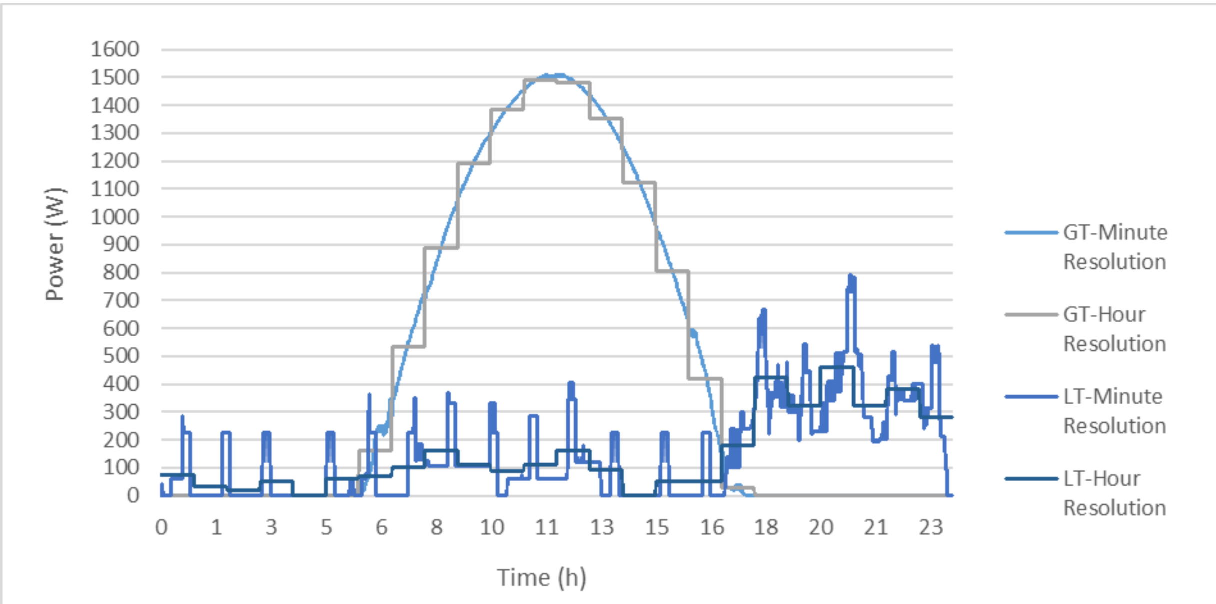

Figure 4.16. Electricity consumption profile, L(t) and on-site generation profile, G(t) of a sample in a dry season day with clear sky.

