Shaping the future energy markets with hybrid multi-microgrids by sequential least squares programming

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Abstract

This paper presents a techno-economic model of two interconnected hybrid microgrids whose electricity– and thermal dispatch strategy are managed with Sequential Least Squares Programming (SLSQP) optimization technique. Microgrids (MGs) combine multiple thermal- and electric power generation, transmission, and distribution systems as a whole, to gain a tight integration of weather-dependent distributed renewable generators with multiple stochastic load profiles. Moreover ~~MGs~~microgrids allow to achieve an improvement in the return of investment and better cost of energy. The first part of the work deals with a method to obtain an accurate prediction of climate variables. This method makes use of Fast Fourier Transform and polynomial regression to manipulate climate datasets issued by the European Centre for Medium-Range Weather Forecasts (ECMWF). The second part of the work is~~is focu~~ focused on the optimization of interconnected MGs operations thru the SLSQP algorithm. The objective is to obtain the best financial performance (IRR)~~s~~ when clean distributed energy resources (DERs) are exchanging both thermal and electric energy. SLSQP optimizes the energy flows by balancing their contribution with their nominal Levelized Cost of Energy (LCOE). The proposed algorithm is used to simulate innovative business scenarios where revenue streams are generated via sales of energy to end users, sell backs and deliveries of demand response services to the other grids. A business case dealing with two MGs providing clean thermal and electric energies to household communities nearby the city of Bremen (Germany) is examined in the last part of the work. This business case with a payback in two years, an internal rate of return at 65% and a levelized cost of energy at 0,14 €/kWh, demonstrates how the interconnection of multiple hybrid microgrids with SLSQP optimization techniques, makes renewable and distributed energy resources outcompeting and could strand investments in fossil fuel generation, shaping the future of clean energy markets.

Keywords: *Distributed Energy Resources, SLSQP, Interconnected Hybrid Microgrids, FFT, IFFT, 3Renewable Energy Systems, Microgrid Optimization, techno-economic assessment.*

1. Introduction

The world is currently facing massive energy- and dramatic environment challenges caused by global warming and increase of energy demand. The —Intergovernmental Panel on Climate Change (IPCC) on December 2019 assessed that human activities have already caused approximately 1.0°C of global warming above pre-industrial levels and a 1.5°C warmer world is likely between 2030 and 2052, if business models and energy policies proceeds as today.

Climate models predict hot extremes in most inhabited regions, heavy precipitation in several regions and the probability of drought and precipitation deficits in some regions. Limiting global warming to 1.5°C is mandatory to reduce increases in ocean temperature, health, livelihoods, food security, water supply, human security, and economic growth. The European Union has defined an ambitious climate and energy framework to support a sustainable low-carbon energy transition with targets and policy objectives until 2030 to realize at least 40% reduction in greenhouse gas emissions as compared to 1990 levels, at least 32% share for renewable energy and at least 32.5% improvement in energy efficiency. Achieving these goals requires– a quick adoption of new technologies and new approaches fostering a tight integration of highly intermittent renewable energy systems (RESs) such as photovoltaic systems and wind turbines, with stochastic loads of residential, commercial and industrial buildings.

A microgrid (MG) is a controllable, independent small energy system comprising distributed generators (DGs), loads, energy storage systems (ESs), and control devices. ~~A~~ The MG is a promising ~~choice~~concept to overcome energy balance issues and thus to secure the energy supply, ~~and improve~~reduce the overall cost of energy generated from alternative energies (i.e. RES).~~ by integrating the whole distributed RESs with generators, energy storage facilities and loads.~~ University campus microgrids, residential, commercial, industrial districts, off-grid users in remote area, not connected to any utility grid, datacenter, telecom-towers are examples of MG applications. This study explores the route of interconnection of optimized MGs that embed a mix of clean thermal- and electric DERs. The main ~~objective~~scope of this work is to analyze their ~~financial~~economic ~~performance~~throughputs when swarmed thermal and electric ~~costs and revenues of~~ energy flows are optimized thru an SLSQP algorithm.

In the first part of this work, different methods to obtain an accurate prediction of climate variables are described. Fast Fourier Transform and polynomial regression to manipulate climate datasets issued by the European Centre for Medium-Range Weather Forecasts (ECMWF) are outlined.

The second part of the work is focused on detailing the analytical techno-economic models (ATE) of the DERs which are embedded in two interconnected microgrids (MG_A, MG_B). In fig. [1] are represented the inner and outer exchanges of thermal, electric energy. Here, the water generated with fuel cell systems is also indicated. This additional 'by product' contributes to the revenues streams.

In the third part, the cost-revenues objective function, the constraints to balance the thermal and electric energy flows and related boundaries associated to the SLSQP algorithm are outlined. The overall framework of the models and their interrelations are depicted in fig.[2].

In the final part of this work, the result of simulation of two microgrids giving thermal and electric energies to neighbouring communities nearby the city of Bremen (Germany) are introduced. The business cases treat revenue streams which are achieved thru sale of energy to end users, sell-backs to the nearby microgrid and the deliveries of demand response services, electricity sell-back to utility grids.—

1.1 Prediction of climate variables

Within the techno-economic model (ATE) of a MG, the accuracy of climate datasets plays an important role for the prediction of power generated by DERs. Thus, at the beginning of this work, We investigated the use of recent monthly daily means datasets covering Earth's areas by latitude and longitude coordinates, which are available from historical archive of ECMWF (European Centre for Medium-Range Weather Forecasts). The periodic components of solar radiation, wind speed, temperature, cloudiness are generated with Fast Fourier Transforms (FFT) and then filtered. These climate datasets are subsequently extrapolated over timeframe of the project, with, inverse FFT (IFFT). Polynomial and forest tree regression methods are also used to correlated coupled of best fitting variables. The spectral transform method has been successfully applied in climate datasets for more than thirty years, with the first spectral model introduced into reanalysis at ECMWF in April 1983 and it performs well. Fourier Transform method was introduced to numerical weather prediction starting from the work of Eliasen et al. (1970) and Orszag (1970) who achieved high efficiency by alternating the computations between a grid-point and a spectral representation at every time-step. Joly and Voldoire, (2009) have developed a method to manipulate gridded datasets with Fast Fourier Transform (FFT) to better understand the coupled ocean–atmosphere processes. Inter-annual variability has been studied by filtering long-term change data in both the observed and simulated time-series. Kent at al. (2013) reanalyzed in situ measurements and satellite retrievals of monthly mean marine wind speeds.

The results have been used to validate the accuracy required in calculation of air–sea heat fluxes. Wang and Zeng (2015) have used observed data to quantify the land surface air temperature, which is one of the fundamental parameters to represent heat transfer and to modulate the moisture cycle between land and atmosphere. Amendola at al. (2017) used FFT to recombine Gaussian distributions of monthly datasets obtained via a neural network for seasonal weather forecasts.

Different approaches have been adopted to convert the monthly mean of solar radiation and wind speed variables into hourly mean time-step of the analytical techno-economic model. For the solar radiation, in this work an empirical model deriving from the literature and validated with experimental results, has been used. The model is based on the work of Liu and Jordan in 1960 and several other researchers, i.e. H. P. Garg at al. (1987) and Jain (1988) who improved the hourly horizontal global radiation with a Gaussian function. The cloudiness effect is then added to the solar radiation with a normal probability density function. The hourly mean average for wind speed is obtained via a normal distribution of the wind speed values at 50 m above the surface of the earth. A global wind speed distribution is obtained from the NASA surface meteorology and solar energy database.

1.2 Electric system operations

The hourly mean climate ~~variables~~datasets are ~~used~~utilized to calculate the renewable thermal- and electric energy generated by wind turbines (WT), photovoltaic panels (PV) and solar thermal collectors (ST) net of losses and actual efficiencies, deriving from the remaining useful life (RUL) under the steady state conditions.

~~Combined heat and power fuel cells~~Combined Heat and Power Proton Exchange Fuel Cell (PEMFC-CHP), diesel gensets (OG), electrolyzers (EC), electric boilers (EBOY), stand alone heat pumps (HP), heat pumps combined with ST (STHP) inverters (INV) thermal (~~ESTH~~TES) and electric energy storage systems (ESS) are additional ~~energy systems~~distributed energy resources contemplated in the ~~MGs~~microgrids' configurations of this work. The techno-economic model keeps updated the states of health of each DG every time-step, in relation to their actual calendar lifetime and lifecycles (number of start-stops, charge/discharge).

