LOAD MATCH OPTIMIZATION OF A RESIDENTIAL BUILDING CASE STUDY: A CROSS-ENTROPY BASED ELECTRICITY STORAGE SIZING ALGORITHM

Francesco Guarino*[1], Pietro Cassarà[2], Sonia Longo[1], Maurizio Cellura[1], Erina Ferro[2]

[1] Università degli studi di Palermo, Dipartimento di energia, ingegneria dell'informazione e modelli matematici. Viale delle scienze edificio 9, 90128 Palermo, Italy

[2] Istituto di Scienza e Tecnologie dell'Informazione – CNR. Via G. Moruzzi 1, 56124 Pisa, Italy

*Corresponding Author. Email: francesco.guarino@unipa.it

Abstract

The EU EPBD recast regulation marked the application of the net zero energy building (Net ZEB) concept in all fields of building construction in Europe as a building able to generate as much energy as it consumes over a selected time frame. A more detailed insight is however needed, as even if a building achieves a long-term energy balance between energy generated and consumed, smaller time scales must also be considered. For example, from the utility's point of view, if a Net ZEB is a heavy consumer in the winter, it will appear to be quite similar to a conventional building, requiring the use of additional generation. The increase in the generation-load match means reducing the stress to the energy grid, the peak system energy required, and the wasted energy, thus avoiding unnecessary generation and, consequently, limiting carbon-related emissions.

In this paper, the authors address the problem of determining the optimal storage size starting from the data of an Italian nearly net zero energy building that produced a detailed database on generated and consumed electricity.

The study presented in this paper analyses the following steps: modelling of energy consumption through non-parametric estimators, modelling of energy generation through detailed models available in the literature, quantification of the load match levels for existing case studies, analysis of the state of charge (SOC) for a given model of the energy consumption probability distribution, and the identification of the minimum size of the storage required to improve energy load match. The results show that even when selecting unfavourable boundary conditions it could be possible to lower the energy import from the electricity grid by approximately 40%.

Nomenclature
LMI stands for load match index
i is the timestep [hours]
G is the generated energy [kWh]
Sd is the stored energy [kWh]
St is the state of charge of the battery [kWh]
C is the consumed energy [kWh]
p is the sampling density
s is the target density
g is the updated sampling density
X is the empirical data vector
pdf is the probability density function
K is a vector of Kernel functions
λ are the weights used in the pdf estimation
St refers to the storage process
ΔS is the function of the storage increment
l is the probability of exceeding the storage capability
$f^C(x)$ and $h^P(x)$ are the initial pdfs of the involved processes
$\hat{f}^C(x)$ *and* $\hat{h}^P(x)$ are the importance sampling pdfs

1. INTRODUCTION

In recent decades, buildings have been considered passive consumers, receiving energy from the electrical grid to cover their own needs. The current trend in the development of residential building points towards a growing integration between energy generation and consumption. In the recent EU EPBD [1] regulation, the application of the concepts of the net zero energy buildings (Net ZEBs) to all fields of building construction in Europe is strongly recommended. The main challenge for Net ZEBs is the inability to provide reliable power on a desired schedule due to the intermittency of renewable energy sources. This problem can be addressed by smart energy grids that can match energy demand and supply on a moment-by-moment basis to maintain grid functionality and stability. As the penetration level of intermittent and non-dispatchable renewable energy increases, the electric grid must rely on other low-carbon methods of balancing supply and demand that require a more refined coordination of diverse resources in space and time.

One principal approach to balancing an electric power system with a high penetration of time-varying renewable resources is energy storage. The storing of excess energy for delivery during periods of lower supply is the most obvious approach to matching the electric demand with the supply because it readily fits into the traditional design philosophy of the grid. A variety of electric storage technologies are known and have been tested on a broad range of scenarios at different time scales, such as seasonally, daily, hourly and second by second. Short-term storage may also be used to improve electric power quality and local reliability.

In the NZEB [2-4] field, even though the zero-energy balance might be fulfilled, other problems may arise. For example, a photovoltaic-driven generation system generates more energy during the day than needed but is inactive during the night, while electrical consumption can occur in the morning as well as in the night. Increasing the load-match between generation and consumption must then be the main target for Net ZEBs, reducing the sizing of storage devices that entail consistent costs for photovoltaic systems. The importance of modelling the consumption is clear[5], additionally considering that an accurate consumption model can be useful for most of the commercially available tools for quantifying energy generation.. A system characterised by a weak load match between generated and consumed energy suffers in terms of energy balance, as low energy load match has repercussions in terms of wasted energy and grid stability. Hence, even for grid-connected buildings, energy storage can be advisable in order to increase the load match. The detailed modelling of a household's energy consumption is a complex task that involves technical skill in different areas. Nevertheless, simulation tools based on stochastic models already exist for energy spent in heating and cooling. In general, we can assert that the study of a consumption model, as well as of the required storage to improve the energy load match, requires a variety of mathematical and technical expertise, ranging from stochastic prediction theory to Markov chain and time series analysis.

In this paper, the authors address the problem of minimising storage, starting from the data of the Leaf House (LH), a case study analysed in [6-8] that produced a detailed database on generated and consumed electricity; by using these data, the load-match for a Net ZEB can be studied.

The core of the paper is to provide a theoretical study to characterise the consumption profile for a building and to develop an algorithm able to identify the minimum storage required to improve the load-match level in the case-study.

The consumption profile for a building can be evaluated through the generalised cross-entropy (GCE) [9] theory, which provides a non-parametric estimation method for the density probability. Through the GCE, the density probability distribution of the consumed energy can be estimated starting from measured data. Roughly speaking, the GCE method provides an iterative procedure that starts from a prior information-less probability distribution and updates this prior distribution step by step with the objective of minimising a risk function. The minimum required storage is evaluated by analysing the state of charge (SOC) of the battery when the estimated consumption distribution probability is taken into account. In this case, the system constituted by the energy generator, the energy consumer and the storage is modelled as a queue with D/G/K, that is, a queue with deterministic arrivals (D), the consumptions distributed with a general shape (G) and storage with finite capacity (K). To study this queue, we propose in this paper a cross-entropy-based simulator (CE).

The study presented in this paper can be summarised as follows:

- Modelling of the energy consumption through non-parametric estimators;
- Modelling of the energy generation through detailed models available in the literature, e.g., [10];
- Quantification of the load match levels for the existing case studies; and
- Analysis of the SOC for a given model of the energy consumption probability distribution and for a given model of the storage.

Finally, in the Numerical Results Section, the authors will show how, through the GCE theory and the CE-based simulator, notable results can be obtained that are useful for the design of the Net ZEBs.

2. STATE OF THE ART

The literature taken into account in this section concerns models available to describe energy consumption, the energy production of photovoltaic systems, the main results of functions linked to energy storage and storage minimisation approaches that already exist to address problems such as load match index optimisation.

The modelling of electricity consumption was approached extensively in the past. Most developed electricity consumption models can be classified as top-down models, bottom-up models and hybrid/statistical-engineering models.

Top-down methodologies [11-13] take into account the data from analyses performed by national energy agencies. These methods are able to classify electricity consumption through data available for a given set of households characterised through predefined features. These methods might assess future trends starting from past ones. As an example, Saha and Stephenson in [14] developed a top-down model for the consumption of the New Zealand, providing models for heating, domestic hot water consumption and cooking consumption based on different sub-models, and the results from each model are added up to obtain the total consumption. The authors used historical data to predict future energy use levels as functions of stock, ownership, appliance ratings and use factors. The prediction developed by the authors was excellent for the 1960s, but in the 1970s, due to changes in home insulation levels, the deviation between monitored and simulated data grew.