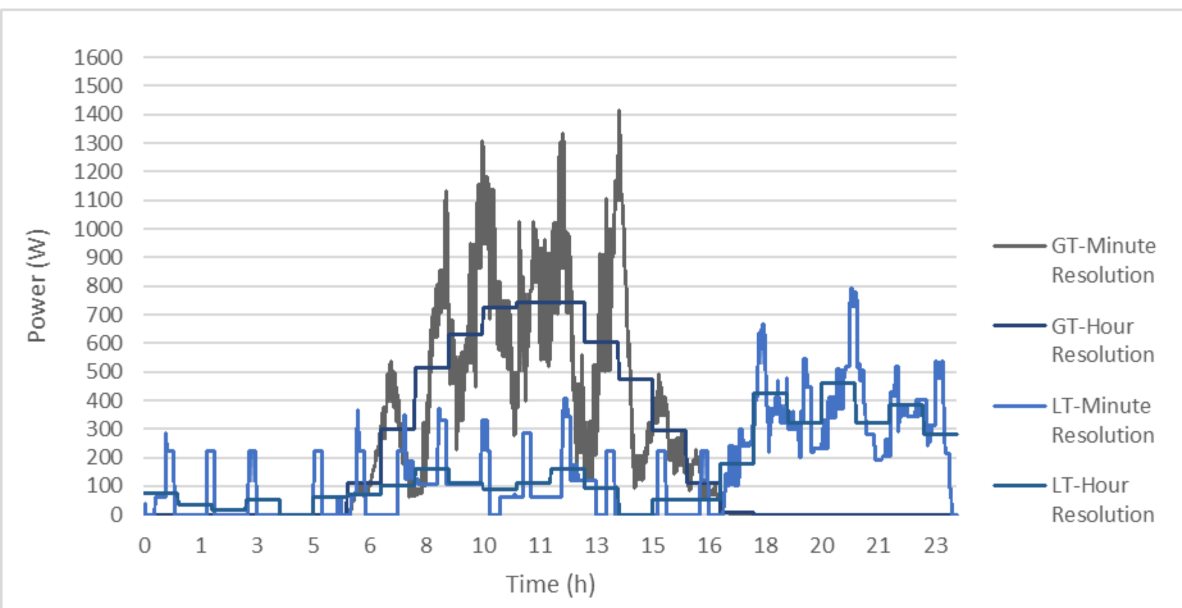

Figure 4.17. Electricity consumption profile, L(t) and on-site generation profile, G(t) of a sample in a dry season day with partially cloudy sky.

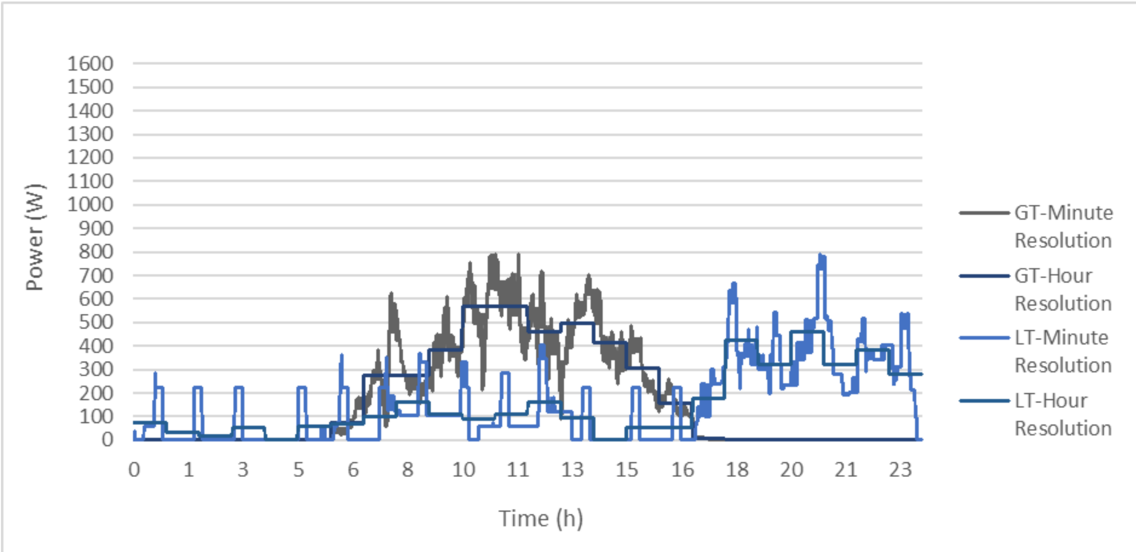

Figure 4.18. Electricity consumption profile, L (t) and on-site generation profile, G(t) of a sample in a dry season day with cloudy sky.

It is important to consider that the long sharp spikes (load peaks) or the continuous serrate form (base-load) in the demand curve are mostly sensitive to the averaging effect of coarser resolutions, therefore large errors in the matching result are more likely to occur when the high-resolution PV generation curve frequently crosses these intermit- tent long sharp spikes or the continuous serrate form in the demand curve (Cao & Sirén, 2014).

Then, with the profiles corresponding to the month of March, the OEM and OEF were calculated. The results are shown in Table 4.8.

Table 4.8. OEM and OEF results in different sky conditions of a weekday in the month of March

Clear Day			Partially Cloudy Day			Cloudy Day		
	OEF	OEM		OEF	OEM		OEF	OEM
Minute Resolution	0,128	0,390	Minute Resolution	0,0889	0,561	Minute Resolution	0,0761	0,633
Hour Resolution	0,141	0,430	Hour Resolution	0,124	0,771	Hour Resolution	0,105	0,872
Daily	0,328	1	Daily	0,159	1	Daily	0,120	1

The values of the matching indexes can fluctuate from 0 to 1. The best scenario is when both indexes are equal to unity, which indicates that the load is entirely covered by the on-site generation and at the same time all the power produced is consumed.