Lifecycle and calendar lifetime of lithium ion batteries is modeled with a function having an "Arrhenius-like" form that takes into account for the time, temperature, SOC, and Delta % SOC of the batteries. These models were developed according to the results of test conducted on 18650-size, lithium-ion battery cells by the US Department of Energy in 2001.

The model of thermal- and electric load demands are based on the result of statistical analysis carried on by K. Konstantinos in 2017 with loads of more than 100 households. Additional stochastic virtual load profiles such as load shedding and load shifting are introduced in the techno-economic model. This contribution simulates additional energy services that the MGs can provide as controlled options to respond to unplanned energy flows that occur in the main electric power grid.

A sub-model to simulate the purchase and sellback of electric energy to the main grid is also considered in conjunction with stochastic grid outage events.

1.3 Outline of the proposed optimization strategy

Based on the thermal- and electric distributed energies resources which have been discussed in the previous paragraph, the objective of this ~~paper~~work is to analyze how two interconnected MGs, whose energy flows are governed by the sequential least squares programming (SLSQP) algorithm, improve~~ the quality of energy generated by RES~~ resilience of energy systems embedding RESs~~, increase power resilience~~, reduce the cost of energy, increment IRR while providing electric, thermal energy and water to users and demand response services to the main grid. We remark that enhancement of the energy system resilience is one of the main scope of our SLSQP application and it is obtained with the successful balancing of the constrained energy flows.-

At each time-step, the proposed optimization algorithm, minimizes a nonlinear objective function composed by the difference of two terms: to the first term that groups the costs inherent the generation of energy, the revenues stream (deriving from the use of energy) are subtracted. Costs and revenues are obtained as the product of the average energy flow in the time-step and respectively the nominal LCOE and the levelized sale of energy (LSOE). The estimation of LCOE is based on a simplified model of Department of US Energy 2001.

The revenue streams are generated from contemporary sale of energy to the end users and sale of energy demand response services. Nominal LCOE~~,~~ (Levelized cost of energy) LSOE (~~,~~Levelized sale of energy) sellback prices and remunerations prices (for demand response services) act as weights in the objective function to balance the thermal and electric energy flows. The SLSQP algorithm searches the best contribution of energy flow for each DERs that maximizes the whole economic performance. The calculation is executed, respecting the set of constrains related to thermal and electric power flow under the steady state conditions.

The range of the boundaries of each DERs are dynamically shaped in relation to the available energy they can provide each time-step.

The results given by SLSQP feed a financial model. Maintenance and operational costs (OPEX) are added to the initial investment costs (CAPEX) to obtain the total cost of ownership (TCO). Total revenues, contribution margin, total energy generated, actual LCOE and the following key financial performance indicators are finally calculated: the Net Present Value (NPV) and the Internal Rate of Return (IRR) of the MGs.

Optimizations of electric system operations have been recently the subject of several recent works. S. Wang at al. (2015) proposes an optimization method based on differential evolution for dynamic economic dispatch of a microgrid, considering various distributed generations, energy storage systems, the transaction between the microgrid and power grid, as well as multiple kinds of loads. J. Radosavljević, at al. (2015), proposed an efficient algorithm based on particle swarm optimization (PSO) for energy and operation management (EOM) of a microgrid including different distributed generation units and energy storage devices. PSO minimizes the total energy and operating cost of the microgrid via optimal adjustment of the control variables of the EOM, while satisfying various operating constraints. Owing to the stochastic nature of energy produced from renewable sources, i.e. wind turbines and photovoltaic systems, load uncertainties and market prices, a probabilistic approach in the EOM is proposed.

Soares et al. (2017) have proposed an evolutionary algorithm to offer residential end-users an integrated management of energy resources minimizing the electricity bill while keeping the best possible quality of energy service. Simulation results show that a minimum savings of 10% might be achieved by optimizing load scheduling, local micro-generation, and storage systems including electric vehicles (EVs) in both grid-to-vehicle (G2V) and V2G (vehicle-to-grid) modes. Jamaledini et al. (2018) introduced an evolutionary algorithm based on the multicellular organism mechanism applied to microgrid operations. For optimization, both differential evolution (DE) and PSO algorithms is used for comparison of results.–

More recently (2019), Nagapurkar P. et al. presented a methodology that assessed the techno-economic and environmental performance of microgrid-conventional grid integration scenarios for homes located in US cities. A genetic algorithm optimization technique is implemented to determine the lowest levelized cost of energy for different microgrid-conventional grid integration and carbon taxes scenarios.

Based on the state of art that has been above discussed, this work proposes to extend the analysis at the optimization of interconnected heat and power (hybrid) microgrids through the SLSQP algorithm.

2. Methods of c~~Case study: C~~limate data processing~~sets~~

2.1 Prediction of datasets by Inverse Fast Fourier Transform

Fourier analysis is a method for expressing a function as a sum of periodic components and for recovering the function from those components. Cooley and Tukey (1965) and more recently Press et al. (2007) provided a computing approach to Fourier analysis for discretized counterparts: the Fast Fourier Transform (FFT), attributed to Gauss (1805).

The following reanalyzed monthly mean type of ~~datasets of~~ daily means datasets issued by ECMWF have been considered: ssr[n] (solar net surface radiation), 10si[n] (10 meter wind speed),– t2m[n] (Temperature at 2 meters from soil), tcc[n] (total cloud cover). Here ~~, where~~ the number of months ~~here~~are named 'n' and a sequence of- month: n = ~~are equal to~~ 84 is considered.

With these datasets, ~~We have generated~~ two predictive discrete curves of N_i-dimension: $X_d(n)$ and $X_f(n)$ have been generated. The first set of data has respectively a dimension N_1=72 and it is used to train the IFFT model (January 2010 to December 2015). The second dataset with dimension N_2=12, is used to test the model (June 2017 to June 2018). A one-year timeframe is chosen as it is the typical test period for simulations of microgrids and it is suitable for conversion in hourly solar radiation data (T. Khatib, at al., 2015) as described later in this paper. The following relation:

$$Y_d(k) = \sum_{n=0}^{N-1} e^{-2\pi j \frac{kn}{N}} x_d(n)\,, \qquad [1]$$

transforms the climate datasets array $x_d(n)$ from the time domain to different complex arrays $Y_d(k)$ of K_i-dimension where k is the index of the complex element. A first complex array of K_1-dimension is generated in the frequency domain from the original N_1 dataset. The monthly averages of the original N_1 over a five years period has been used to generate a second complex array of K_2-dimension.

A third complex array is generated from an optimized subset of the original K-complex array thru a low-pass filter (LPF) that iterates until the cut-off frequency. This third optimized complex array has a K_3-dimension. The LPF algorithm minimizes the mean squared error (MSE). As described in the the following function [2], the array in the time domain, $X_p(n)$ obtained with an optimized subset (K_3) of K is compared with the original, until MSE is minimized.

$$\min f(k) = \frac{1}{N_1} \sum_{n=1}^{N} \left(x_d(n) - \frac{1}{P} \sum_{k=0}^{P-1} e^{2\pi j \frac{kn}{P}} y_p(k) \right)^2 . \qquad [2]$$

Here $f(k)$ is the objective function MSE to minimize and ~~N~~K_3 is the dimension of training (original) dataset, $x_d(n)$ is the n-element of training dataset $X_d(n)$, k is the index of the k-element of the complex array, P is the dimension of complex array, $y_p(k)$ is the k-complex element.

The three complex arrays return then, into the time domain by the inverse discrete transform as follows:

$$X_f(n) = \frac{1}{F} \sum_{k=0}^{F-1} e^{2\pi j \frac{kn}{F}} y_f(k)\,. \qquad [3]$$

Here $X_f(n)$ represent the predicted dataset in the time domain of n elements $x_f(n)$. F is the dimension of the best subset of complex arrays, $y_f(k)$ is the k-complex element of the best complex array.

And finally the coefficient of determination named R^2 which estimates the ratio between the square error and the variance is used to compare the performances against the test datasets.

$$R^2 = 1 - \frac{\sum_{n=1}^{N} \left(x_d(n) - x_f(n)\right)^2}{\sum_{n=1}^{N} \left(x_d(n) - \mu_x\right)^2}, \qquad [4]$$

where μ_x denotes the sample mean of the corresponding feature.