Bottom-up methodologies take into account data that come from a small set of samples that are representative of a large group of consumers [15-17]. The results obtained for the reference area can be extended to a larger one through interpolation techniques. These models are often based on very detailed information, energy labelling services, appliances and occupancy modelling. As examples, Widen et al. in [18] proposed a Markov chains model for energy consumption based on the time use data (TUD) information for Sweden. TUD were used to describe occupancy patterns, which allowed evaluating the transition probabilities of their 3-state energy consumption model: outside home, active at home, and passive at home. The model has been developed in the fields of electrical and lighting demand. Widen et al. used detailed modelling of the time use for each occupant. The core of their paper is the mapping of the TUD to occupancy levels. The profiles of energy consumption can be obtained through the use of different occupancy patterns by converting the functions for each appliance.

Ortiz et al. and Guarino et al. in [5, 19] proposed different stochastic models implemented using TRNSYS software [20]. The data available from a national Spanish project were elaborated upon, introducing parameters to adapt them to a transient hourly simulation.

The idea of quantifying the load match between energy generation and consumption and the interaction of the single building with the grid is well-investigated in the literature [2, 21-23], and it can be characterised through a wide set of indicators useful to quantifying different aspects of the problem. Load matching refers to how the local energy generation compares with the building load, while grid interaction refers to the energy exchange between the building and the power grid to which it is connected: those are independent but closely related issues. The main distinction is that load-matching indicators measure the degree of overlap between the production and the load profile (e.g., the percentage of load covered by on-site generation over a period of time), whereas grid interaction indicators take aspects of the unmatched components of generation or load profiles into account.

In [24], the authors used a set of simulated hourly data for an experimental house to test the load match and grid interaction (LMGI) indicators, defined in their work as the amount of local energy generation compared to the building load given the energy exchange between the building and an energy infrastructure, typically, the power grid. Data came from the Bergische Universitat Wuppertal team that participated in the Solar Decathlon Europe competition in 2010. The building is a Net ZEB, using solar energy as the only energy source. There are two PV generator systems that are placed on the roof and on the south facade, with energy production levels of 6.4 kWh and 3.6 kWh, respectively. The system is equipped with a battery with energy capacity of 6 kWh, allowing different uses of the system (e.g., grid connected, stand-alone, and grid-connected with storage). The results show that the LMGI indicators may assess the effect of load management strategies and gauge the flexibility of a building design to respond to variable generation levels, loads and grid conditions. The use of a storage device would allow the load match indicators to double and nearly guarantee the coverage of all energy needs.

In the aforementioned works, the framework of the load match themes is explored as well as the potential implications of using a storage device to improve the performance of the building. There is not, however, a particular focus on the problem of optimal storage sizing to increase the load match.

In the literature, the application of cross-entropy-based techniques to energy optimisation problems is not widespread. However, some applications to probability density estimations are available, as well as some specific optimisation problems applied to energy-related concepts, as will be briefly discussed below.

Moeini et al. [25] proposed a cross-entropy method developed in the context of the maximum likelihood estimation of a three-parameter Weibull distribution. The authors chose an independent normal distribution as the driving distribution for generating solutions, motivated by the availability of fast normal random number generators, and implemented an algorithm that comprised a selection of the starting values for the three Weibull parameters, the generation of a random vector sample distribution and iterations, based on the Kullback-Leibler distance minimisation.

Kantar et al. in [26] applied the cross-entropy method to model the diurnal, monthly, seasonal and annual wind speed distributions. The results prove promising and led the authors to state that such a principle can be used as an alternative to the standard Weibull's probability density function (pdf)based approach.

Selvakumar [27] proposed an application of the cross-entropy theory to a dynamic economic dispatch problem, aiming to schedule the energy generators over the dispatch horizon to meet the forecasted load profile. While doing so, system and generator constraints must be satisfied by means of the solution of an optimisation problem. As conclusions, authors proposed an improved cross-entropy algorithm able to handle the nonconvex solution space of dynamic dispatch problems more effectively than the metaheuristic algorithms described and tested in the paper for comparison.

The stochastic approach to the modelling of residential electricity consumption is a viable approach given that it is able to capture the random nature of the consumption.

The storage sizing problem for electricity has, in the vast majority of cases, been approached in order to guarantee a sufficient number of days of autonomy when the generation was intermittent (e.g., isolated communities powered by renewable energy technologies)[28-30]. Although many studies are available in the literature on the optimisation of storage sizing, they are usually connected to energy planning and optimal distributed energy generation sizing for stand-alone applications [31, 32] or cost optimisation in both the stand-alone and grid-connected applications [33-36].

In this paper, the authors propose to adopt a GCE method to characterise energy consumption and propose an innovative storage sizing algorithm based on pure energy load match considerations. The load match problems were studied in the literature before, but an in-depth analysis of storage sizing optimisation for buildings has not yet received wide attention.

3. METHODS

3.1 The case study

Our goal is to find a method to evaluate the minimum size of the storage necessary to improve load match for a Net ZEB given a consumption distribution and a model of the system. In this case, the system taken into account is the previously mentioned Leaf House (LH), a single house located in S. Angeli di Rosora (Marche, Italy), which is one of the first examples of an Italian nearly net zero energy building. The building contains three floors with two apartments per floor; the flats on the ground and first floors measure 85.39 m^2 each, while the flats on the second floor measure 70.1 m^2 and are used as offices.

As implicit in the NZEB definition, the LH implements features and solutions connected to the bioclimatic and passive design approach. Windows are small on the eastern, northern and western facades (with a wall porosity from 6 to 10%) and larger on the southern facade (with a wall porosity about of 20%) to maximise the solar passive gains during the winter. The southern facade's windows are all shaded; both the balconies and the solar thermal panels shade the larger windows on the south. Note that all windows can be shaded using rolling devices.

The electricity generation in the LH is carried out by a photovoltaic system located on the south face, tilted at 18° with respect to the roof's surface. The peak power of the PV system is approximately 20 kW, the system covers approximately 150 m^2, and each photovoltaic module has a declared efficiency of 12%. A building automation system optimises the energy performance of the LH. For example, the heating, ventilation and air conditioning systems are switched off if the windows are opened, the inlet temperature of the water in the radiant floors is regulated according to the external temperature, and the air flow rate is regulated according to the CO_2 level in each apartment. The monitoring and control of the LH is handled by more than 1,200 devices, including sensors and actuators integrated into the drivers that allow communication between devices and systems. The sensors are classified into three main groups: room sensors (e.g., CO_2 concentration, air temperature, and humidity), thermal plant sensors (e.g., thermal energy meters and water flow meters), and weather station sensors.

The average yearly electricity consumption of the building is approximately 25 MWh. The highest contribution to the electricity use comes from the heat pump, approximately 35%, and lighting and plug loads, 35%, while the pumps, auxiliary loads, and the air handling unit account for the remaining 30% of the total consumption. Figure 1 shows the monthly aggregate energy generation, the energy requested by the loads, and the energy balance for the LH.

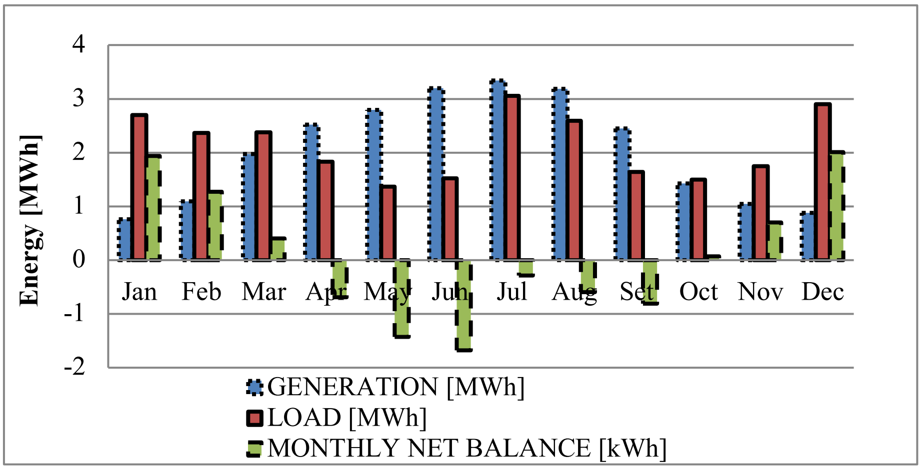

Fig. 1 – Energy Data for the LH Case Study

In order to quantify the load match in the building, several indexes are available in literature, the two most relevant being the load match index and the load cover factor index. The two factors aim towards the description of the same concept but, as described in [37], the load cover factor offers a mathematical formulation more intuitive, it is simpler to use because of the possibility of using average values instead of integrated ones and fits into a framework of other indicators e.g. Supply cover factor, that may give more detailed insights on the concept.