According to Molar (2015), a higher OEM indicates that a higher share of the generated energy with PVs is used to cover de household demand instead of being dumped or exported. Other important factor is that the OEF can never have the value of 1, because the PVs can only cover existing demand at daylight. Hence, the OEF has smaller values in partially cloudy and cloudy sky conditions.

When coarser resolutions are used, the value of OEF is larger. This means that there is an existing lost in the demand and production curves. At calculating the OEF per day, the result is 0.33 (see Table 4.8); if all analyses were made with this resolution, it can be concluded that on a sunny day, the PVs cover approximately 32% of demand when in fact the PVs cannot cover more than 12.7% of demand as the more detailed curves (1-minute resolution) shows.

On the other hand, the OEM may itself have values of 1. This is a situation where all the energy produced by the PVs is used to cover part of the demand. This means that even if there is little production of power; most of it is consumed. As well, that is one of the reasons why the OEM values are greater for partially cloudy and cloudy sky conditions.

As with the OEF, having higher resolutions overestimates the value of OEM. In Table 4.8, it can be seen that if the daily profile is taken, the assumption is that all the PV power produced was used, although the 1-minute resolution results shows that only 39% was used.

This shows the importance of working with high-resolution profiles. It relies on the accuracy and precision of the results. Also, for energy matching, it is ideal to work with instant data; consequently, using finest data implies obtaining results more accurate.

To better appreciate the cause of the variations in energy matching indexes results, one hour of the partially cloudy sky conditions March data set was randomly chosen. Analysing the use resolution per hour, the result is that the minimum between de PV power on site production and the electricity demand is the electricity demand (see Table 4.9). Nevertheless, it can be seen in Table 4.10 how in some cases the minimum is the demand meanwhile in other cases the minimum is the production.

Table 4.9. Hourly resolution between the PV power on-site production and the electricity demand.

Hour	PV power on site	Electricity demand	Minimum
11	741,1954	726,1667	726,1667

Table 4.10. Minimum minute resolution between the PV power on-site production and the electricity demand.

Minute	PV power on site	Electricity demand	Minimum
1	386,5208	420	386,5208
2	453,4678	420	420
3	376,8108	420	376,8108
4	612,6809	670	612,6809
5	983,5963	670	670
6	1024,062	670	670
7	842,4668	730	730
8	829,5485	730	730
9	776,2001	730	730
10	581,2827	730	581,2827

11	689,1612	480	480
12	830,6816	480	480
13	620,952	480	480
14	721,9444	480	480
15	656,4412	480	480
16	650,7575	480	480
17	396,1023	780	396,1023
18	626,3611	780	626,3611
19	743,047	780	743,047
20	612,2126	780	612,2126
21	647,6705	780	647,6705
22	583,9078	780	583,9078
23	683,2088	780	683,2088
24	774,5214	780	774,5214
25	785,9669	780	780
26	778,8127	780	778,8127
27	788,5008	780	780
28	830,0756	660	660
29	959,4792	660	660
30	818,6088	660	660
31	1024,433	660	660
32	995,5454	660	660
33	945,0666	660	660
34	996,9891	660	660
35	932,1534	660	660
36	962,4169	660	660
37	845,5437	780	780
38	862,7627	780	780
39	936,0875	780	780
40	885,7419	660	660
41	891,5363	660	660
42	637,2717	660	637,2717
43	539,7469	660	539,7469
44	580,6515	660	580,6515
45	706,9165	660	660
46	714,0692	660	660
47	857,1063	660	660
48	898,7705	660	660
49	678,4812	660	660
50	963,1692	660	660

51	917,0922	660	660
52	918,578	660	660
53	826,679	660	660
54	587,509	660	587,509
55	601,6464	660	601,6464
56	533,9221	1590	533,9221
57	528,3107	1590	528,3107
58	518,468	1590	518,468
59	549,4288	1590	549,4288
60	570,582	1590	570,582