2.2 Prediction of datasets by regression models

In the following part of the work we analyzed different regression models to identify interrelations among the four climate variables. The scope was to setup an indirect method to build quickly accurate predicting curves, among best-fitting coupled variable. We utilized exploratory data analysis to identify the presence of outliers, the distribution of the data, and the relationships between the variables, then We created a scatterplot matrix to visualize the pair-wise correlations. In order to quantify the linear relationship between the variable, we proceed to build a correlation matrix embedding the Pearson product-moment covariance coefficients as follows:

$$P_{x,y} = \frac{\sum_{n=1}^{N} \left[\left(x_d(n) - \mu_x\right)\left(y_d(n) - \mu_y\right)\right]}{\left[\sum_{n=1}^{N} \left(x_d(n) - \mu_x\right)^2\right]^{-2} \left[\sum_{n=1}^{N} \left(y_d(n) - \mu_y\right)^2\right]^{-2}}. \qquad [5]$$

Here μ denotes the sample mean of the corresponding variable, $x_d(n)$ and $y_d(n)$ are correlated training datasets. As introduced by S. Raschka (2015) the linear dependence between pairs of variables is strictly related to the value of Pearson coefficient within the range -1 and 1. A perfect positive linear correlation is expressed by $P_{x,y}$ =+1 / -1, while no correlation if $P_{x,y} = 0$. The relationship among monthly climate variables with the Pearson's coefficient higher than 0.7 has been modeled by using: linear, quadratic and cubic polynomials. For variables with a weakest Pearson's coefficient, as proposed by A. Liaw and M. Wienerthe (2002) the random forest method has been used.

This further method allows dividing the continuous regression curve into a sum of linear functions. The decision tree is generated by splitting its nodes until the Information Gain (IG) is maximized ~~as follow~~as follows:

$$IG\left(D_p, x\right) = I\left(D_p\right) - \frac{1}{Np} I, \qquad [5b]$$

where, x is the feature to perform the split, Np is the number of samples in the parent node, I is the impurity function (i.e. MSE), Dp is the subset of training samples in the parent node. The performance of the forest regression is again evaluated with R^2 parameter.

3. Techno-economic models of the distributed energy resource

This section is dedicated to describe all the techno-economic models that are used in the optimization algorithm for the objective function, the boundaries and constrains.

3.1 Photovoltaic Panels

For a PV system, the calculation of the hourly mean power generated, starts with an expression to convert the daily mean solar radiation into hourly solar radiation. The Cooper relation defined in eq. [6], is commonly used to detect the angle between the equatorial plane and a straight line drawn between the centre of the Earth and the centre of the sun for every day of the year. This angle is known as the solar declination, δ. For our present purposes, it may be considered as approximately constant over the course of any one day. If angles north of the equator are considered as positive and south of the equator are considered negative, the solar declination $\delta(n)$, can be described as:

$$\delta(n) = 23.45^{o} \sin\left[360^{0} \cdot \left(\frac{284+n}{365}\right)\right], \tag{6}$$

where n is the number of the day. The standard deviation is then calculated:

$$\sigma_g(n,\theta) = 1.983 - 0.022 \cdot \arccos\left[-\tan\theta \cdot \tan\delta(n)\right], \tag{7}$$

where θ is the latitude.

Finally the normal distribution is calculated as follows:

$$g(t_s,n,\theta) = \frac{1}{k_a \cdot \sigma_g(n,\theta)} e^{-\frac{(t_s - 12)^2}{k_c \cdot \sigma_g(n,\theta)^2}}. \tag{8}$$

In relation [8], t_s represents the time unit for the calculation of mean values expressed in hourly value and k_a and k_c are constants. The choice of a time unit t_s with a step of one hour (referred later in the paper as time-step), permits to express the terms of energy equal to the hourly power average.

The conversion between the mean monthly value and the mean hourly value is done via the following eq. [9]:

$$G(t_s,\theta,\phi) = g(t_s,\theta,n) \cdot H(\theta,\phi,n), \tag{9}$$

where $H(\theta,\phi,n)$ is the daily radiation monthly means returned by equation [3] and ϕ is longitude. These values are delivered for the tilted angle $\beta_o = 0$. Then, the probability density function of the normal distribution, (defined here as $N(\mu,\sigma)$) is used to adjust the hourly radiation with the monthly mean cloudy cover datasets; therefore the final expression of the hourly radiation mean with the cloudy effect can be calculated as follows:

$$G_c(t_s,\theta,\phi) = G(t_s,\theta,\phi) \cdot \left(1 - N\left(\mu\left(t_s,\theta,\phi\right),\sigma\right)\right), \tag{10}$$

where ϕ is the longitude. The random number generator, $N\left(\mu\left(t_s,\theta,\phi\right),\sigma\right)$, returns a uniformly distributed random number within the range $0 \le G_c(t_s,\theta,\phi) \le G(t_s,\theta,\phi)$. Here $\mu\left(t_s,\theta,\phi\right)$ denotes the daily monthly mean cloudiness dataset and σ is standard deviation defined as a constant (e.g. 0.25). The mean hourly radiation with clouds is finally modified with the vegetation by multiplying $v\left(\theta,\phi\right)$ with eq. [11]:

$$G_{vc}(t_s,\theta,\phi) = G_c(t_s,\theta,\phi)\cdot\left(1 - v\left(\theta,\phi\right)\right), \qquad [11]$$

where $v(\theta,\phi)$ assumes only the value '0' , if the vegetation is not present or '1' if the ground is vegetated. The function $G_{vc}(t_s,n,\theta,\phi)$ is then adjusted taking into the account the angle between the horizontal plane and the solar panel which is called the tilt angle. As proposed by A. Luque and S. Hegedus in 2011, the optimal inclination angle, can be obtained with the following linear eq.~~uation~~ [12]:

$$\beta_{\text{opt}} = 3.7 + 0.69\,|\,\phi\,|, \qquad [12]$$

where β and ϕ are given in degree. Thus, with a second-order polynomial equation the ratio between radiation and a different tilt can be described with accuracy ~~as followas~~ follows:

$$g\left(\beta,\beta_{opt}\right) = 1 + p_1\left(\beta-\beta_{opt}\right) + p_2\left(\beta-\beta_{opt}\right)^2 \qquad [13]$$

where, $$\frac{G_c(\beta)}{G_c\left(\beta_{opt}\right)} = g\left(\beta,\beta_{opt}\right). \qquad [14]$$

Hence, the maximum radiation can be calculated, combining the hourly mean radiation with clouds described in eq. [11] which is related to $\beta_o = 0$, to the polynomial e~~E~~q [14]:

$$G_{vc}(t_s,\theta,\phi,\beta_{opt}) = \frac{G_{vc}(t_s,\theta,\phi)}{g\left(\beta_o,\beta_{opt}\right)}. \qquad [15]$$

Eq. [14] can be used again to adjust~~ed~~ the title angle in the radiation ~~as followas~~ follows:

$$G_{vc}(t_s,\theta,\phi,\beta) = G_{vc}(t_s,\theta,\phi,\beta_{opt})\cdot g\left(\beta,\beta_{opt}\right). \qquad [16]$$

The further step is the definition of a model for the temperature which is used in ATE of DGs. The Pearson's coefficient indicates that this variable can be derived from the hourly mean solar radiation via a linear regression model as follows:

$$T_{amb} = w_o + w_1\cdot G_{vc}(t_s,\theta,\phi). \qquad [17]$$

Here the weight w_o represents the y-axis intercept and w_1 is the coefficient of the explanatory variable G_{vc}. Finally, the total available power generated by the photovoltaic panels can be derived from the adjusted hourly radiation, the solar panel yield and the power losses due to temperature, power conditioning (i.e. MPPT), AC/DC cables, shading, snow, dust is described as follows:

$$P_{pv\_available}\left(t_s,\theta,\phi,\beta\right) = \lambda_{st}\cdot G_{vc}(t_s,\theta,\phi,\beta)\cdot\prod_i^N\left(1-\eta_i\right)\cdot A_{pv}, \qquad [18]$$

where: λ_s is the PV solar yield, N is the dimension of the power losses η_i are and A_{pv} is the surface of the PV panel. Also for thermal solar, the total available power generated derives from the hourly net radiation, the solar panel yield and the power losses due to temperature, shading, snow, dust and tilt is described as follows:

$$P_{st\_available}\left(t_s,\theta,\phi,\beta\right) = \eta_{st}\left(\Delta T_{st}\left(t_s,\theta,\phi\right)\right)\cdot G_{vc}(t_s,\theta,\phi,\beta)\cdot\prod_i^N\left(1-\upsilon_i\right)\cdot A_{st}, \qquad [19]$$

$$\eta_{st}\left(\Delta T_{st}\left(t_s,\theta,\phi\right)\right) = \eta_o + k_o\left(T_{in} - T_{amb}\left(t_s,\theta,\phi\right)\right), \qquad [20]$$

eq. 19 is the relation for the thermal solar collector efficiency which has a linear correlation with the difference between the input collector mean (T_{in}) and the environmental temperature (e~~E~~q. [17]) and the terms υ_i represent the power losses while A_{st} is the area of the solar panel.

