

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

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

Sophia Ruiz-Vásquez<sup>1</sup>, Carlos Roldán<sup>2</sup>, Vicky Cheng<sup>3</sup>

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- 1 Environmental Engineering Student. School of Chemistry, Instituto Tecnológico de Costa Rica, Cartago, Costa Rica. E-mail: [sruiz9203@gmail.com](mailto:sruiz9203@gmail.com)
- 2 Coordinator of the Renewable Energy Program (Programa de Energías Limpias). Instituto Tecnológico de Costa Rica, Cartago, Costa Rica. E-mail: [croldan@itcr.ac.cr](mailto:croldan@itcr.ac.cr)
- 3 Research Group Leader-Energy Efficient and Smart Cities, Technische Universität München. Munich, Germany. URL: [eesc.mse.tum.de](http://eesc.mse.tum.de)

## Palabras clave

Alta resolución; frecuencia temporal; modelo de consumo eléctrico residencial; producción de energía solar in situ; índices de energía.

## Resumen

Con el fin de apoyar de manera sostenible los múltiples sistemas de energía, las estrategias de mejoramiento de sistemas de eficiencia energética implican la integración y aplicación de herramientas de análisis de energía urbanas. Los sistemas de energía, como la energía solar intermitente, requieren investigación sobre la capacidad de adaptación entre la demanda y la producción. El análisis de coincidencia de energía requiere de fuentes de error mínimas, con el fin de obtener resultados más puntuales.

En ciertas aplicaciones de simulación de energía, el intervalo de tiempo de uso común es de una hora, sin embargo, estudios han demostrado que esto puede ser una fuente significativa de error. Por ende, para la identificación del impacto que tiene la frecuencia temporal en las simulaciones, se crearon modelos holísticos en alta resolución. Con estos modelos, se pretende la representación y obtención de resultados más precisos y exactos.

El modelo de producción de energía fotovoltaica generada in-situ, se basa en un modelo desarrollado por el grupo de investigación Energy Efficient and Smart Cities (EESC). Datos pertinentes, tales como la radiación incidente y la radiación global se obtuvieron del software Meteonorm. Para la elaboración del modelo de alta resolución de la demanda eléctrica doméstica, el modelo desarrollado por Centre for Renewable Energy Systems Technology of Loughborough University, fue utilizado y modificado usando información pertinente de Costa Rica.

Estos modelos, implican módulos fotovoltaicos con producción energética in-situ y representan adecuadamente la demanda de electricidad doméstica. Por lo tanto, el cálculo de los análisis de la capacidad de adaptación de energía pudo ser efectuado. Dichos cálculos involucran los índices OEF y OEM, que se refieren a la fracción de energía in situ y la coincidencia de energía en las instalaciones, respectivamente. Mediante estos cálculos, se mostró que el uso de las resoluciones más gruesas en el análisis de energía conduce a la sobreestimación, y a su vez el porcentaje de error incrementa.

## Keywords

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

## Abstract

Strategies towards more energy-efficient systems imply the integration and application of urban energy analysis tools in order to support the sustainable energy systems. Energy systems such as intermittent solar power, requires research into the comprehensive analysis of the matching capability between the demand and the production. In order to perform the energy matching analysis, the aim must involve minimal source of error therefore, more accurate results can be obtained.

In certain applications of energy simulation, the commonly used time step is one hour, nevertheless studies have shown that this can be a significant source of error. For the identification of the impact that time-step have in simulations, holistic models in high resolution

were created. With the models, using time a time step of 1 minute, more precise and accurate results could be obtained.

The generated PV on-site production model is based on a model developed by the research group Energy Efficient and Smart Cities (EESC). Relevant data needed for the model, such as irradiance and incident global radiation; was obtained using the software Meteonorm. For the high-resolution model of domestic electricity demand, the model developed by the Centre for Renewable Energy Systems Technology of Loughborough University, was used and modified using relevant information from Costa Rica.

This model implicates PV modules on-site production and adequately represents the domestic electricity demand. Hence analyses of energy matching capability calculations, 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; showed that the usage of coarser resolutions leads to overestimated this capability, and the same time the error percentage is bigger.

## Introduction

Costa Rica enjoys abundant renewable energy resources but lacks policies to put them in effective use. A renewable-based energy system that supports sustainable and socially just forms of urbanizations can provide solutions to the challenges of meeting the rapid increase in energy demand in urban areas. 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. This technology, which is low-carbon and sustainable, 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.

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 analyzed using the on-site energy fraction (OEF) and the on-site energy matching (OEM) in different resolutions, to precisely estimate how much demand can be covered or how much on-site generation can be consumed.

Therefore, creating 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 more precise and accurate application of the PV technology. The use of high-resolution model can eliminate the averaging effect, which leads to a significant improvement in energy efficiency by identifying inaccuracies in simulations and decreasing the error. Also, the economic analysis, the financing and after-sales service is taken into account.

## Costa Rica Energy Scenario

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 the transportation sector is the major consumer and generator of emissions [2].

However, there has been 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 [18]. 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 [2].

**Table 1.** Costa Rica Environmental Indicators [8].

	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 Consumption (TJ)	118.094	120.480	122.049	125.619	126.177
Secondary Energy Consumption Growth %	-1,7	2	1,3	2,9	0,4
Hydrocarbons	72,2	72,2	72,4	72,2	71,9
Biomass %	0,03	0,03	0,03	0,03	0,03

Before 2007, electricity demand increased on average 5% per year [11]. As shown in table 1, in 2013 the electricity demand increased only 0.9%, although electricity generation from bunker and diesel grew by 44.1%. This has 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 [11].