5. CONCLUSIONS AND RECOMENDATIONS

5.1. CONCLUSIONS

- Monthly and yearly profiles were found due to the computational changes made in the high-resolution model of electricity demand.
- In the evaluated scenarios, it was shown that the model data overall compares satisfactory with the measured data.
- In various cases, the monthly and annual generated daily profiles do not match precisely with the mean energy demand due to several factors that are driven by complex human interactions and are not considered explicitly in the model.
- The synthetic data sets obtained from the high-resolution on-site PV power generation model overall match with the on-site measured data with a relative low statistic difference.
- The PV on-site energy production model can simulate appropriately different sky conditions.
- Having a flexible model to calculate the PV power output for any area and information of rooftop characteristics allows the modelling of different on-site generation scenarios like that ones considered in this study,
- The 1-minute resolution curves clearly take into account the intermittent and fluctuated long spikes.
- The coarser resolutions average the existing demand profile spikes into much more continuous and flatter profiles leading to an inaccurate representation of the overall demand profile.
- The hourly averaging effect during the numerical simulations has higher probabilities to hide the intermittent characteristic of the solar radiation, which determinates the output PV power generation.
- Partially cloudy sky conditions represent a matching error of 39,18%, which was the highest in comparison to the other sky conditions. This is attributed to the fact that the error is correlated to the frequency of the distribution of the long spikes within 24 hours.

- The possibility of encountering noticeable errors in the matching result under partially cloudy sky conditions is higher than under other clear and cloudy sky conditions.
- With a 1-min resolution, both the demand and generation curves are fluctuated with spikes and serrate form profiles, whereas with a 1-h resolution, both curves are averaged into much flatter profiles
- It was shown daily resolution profiles conduce to the assumption that all the PV power produced is used to cover the house demand, although the 1-minute resolution results show in one of the studied case that only 39% could be used with this purpose.
- Fine resolutions should be selected for demand and electricity power production profiles, where long sharp spikes appear in a frequent form in order to avoid the appearance of large errors.
- The instantaneous matching of the production and demand aims and prevent the increase in the probability of a destabilising the voltage and capacity limitations of the electrical grid.
- Analysing the matching of the electricity demand and supply at different time steps is an important phase for the energy planning process as important conclusions regarding energy planning could be drawn.
- Due to the common fact that the long sharp spikes (load peaks) or the continuous serrate form (base-load) in the demand curve are mostly sensitive to the averaging effect of coarser resolutions, large errors in the matching result are more likely to occur when the high- resolution PV generation curve frequently crosses these intermittent long sharp spikes or the continuous serrate form in the demand curve.
- The energy matching capability tends to be overestimated when coarser resolutions are used because of the averaging effect that occurs on both: the generation and demand profiles.
- Overall, the tools provide valuable information for further investigations. Power, energy reserves, downtimes, start-up times, resulting efficiency and other factors could be taken into account in a detailed form.

5.2. RECOMENDATIONS

- For having more accurate, precise and detailed results numerous modifications, improvements and refinements shall be incorporated in the high-resolution household energy demand model.
- Ii is recommended to compute the model in a different computational language that can support large data sets. The goal is to improve the duration time of simulation.
- More measured data that include different scenarios variations have to be taken into account to better statically compare it with the synthetic data in the dwelling energy demand model.
- Adequate modifications to the algorithms of the model with national statistical data have to be performed in order to have a better match within the profiles.
- It is recommended to incorporate a national, actualized and complete TUS in high resolution. This will lead to modifications in the model that will have a great impact in the precision of the results.
- Ii it necessary to define more detailed activity categories and more extensive data on appliance ownership to increase the diversity scenarios among dwellings.
- Further studies might be performed to include the modelled of small gadgets such as mobile phones chargers and all kind of timers to run appliances to simulate volatility of energy demand appropriately.
- Using a database of irradiance profiles with 1-minute resolution for each day of the year in the demand model will lead to have more accurate results for monthly and yearly profiles. This will have a direct effect in the demand of electricity of the households, therefore the statistics will have to be arranged in order to include this database and obtained exclusive and precise results.
- In order to have more truthful results regarding the mean demand energy, better and more complete datasets with accurate information regarding the duration of the lighting unit usage and distribution of different lighting unit power ratings within dwellings must be included.