To quantify the load-matching levels for the case study, the load cover factor index (γ_{load}) [2, 24] is calculated as in eq.1. This index describes the matching in the time between the electricity generation and the consumption.

$$\gamma_{load} = \frac{\int_{\tau_1}^{\tau_2} \min[(g(t)\text{-}S(t),l(t)]dt}{\int_{\tau_1}^{\tau_2} l(t)dt} \qquad \text{(eq. 1)}$$

where:

- l is the load [kWh];
- g is the generated energy [kWh];
- S is the energy storage balance [kWh].

A simplified scheme is following, recapping all the terms referenced and the energy flows considered in the case study analysed in Eq.1.

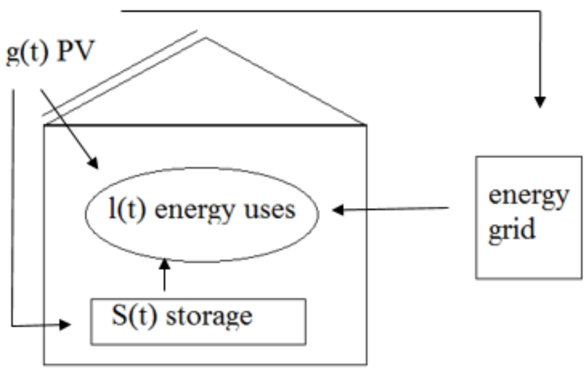

Fig. 2 – Schematic recap of the energy flows

This parameter has a theoretical upper value equal to 1. The importance of the choice of the time quantum is one of the most significant assumptions in the analysis. In fact, small time quanta, such as one hour, allow an accurate analysis of the load-match's fluctuations. In our case study, using a photovoltaic system for energy generation, the γ_{load} could be very variable during the day. Hence, the yearly or monthly average load cover factor could be excessively low for a too-small observation interval.

From the data available for our case study, we determine that the load cover factor may have significantly different values; for example, for an observation time of one hour, the load cover factor is approximately 30%, while for an observation time of one month, it increases to 78%.

3.2 The GCE Algorithm

In this section, the numerical methods used to estimate all the variables and the processes of interest are described.

Two main algorithms based on the idea of cross-entropy (CE) will be introduced; the first is the GCE algorithm with application to the pdf estimation, and the second is a CE algorithm used for the simulation of the system's behaviour modelled through a D/G/ K queue. The GCE algorithm is used to estimate the pdf of the user energy consumption given a set of measured energy consumption over a long-range time period. The CE algorithm is used to simulate the energy storage's behaviour in the time domain and to evaluate the probability of exceeding the maximum storage capacity for given distributions of the energy production and consumption. The known variables for the model are functions about the production of a photovoltaic system with a power peak of 20 kW and the hourly consumption of electricity, which are characterised through data acquired from the monitoring system. The monitored consumption is used in the GCE algorithm, while the generation is used "as-is" for consumption-generation matching considerations and in the CE algorithm.

The GCE method is useful for non-parametric density estimation determining the sparsest model that explains a given set of empirical data while using as few assumptions as possible. The GCE [38] is an iterative method for stochastic optimisation and machine learning applications. The method iteratively updates a given prior sampling density ***p*** on the basis of empirical data; thus, the aim of the algorithm is obtain a better probability ***g*** model for the unknown process that generated the data. Let the target density that solves the simulation optimisation or learning problem be denoted by ***f***, then the prior density ***p*** is updated to ***g*** by using the CE postulate solving the distance minimisation problem between ***g*** and ***f***. Basically, it is assumed that the empirical data are the vector $\mathbf{X} = [X_1 \dots X_m]$, that in the selected case represents the energy consumption; hence, the aim of the model is to extract the pdf of the underlying process by the following considerations:

- The prior pdf, i.e., step ***0*** of the iterative method, of the energy consumption is assumed to be uniform
- The prior pdf ***p*** at step ***i*** has a better probability ***g*** than step ***i-1***, and the estimated target pdf ***f*** is the pdf ***g*** at the last step of the procedure
- It is necessary to minimise the distance between ***g*** and ***p*** step by step, in the CE sense,

$$\min_{g \in G} D(g \to p) \text{ where } G = \{g\colon \int g(x)dx = 1,\ g(x) \geq 0, x \in \mathbb{R}\}$$

- It is necessary to take into account the set of constraints:

$$\int g(x)K_i(x)dx \geq \hat{\kappa}_i = \frac{1}{m-1}\sum_{j \neq i} K_i(X_j) \qquad \text{(eq.2)}$$

$$\int g(x)K_i(x)dx \geq \hat{\kappa}_i = \frac{1}{m-1}\sum_{j \neq i} K_i(X_j) \qquad \text{(eq.3)}$$

where $i=1...m$ is the number of samples of empirical data.

Note that to estimate a better pdf $\boldsymbol{g}$ from empirical data X_j, the GCE method uses a set of kernel functions K_i that in the selected case is a set of Gaussian functions $K_i(X_j) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(X_i-X_j)^2}{2\sigma^2}\right)$.

The optimisation problem stated above can be solved by its dual formulation:

$$(\sigma^*, \boldsymbol{\lambda}^*) = \left\{(\sigma, \boldsymbol{\lambda}) : \mathbf{1}^T\boldsymbol{\lambda}(\sigma) = \boldsymbol{\lambda}(\sigma) = \min_{\boldsymbol{\lambda}\geq\mathbf{0}} \left(\frac{1}{2}\boldsymbol{\lambda}^T\mathbf{C}(\sigma)\boldsymbol{\lambda} - \boldsymbol{\lambda}^T\hat{\boldsymbol{\kappa}}\right)\right\} \quad \text{(eq.4)}$$

which allows to evaluate the weights to calculate the consumption's pdf by the following equation:

$$f(x|\mathbf{X},\sigma) = \sum_{j=1}^{m} \lambda_j K(x, X_j);\ \mathbf{X}=[X_1 \ldots X_m] \quad \text{(eq.5)}$$

The weights λ_j in equation 4 are the Lagrange multipliers obtained through the minimisation problem in equation 3. In this equation, $\boldsymbol{\lambda} = [\lambda_1 \ldots \lambda_m]$, matrix $\mathbf{C}(\sigma)$ is the covariance matrix of the kernel functions, where

$$C_{ij} = \frac{1}{\sqrt{4\pi}\sigma}\exp\left(-\frac{(X_i-X_j)^2}{4\sigma^2}\right) \quad \text{(eq.6)}$$

and $\hat{\boldsymbol{\kappa}} = [\hat{\kappa}_1 \ldots \hat{\kappa}_m]$ is the vector of the estimated mean values of the kernel functions over the measured data, where

$$\hat{\kappa}_i = \frac{1}{m-1}\sum_{j\neq i} K_i(X_j) \quad \text{(eq.7)}$$

Again, in equation 2, it is necessary to estimate parameter σ^*, that is, the bandwidth parameter for each of the kernels. The approach used in the GCE is to obtain a family of solutions of the optimisation problem in equation 2, indexed by σ. Most of the solutions fail to be non-negative functions; out of this set of solutions, we selected one that is a proper pdf and that provides the lowest distance between the empirical and estimated pdfs.