### Electricity Generation

The electricity generation capacity reached an installed capacity of 2,731 MW. Of that total, 78% corresponds to own plants operated by the two national energy companies of Costa Rica (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 [1].

As for the generation of clean energy, in recent years the installed capacity has shown wide variations. 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 [12].

### Renewable Energy Potential

Although the country has a potential of 9,051 MW identified, the effective power was exploited until 2012 (the most recent estimate available) was 2,147 MW, less than 25% of the local energy potential (see table 2). The biggest contribution is electricity generated by hydropower (1,768 MW), followed by geothermal (195 MW) and wind (144 MW) [8].

**Table 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

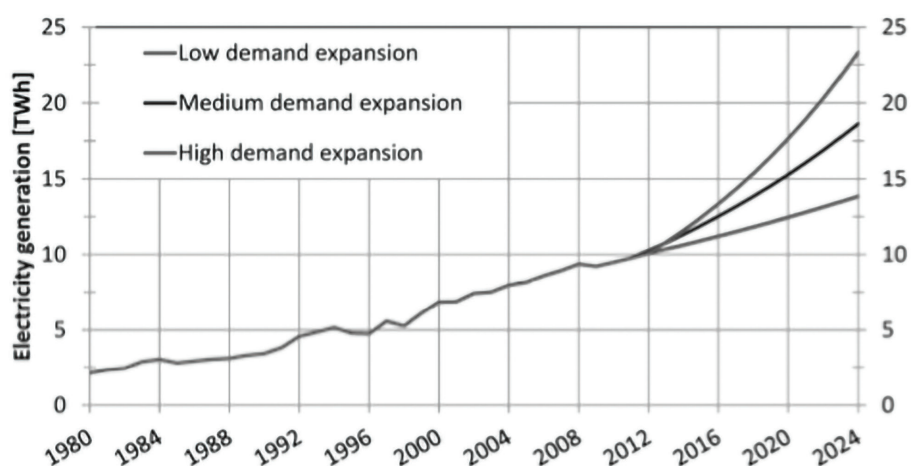
\*The identify potential was obtained by the sum of different projects and it includes the capacity installed.

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

### Energy demand

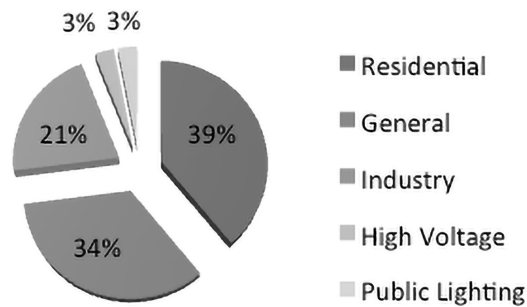
Energy demand and the emissions that it generates represent a large proportion of the ecological footprint of Costa Rica (about 31.1%) and it is the main factor driving the growth of it. The postponement of political decision jeopardizes the sustainability of the sector, especially the lack of clarity and consensus on the path to be followed to meet the challenges in this area [8].

Various studies expect vast increase of the electricity demand in the upcoming years. In figure 1, its shown the development of the Costa Rican net electricity generation since 1980 and projections of three different scenarios from 2014 to 2024 [21].



**Figure 1.** History and forecast of the net electricity generation.

In 2014, as shown in figure 2 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.** The share of the electricity consumption in 2014 for each sector [13].

## 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 [5]. The appliances can be categorized as flexible and non-flexible, and it depends by the way that the user controls them. 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 [10].

