Study of a Smart Energy Community PV and Storage Requirements
A Modeling Approach Towards Net-Zero Energy

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Abstract—**The paradigm of smart energy community refers to a set of households that share a Microgrid and have local renewable production and distributed energy storage. In this context, the main issue is the low dispatchability of the renewable generation, which requires large storage capacities to maximize the degree of self-consumption. A more favorable scenario is found when considering a grid connected system, which reduces the dependence on the stochastic nature of renewable resources, allowing the consumers to import energy from the grid when neither local production nor storage is available. Moreover, the surplus generation could also be injected into the electrical network, having in some cases feed-in tariffs. Thus, this paper aims to present a simulation scenario where the interaction between a Smart Community with high penetration of Photovoltaic generation and the main grid is studied, and how this integration can drive to a net-zero energy system. Results for self-consumption and self-generation indexes are presented for different Photovoltaic power rates and storage capacities, showing that net-zero smart energy communities are a plausible scenario when bidirectional energy flows with the grid are considered.**

Keywords–smart energy community; solar power generation; energy storage; load modeling; net-zero energy buildings.

I. INTRODUCTION

Among all the energy demand, the residential sector represents an average 30% of the total energy consumption in most of the developed countries, showing an upward trend in the last 10-years period with an average growth of about 5% in the European Countries. In parallel with the consumption, the electricity production also presented an average 30% increment from 1990 to 2010, but with a clear decrement of the energy produced from solid fuels (18.8%) and a higher penetration of new renewable sources whose annual average growth rate is currently 7% [1].

However, the strong mutual dependence between the renewable sources production and the weather conditions reduces the operational flexibility and the dispatchability of these generations at utility-scale, and usually requires complex forecasting models and high temporal resolution data in order to assure and planning an uninterruptible power supply within the quality standard requirements [2].

Due to the limitations of renewable resources, the classical concept of a centralized grid is moving forward to a distributed scheme, where the solar, wind or hydro production is not tied to the grid, but to the load or the consumers, creating small subsystems usually referred as Microgrids or Smart Communities. These systems have more control capabilities than a large network, can integrate different types of distributed energy resources (DER), as well as energy storage systems (ESS), and can be either connected or disconnected from the main grid [3].

Nevertheless, the evaluation of the production and storage requirements is the main issue in these networks and it needs a previous knowledge of the electricity demanded by the Microgrid or Smart Community and the available production along the year. Moreover, in the case of DER, both production and demand must be known with a sufficient resolution, especially in solar power system, where the maximum production peak and the maximum power demand are hardly ever coincident [4]. These models, together with the usage of historical data of DER, constitute the main tools for the estimation of the system requirements.

In this field, high-resolution demand modeling techniques have shown the ability to generate detailed consumption profiles. These techniques do not only take into account the seasonality of the consumption, but also predict the daily variations which cause the non-time coincidence between production and demand. In addition, some of these models allow testing future scenarios or energy policies due to their high flexibility [5][6][7].

In addition, the impact of different DER penetration rates has to be quantified in the context of load matching, meaning the evaluation of the interplay between the DER, the consumers' demand and the availability of ESS. In this field, previous work has proposed a set of indexes that study this relationship with different temporal resolutions [8][9].

In this paper, the benefits of high-resolution modeling techniques and the usage of real production data will be addressed in the context of a smart energy community to achieve a net-zero energy interaction during 1 year, but using 1-minute resolution data, so the variations in production and consumption are taken into account.

The paper is structured as following. In Section II, the methodology of the simulation model is discussed, exposing the different parts that made up the simulation system. Section III will provide and discuss the result obtained for the simulation scenario. Finally, Section IV is dedicated to the conclusions obtained from the study and the future works.

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II. METHODOLOGY

In order to study the interaction between the DER, the ESS, the consumers' consumption and the grid, a simulation framework was developed. For this aim, a community composed of 200 households is simulated which share a common low voltage network and a unique feeder and whose different blocks are represented in Figure 1.

Each household is considered to have different AC loads, as well as on–site Photovoltaic (PV) generation and a local home energy storage system (HESS). The PV panels are connected through an unidirectional DC/AC converter to the household network, whereas the home ESS converter is bi-directional. In addition, each home has a bi-directional Smart Electricity Meter to quantify the energy interchanged with the grid.

On the top of this conceptual definition, the DER and HESS of each household are controlled by a centralized Smart Community Energy Management System (SCEMS). The different blocks are explained in the following sections.