3.2 Wind Turbines

For this RES, the definition of the techno-economic model starts with the average of wind speed daily mean, here defined as $w\left(t_s,\theta,\phi\right)$, that is converted into an hourly mean dataset by the probability density function of the normal distribution as the following relation.

$$W_s(t_s,\theta,\phi) = \begin{cases} N\left[w\left(t_s,\theta,\phi\right),\sigma_s\left(\theta,\phi\right)\right] \\ 0 \le W_s(t_s,\theta,\phi) \le w\left(t_s,\theta,\phi\right) \end{cases} \qquad [21]$$

The standard deviation $\sigma_s\left(\theta,\phi\right)$ for each geographic location, can be derived from the NASA Surface meteorology and Solar Energy (SSE) database (https://power.larc.nasa.gov). The available power generated by a wind turbine is a function of the hourly mean wind speed and the characteristic curve of wind turbine delivered by the manufacturer that correlates power of the wind turbine to the wind speed. The sum of the losses, η_i caused by the cables, MPPT will be deducted to obtain the available wind power as:

$$P_{wt\_available}\left(t_s,\theta,\phi\right) = P_{wt}\left(W_s(t_s,\theta,\phi)\right)\cdot\prod_i^N\left(1-\eta_i\right). \qquad [22]$$

3.3 Thermal and electric load profiles

Two different profiles of load has been considered: thermal and electrical loads. These loads represents a sum of multiple loads which are powered by the microgrids. The monthly profiles of the thermal loads (P_{th_load}) and electric loads (P_{el_load}) are obtained from the input of minimum and maximum daily mean power (respectively, P_{max}, P_{min}) as follows:

$$P_{a\_load}(m) = \cos\left(\frac{4\pi}{12}m\right)0.5\left(P_{max}-P_{min}\right)+0.5\left(P_{max}+P_{min}\right) \qquad [23]$$

$$P_{b\_load}(m) = \sin\left(\frac{4\pi}{12}m\right)0.5\left(P_{max}-P_{min}\right)+0.5\left(P_{max}+P_{min}\right) \qquad [24]$$

$$P_{el\_load}(m) = \begin{cases} P_{load\_a}(m) & peak\ \ in\ \ first\ \ semester \\ P_{load\_b}(m) & peak\ \ in\ \ second\ \ semester \end{cases} \qquad [25]$$

$$P_{th\_load}(m) = P_{a\_load}(m) + P_{b\_load}(m), \qquad [26]$$

where m denotes the number of the month.

Based on the work done by A.M. Breipohl et al. 1992, the Gauss Markov function, defined in the following eq. [27] with the term "f_{gm}" is used to convert a monthly load profile into a stochastic daily electric load. The mean and standard deviations inside eq. [27] (μ_l, σ_l), are derived from a statistical analysis of electric loads profiles of more than 100 households. This work has been conducted by K. Konstantinos and converted into a library of python programming language in 2017:

$$P_{elst\_load}(t_s) = f_{gm}\left(\left(P_{el\_load}(m), \quad N(\mu_l \quad \sigma_l), \quad t_s\right).\right. \qquad [27]$$

Finally, a stochastic electrical load profile is drawn from a normal distribution in the following eq. [28]. The mean derived from the previous eq. ; while the standard deviation (σ_{noise}) is given as input.

$$P_{el\_load}(t_s) = N(P_{elst\_load}(t_s), \quad \sigma_{noise}). \qquad [28]$$

The thermal load $P_{th}(t_s)$ is defined with the following relation [29] with a similar approach ~~as for~~of eq. [27]. Here two periodic peaks simulate heating in winter and cooling in summer:

$$P_{th\_load}(t_s) = f_{gm}\left(\left(P_{th\_load}(m), \quad N(\mu_l \quad \sigma_l), \quad t_s\right).\right. \qquad [29]$$

Load shedding and load shifting (peak-shaving) are then applied as a controlled option to respond to unplanned electric power underflow. Simulation of a demand response mechanism that makes the load profile less peaky has been introduced to explore in a micro-grid paradigm, the economic benefit of providing energy services. The electric load profile is analyzed per monthly period and the peak hours have their load shifted to low load hours or are shaved. When not shaved, the total load is the same as that one from the original, otherwise it is smaller due to the shaved peaks. The peak load is reduced by a predefined percentage. The electric load profile corresponding to the desired demand response profile is obtained by:

$$P_{eldr\_load}(t_s) = f\left(P_{elst\_load}(t_s), \quad k_{hm} \quad , \quad k_{shifted}\right) \cdot \left(1 - k_{shedding}\right), \qquad [30]$$

where the parameters: $k_{shedding}$, k_{hm}, $k_{shifted}$ express the whole fraction of load to cut, fraction of hours to shift, fraction of energy to shift respectively.

3.4 Energies exchanged among interconnected microgrids

Outflow and inflow energies exchanged among microgrids and the main grid are respectively represented by the following relationship :

$$P_{grid\_sellback,grid\_buy}\left(t_s\right) = N(\left[0,1\right], p) \cdot P_{grid\_sb,grid\_by}\left(t_s\right). \qquad [31]$$

Where the index "grid_sellback" and "grid_buy" represents respectively the outflow energy and inflow energy for each MG and the main grid.

$N(\left[0,1\right], p)$ is a random number generator that returns a sample from the given 1-D array [0,1] to consider grid outage events spread with the probability ~~'~~p~~'~~.

3.5 Thermal and electric distributed generators

Two type of Electric Distributed Generators ($P_{der,j}$) are considered: combined heat and power fuel cell systems and traditional internal combustion electric generators. The mean power they deliver in each time-step (t_s) is defined respectively as: $P_{fc}(t_s)$ and $P_{genset}(t_s)$. On the contrary the mean power absorbed by an electrolyzer to convert electric energy into chemical energy (H_2) is denoted as: $P_{ec}(t_s)$. The efficiency of the conversion from electricity into hydrogen is equal to the energy content (based on the higher heating value) of the hydrogen produced divided by the amount of electricity consumed.

For the thermal generators, the following relations correlate the hourly mean energy produced respectively by electric boilers, heat pumps stand alone and combined to solar panels as follows:

$$P_{eboy}(t_s) = \eta_{eboy} \cdot P_{el\_eboy}(t_s) \qquad [32]$$

$$P_{hp}(t_s) = \eta_{hp} \cdot P_{el\_hp}(t_s) \qquad [33]$$

$$P_{sthp}(t_s) = \eta_{sthp} \cdot P_{el\_sthp}(t_s), \qquad [34]$$

where η represents for each DG the efficiency in the conversion from electric to thermal energy.

A DG is converting the chemical energy of a fuel into electric energy. From the Techno-economic point of view, to the fuel is associated a purchase cost per liter and a transportation cost which are respectively denoted as :C_{fuel}, C_{trp} . The conversion of energy occurs with a certain efficiency ($\eta_{dg,g}$) depending upon the type of DG. For example, in the fuel cell, the efficiency is defined as a ratio between the electricity produced and the hydrogen consumed. The efficiency is related to the performance of the fuel cell stack, the balance of plant and the reformer unit, if installed. The overall costs are then related to the volumetric energy density of the fuel (V_{ed_fuel}).

For heat pumps, the efficiency is denoted by the c~~C~~oefficient o~~O~~f p~~P~~erformance (COP). This term is determined by the ratio between energy usage of the compressor and the amount of useful cooling at the evaporator. For a heat pump a COP value of 4, means that the addition of 1 kW of electric energy is needed to have a release of 4 kW of heat at the condenser.