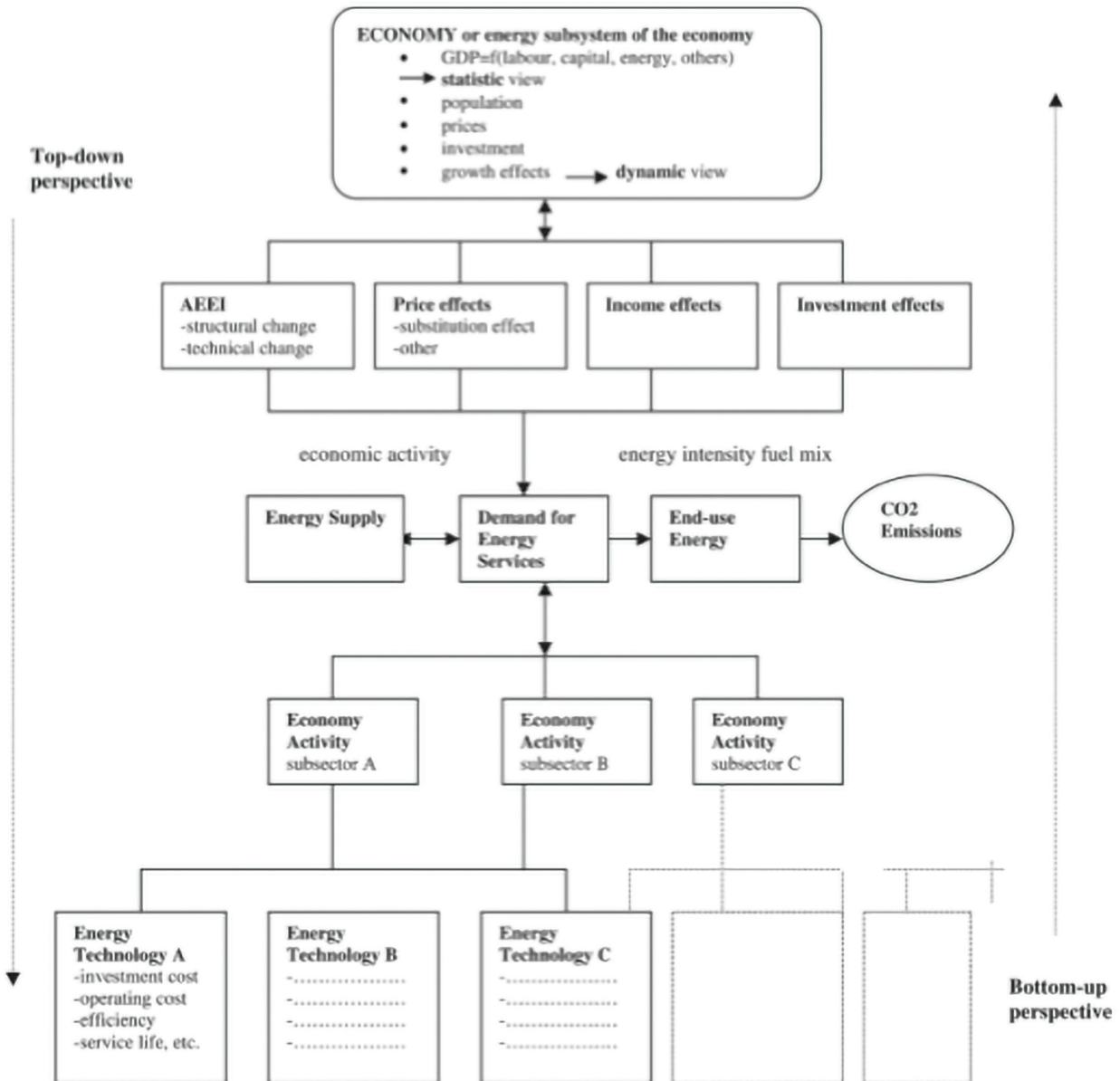
“Income and energy prices affect the way energy is consumed in the residential sector. However, residential energy use also is affected by various other factors, such as location, building and household characteristics, weather, type and efficiency of equipment, energy access, availability of energy 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.” [20].

## Modeling household energy demand

Comprehensive models, that predict or simulate energy demand, are some of the significant tools necessary to use in city transformation plans. Therefore, it enables the analysis of different aspects of urban energy demand and, as well enables to have a notion of the behavior of the energy flow in this area. Besides, the models provide an insight of possible consequences regarding new energy policy initiatives [16]. Nowadays, the top-down and bottom-up techniques are commonly used to estimate residential energy demand, as shown in figure 3, the approaches of the models contrast between each other.

### Top-down modeling

The top-down modeling approach is also known as a statistical modeling- works at the aggregated and macro level [16]. “Its aim 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, for instance, seasons and weekdays can be found for a specific region. Top-down approaches are usually used to investigate the interrelationships between the energy sector and other aspects (e.g., socioeconomic factors, demographic tendencies, weather conditions, fuel prices or building typologies) since they help to understand the main influence factors” [17]). This kind of models don’t rely on individual physical factors that can influence energy demand, instead, the model rely on past energy-economy interactions and place the emphasis on the macroeconomic trends and relationships observed in the past [15]. Thus, a significant disadvantage of this type of model is that there is no information about the components of the extracted profiles [4].



**Figure 3.** Top-down and Bottom-up model perspectives [15].

### Bottom-Up Modeling

Bottom-up modeling 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, Pereira, Pereira, & Seixas, 2014)[15]. The components are combined according to their individual contribution on the energy usage, therefore are useful in terms of calculating the impact on CO2 emission reduction as a consequence of an action to improve energy efficiency [15].

The key advantage of bottom-up modeling lies in the randomly determined process for the generation of detailed individual load profiles; nonetheless this implies the accurate modeling of human behavior, which is one of the main difficulties [17].

On the other hand, this type of modeling 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 [15].

## PV Power generation

The substitution of conventional fossil-fuelled power generation for renewable energy resources has been increasing throughout the years. Among renewable energy resources, the fastest growing resource with the highest power has been solar photovoltaic cells [14].

### Generalities and components

PV cell is the main component of the system; it functions as a semiconductor, with a maximized absorbing surface.

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 [14]. 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 because DC t is for electricity consumption meanwhile AC is for household appliances energy demand. As well, as shown in figure 4, 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 [9].