We introduce now the application of the CE algorithm [39] to simulating the energy storage's behaviour in the time domain, and then to evaluate the probability of exceeding the maximum capacity of the storage for given distributions of the energy production and consumption. We assume that the energy storage can be modelled through a G/G/ ∞ queue, so through Lindley's equation we can model the incrementation of the storage over time (eq. 8):

$$S_{t+1} = max\{0, S_t + \Delta S(P_t, C_t)\} \quad \text{(eq. 8)}$$

where S_t is the storage process, and $\Delta S(P_t, C_t)$ is the function of the storage increment as a function of the energy production and energy consumption at time t. In this paper, we assume that the energy production is distributed as registered by the monitored data, while the consumption process follows the distribution $f(x) = \sum_{j=1}^{m} \lambda_j \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{\left(x-x_j\right)^2}{2\sigma^2}}$ estimated through the GCE algorithm discussed in the previous section.

We are interested in estimating the probability $l = \mathbb{P}\{S \geq \gamma\}$ that the energy storage process exceeds the maximum capacity γ, given that the behaviour of the system is observed for a time window length of T. Using the regenerative method, the probability l can be evaluated as

$$l = \frac{\mathbb{E}\left[\sum_{t=1}^{\tau} I_{\{S_t \geq \gamma\}}\right]}{\mathbb{E}[\tau]} \quad \text{(eq.9)}$$

Equation 5 means that probability l can be evaluated as the average number of instants where the maximum capacity γ is exceeded over the mean value of the time over which these instants of time arise, given that the observation window is T.

Taking into account the pdfs of the production and consumption processes and again the regenerative method, probability l can be evaluated per eq. 10:

$$l = \frac{\mathbb{E}\left[\sum_{t=1}^{\tau} I_{\{S_t \geq \gamma\}}\right]}{\mathbb{E}[\tau]} = \frac{\frac{1}{N}\sum_{t=1}^{\tau} I_{\{S_t \geq \gamma\}} W_t}{\mathbb{E}[\tau]} \quad \text{(eq. 10)}$$

Equation 8 allows estimating the average number of instants where the maximum capacity γ is exceeded by the arithmetic mean. Note that to minimise the variance of the estimation, we weigh the sample with the W_t values. These weights are calculated as in Equation 7 through importance sampling (IS) techniques. IS allows finding the change of measure [40] to minimise the variance of the estimation of the probability l, starting from the initial pdfs of the production and consumption processes. In equation 11, $f^C(x)$, $h^P(x)$ are the initial pdfs of the involved processes, while $\hat{f}^C(x)$, $\hat{h}^P(x)$ are the IS pdfs evaluated at each step of the CE algorithm.

$$W_t = W_{t-1} \frac{f^C(x) h^P(x)}{\hat{f}^C(x) \hat{h}^P(x)} \quad \text{(eq. 11)}$$

In the following, the developed CE-based algorithm is shown aiming to evaluate the probability l through the theory behind the equations (7-9).

The authors assume that the observation window of the storage process is the time interval $[0, T]$ and that it is discretised in $T + 1$ intervals of length 1. For each interval of the observation window we need to generate N samples of the storage process. Hence, $N \times (T + 1)$ samples $S_t^n, t = 0 \ldots T; n = 1 \ldots N$ are generated, through equation (3) drawing from $f^C(x)$ and $h^P(x)$ the consumption and production samples for each of the time intervals, respectively. The following scheme summarises the already described process.

Algorithm Probability Estimation of the Storage Exceeding the Theoretical Capacity

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Step 0 $f^C(x) = \sum_{j=1}^{m} \lambda_j \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{\left(x-X_j\right)^2}{2\sigma^2}}$; $\sigma_0 = \sigma_1 = 1$;

For $\boldsymbol{\gamma = \gamma_1 : \gamma_2}$

1. N samples of the storage process for the window time [0…T] are generated

$$\bar{S}^n = [S_0^n \dots S_T^n];\ n = 1 \dots N;$$

2. The set of samples $\bar{S}^n = [S_0^n \dots S_T^n];\ n = 1 \dots N$ are sorted in ascending order

3. For each set of samples $\bar{S}^n, n = 1 \dots N$, the lowest time instant t_n is selected such that the storage sample exceeds the maximum capacity γ

$$\left\{S_{t_1}^1 \dots S_{t_N}^N\right\}$$

4. The IS weights are evaluated for the set of time instants $\{t_1 \dots t_N\}$

$$W_{t_n} = \prod_{i=1}^{t_n} \frac{\sum_{j=1}^{m} \lambda_j \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{\left(X_i^n - X_j\right)^2}{2\sigma_1^2}}}{\sum_{j=1}^{m} \lambda_j \frac{1}{\sqrt{2\pi\sigma_0^2}} e^{-\frac{\left(X_i^n - X_j\right)^2}{2\sigma_0^2}}}$$

5. The parameter of the new $\hat{f}^C(x)$, estimated through IS, is evaluated

$$\sigma_1^2 = \frac{\sum_{n=1}^{N} I_{\left\{S_{t_n}^n \geq \gamma\right\}} W_{t_n} \sum_{i=1}^{t_n} \left(X_i^n - X_j\right)^2}{\sum_{n=1}^{N} I_{\left\{S_{t_n}^n \geq \gamma\right\}} W_{t_n} S_{t_n}^n}$$

6. For each γ, probability *l* is evaluated.

End For

Hence, the algorithm presented above allows estimating the probability that the storage maximum is exceeded for values of maximum capacity between $\boldsymbol{\gamma_1 : \gamma_2}$.

4 RESULTS

4.1 Validation

In this section, the main results relevant to the estimation of the consumptions' pdf and the minimisation of the energy storage are shown.

The estimation of the consumptions' pdf was performed starting from the acquired energy consumption data; the acquisition frequency is 1 sample per hour, for a window time of 1 year. Data are clustered in the range of 0 kWh – 20 kWh with a quantisation step of 1 kWh, and for each class, the occurrence probability has been evaluated. Figure 3 shows the pdf obtained through the acquired data.

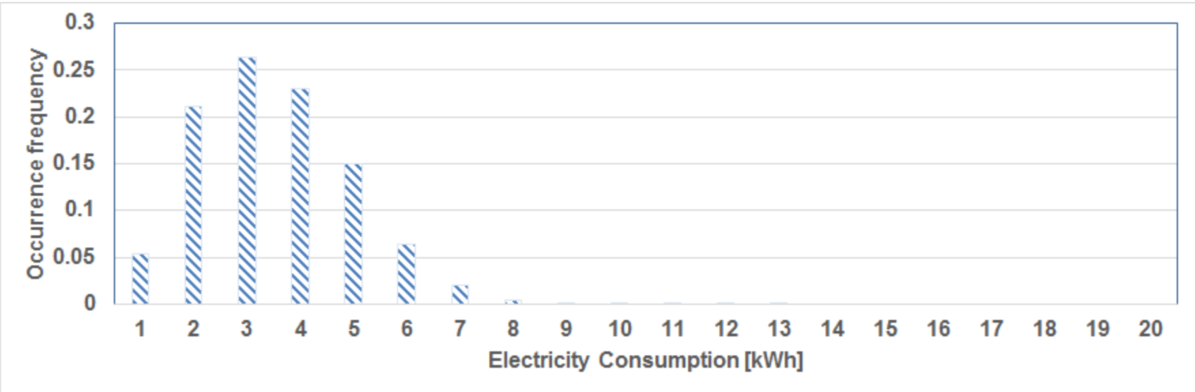

Fig. 3. PDF of the consumption for the LH case study

The pdf obtained by the empirical data is used to verify the exit condition in the procedure to evaluate the σ^* parameter. In fact, σ^* is evaluated by choosing the value that minimises the KL-distance between the empirical and the estimated pdf. Again, the shape of the empirical pdf in Figure 2 clearly shows that the choice of the Gaussian kernel functions is justified for the pdf estimation; we have set the number of samples $m = 100$, the initial value of $\sigma = 0.005$, and the discrepancy of the KL-distance between empirical and estimated pdf $\varepsilon \leq 5\%$. In Figure 4, the comparison between the estimated and empirical pdf is shown. It is clear that the GCE method provides a very reliable estimation of the empirical pdf.