3.6 Thermal and electric energy storage systems

The techno-economic model of the electric energy storage systems (ESS) and the thermal energy storage system(TES) ~~is~~are defined with a set of equations that describe charging and discharging hourly mean power (energy charged and discharged in the time-step of 1 hour) in relation to *SoC* (State of Charge), *SoH* (State of Health), $P_{ess\_rated\_capacity}$, $P_{ess\_aged\_capacity}$ (rated and aged energy capacity).

The C-rate function, i.e. $C_{ess\_charge\_rate}(t_s)$, is a function of the rate at which the battery is discharged/charged and the maximum capacity. We assume the convention that the energy flows coming out the ES,~~MG~~ are~~is~~ negatives (charging storages, absorptions of loads, sellback to main grid).

$$P_{ess\_aged\_capacity}(t_s) = f\left(P_{ess\_rated\_capacity}, SoH_{ess}(t_s), T_{amb}(t_s)\right) \qquad [35]$$

$$P_{max\_aged\_capacity}(t_s) = P_{ess\_aged\_capacity}(t_s) \cdot SoC_{ess\_max} \tag{36}$$

$$P_{ess\_aged\_charge\_min}(t_s) = \begin{cases} P_{ess\_storage}(t_s) - P_{max\_aged\_capacity}(t_s) \\ P_{ess\_aged\_charge\_min}(t_s) < 0 \end{cases} \tag{37}$$

$$P_{ess\_aged\_charge}(t_s) = \begin{cases} -P_{ess\_aged\_capacity} \cdot C_{ess\_charge\_rate}(t_s) \\ P_{ess\_aged\_charge\_min}(t_s) \leq P_{ess\_aged\_charge}(t_s) \leq 0 \end{cases} \tag{38}$$

$$P_{min\_aged\_capacity}(t_s) = P_{ess\_aged\_capacity}(t_s) \cdot SoC_{ess\_min} \tag{39}$$

$$P_{ess\_aged\_discharge\_max}(t_s) = \begin{cases} P_{ess\_storage}(t_s) - P_{min\_aged\_capacity}(t_s) \\ P_{ess\_aged\_discharge\_max}(t_s) > 0 \end{cases} \tag{40}$$

$$P_{ess\_aged\_discharge}(t_s) = \begin{cases} P_{ess\_aged\_capacity} \cdot C_{ess\_discharge\_rate}(t_s) \\ 0 \leq P_{ess\_aged\_discharge}(t_s) \leq P_{ess\_aged\_discharge\_max}(t_s) \end{cases} \tag{41}$$

Each thermal generator is coupled with a thermal storage (TES~~ESTH~~); the hourly mean power discharge is defined in eq. [43] as the minimum among the discharge rate of the thermal power capacity and the thermal energy storage in the "*i*" tank. Similarly, the hourly mean power charge can be defined as the minimum among the charge rate of the thermal power capacity, the remaining thermal energy storage to fill the "i" tank as described in eq. [45].

$$P_{esth\_aged\_capacity,i}(t_s) = f\left(P_{esth\_rated\_capacity,i}(t_s), SoH_{esth,i}(t_s), \eta_{esth,i}\right) \tag{42}$$

$$P_{esth\_discharge,i}(t_s) = \begin{cases} P_{esth\_aged\_capacity,i}(t_s) \cdot C_{esth\_discharge\_rate,i}(t_s) \\ 0 \leq P_{esth\_discharge,i}(t_s) \leq P_{esth\_storage,i}(t_s) \end{cases} \tag{43}$$

$$P_{esth\_aged\_charge\_min,i}(t_s) = \begin{cases} P_{esth\_storage,i}(t_s) - P_{esth\_aged\_capacity,i}(t_s) \\ P_{esth\_aged\_charge\_min,i}(t_s) < 0 \end{cases} \tag{44}$$

$$P_{esth\_aged\_charge,i}(t_s) = \begin{cases} -P_{esth\_aged\_capacity,i}(t_s) \cdot C_{esth\_charge\_rate,i}(t_s) \\ P_{esth\_aged\_charge\_min,i}(t_s) \leq P_{esth\_aged\_charge,i}(t_s) \leq 0 \end{cases} \tag{45}$$

4.Optimization algorithm and techno-economic model

SLSQP is a sequential least squares programming algorithm that evolved from the least squares solver proposed by Lawson and Hanson in 1974. The optimizer uses the Han–Powell method and the Broyden–Fletcher–Goldfarb–Shanno (BFGS) update of the quasi-Newton Hessian approximation for nonlinear programming (NLP) in the line search algorithm. Dieter Kraft has originally applied in 1988 this algorithm to aerodynamic and robotic trajectory optimization.

The Sequential Least Squares Programming (SLSQP) method minimizes a function of several variables with any combination of bounds, equality- and/or inequality constraints. It can be used to solve linear and nonlinear programming problems to minimize scalar functions. In this work, the off-the-shelf SLSQP optimizer available in SciPy (https://www.scipy.org) has been used. SciPy is a Python-based ecosystem of open-source software for science, and engineering.

In each time-step, SLSQP minimizes a nonlinear objective function that contains costs and revenues, while the thermal and electric power and the interconnected energy flows are balanced. The objective function is the difference between the sum of costs and revenues. The firsts are related to: the energy inflows from DG to the MGs, the energy to generate hydrogen, the purchase of energy from others MG and the main grid and the discharge of storage storages. The revenues are inherent to the electric and thermal load consumptions, the sellback of electricity and heat to other MGs, the generation of water by PEMFC-CHP, the delivery of energy services (load shedding, peak shaving, load shifting), the sellback electricity to the main grid. Costs and revenues are calculated as product between the levelized cost of energy (LCOE), levelized sale of energy (LSOE) and the related energy generated and consumed in each time-step.

LCOEs are the ratio between the initial costs, the nominal operational and maintenance costs along the lifetime of the DER and the whole energy generated during the lifetime. The general expression of the objective function can be summarized ~~as follow~~as follows:

$$f(x) = \sum_{c=1}^{C} LCOE_c \cdot x_c - \sum_{r=1}^{R} LSOE_r \cdot x_r \,. \qquad [46]$$

Where $x_{i,j}$ -is the element of the X-array indicated in [46b]. It represents the energy flows to optimize, ~~-in~~ every time-step~~s-~~ ~~follow~~as followss:

$$X = \left[x_1(t_s)_1, \ldots, x(t_s)_{C,R} \right]. \qquad [46b]$$

The final profitability depends on the assumed values of the X-array~~ in [46b]~~. Therefore the elements of the X-array have to be optimized for obtaining the best profitability. The contribution to the profitability of each single element is detailed in the following paragraph 4.1.

The weights (LCOE, LSOE) direct the SLSQP algorithm to choose the optimal bounded value for every element of X to maximize the right terms ($LSOE \cdot x_r$) while minimizing the left terms ($LCOE \cdot x_c$).

In other words, SLSQP acts to a better counterbalance for the energy flows with the weight mechanism. The highest costs of generation are penalized while on the contrary, the highest revenue streams are prioritized.

The LCOE for each inlet thermal and electric i-DER can be obtained from the definition of LCOE:

$$LCOE_i = \frac{\sum_{j=1}^{n} \frac{C_j + O_j + F_j}{(1+r)^j}}{\sum_{j=1}^{n} \frac{P_j}{(1+r)^j}}, \qquad [47]$$

where:

C_j are the investment expenditures in year j (including financing),O_j are the operations and maintenance expenditures in year j, F_j are the fuel expenditures in year j (only for DG),P_j Electricity generation in year j;

r is the d~~D~~iscount rate– and– n is life of the system expressed in years.

It is relevant to note that while in the objective function, the terms LCOE and LSOE are constants, in the final financial analysis (reported in the following paragraph 4.4), they are computed considering the actual costs and revenues deriving from the former optimization.

4.1 Models of DERs costs

This paragraph draws in details the costs and revenues embedded into the eq. [46].

The mean hourly cost of energy generated by the renewable energy source (RES) is– obtained as:

$$C_{res}\left(t_s\right) = \sum_{i=1}^{M} \frac{\sum_{j=1}^{n} \frac{C_{res,j,i} + O_{res,j,i}}{(1+r)^j}}{\sum_{j=1}^{n} \frac{P_{available,j,i}(t_s,\theta,\phi,\beta)}{(1+r)^j}} \cdot x_{res,i}\left(t_s\right). \qquad [48]$$

Where i is the type of electric RES (PV, WT) and ST.