### Power production

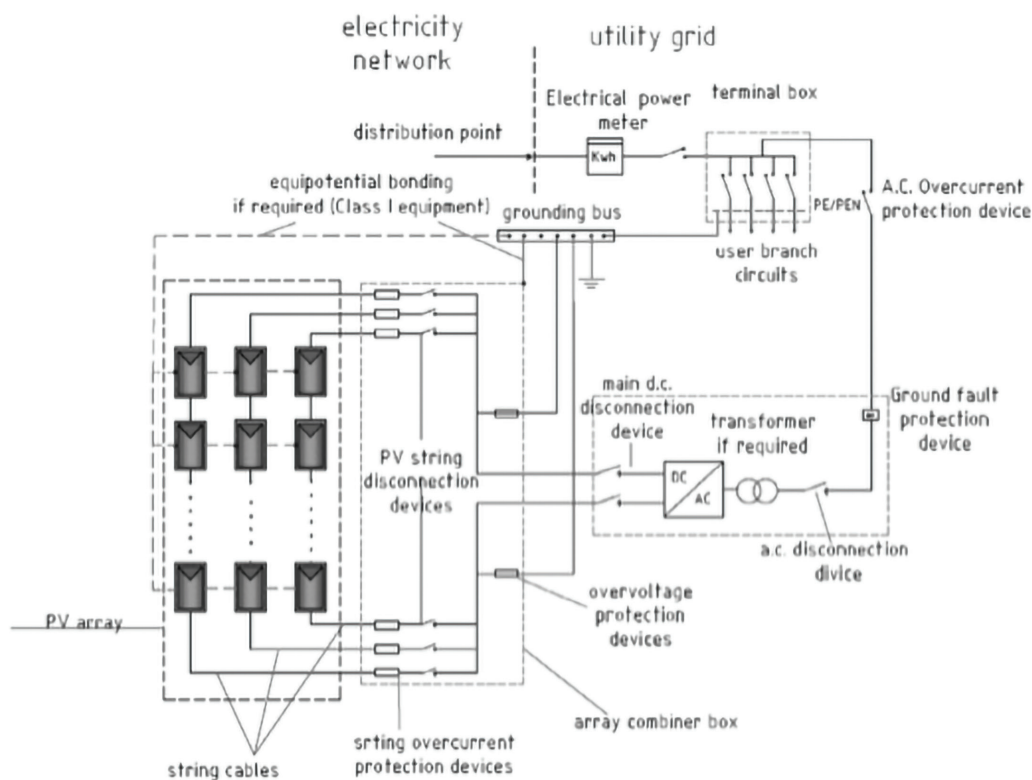
The magnitude of electricity produced from PV relies directly on intensity of sunlight; therefore the penetration of PV depends on incident solar radiation (often referrer to as global radiation). The total incident solar radiation on a tilted surface involves beam, diffuse and reflected radiation power 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 [6].

Likewise, due to changes in weather conditions like rainfall and movements of the clouds, affect the PV power output. Consequently, the output fluctuates daily, hourly, per minute and even per second (Shivashankar et al., 2016). Simulations in Solar Process Design

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 behavior of the system in study [6].





**Figure 4.** Typical PV system layout with one array [9].

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 [6].

## Computing process

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

### Household energy demand model

The statistics, technology data, lighting model and equations of the bottom-up model develop by the Centre for Renewable Energy Systems Technology of Loughborough University, were used. 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 modeling and quantify the potential impacts and benefits of low-carbon measures [19]).

#### *Appliances*

At first instance the common appliances of a dwelling are identified and these appliances are used as the basic block of the model. The appliance category division is: Cold, Consumer Electronics + ICT, Cooking, Wet, water heating and Electric Space Heating.

Then, to effectively represent time-correlated appliance use, in the model the appliances are described by their mean total annual energy demand and associated power characteristics. Are configured using statistics data and based on measurements. Few of the most relevant factors for the appliance demand configuration are: Mean power factor, base cycles/year (n), time running in a year (m), time not running in a year (m), minutes in year when event can start (m), total energy (kWh/year), energy used when on (kWh/year) and energy used on standby (kWh/year), etc.

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.

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.

### *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 behavior 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. This was compared with national data from Costa Rica, obtained from a survey made in the country by the entity Ministerio del Ambiente y Energía in the year 2006 (Carazo, Ramírez, & Alvarado, 2006)

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 Costar Rican behavior, since there are not studies of this kind available. 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 ae the same time were based in these aspects.

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

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.

### *Switch-on events*

The model works with two sets of data: weekday data and weekend data. Each set represent different characteristics since the behavior of the inhabitants differs significantly. Therefore 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.

Once the activity probability is calculated, the switch-on probability can be determined by using a calibration scalar. Each appliance have a calibration scalar, the purpose of this is assert the mean annual consumption of the appliance.

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.

### *Programming*

The model sample available creates synthetic data with a temporal resolution of 1-minute, it express results of one day, therefore to have monthly and annual results, new scripts were done.

### *Annual averages*

First, to estimate de power demand average over a year expressed in one day the model 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.

This process is repeated for each month of the year, therefore the data is stored and added successively from January to December, to have averages through the year at the end of the process.

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

### *Monthly averages*

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

### *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 Eergy, the company have 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.

## PV on-site energy production

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

$$P_{pv} = A_c G_T \eta_{pv} \eta_{inv} (1 - C_{loss}) \quad (1)$$

In which,

$P_{pv}$ : Output from PV module (W)

$A_c$ : Total PV array area (m<sup>2</sup>)

$G_T$ : Incident solar irradiance on PV (W/m<sup>2</sup>)

$\eta_{pv}$ : PV module efficiency (in maximum power point conditions)

$\eta_{inv}$ : DC to AC conversion efficiency

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

$$\eta_{pv} = \eta_{ref} * (1 - \beta (T_c - T_{c,ref}) + \gamma \log \left( \frac{G_T}{T_{c,ref}} \right)) \quad (2)$$

In which,

$\eta_{pv}$ : PV module efficiency (in maximum power point conditions)

$\eta_{ref}$ : PV module efficiency

$\beta$ : PV module temperature coefficient of power

$T_c$ : PV cell temperature (°C)

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

$G_T$ : Incident solar irradiance on PV (W/m<sup>2</sup>)

$G_{T,ref}$ : Incident solar irradiance on PV when  $\eta_{ref}$  is measured (W/m<sup>2</sup>)

$\gamma$ : PV module solar irradiance coefficient of power---assume 0.12 for silicon solar cells.