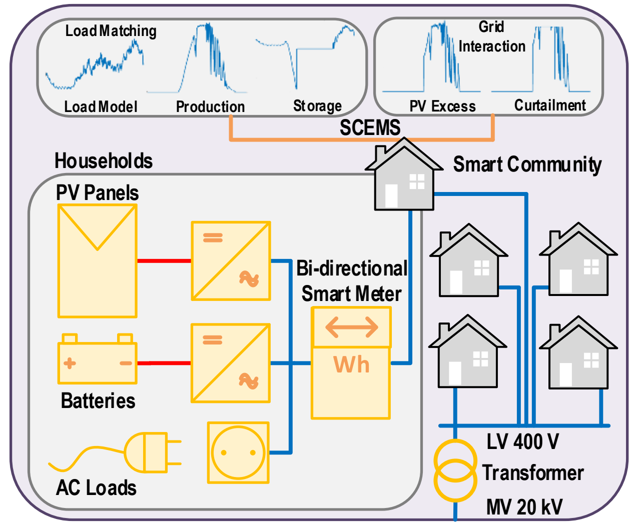

Figure 1. Conceptual Schema of the Smart Community being modeled.

A. Demand Model

The consumption profiles of each home were obtained using a stochastic model based on Markov-Chains probability theory and Monte-Carlo techniques. The model is composed of four algorithmic blocks that estimate the daily occupancy profiles, the lighting system demand, the consumption of home appliances and the energy needs of cooling and heating equipment respectively. The model was developed using the JAVA high-level programming language, and the simulations are requested and accessed through a RESTFul API.

The residents' behavior is the common influence factor in determining the energy consumption, as it has been shown by previous work [10]. Therefore, the lower level block was the one responsible for calculating the daily occupancy profile for a given household. The algorithm has a 10-minutes resolution, and its input parameters comprise the number of residents, the location and the type of day (weekday or weekend).

The occupancy model is based on non-homogeneous Markov-Chains. Therefore, for each 10-minutes instant (144 in a day), the probability transition matrices were calculated. For this aim, the Time Use Survey (TUS) was employed [11]. In this survey, carried out in most European countries, the interviewees wrote down in a diary information about the activities performed during the day, where they took place and whether they were accompanied.

Above this block, and using the generated occupancy profiles as an input dataset, the power demand was calculated applying the three other blocks, each one with specific influence factors and with a 1-minute resolution.

The lighting demand block is influenced by the solar irradiance profile, which determines the hours of the day where it is more likely to have electricity consumption due to the home lighting system. In addition, the lighting spots of the household are randomly selected, based on a probability distribution of lighting technologies and powers. As in the case of the occupancy model, the lighting consumption block has been already validated and published by the authors [5].

In the case of the appliances consumption block, besides the occupancy profile, the daily probability for different activities was taken into account. These activities are: doing the laundry, ironing, cleaning the house, watching the TV, washing and dressing, cooking, and using the PC, and their probability distributions were extracted from TUS. The usage of each home appliance is linked to one of those activities.

Finally, the block that estimates the cooling and heating consumption uses the daily ambient temperature profiles and the annual seasonality as influence factors. In this way, the usage of either cooling or heating systems could be determined during the year, as well as the hours of the day with the higher probability of consuming energy.

B. Production Data

The photovoltaic production was emulated using monitored data, obtained from historical registers of a rooftop PV installation located in Cordova (Cordoba), Spain, during 3 years. The system studied is composed of 3 similar sectors. Each sector has 36 solar modules with a peak power of 165 W, which results in a total peak power of 5,940 W per sector.

At the same time, the sectors are associated with an inverter of 5,000 W. The inverters are capable of monitoring parameters such as the input DC voltage and DC current, global irradiance, output AC voltage and AC current, frequency and power, all of them with a 5-minutes resolution.

The output AC power of each inverter was used for the simulation since it already takes into account both the losses and the efficiency of the system. This variable was linearly scaled using the quotient between the selected PV peak per household and the original one of the installation.

In addition, due to the different temporal resolutions of the historical production data (5-minutes) and the consumption model (1-minute), the output power of the inverter was linearly interpolated. This approximation is fully justified, since the power fluctuations that might be produced by the clouds are much slower.

C. Battery Storage

As it was indicated in Figure 1, each household is also considered to have an attached HESS. For our study, a simplified battery model was selected, whose basic operation is ruled by (1), which represents the charge and discharge process, and whose operative range is denoted in (2).

$$E_B(t) = E_B(t-1) + T \cdot P_B(t) \tag{1}$$

$$E_{B_{min}} < E_B(t) < E_{B_{max}} \tag{2}$$

In this equation, t represents the simulation time in minutes, $E_B(t)$ is the stored energy for each simulation step in Wh, P_B is the instant power applied to or supplied by the storage system in W, and T is the simulation step, selected to be 1 minute, but since E_B is in Wh its value is $1/60$. Regarding (2), $E_{B_{min}}$ is the maximum discharge level sometimes referred as a percentage of the maximum capacity and $E_{B_{max}}$ is the maximum charge threshold.