The general expression of the cost and revenues for the thermal (~~ESTH~~TES) and electric (ESS) energy storages is denoted in the following eq.:

$$V_{es}\left(t_s\right) = \begin{cases} \sum_{t=1}^{T} \frac{\sum_{j=1}^{n} \frac{(C_{es,j,t} + O_{es,j,t})}{(1+r)^j}}{\sum_{j=1}^{n} \frac{P_{es\_rated\_discharge,j,t} \cdot \eta_t}{(1+r)^j}} \cdot x_{es,t}\left(t_s\right) & if \quad x_{es,t} \geq 0 \quad (discharge) \\ \sum_{t=1}^{T} \left[S_t\left(t_s\right) - \frac{\sum_{j=1}^{n} \frac{(C_{es,j,t} + O_{es,j,t})}{(1+r)^j}}{\sum_{j=1}^{n} \frac{P_{es\_rated\_discharge,j,t} \cdot \eta_t}{(1+r)^j}} \right] \cdot x_{es,t}\left(t_s\right) & if \quad x_{es,t} \leq 0 \quad (charge) \end{cases} \qquad [49]$$

The cost contribution of the thermal (EBOY, HP, STHP) and electric Distributed Generators (~~FC~~PEMFC-CHP, O~~D~~G) can be described as follows:

$$C_{dg}\left(t_s\right) = \sum_{g=1}^{G} \frac{\sum_{j=1}^{n} \frac{C_{dg,j,g} + O_{dg,j,g} + \frac{(C_{fuel,j,g} + C_{trp,j,g})}{V_{ed\_fuel,g} \cdot \eta_{dg,g}}}{(1+r)^k}}{\sum_{j=1}^{n} \frac{P_{dg,j,g} \cdot G_t}{(1+r)^j}} \cdot x_{dg,g}\left(t_s\right). \qquad [50]$$

where g is the type of DGs.

The term G_t ,– is correlated to the "products"– that are generated and it assumes a different– value as follows:

$$G_t = \begin{cases} 1 & others \\ 2{,}5 & fuel \quad cell \quad system \quad (electric, \quad heat, \quad water) \end{cases} \qquad [50b]$$

According to the research of K. D. Hristovski *et al.* in 2009 the harvesting water from fuel cells should be considered as a by-product of operation. The overall results of this study indicate that water generated from fuel cells is very pure, with contaminant levels lower than the MCL (Maximum Contaminant Level) values. Typically, a fuel cell is operated at its peak power output, which corresponds to a current density of 1 A/cm2, which results in a ratio of $0{,}5l/kWh$.

The costs and revenues associated to the exchange of electric and thermal energy among micrograds and main grid is represented as follows:

$$V_{grid}\left(t_s\right) = \begin{cases} \left[LCOE_{grid} + \dfrac{\sum_{j=1}^{n} \frac{C_{grid,j} + O_{grid,j}}{(1+r)^j}}{\sum_{j=1}^{n} \frac{P_{grid,j}}{(1+r)^j}} \right] \cdot x_{grid}\left(t_s\right) \;\; if \;\; x_{grid} > 0 \\ \left[LSOE_{grid} - \dfrac{\sum_{j=1}^{n} \frac{C_{grid,j} + O_{grid,j}}{(1+r)^j}}{\sum_{j=1}^{n} \frac{P_{grid,j}}{(1+r)^j}} \right] \cdot x_{grid}\left(t_s\right) \;\; if \;\; x_{grid} < 0 \end{cases} \qquad [51]$$

In the microgrid there are several thermal- and electric loads. They are one of the main sources of the revenue stream. The expression to describe their economic contribution is denoted as follows:

$$R_{load}(t_s) = S_{th}\left(t_s\right) \cdot x_{th\_load}\left(t_s\right) + S_{el}\left(t_s\right) \cdot x_{el\_load}\left(t_s\right). \qquad [52]$$

Where $S_{th}\left(t_s\right)$ and $S_{el}\left(t_s\right)$ are the unit price of the thermal and electric energy sold to the end-user. The subscripts th_load, el_loads are respectively thermal and electric loads.

An additional source of revenues coming from electric loads is the services to the main grid. Electric loads of MG can contribute in the future to balance the main grid by taking part at demand response programs or frequency response markets. The framework of these programs can foresee incentives to users when they provide additional power or reduce their consumptions from the grid at peak periods.

The following equations [53-55] proposes a scheme to calculate a revenues streams issued by grid services (DR) :

$$R_{dra}(t_s) = P_{eldr\_load}(t_s) \cdot S_{eldr}\left(t_s\right) - \left(x_{el\_load}\left(t_s\right) - P_{eldr\_load}(t_s)\right) \cdot C_{dr}\left(t_s\right) \qquad [53]$$

$$R_{drb}(t_s) = x_{el\_load}(t_s) \cdot S_{eldr}\left(t_s\right) - \left(P_{eldr\_load}(t_s) - x_{el\_load}\left(t_s\right)\right) \cdot C_{dr}\left(t_s\right) \qquad [54]$$

$$R_{dr}(t_s) = \begin{cases} R_{dra}(t_s) & if \quad x_{el\_load}\left(t_i\right) \quad > \quad P_{eldr\_load}(t_i) \\ R_{drb}(t_s) & if \quad x_{el\_load}\left(t_i\right) \quad < \quad P_{eldr\_load}(t_i) \end{cases} \qquad [554]$$

Where P_{eldr_load} is the energy demanded by the main grid,– S_{eldr} is the remuneration per kWh for the demand response service while C_{dr} is the penalty for exceeding energy absorbed by the load.

These relations describe possible business scenarios to foster the diffusion of prosumers communities (who consumes and produces energy). EC is a special internal load that absorbs electric energy to convert it into hydrogen, an energy carrier that can be converted later in electric energy. The term η_{he} represents the efficiency in the conversion of electric energy to hydrogen back and forward.–

The contribution in term of revenue streams of the EC is expressed with the following eq. [56]:

$$R_{ec}(t_s) = \left[S_{el}\left(t_s\right) \cdot \eta_{he} - \frac{\sum_{j=1}^{n} \frac{(C_{ec,j} + O_{ec,j})}{(1+r)^j}}{\sum_{j=1}^{n} \frac{P_{ec,j}}{(1+r)^j}} \right] \cdot x_{ec}\left(t_s\right) . \qquad [56]$$

4.2 Objective ~~F~~function and ~~C~~constraints

In this paragraph the terms of the nonlinear objective function indicated in eq. [46] ~~are describedare~~ decomposed and thus the contribution to costs and revenues of each DER is indicated.~~ in details.~~

The overall revenue streams R generated by the thermal, electric load, DR and EC is the following:

$$R\left(t_s\right) = R_{load}(t_s) + R_{ec}(t_s) + R_{dr}(t_s) . \qquad [57]$$

In addition to [57], grids sellback and ES charging functions are further additional contribution to the revenues embedded in the "V" terms of the following eq. [58]. Therefore the objective function indicated in [46] ~~is~~can be expressed~~ in details~~ as follows in eq. [58]:

$$f\left(x\right) = \left[C_{res}\left(t_s\right) + C_{dg}\left(t_s\right) \pm V_{es}\left(t_s\right) \pm V_{grid}\left(t_s\right)\right] \cdot k_c - R\left(t_s\right) \cdot k_r , \qquad [58]$$

where k_c, k_r are parameters to calibrate the weights of the two terms.

The objective function in eq. [58] is solved by keeping balanced the energy flows. Here is assumed the convention that the outer energy flows of each DER and MG are negative. The unequal constrains equations are nonlinear and respectively express the thermal- and electric balances:

$$\begin{cases} \left[g_{el\_der}\left(t_s\right)\right] \cdot k_{der} - \left[g_{el\_load}\left(t_s\right)\right] k_l \geq 0 \\ \left[g_{th\_der}\left(t_s\right)\right] \cdot k_{der} - \left[g_{th\_load}\left(t_s\right)\right] k_l \geq 0 \end{cases} . \qquad [59]$$

These terms are detailed in the following equations [60-63] :

$$g_{el\_der}\left(t_s\right) = \sum_{i=1}^{Me} x_{el\_res,i}\left(t_s\right) + \sum_{i=1}^{Te} x_{ess\_disch,i}\left(t_s\right) + \sum_{i=1}^{Ge} x_{el\_dg,i}\left(t_s\right) + x_{grid\_buy}\left(t_s\right) \qquad [60]$$

$$g_{el\_load}\left(t_s\right) = \frac{\sum_{i=1}^{Ge} x_{th\_dg,i}\left(t_s\right)}{\eta_{dg\_thermal,i}} + x_{el\_load}\left(t_s\right) + x_{grid\_sellback}\left(t_s\right) + \sum_{i=1}^{Te} x_{ess\_ch,i}\left(t_s\right) + x_{ec}\left(t_s\right) \qquad [61]$$

$$g_{th\_der}\left(t_s\right) = \sum_{i=1}^{Mh} x_{th\_res,i}\left(t_s\right) + \sum_{i=1}^{Th} x_{esth\_disch,i}\left(t_s\right) + \sum_{i=1}^{Gh} x_{th\_dg,i}\left(t_s\right) + k_{chp} \cdot x_{fc}\left(t_s\right) \qquad [62]$$

$$g_{th\_load}\left(t_s\right) = x_{th\_load,i}\left(t_s\right) + \sum_{i=1}^{R} x_{esth\_ch,i}\left(t_s\right). \qquad [63]$$

Where *Me, Te, Ge* are respectively a subsets of electric RESs, ESs, DGs, while *Mh, Th, Gh* are respectively a subsets of thermal RESs, ESs, DGs.