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

In which,

$T_c$ : PV cell temperature (°C)

$T_a$ : Ambient air temperature (°C)

$G_T$ : Incident solar irradiance on PV (W/m<sup>2</sup>)

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

$V_w$ : Wind speed (m/s)

$T_{NOCT}$ : Normal operation cell temperature (°C)

$T_{a, NOCT}$ : Ambient air temperature when NOCT is measured (°C)

$\eta_{ref}$ : PV module efficiency

$t\alpha$ : Transmittance and absorbance product

$NOCT$ : normal operating cell temperature

**Table 3.** Categorization of the equations and values for standard PV test.

User input/manufacturer data	Extracted from Meteonorm Software
$A_C$	$G_T$
$\beta$	$T_a$
$\eta_{inv}$	$V_w$
$\eta_{ref}$	
$T_{NOCT}$	
Possible values of the inclination of the roof = 15°, 20°, 25° and 30°.	
Values assume for standard PV test	
$T_{C, ref} = 25^\circ\text{C}$	

#### 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 2000-2009.

#### Steps for using the Meteonorm software

- a) *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, a latitude of 10.017 °N and a longitude of -84.267 °E.
- b) *Specifications of the location specific parameters.* In here, the azimuth and inclination angle were modified: the azimuth angle assigned was 0° and the inclination angles used were: 15°, 20°, 25° and 30°.
- c) *Definition of the time parameters and advance 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 radiation model correspond 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 thru the software.

d) *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.

#### *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 that consist in monitoring the installed systems, performed de adequate maintenance of the installed PV systems, better detection of problems, identify improvement potentials and also, they aim to collect real-time data of the PV power production on-site for further analysis. This data is collected in multiple time step resolutions: day, hourly, and 5-minute. Throughout Enphase Energy microinverters this can be accomplished. This microinverters are directly connected to Enlighten monitoring software using a networking hub, therefore real time and module level performance are accomplished. The envoy of the software allows a bi-directional a communication, this means that the data performance from the microinverters to the Web and at the same time carries the system updates from the Web to the microinverters [7].

#### **Matching indexes**

The matching of the high-resolution energy demand and production can be quantify 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:

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

$$OEM = \frac{\int_{t_1}^{t_2} \text{Min} [G(t); L(t)] dt}{\int_{t_1}^{t_2} g(t) dt} ; \leq OEM \leq 1 \quad (5)$$

In which,

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

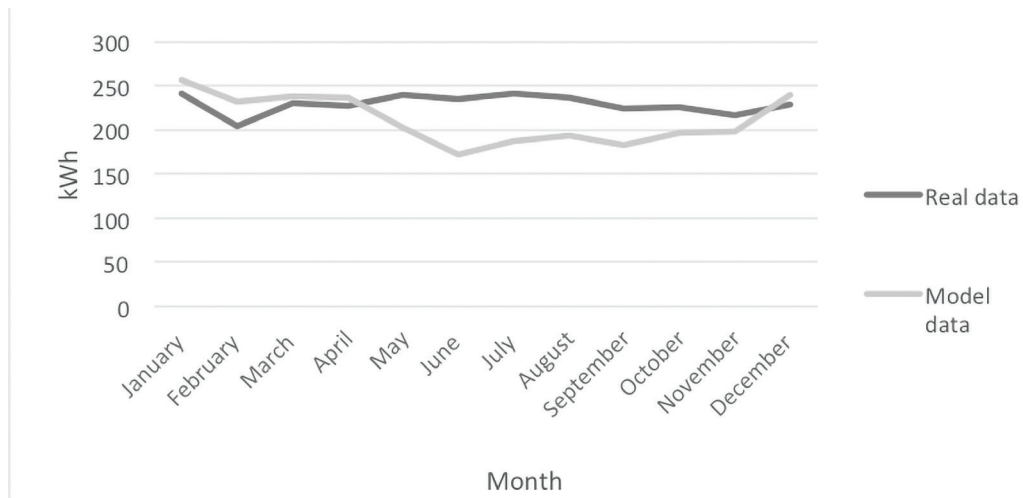
$L(t)$ : electricity demand

$dt$ : 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 this variables and  $dt$ , the indices of a certain period can be calculated.