Both $E_{B_{max}}$ and $E_{B_{min}}$ are the main influence parameters in the simulation, since they will determine the effective capacity of the system. Different technologies will differ in the maximum deep of discharge that can be applied ($E_{B_{min}}$). Moreover, the maximum capacity of the system ($E_{B_{max}}$) could be varied along the years to simulate the aging effect, although in this study, it has not been considered.

It should also be pointed out, that although the battery system seems to be extremely simple, it allow us to represents the basic operation of the ESS as an energy reservoir. Nevertheless, current efforts are focused on the improvement of this model, so performance ratios of different technologies, as well as operation procedures, are included in the model.

D. Evaluation Indexes

The performance of DER for different values of PV power and storage capacities for de HESS were analyzed with a set dimensionless indicators. Two indicators were selected in order to study the variations in the supply utilization, the percentage of self-consumption and the amount of energy that can be injected into the grid.

The first index was the demand cover factor (DCF), which evaluates the percentage of demand that can be supplied by the PV power installed. The second was the supply cover factor (SCF) that indicates the percentage of utilization of the local generation. These two indicators are well defined in the literature, although different names are given for them [9][8].

Their expressions are indicated in (3) and (4) respectively, where $P_{PV}(t)$ is the instantaneous PV production, $P_B(t)$ is the instantaneous power supplied by ($P_B > 0$) or applied to ($P_B < 0$) the battery, and $P_D(t)$ is the power demand. Therefore, these indexes can be calculated for different periods of time, but using the instantaneous power, so the non-temporal coincidence between production and demand is considered.

$$DCF = \frac{\sum \min\left[P_{PV}(t) + P_B(t), P_D(t)\right]}{\sum P_D(t)} \tag{3}$$

$$SCF = \frac{\sum \min\left[P_{PV}(t) + P_B(t), P_D(t)\right]}{\sum \left(P_{PV}(t) + P_B(t)\right)} \tag{4}$$

E. SCEMS Strategy

The last block of the simulation is the SCEMS, which controls the power interchange between the different units in the system that are the consumer loads, the DER, the HESS and the grid. The interaction defined between the system elements is indicated in Figure 2. It was implemented using MATLAB-SIMULINK environment, so the production data are loaded from a developed database, and the consumption profile obtained using the above-mentioned RESTFul service of the demand consumption model.

$P_{net}(t) = P_{PV}(t) - P_D(t)$
$E_B(t) = E_B(t-1) + T \cdot P_{net}(t)$
if $E_B(t) > E_{B_{max}}$ **then**
  $P_G(t) = E_{B_{max}} - E_B(t)$
  $E_B(t) = E_{B_{max}}$
else if $E_B(t) < E_{B_{min}}$ **then**
  $P_G(t) = E_{B_{min}} - E_B(t)$
  $E_B(t) = E_{B_{min}}$
else
  $P_G(t) = 0$
end if
$P_B(t) = -[P_{net}(t) + P_G(t)] = P_D(t) - P_{PV}(t) - P_G(t)$

Figure 2. Pseudocode of the interaction between the PV generation, the demand, the storage system and the main grid.

The control algorithm aims to maximize the autonomy of the Smart Community, controlling the energy stored in the HESS denoted as $E_B(t)$. Therefore, the distributed storage is charged as soon as the different between PV production and consumption P_{net} is positive, ($P_{net} > 0$) in order to accumulate energy for the non-production period.

This process can continue until the batteries reach their full charge ($E_{B_{max}}$), in this moment, the smart community start to interact with the grid and the production surplus that can not be stored is injected into the grid ($P_G < 0$).

On the other hand, when the available PV production is too low or zero ($P_{net} < 0$), the consumers' demand is supplied by the batteries until they reach the lower operative threshold ($E_{B_{min}}$), in this moment, the energy demanded by the community is imported from the main grid ($P_G > 0$).

After considering the above-exposed cases, the SCEMS strategy determines the instantaneous power supplied by ($P_B > 0$) or applied to ($P_B < 0$) the storage system, that will be such that the net power sum equals zero without taking into account additional losses in the system.

III. Results

Following the previously exposed methodology, a simulation scenario is presented, where the influence of the PV power and the storage capacity on the above-mentioned indexes, according to the SCEMS strategy, in the context of a 200 households community is studied.

The obtained results are shown in Figure 3, where the X-Axis represents the installed PV power peak per household, whereas the Y-Axis indicates either the annual DCF (solid lines) or the annual SCF (dashed lines), calculated with 1-minute resolution during a whole year, using the real production data, and the demand profiles simulated with the exposed model. In addition, the different results for a set of HESS capacities per house are illustrated in different colors.