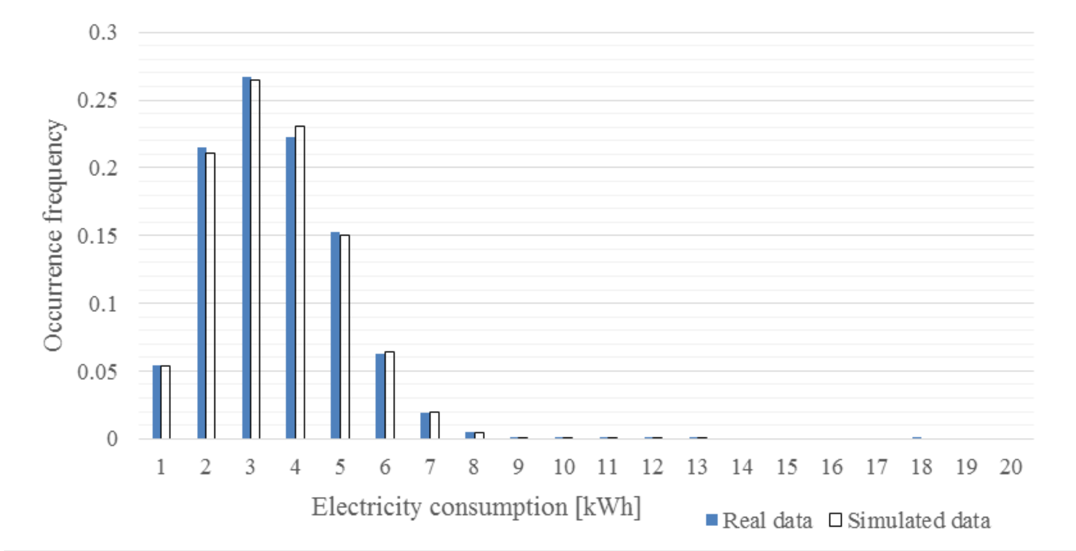

Fig. 4- Comparison between empirical and estimated density

Long-range analysis has been conducted on the empirical data to verify if some type of memory arises on the consumption process; for this reason, Hurst's parameter has been evaluated. In this case, Hurst's parameter, evaluated over the empirical data, is $H = 0.9797$, showing that the process suffers from long-range dependency. The window time taken into account to evaluate the parameter H is 1 year. For this type of process, in order to guarantee the goodness of the estimated pdf, it is enough to verify the accuracy of the estimated pdf and of the second-order statistics of the generated data, such as the cross-covariance. In fact, the cross-covariance allows quantifying the phenomenon of memory of a process and how much it can affect the performance of the system. Figure 5 shows the comparison between the cross-covariance for the data set drawn from the estimated pdf and the cross-covariance evaluated on a set of empirical data; the time window taken into account is one year.

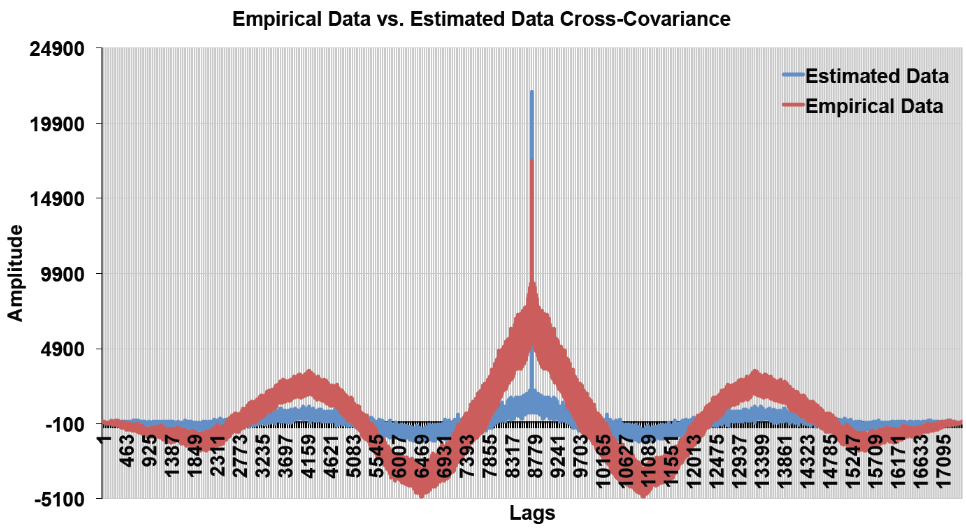

Fig. 5- Cross-Covariance Comparison

The comparison shows that the cross-covariance from the estimated data does not provide a good fit to the cross-covariance evaluated over the empirical data. Even so, the results in the following show that the estimated pdf is suitable for capturing the behaviour of the system because the system is able to mitigate the memory effect due to the energy consumption process. In this case study, we can assert that the energy storage accumulates energy and feeds the loads, independent of the length of the memory inherent in the consumption process.

The model adopted for the storage uses a simplified approach, which is summarised in the following:

1) The storage is viewed as a buffer;

2) The SOC at the n^{th} time point is a function of the SOC, of the generated and consumed energy at the $n-1^{st}$ time point;Charge and discharge processes are linearized, and they are functions of the energy generated and consumed, respectively, at the given time point by using the formulation reported in eq.11

$$st_{(t)} = [st_{(t-1)} + g_{(t)} - l_{(t)}] \qquad \text{(eq.11)}$$

where $st_{(t)}$ and $st_{(t-1)}$ represent two consecutive timestep values of the state of charge of the modeled battery. Boundary conditions are also added to the problem formulation fixing upper and lower boundary of the storage device;

3) Efficiencies are only applied when it has been determined if the net energy flux is mainly a discharge or a charge one. The charge and discharge are modelled with constant efficiency (0.9).

In the following, we investigate whether such a model can capture the general trend in the storage state of charge behaviour and how much it can differ from the real monitored data.

Monitored data are acquired from the real storage system of the LH in terms of SOC, energy consumption, and energy generation. Figure 5 shows an example of the comparison between measured and simulated data for a week in December 2012.

Figure 6 shows that the model adopted for the storage, as well as the estimated pdf of the consumption, accurately fits the analysed processes.

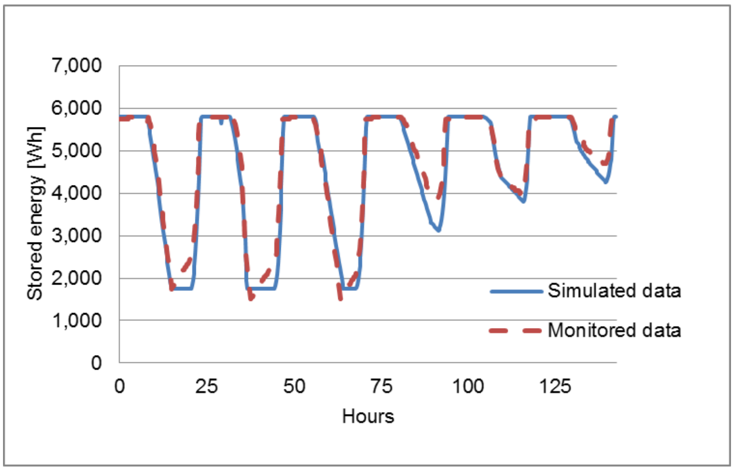

Fig. 6 – Comparison between Weekly Simulated and Measured SOC

A typical daily trend of the charge-discharge cycle for a single day in December is shown in Figure 7, where it is evident that the model captures the general trends of the process.