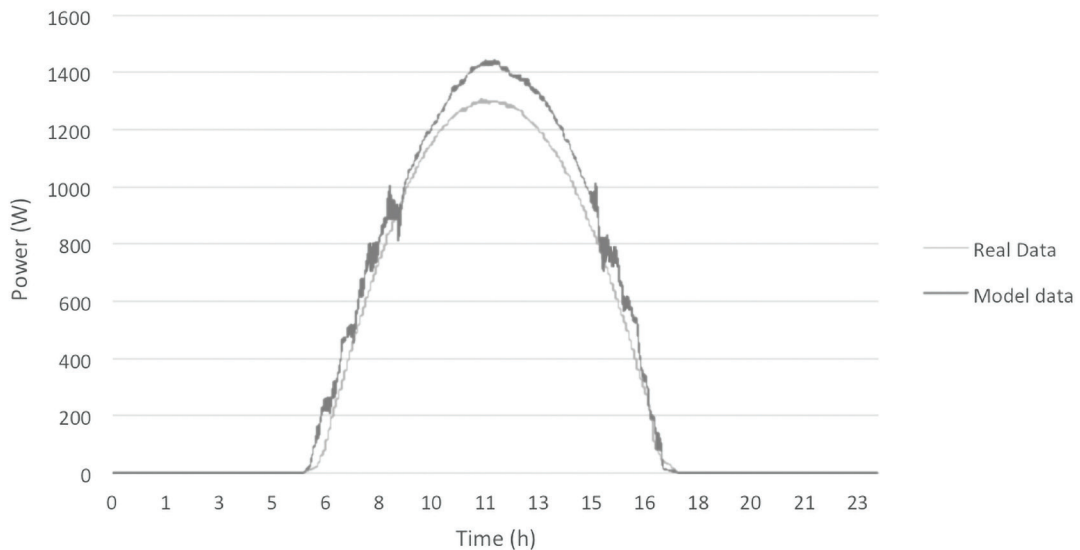
### Simulated PV data

The 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, 2% to wiring and because the inverter efficiency is 98% an additional loss of 2% is consider.

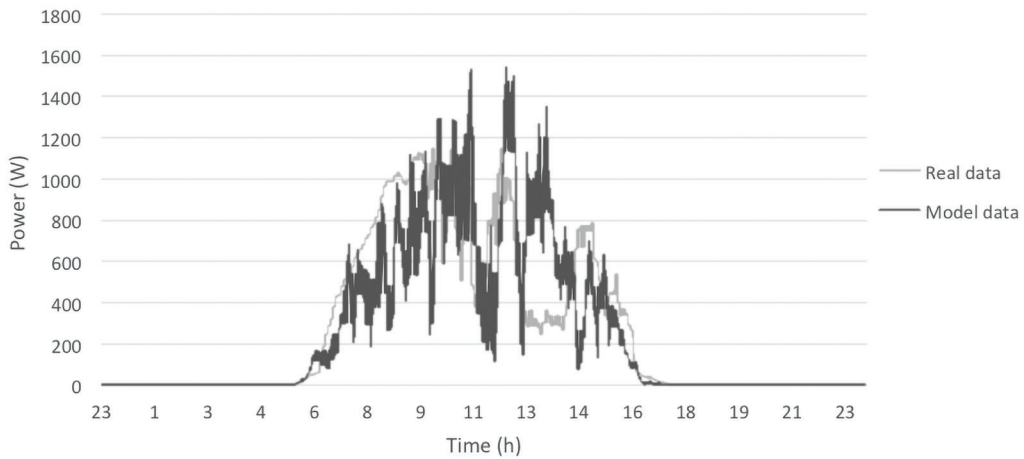


**Figure 5.** System of 6 micro inverters annual profile.

The following charts were formulated using minute data of February 2015 of the system with 6 micro inverters.



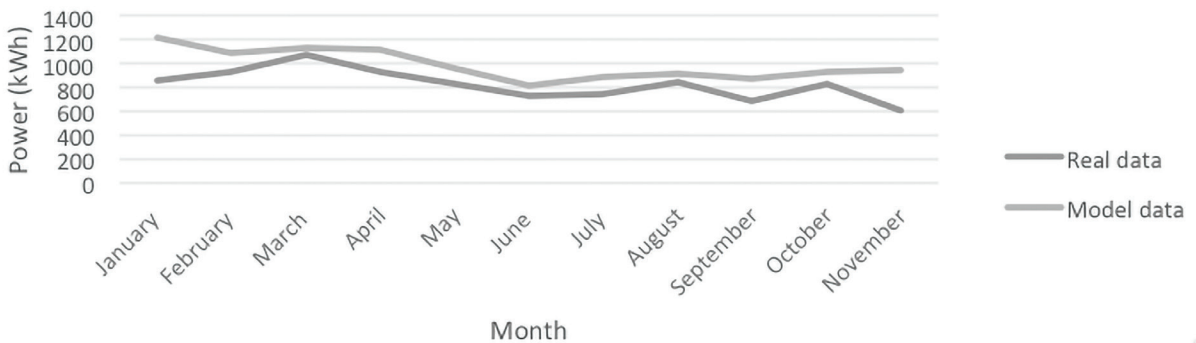
**Figure 6.** On-site PV power generation in a clear sky day.