- The fit of switch on schemes of the aggregate load curves with the known peak powers should be increased. This will help to minimize the discrepancy between the synthetic and measured data.
- There must be included in the model different categorizations of energy savings tools and variations, such as solar water heating systems, combination of the solar system with the electric boiler and a storage tank for water, among others.
- For the on-site PV power generation model, it should be taken into account the efficiency of the regulator/inverter since it is instantaneously variable.
- It is important to carry out a study to calculate the magnitude of the error caused by the coarser resolution dependant significantly upon the PV output levels (i.e. PV areas) and designated resolution.
- To improve the irradiation data sets, it is recommended to use a sky imagery tool to model the total incident solar radiation on a tilted surface obtaining 1-minute resolution profiles of the exact location in study.
- A PV penetration study regarding the effect of the orientation of the PVs and the effect of load shifting has to be carried out in order to analyse the different available scenarios. In here, it can be determined the time of peak loads according to different orientations and its correlation with the OEF and OEM indexes.
- A model of the grid (transmission and distribution) can be created to see local stress resulting from different types and locations of PV systems.
- An energy storage study could be introduced in order to analyse the possible effects and the response on the matching indexes in different scenarios.
- There should be used geo-referenced data sets (Geographical Information Systems i.e.) in order to incorporate a holistic city model that captures the interaction of consumption and energy production in time and space. This could bring a more complete depiction of the possible future energy scenarios by integrating the explicit importing and exporting of data between the modalities.
- It is valuable and viable to expand the model to other categories apart from dwellings, like industries, stores, buildings, etc.
- Performing an economic analysis to understand the impact of different resolutions in the cost estimations of the energy systems is necessary. This could also be valuable

for designing and urban planning strategies.

- It is necessary to present the matching errors e_{OEM} and e_{OEF} every month and every year to comprehend different aspects of the influence that coarser resolutions have.
- For both models and energy matching analysis, it is recommended to evaluate the different results using exclusively weekday and weekend data.

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7. APPENDIX

APPENDIX 1: VISUALIZATION OF THE PV ON-SITE POWER PRODUCTION IN DIFFERENT SKY CONDITIONS FOR EXTACTING DAILY PROFILES FROM THE MONTH OF MARCH.

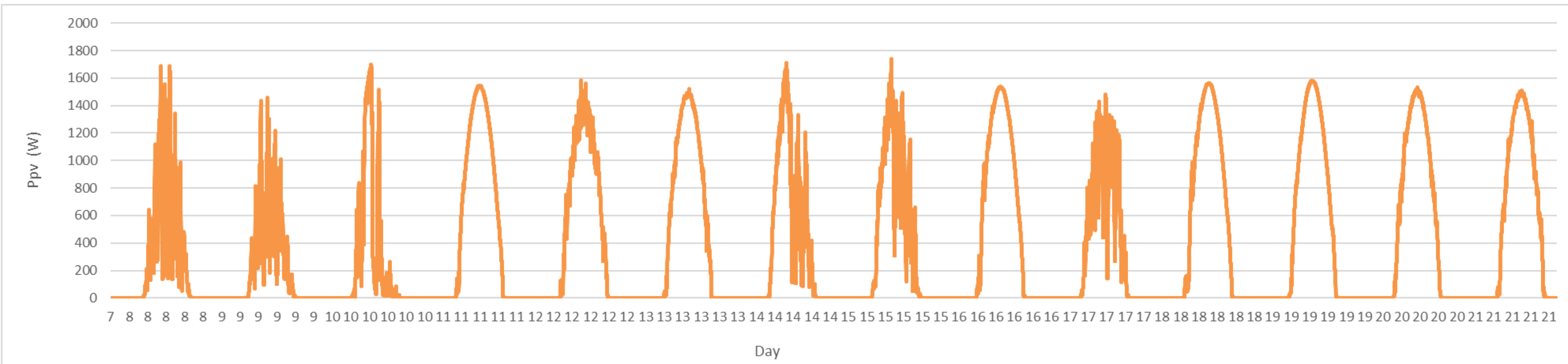

Figure A.5.1 Daily profiles of PV power production from the month of March.

APPENDIX 2: HIGH RESOLUTION DOMESTIC ENERGY DEMAND MODEL

See attached file 1

APPENDIX 3: HIGH RESOLUTION PV POWER ON-SITE PRODUCTION MODEL

See attached file 2

8. ANNEXS

ANNEX 1: ALLOCATION SAMPLE OF THE APPLIANCES

Table An.1.1. Sample of the model's input data based on the characteristics of the first dwelling in study.