The following additional equality constrain is added for both thermal and electric energies, that is exchanged among the interconnected MGs:

$$x_{itc\_i}(t_s) \cdot \left(1 - \eta_{itc}\right) + x_{itc\_j}(t_s) = 0, \quad [64]$$

where η_{itc} are the losses in the MG interconnections.

The elements of the X-array energy flows vary within the boundaries described in the following eq. [65-69]. Their limits are dynamically shaped based on the available mean power that can be calculated with the model defined in the paragraph 3.

$$0 \le x_{res,i}\left(t_s\right) \le P_{res\_available,i}\left(t_s\right) \quad [65]$$

$$0 \le x_{dg,i}\left(t_s\right) \le P_{dg,i}\left(t_s\right) \quad [66]$$

$$P_{es\_aged\_charge,i}\left(t_s\right) \le x_{es,i}\left(t_s\right) \le P_{es\_aged\_discharge,i}\left(t_s\right) \quad [67]$$

$$P_{grid\_sellback}\left(t_s\right) \le x_{grid}\left(t_s\right) \le P_{grid\_buy}\left(t_s\right) \quad [68]$$

$$min(P_{el\_load}(t_s), \quad P_{eldr\_load}(t_s)) \le x_{el\_load,i}\left(t_s\right) \le max\left(P_{el\_load}(t_s), \quad P_{eldr\_load}(t_s)\right) \quad [69]$$

Where with the subscript “i” describes the i-DER.

In conclusion, both constraints and the objective function are nonlinear. These functions are a sum of piecewise-linear convex functions, thus, convex is preserved. We found that the SLSQP optimizer that was specifically designed for NLP, is able to find iteratively in an efficient manner the global solution of our nonlinear constrained convex optimization problem.

4.3 State of Health of DERs.

The optimal configurations of the X-array calculated each time-step by SLSQP, is used to update the States of Healths (SoH). SoH has a relevant role in the calculation of operational costs (OPEX). It is obtained as the ratio among the energy generated until the time-step and the potential energy that can be generated by the DER until the End of Life (EOL). The following eq. [70-77] propose how to estimate SoH of RESs, DGs, and ES in a simplified manner:

$$SoH_{res,i}\left(t_s\right) = min\left(\sum_{h=1}^{s-1} \frac{x_{res,i}\left(t_h\right)}{E_{res\_available\_EOL,i}\left(\theta, \phi\right)}, \sum_{h=1}^{s-1} \frac{h_i\left(t_h\right)}{T_i}\right) \quad [70]$$

$$SoH_{dg,i}\left(t_s\right) = min\left(\sum_{h=1}^{s-1} \frac{x_{dg,i}\left(t_h\right)}{P_{dg,i} \cdot T_i}, \sum_{i=1}^{s-1} \frac{n_i\left(t_h\right)}{N_{cycles,i}}\right) \quad [71]$$

$$SoH_{esth,i}\left(t_s\right) = min\left(\sum_{h=1}^{s-1} \frac{x_{esth,i}\left(t_h\right)}{P_{esth,i} \cdot T_i}, \sum_{h=1}^{s-1} \frac{h_i\left(t_h\right)}{T_i}\right). \quad [72]$$

Where the subscript h is the time-step (one hour), T is the lifetime in hours of each DERs, the term N_{cycles} represents the lifecycles, $n_i(t_h)$ is the n-cycle at the time-step t_i , while $h_i(t_h)$ is cumulative run-hour and $P_{dg,i}$ and $P_{esth,i}$ are the power size of the DER. $E_{res\_available\_EOL,i}$ is the cumulative energy at end of life generable by the RES geo-localized at latitude θ, and longitude ϕ.

The State of health of the lithium battery is composed with two terms: the calendar lifetime and lifecycles. These empirical models proposed by R. B. Wright and C. G. Motloch of DOE in 2001 have been validated with test on commercial 18650 cylindrical cells type with cathodes of LiNiCo, carbon anodes and as electrolyte LiPF6. The results of testing indicate that both the discharge and (R) resistances increased with time at each percentage change (delta%) of the State of Charge (SOC). The magnitude of the discharge and resistance and the rate at which they changed depended on the temperature and delta% of SOC.

T~~T~~he square root of time dependence can be accounted for by either a one-dimensional diffusion type of mechanism type of mechanism, presumably of the lithium ions, or by a parabolic growth mechanism for the growth of a thin film solid electrolyte interface (SEI) layer on the anode and/or cathode.~~,~~

The functional form of the model of the resistances are given by:

$$R(t_s, T_{amb}, SOC_{ess})_{calendar} = \sum_{h=0}^{s-1} \left[a\left(SOC_{ess,h}\right) \cdot e^{\frac{E_{act\_acal}}{RT_{amb}(t_h)}} \cdot \sqrt[2]{t_h} + c\left(SOC_{ess,h}\right) \cdot e^{\frac{E_{act\_ccal}}{RT(t_h)}} \right] \quad [73]$$

$$R(t_s, T_{amb}, SOC_{ess}, \Delta SOC_{ess})_{lifecycle} = \sum_{h=0}^{s-1} \left[a\left(SOC_h, \Delta SOC_{ess,h}\right) \cdot e^{\frac{E_{act\_acy}}{RT_{amb}(t_h)}} \cdot \sqrt[2]{t_h} + c\left(SOC_h, \Delta SOC_{ess,h}\right) \cdot e^{\frac{E_{act\_ccy}}{RT(t_h)}} \right] \quad [74]$$

Where a, c are constants. E_{act_acal}, E_{act_ccal}, E_{act_acy}, E_{act_ccy} are the further constant related to the activation energy. These parameters can be obtained thru characterization tests. ~~T~~T_{amb} is the environment temperature dataset ~~and~~while R is the gas constant and~~.~~ $\Delta SOC_{ess,h}$ is the state- of-charge swing during the cycling.

$$SoH_{ess}\left(t_s\right)_{calendar} = 1 - \frac{R(t_s, T_{amb}, SOC_{ess})_{calendar}}{R_{calendar\_max}} \quad [75]$$

$$SoH_{ess}\left(t_s\right)_{lifecycle} = 1 - \frac{R(t_s, T_{amb}, SOC_{ess}, \Delta SOC_{ess})_{lifecycle}}{R_{lifecycle\_max}}. \quad [76]$$

After the calculation of the above terms, the State of Heath of the lithium battery is defined as follows:

$$SoH_{ess}\left(t_s\right) = min\left(SoH_{ess}\left(t_s\right)_{calendar}, SoH_{ess}\left(t_s\right)_{lifecycle}\right). \quad [77]$$

4.4 The financial models

The State of Health is used to calculate the replacement costs (REPEX), added to operational costs (OPEX), and initial costs to obtain the Total Cost of Ownership (*TCO*). At the end of the calculation of all time-step, the yearly TCO is obtained by the following expression [78]:

$$TCO_t = \sum_{j=1}^{J} \sum_{h=1}^{8760} \left[\left(N_{der,j}\left(t_h\right) + 1 - SoH_j\left(t_h\right) \right) \cdot C_{der,j} + O_{der,j}\left(t_h\right) + \frac{\left(C_{fuel,j}\left(t_h\right) + C_{trp,j}\left(t_h\right)\right)}{V_{ed\_fuel,j} \cdot \eta_{dg,j}} \right] \quad [78]$$

the yearly energy generated (~~E~~E_t), consumed by thermal and electrical loads, and sell-back is given by eq. [79]:

$$E_t = \sum_{j=1}^{J} \sum_{h=1}^{8760} \left[x_{th\_load,j}\left(t_h\right) + x_{el\_load,j}\left(t_h\right) + x_{th\_sellback,j}\left(t_h\right) + x_{el\_sellback,j}\left(t_h\right) \right] . \quad [79]$$

And the yearly revenue stream (R) with:

$$R_t = \sum_{j=1}^{J} \sum_{h=1}^{8760} \left(R_{th\_load,j}\left(t_h\right) + R_{el\_load,j}\left(t_h\right) + R_{th\_sellback,j}\left(t_h\right) + R_{el\_sellback,j}\left(t_h\right) + R_{dr}\left(t_h\right) + R_{water}\left(t_h\right) \right). \quad [80]$$

Where j and J identify the type of DER, h is the index of time-step, N_{der} , C_{der} O_{der} are respectively the replaced number, the capital expenditures, operating expenditures of DG,RES, ES, EC, INV.