**Figure 7.** On-site PV power generation in a cloudy sky day.

**Table 5.** Data obtained and simulated of a system with 28 micro inverters.

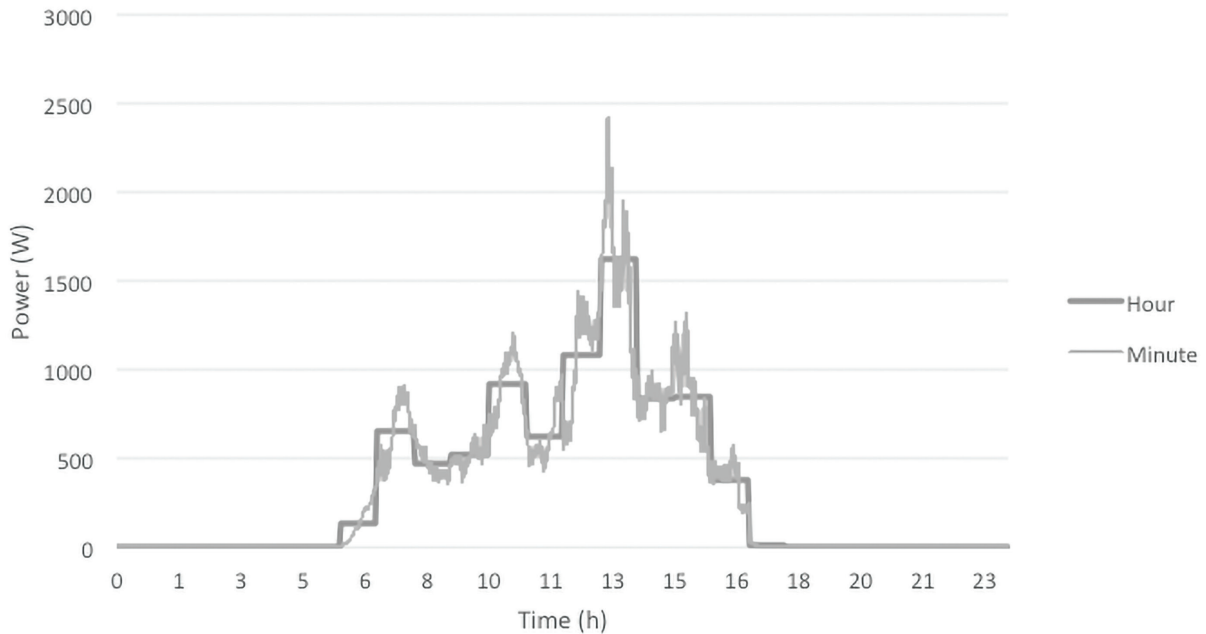
Month	Real Data (kWh)	Model Data (kWh) with losses	Error %
January	855,444	1212,976	-0,418
February	937,339	1091,07	-0,164
March	1071,717	1125,007	-0,041
April	929,943	1119,206	-0,204
May	828,573	956,56	-0,155
June	729,022	812,2439	-0,114
July	741,472	882,1547	-0,181
August	842,333	919,3702	-0,091
September	692,273	868,0928	-0,254
October	825,076	932,012	-0,121
November	607,608	939,359	-0,546
December	-	-	-
Total	9060,8	10858,05	-0,198



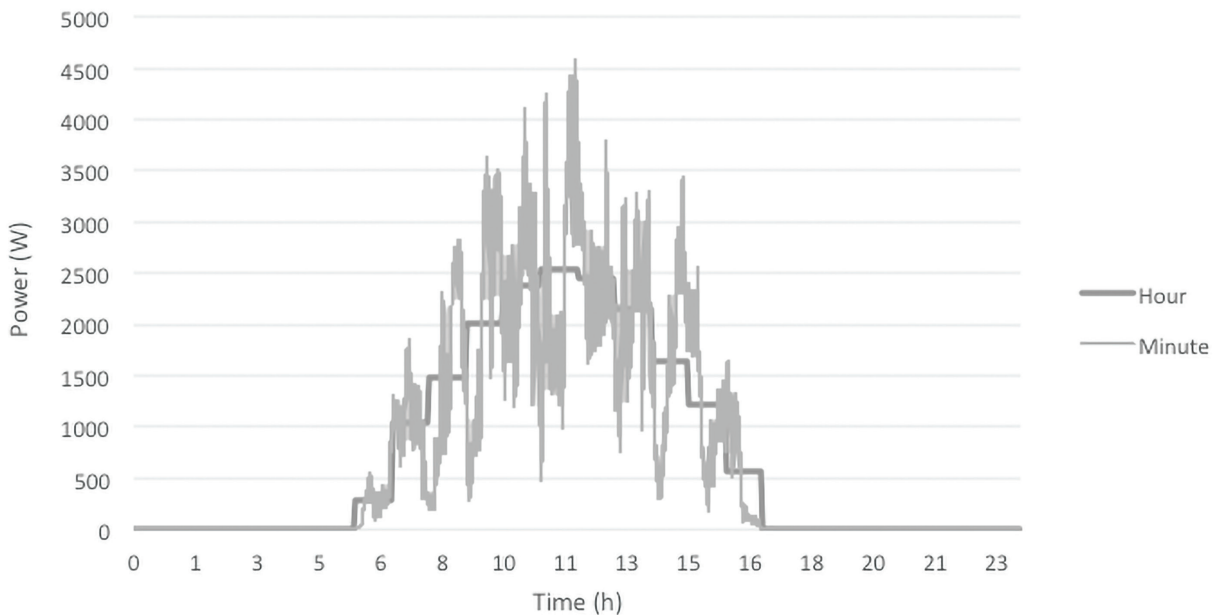
**Figure 8.** System of 28 micro inverters annual profile.



The following figures were formulated using simulated data with the characteristics of the system with 28 micro inverters, to appreciate the difference between minute resolution and hour resolution.