Appliance category	Appliance type	Dwelling Configuration
		Has appliance?
Cold	**Chest freezer**	NO
	Fridge freezer	YES
	Refrigerator	YES
	Upright freezer	YES
Consumer Electronics + ICT	**Answer machine**	NO
	Cassette / CD Player	YES
	Clock	YES
	Cordless telephone	YES
	Hi-Fi	YES
	Iron	YES
	Vacuum	NO
	Fax	NO
	Personal computer	YES
	Printer	YES
	TV 1	YES
	TV 2	NO
	TV 3	NO
	VCR / DVD	YES
	TV Receiver box	YES
Cooking	**Hob**	YES
	Oven	YES
	Microwave	YES
	Kettle	YES
	Small cooking (group)	NO
Wet	**Dish washer**	NO
	Tumble dryer	NO
	Washing machine	YES
	Washer dryer	NO
Water heating	**DESWH**	NO
	E-INST	NO
	Electric shower	YES
Electric Space Heating	**Storage heaters**	NO
	Other electric space heating	NO
Lighting	**Lighting**	YES

Table An.1.2. Sample of the model's input data based on the characteristics of the second dwelling in study.

Appliance category	Appliance type	Dwelling Configuration
		Has appliance?
Cold	Chest freezer	NO
	Fridge freezer	YES
	Refrigerator	YES
	Upright freezer	YES
Consumer Electronics + ICT	Answer machine	NO
	Cassette / CD Player	YES
	Clock	YES
	Cordless telephone	YES
	Hi-Fi	YES
	Iron	YES
	Vacuum	NO
	Fax	NO
	Personal computer	YES
	Printer	YES
	TV 1	YES
	TV 2	YES
	TV 3	YES
	VCR / DVD	YES
	TV Receiver box	YES
Cooking	Hob	YES
	Oven	YES
	Microwave	YES
	Kettle	YES
	Small cooking (group)	YES
Wet	Dish washer	NO
	Tumble dryer	NO
	Washing machine	YES
	Washer dryer	NO
Water heating	DESWH	NO
	E-INST	NO
	Electric shower	NO
Electric Space Heating	Storage heaters	NO
	Other electric space heating	NO
Lighting	Lighting	YES

ANNEX 2: MONITORING DEVICES OF ENLIGHTEN

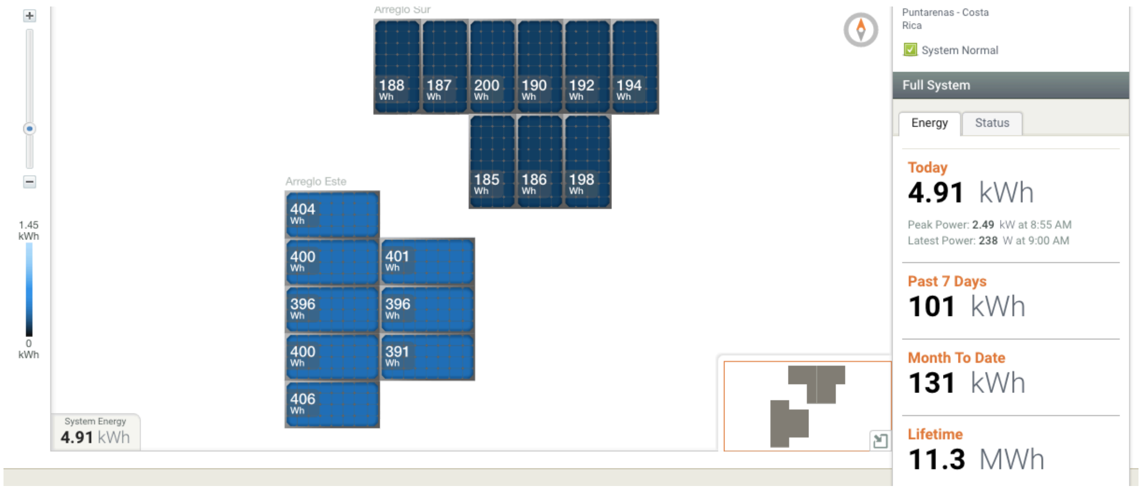

Figure A.2.1. One of the monitored devices: PV system of 17 micro inverters.