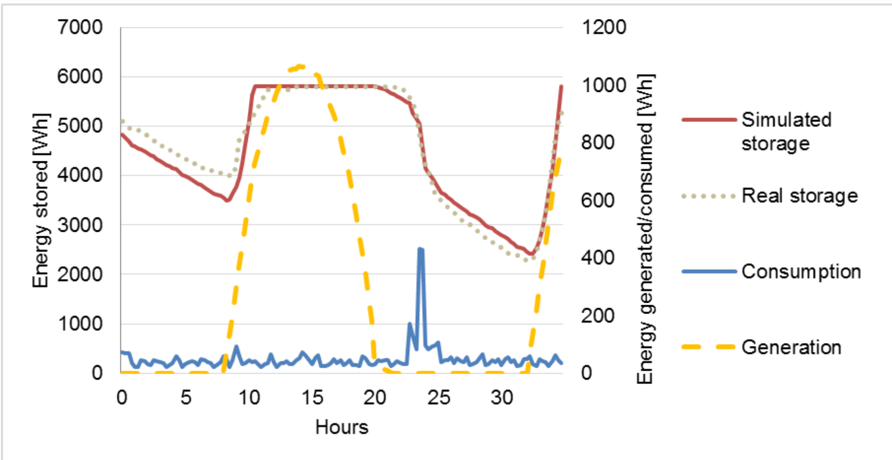

Fig. 7- Daily Trend for the Measured and Simulated Storage

The model is able to follow the real process both during the discharge phase due to the energy consumption and during the charge phase. Note that due to strong consumption during the evening hours between hours 22-25, the slope of the discharge curve is very different from that between the hours 25-30. Thereafter, the charge cycle restarts for the following day.

The performance evaluation of the models discussed above is based on the error analysis of the discrepancy δ_{SOC} between the SOC trend for both the measured and the simulated data. The analysis period is approximately one month, between

December 2012 and January 2013. This period was chosen because it is a nearly flawless data series, registered with no malfunctions in the acquisition system; moreover, the time window is long enough to validate our models. The errors have been normalised with respect to the maximum theoretical energy that can be stored in the real system. For example, if δ_{SOC} is 600 Wh and the maximum storage available is 6 kWh, then the error is $\frac{600}{6000} \times 100 = 10\%$;

Table 1 shows the error between simulated and measured data in the time window taken into account.

	Percentual Error
MIN	0%
10%	0%
25%	2.62%
MEAN	5.97%
75%	9.67%
90%	17.48%
MAX	39.39%

Tab 1 - Error distribution data between measured and simulated SOC

Mean error is around 6% while 75% of the data are below the 10% error threshold. Around 86% of the simulated data are below the 15% error level and only a limited range of data (around 5-6%) is higher than 20%.

Considering the simplified nature of the modelling approach, the main aim of this modelling (that is the testing of the Cross-Entropy algorithm) and that it may be enough to remain between a 10-15% error [41] output in energy simulations according to ASHRAE guidelines, authors claim the errors described acceptable.

The main goal of the algorithm is to evaluate the probability P_{es} of exceeding the maximum storage available for a given profile of energy generation and consumption. P_{es} quantifies the probability that the storage is inadequate to store all the electricity generated that is not consumed on site.

4.2 Load match optimization

Figure 9 shows the main results of the performed analysis, where both P_{es} and γ_{load} are evaluated for values of storage between 1 kWh and 90 kWh, with a step of 5 kWh in a yearly simulation. A complementary trend for the two parameters is observed; in fact, the greater the storage, the greater the load cover factor is, because the storage is able to supply the loads even when the generation is off, while, at the same time, the probability P_{es} decreases because the storage is able to receive more and more energy. As the storage is a costly element of the system, in terms of cost per capacity, maintenance and physical size, it should be as small as possible.

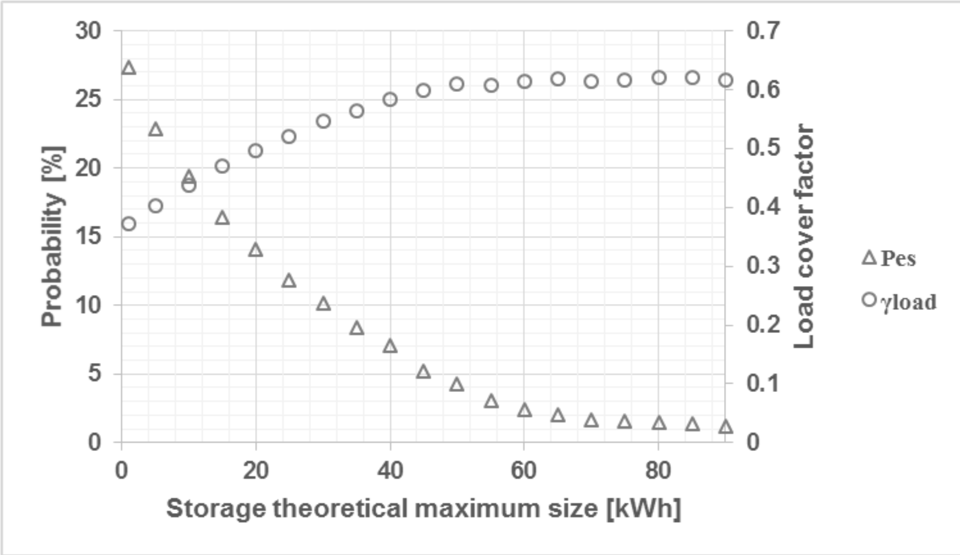

Fig. 8 – γ_{load} and P_{es} Simulations vs. Maximum Storage

For each value of the maximum available storage, the γ_{load} values are calculated on an hourly basis and then averaged. Figure 8 shows that the γ_{load} grows jointly with the storage for the initial values of storage, but after reaching the storage threshold of 45 kWh, the effect of the storage on the γ_{load} is close to zero because the cyclic nature of the photovoltaic generation is made null by the large size of the storage, which works like a fly-wheel for the generated energy.

At the same time, for the P_{es} curve with a storage of 45 kWh, the probability to exceed the maximum storage is equal to 5%, which is an acceptable value for our system, taking into account that the gain for the γ_{load} is very small upon increasing the storage size, whereas the size of the storage, and consequently the price, increases rapidly. Hence, we can assert that our CE algorithm allows efficiently identifying the best minimum size of the storage.

The selected approach is in opposition to most storage sizing techniques, which oversize the storage to guarantee days of autonomy. As discussed in paragraph 2 – Literature review, most of the literature approaches towards electricity storage focus either on cost reduction through optimization approaches or towards stand alone applications. Since economics calculation are not in the scope of the paper, such approaches will not be taken in consideration. As a comparison with all due differences between the two cases. As a figure of comparison with all due differences between the two cases (and considering that for stand-alone applications it would be required to oversize also the PV generator), if the standard stand-alone three days of autonomy [42] storage systems sizing process would be used, the result would yield a nearly 120 kWh theoretical storage system.

The proposed approach instead aims to find the best trade-off between storage size and system efficiency; this approach can be useful during the preliminary design of the building or in the case of retrofitting that heavily relies on on-site renewable energy generation.

Assuming for our LH system a storage capacity of 45 kWh, Figure 9 shows the main energy flows of consumption, generation, state of charge of the storage system, and energy being discharged from storage to be consumed, assuming a time window of 48 hours in February.