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Figure 3 depicts that *DCF* (solid lines) increases when the PV power peak increases, whereas the *SCF* (dashed lines) the opposite trend is observed. In contrast, for a given PV power peak, if the capacity of the HESS is increased both the *DCF* and the *SCF* are improved, but not by the same percentage.

Further conclusions can be extracted if the interaction between the *DCF* and the *SCF* is analyzed. Both indexes intersect for a given battery capacity when the PV power peak is variated. In these points, the *SCF* and *DCF* have the same value, which means that the percentage of demand that cannot be covered with the DER and the HESS equals the generation that can be neither consumed nor stored.

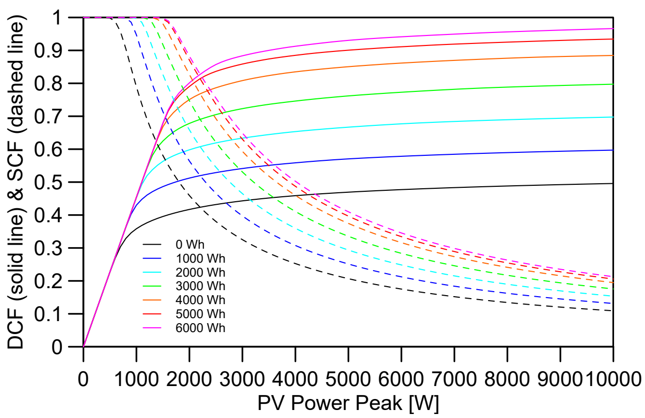

Figure 3. *SCF* (dashed lines) and *DCF* (solid lines) variation with the installed PV power and the storage capacity.

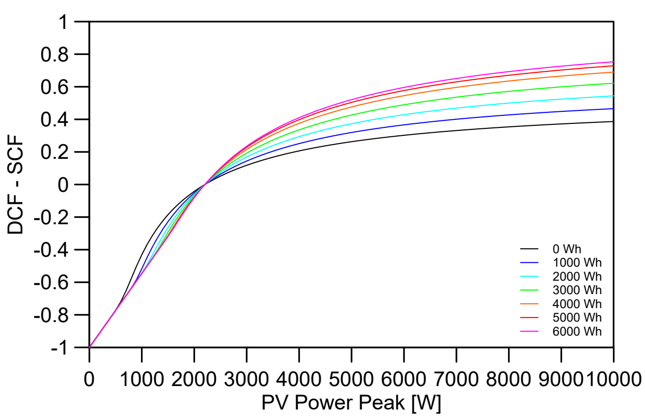

Figure 4. Difference between *DCF* and *SCF*.

However, when the system is considered grid-connected, the excess of generation $(1-SCF)$ could be injected into the grid, whereas the demand that cannot be covered $(1-DCF)$ must be supplied from the main grid. Hence, in this point, the exported and imported energy are similar, and the Smart Community would achieve an annual net-zero energy.

Further conclusions can be extracted if the difference of these both indexes is considered. As illustrated in Figure 4, *DCF*, and *SCF* intersect always for a similar PV power peaks independently of the battery capacity. This can be proved if (3) is divided by (4) and the both terms are multiplied by the time period T, so the power expressions can be transformed into energy units.

$$\frac{DCF}{SCF} = \frac{\sum P_D(t)\cdot T}{\sum (P_{PV}(t)+P_B(t))\cdot T} = \frac{E_D}{E_{PV}+E_B} \qquad (5)$$

In (5), the *DCF* equals the *SCF* if the consumed energy during the day E_D is similar to the energy produced E_{PV} plus the energy exchanged with the storage system E_B. Nevertheless, if the battery is considered to have a cycle per day, the net energy exchanged with the storage system is null and consequently, the intersection of both indexes only depend on the match between generation and consumption.

From (5), it could also be seen that in an ideal context, no battery storage will be necessary to achieve a net-zero energy consumption throughout the year. Nevertheless, in this case, all the produced energy that can be used should be injected to the grid, which in some cases might produce an overload in the existing networks toward the idea of hosting capacity.

If this is achieved, the net energy interchange with the electrical grid will be zero along the year, providing the grid has an infinite capacity, whereas the storage capacity will determine the additional level of the on-site generation that could be later consumed.

IV. Conclusion and Future Work

This paper has presented a comprehensible simulation scenario where the benefits of high temporal resolution models and historical data in the estimation of DER power and HESS requirements of a Smart Community have been shown by means of a set of selected cover indexes, The results have illustrated the possibility of achieving net-zero energy communities if a grid interaction is considered.

More detailed simulation scenarios will be addressed in following works, including parameters, such as the battery performance or the influence of economic factors like feed-in tariffs or variable energy prices. In addition, the system is currently being analyzed in the context of Hosting Capacity, which determines the maximum amount of PV power that can be installed without affecting the quality and reliability of the supply. Regarding this topic, future papers will be published.

Acknowledgment

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