ANNEX 3: SHELL SOLAR SUN PATH DIAGRAMM

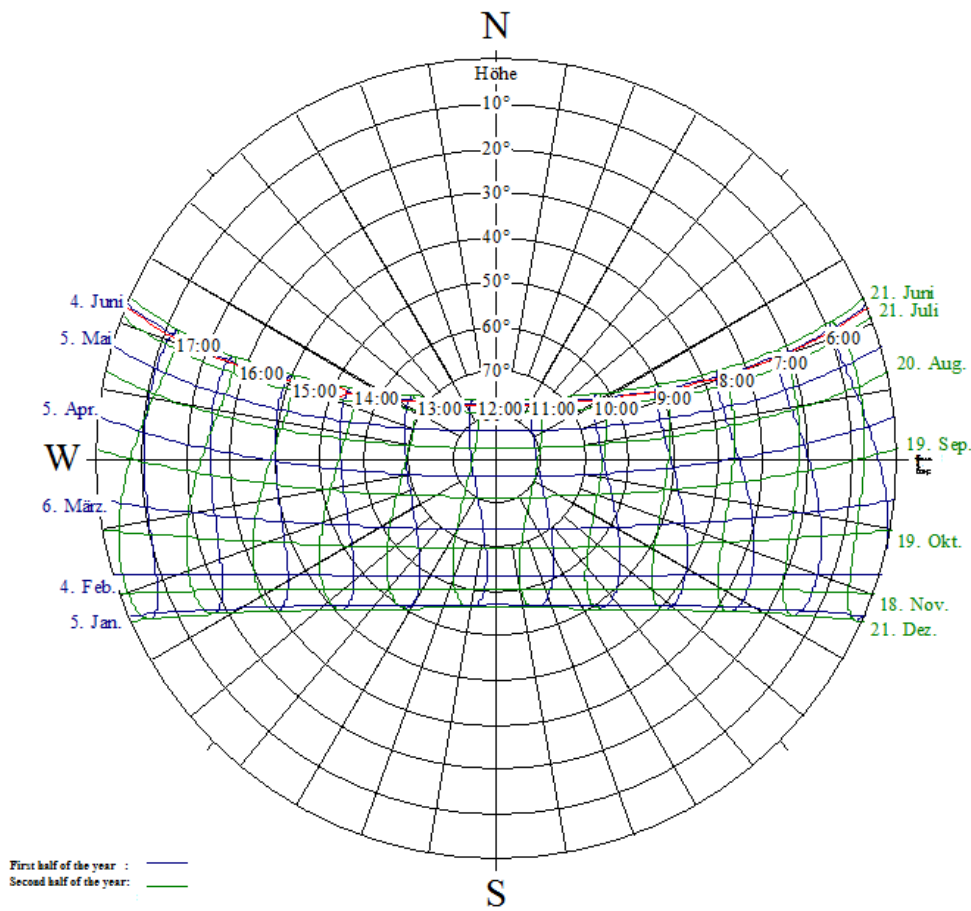

Figure A.3.1. Shell Solar Path diagram for San José, Costa Rica. (Weigl, 2014).

The lines indicate sun's position for every hour of the year. The blue lines correspond to the first half of the year; meanwhile the green lines represent the second half of the year. These lines indicate the time of the day. The distance to the centre indicates the elevation of the sun. The azimuth angle of the sun can be observed by the radial angle. The lines reaching from East to West represent the suns path at the indicated day. So, finding the intersection of the daily horizontal curve with the green and blue vertical lines, gives the suns position. The angles can be read from the black lines subsequently (Weigl, 2014).

"Black concentric circles indicate the elevation of the sun. The centre indicates an elevation of 90°, so a solar radiation which approaches the earth's surface perpendicular. Sun positions further away from the centre, indicate a lower angle. At the outmost circle the suns height is 0°, which is the case at sunrise and sunset. The 36 lines crossing the circles perpendicular indicate the azimuth angle of the sun in steps of 10°. Usually the angle is measured from North, so East represents 90°, South 180° and West 270°. In San José the sun rises with an azimuth angle of 70° in July while in December the angle is 115°" (Weigl, 2014).