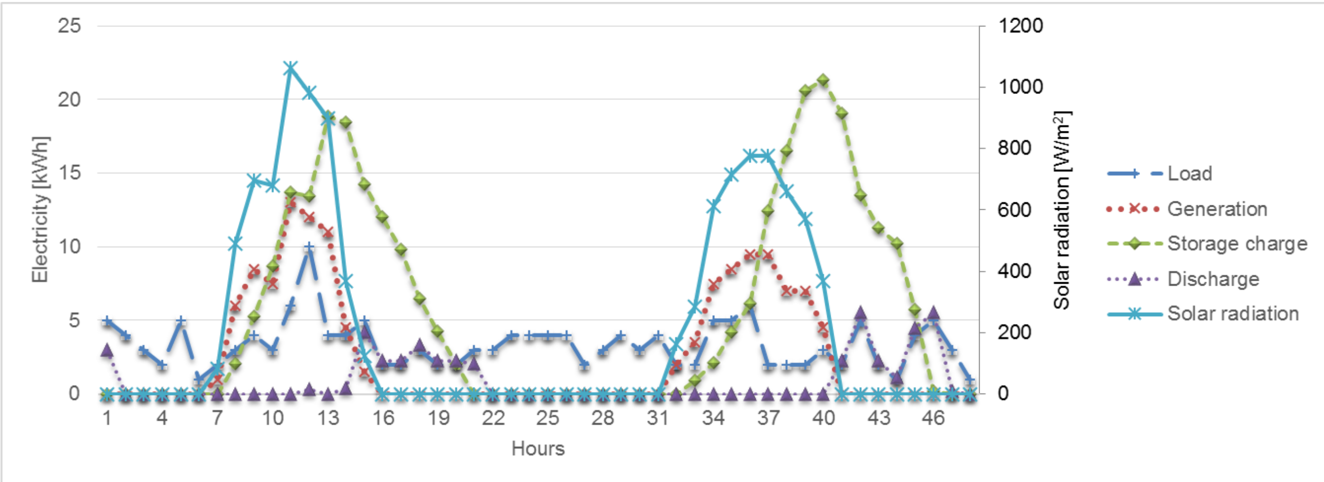

Fig. 9 - Two days profiles of stored energy, consumption and generation

Figure 10 shows the energy required from the grid during the same days, considering both the PV generation alone and the PV generation combined with the storage.

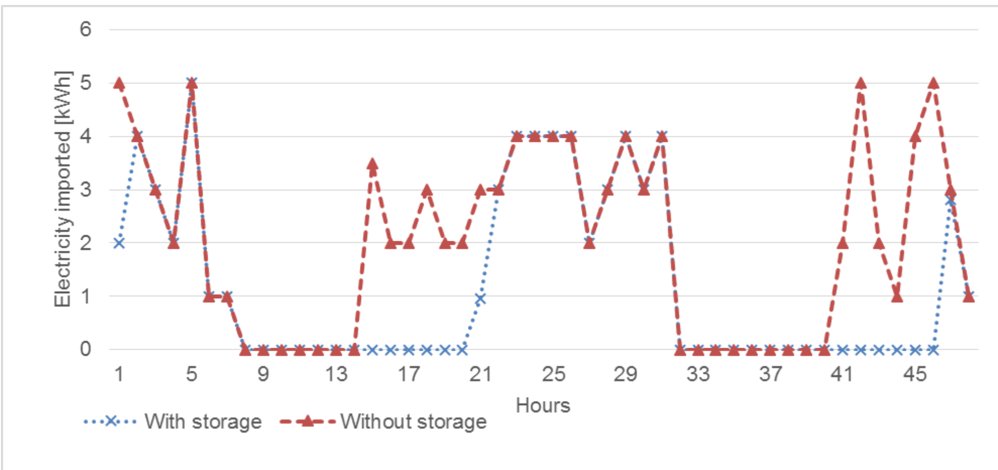

Fig. 10 - Energy required from grid with PV Generation alone and with a combination of PV-Generation and Storage

Although being in the worst condition (winter) and thus not being able to use the maximum storage capacity due to a lower PV production, by using the storage the daily energy request decreases by 40% (38.7 kWh) with respect to when the PV system alone is used. The same approach is followed in Fig.11 and 12, analysing 48 hours in August. The energy import from the grid in summer is particularly clear in Fig.12 where the scenario with storage allows for a 92% reduction of grid energy import.

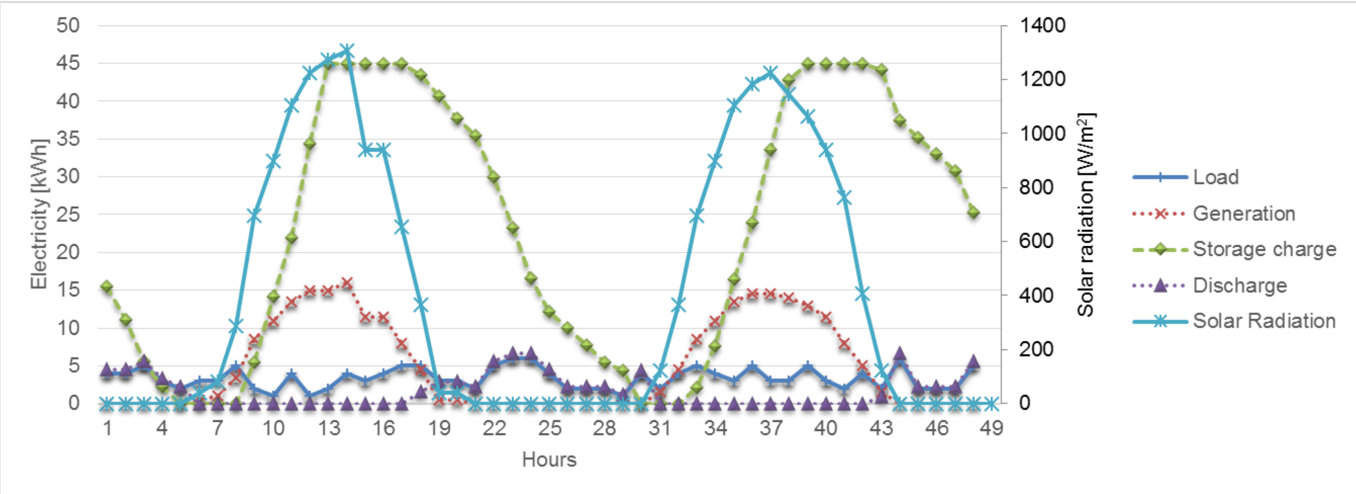

Fig. 11- Two days profiles of stored energy, consumption and generation

Fig. 12 - Energy required from grid with PV Generation alone and with a combination of PV-Generation and Storage

Table 2 recaps the results for Fig. 9-12. The energy imports from the grid avoidable during the analysed summer days reaches the 92% of the total registered.

Tab. 2 – Winter and Summer scenarios recap

	Winter days	Summer days
Energy required from grid (with Storage) [kWh]	57.77	6.50
Energy required from grid (w/o Storage) [kWh]	96.50	81.50
Energy requirements reduction [kWh]	38.73	75
Energy requirements percentage reduction	40.14%	92.02%

A full year simulation is instead described in Tab.3 and in Fig. 13 - 14.

Table 3 lists the overall yearly generation and the grid-imported electricity in the case of the storage simulation and for the simple grid-connected building with no storage systems used.

Tab. 3 – Yearly simulation results

Generation [kWh]	25,651
Imported energy with storage [kWh]	11,369
Imported energy without storage [kWh]	20,029

The reduction of energy import from the grid during the whole year reaches 8,660 kWh and is equal to more than the 43% of the energy import of the scenario without storage.

Fig. 13 describes instead the power required from the grid in both scenarios. The values on the y-axis show the number of hours in which the power required from the grid is the power readable on the x-axis. Data is aggregated with 1 kW step to increase readability, e.g. hours falling under the 3 kW category mean that power requirements is higher than 2 and lower/equal to 3 kW. The use of the selected storage device allows for a reduction of the grid interaction hours of nearly 1,500, while also guaranteeing relevant reductions in the 3-6 kW range of power requirement.