**Figure 9.** Daily profile of the system at hourly and minute step in a cloudy sky day.

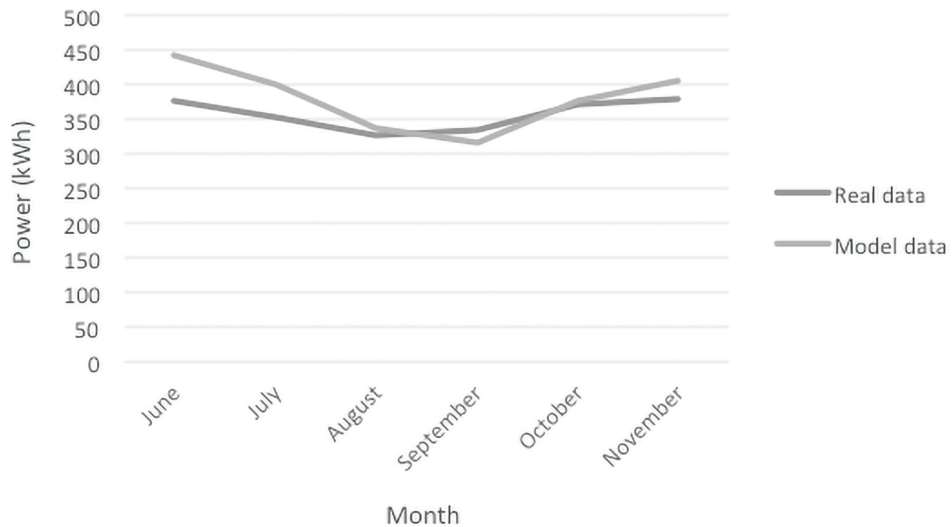


**Figure 10.** Daily profile of the system at hourly and minute step in a partially cloudy sky day.

## Dwelling power demand simulated data

**Table 6.** Obtained and simulated data of one of the houses in study.

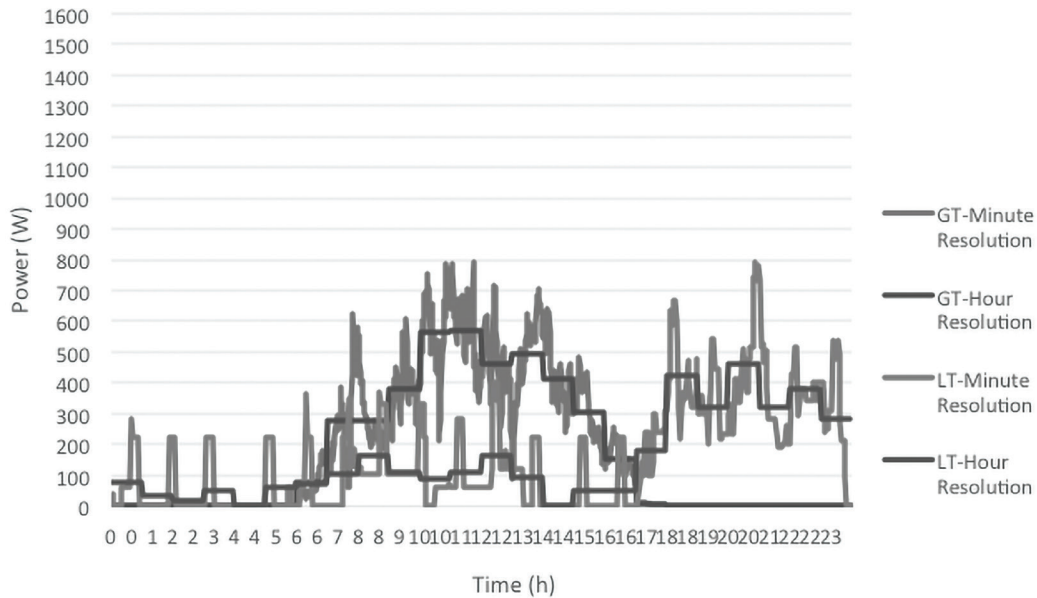
Month	Real Data (kWh)	Model Data (kWh)	Error %
May	377	441,696	-17,161
June	353	399,554	-13,188
July	327	338,154	-3,411
August	336	316,166	5,903
September	373	376,743	-1,003
October	379	406,428	-7,237



**Figure 11.** Annual profile of the house in study.

## Matching energy indexes results

The following graph was generated using the created programs. It shows results of the month of March, which correspond to the Dry Season in Costa Rica.



**Figure 12.** Electricity consumption profile,  $L(t)$  and on-site generation profile,  $G(t)$  of a sample in a dry season day with cloudy sky.

**Table 7.** 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	0.12784769	0.3903732	0.08888717	0.5609696	0.07608281	0.63313091
Hour Resolution	0.14104592	0.43019822	0.12370878	0.77986914	0.10488435	0.87184366
Daily	0.32786263	1	0.15862761	1	0.12030178	1

### Concluding discussion

The results showed above, shows the accuracy in the validation of the models and therefore, the precise results that the computed models can provide. Nevertheless a number of different refinements can be performed. By this, more extensive data on appliances, more division of household categories, incorporated precise and high-resolution data of Costa Rican inhabitants behavior, etc. can improve the dwelling energy demand model. Likewise, incorporations for the PV power on-site model can comprehend: data of total irradiance of the exact localization of the projects and all the different roof angles that the PV modules can have.

For analyzing the matching capability the OEF and OEM indexes were calculated. The OEF represents how much of the demand is covered with the energy produced by the PVs and OEM represents how much of the energy produced by the PVs is used to meet demand, both with values 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.

The OEF can never have the value of 1, because the PVs can only cover existing demand at daylight. Therefore, 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; if all analyzes 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 can not 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. Which means, that even if there is little production of power, most of it is consumed. As well, that's 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. 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.

The importance of working with high-resolution profiles relies on the accuracy and precision of the results. For energy matching, it is ideal to work with instant data. Therefore, using finest data implies obtaining results more accurate.

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