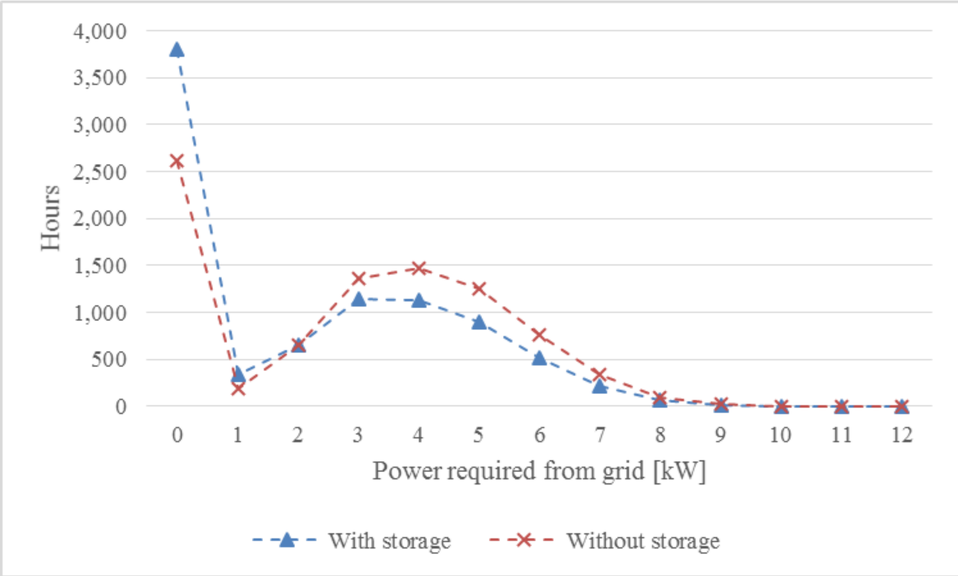

Fig.13 - Power requirements from the grid

Fig.14 shows in detail the monthly aggregation for the electricity import and the relevance of the PV generation increase during the summer months in combination to the possibility of storing that energy to reduce grid interaction.

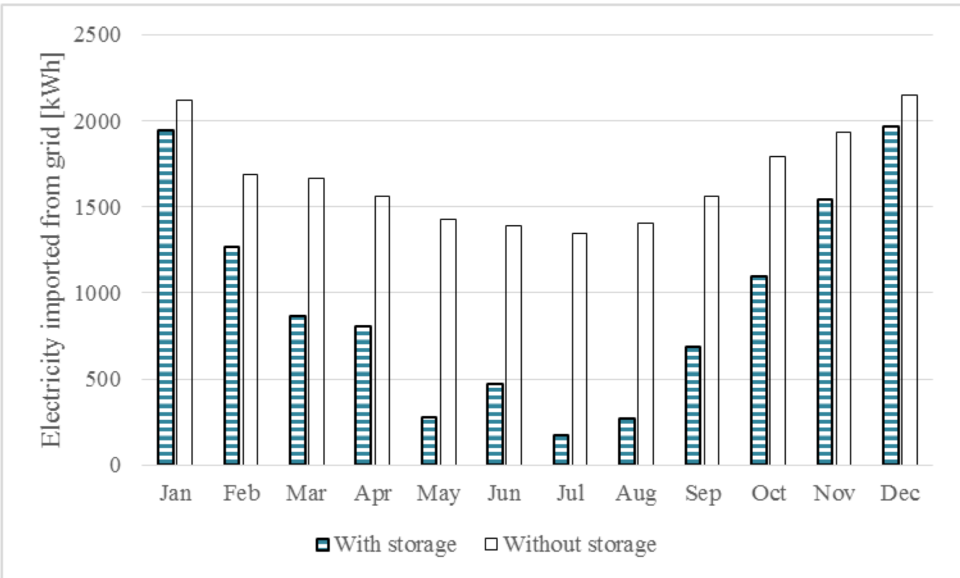

Fig. 14 - Energy required from the grid

5. Discussion

Most design approaches in the sizing of electricity storage devices do not consider the possibility of adopting storage in the case of grid-connected systems. The direct connection of a single building to the energy grid allows, on the one hand, to import energy from the grid when needed and export it as well when generating more than actually needed, but on the other, it allows energy to be wasted if exported during zero-request moments.

From this point of view, there are different aims of the sizing of electrical storage; in the proposed work, the major focus is the optimization of load match of energy demand and generation.

The first step of the results section, describing the general cross-entropy method, shows that the application of such statistical techniques in the field of the determination of probability density of electricity consumption is viable and yields good results.

The storage modelling and optimisation section offer as results parametric curves for both the P_{es}, the probability of exceeding the maximum theoretical storage capacity, and the load cover factor. The trends described in Figure 10 follow a nearly linear trend in the initial section of the curves before transitioning into a horizontal flat line. It is clear that the influence of the storage system is higher for small step increases for lower sizes; the architecture of the energy systems imposes that after a certain limit, the unpredictability and cyclic nature of the photovoltaic generation, its peak power and consumption trends would make any further increase in the sizing of the storage unnecessary.

This is clear P_{es} curve trend that appears to reach a very low sloped curve near zero after 70 kWh. However, it does not reach zero; this means that it would theoretically be possible to increase the energy storage capacity of the system by a further increase of the storage boundaries.

On the other hand, the load cover factor seems to reasonably reach a plateau after the 40 kWh limit storage at a value higher than 60%. This means that even though the storage exceeding probability would continue to decrease in the curve, it would not be by such a vast amount to justify the choice of a larger battery system.

As anticipated in the previous analysis, pure energy considerations might collide with economic reasons; it would not be acceptable to obtain such small gains at the price of doubling the storage capacity. Starting from Fig. 8, it would be a much better solution to size the storage device at approximately 40 kWh of storage capacity, where the load cover factor reaches a near flat plateau; thus any further increase in the storage capacity would yield only limited benefit.

Increasing the load cover factor has implications for the clear reduction of the dependency on the electricity grid and would therefore:

- Reduce wasted energy;
- Reduce transmission losses on the grid side;
- Have significant use phase energy savings for the end user because electricity import would be minor and would be concentrated in the no-generation periods (during the night); and
- On a larger scale, it would help the energy system transition to a distributed energy generation system.

The storage capacity choice that has been made by analysing the trends of the curves presented clearly demonstrates that it would not be convenient to increase the storage capacity for a very limited improvement in the aforementioned parameters. This approach is different from the majority of storage sizing techniques that generally apply oversized generation systems in stand-alone applications to guarantee some days of autonomy.

6. Conclusions

In this work, we propose an innovative approach aimed at proposing a viable method to study the SOC for energy storage through a stochastic approach. This method allows characterising the building consumption, as well as, the size of the energy storage, to guarantee the maximum load-match for NZEBs.

Starting from the data acquired for a case study of NZEBs during a one year test-bed, the energy consumption pdf was estimated by the GCE method, a non-parametric method for the estimation of optimal weights useful for fitting the pdf of the empirical data through a set of kernel functions. The results of the estimated pdf show that the proposed method is able to replicate the empirical data consumption with high accuracy, so we can conclude that such a technique may be extensively applied in the energy sector, which requires statistical analysis and data manipulation in many domains such as residential electricity consumption, climatic analysis of sites, wind frequency analysis, and user behaviour classification.

Using the data consumption drawn from the estimated pdf, the storage analysis has been performed, modelling the storage through a D/G/K queue. Numerical results support our model, so we can claim that the model is detailed enough to be used as a tool for storage analysis.

On the basis of storage analysis and through the CE-based algorithm developed in this paper, authors have evaluated the distribution probability P_{es}, the probability of exceeding the available maximum storage for a given energy production distribution, energy consumption distribution and policy of storage. The probability P_{es} has been evaluated using the objective function load cover factor presented in this paper. Note that our method easily allows the testing of different indicator models. This is a viable approach to performing an optimal sizing of the storage device.; in fact, the results show that by selecting even the most unfavourable conditions, it could be possible to lower the energy import from the electricity grid by approximately 40% in the worst conditions. Standard PV storage sizing methodologies aiming to guarantee days of autonomy to stand-alone systems would nearly suggest three times the storage size required by the proposed approach as checked in the paper: it is therefore required to obtain a trade-off between grid interaction reduction and auto consumption and load cover factor increase.

The main strength of the work is the development of a methodology for appropriately sizing energy storage systems for any energy generation process, energy consumption process and adopted storage policy in grid connected scenarios. The proposed methodology is able to analyse the performance of the system by estimating the distribution or using their analytical models.

The results shown in this paper can be innovative for the field of the energy efficiency, given that the critical point for the newest energy policies is to reduce the stress on the energy grids, peak requests for energy, and wasted energy, thus avoiding unnecessary generation and, consequently, limiting carbon-related emissions.

Acknowledgements

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