After the first year, the time of calculation can be reduced with a one-dimensional polynomial regression to extrapolate *TCO*, *E, R* over the timeframe of the project.

The Return the Internal Rate of Return (*IRR*) is then calculated by solving:

$$\sum_{t=0}^{M} \frac{-\sum_{j=1}^{J} C_{der,j} + R_t}{(1 + irr)^t} = 0 . \quad [81]$$

NPV (Net Present Value) of the cash flow generated during the project is returned by the result of:

$$NPV = \sum_{t=0}^{M-1} \frac{-\sum_{j=1}^{J} C_{der,j} + R_t}{(1 + r)^t} . \quad [82]$$

Where here, t identify the year of the project, M are the total years of the project.

5. Results and discussion

5.1 Manipulation of climate datasets

The techno-economic model and optimization algorithm have been implemented into a p~~P~~ython® script. The FFT-IFFT method, utilized to manipulate original ECMWF datasets of the period from June 2017 to June 2018 has been implemented with the NumPy's, SciPy, Sklearn and Matplotlib libraries.

The reference location for this work is nearby the city of Bremen, with Latitude: 53.0758196 and Longitude: 8.8071646.

Firstly, FFT-IFFT was used to extrapolate a first training dataset based on the original series, a second one based on monthly averages and a third generated with the low pass filter (LPF) cutting off frequencies respectively: 1,16 [Hz] for radiance, cloud cover; 2,83 [Hz] for temperature. The performances of the three training curves, were measured with R^2 index. The low pass filter results the best method to predict the radiance; cloud cover, temperature and wind speed, are best predicted with monthly average datasets.

Then, We verified with the Pearson coefficient the pairwise correlations among variables to use the regression method (~~See~~i.e. f~~F~~ig.[3~~1~~]) in alternative to FFT-IFFT. The best fitting linear correlation is among the radiation and the other climate variables that are characterized by values higher than 0.6 linear.

From Pearson’s relation it is obvious to implement a linear regression model for those variables to reduce the script runtime. The results delivered with linear, quadratic and cubic polynomial regressions as in f~~F~~ig. [4]~~2~~ were evaluated. The R^2 (0.65) equal for all degree of regressions, confirm the strong linear correlation between these coupled variables. A good level of accuracy obtained with the climate datasets has allowed to obtain an equally sound estimation of the energy generated by RES.

5.2 Main inputs of the two interconnected microgrids

This further part of the work concerns two interconnected community microgrids (MG_A, MG_B) located in the reference location of par.[5.1]. In the following example these microgrids offer a way for two neighborhoods, to meet their thermal and electric energy needs.

~~Three different scenarios have been investigated.~~ Power sizes of the clean DERs populating the two MGs are described in ~~Table~~table [1].

Three different scenarios have been investigated. In the first scenario (Interconnected)~~) scenario~~, an optimized combination of DERs is distributed in two interconnected microgrids: in MG “A”, RES and ~~FC~~PEMFC-CHP have a more pronounced role in the generation than the other MG; in MG_B, the main grid (GRID) is the main external source of electric energy. The backbone of the thermal (ITCTH) and electric (ITCEL) interconnections releases significant energy flows between the two microgrids. The DERs configurations of this scenario have been selected among 7000 trials giving the best combination of IRR and LCOE when the operations are managed by the SLSQP algorithm.

In the second scenario (Not_Interconnected), the absence of interconnections is compensated with a larger power size delivered thru the grid utility (GRID) and RES. Also thermal DERs such as ST, EBOY have thermal storages (Tank ST, Tank EBOY) have a markedly higher size than the previous scenario.

In the third scenario (Only main grid), the loads profiles are powered primarily by the grid utility; EBOY convert electric energy into thermal energy combined with a thermal storage. This scenario simulates a typical residential power system of today.

In all these three scenarios, e~~E~~ach MG is feeding ~~both~~the same ~~a~~ thermal, electric load profiles which are resulting from the aggregation of 10-12 households. The figure~~as in Fig.~~ [5~~3~~] shows the two hourly mean power profiles in each month. The mean daily monthly electric loads is ranging between 43-70 kWh while the mean daily monthly thermal loads is ranging between 350-800 kWh. Working days and weekends are built from different profiles having respectively a different weighting (the energy is split 70% in working day 30%

non working day). The periodic peak daily electric load demand is in the second quarter, while the periodic peak daily thermal load demand is in the first (heat) and second (cool) quarter. Stochastic thermal and electric profiles have been generated with the 'Gauss Markov' algorithm.

The simulations of the revenues streams consider in besides the loads, the delivery of demand response services and energy sellback to a local electric utility. The demand response profiles have been simulated with 5% maximum value for load shedding, 25% for peak reduction and 15% for peak hours per month.

The price structure of the services offered to the electric utility and exchanged between MGs are showed in t~~Table~~able [2]. The calculation of the hourly mean available energy from solar radiation and wind, has been executed with the power losses inputs described in ~~T~~table [3]. –

The hourly dataframe of the environmental temperature is extrapolated with ~~relation~~eq. [17].

The ESS is characterized by a charge/discharge profile (0.25C for charge and 0.5C for discharge), a round trip efficiency (98%), deep of discharge (3% to 98%). The performance curve of the battery in relation to the temperature is utilized to obtain the hourly aged capacity of the ESS with equation [36].

In ~~our~~these simulations, in addition to RES, We consider a PEMFC-CHP (Combined Heat and Power Proton Exchange Fuel Cell). This type of FC converts the whole chemical energy of hydrogen into electricity and heat and so the efficiency goes up to 95%. Hydrogen tanks at 200 bar are chosen to feed the FCs and the fuel is transported once a day and has been considered— total cost for hydrogen of 3 Euro/kg. This values is coherent to the report published in January 2020 by the Hydrogen Council. The cost of renewable hydrogen produced from offshore wind in Europe starts at about USD 6 per kg in 2020. This rate is expected to decline by about 60 per cent by 2030 to approximately USD 2.50. –

In the simulated scenarios where FC is installed, the hydrogen is partially generated on site by a PEM electrolyzer (PEMEC), integrated to a 200 Bar pressurized hydrogen tank. Typical commercial electrolyzer system efficiencies are 56%–73% and this corresponds to 70–53 kWh/kg (NREL, 2004). An additional thermal tank is part of the configuration to storage the heat. The EC incorporates a solid proton-conducting membrane rather than the aqueous solution. This type of EC generates pressurized hydrogen and consequently reduces compression losses. The electrolyzer system efficiency considered in the simulations is 53 kWh/kg at nominal power.

The thermal energy is also generated by STs integrated with further thermal storage tanks and auxiliary HTs which are powered by electric energy, with an efficiency at 400%.

Each time-step, the SLSQP optimization algorithm secures the minimum of the nonlinear objective function [58] by choosing the highest energy contribution of RES, DG, ES with the lowest LCOE - indicated in ~~T~~table [45] and– maximizing the contribution of those DERs that in opposite, provide the highest revenues streams.

5.3 Discussion of the results

Table [4] reports the cumulative energy flows among DERs of three alternative scenarios. Among the loads, the thermal loads account for– 95%. The~~ structure of the~~ demand of energy of the loads ~~influences~~is the main ~~the~~ decision driver ~~strategy ~~of SLSQP in the use of the available distributed power sources in all ~~–the~~

scenarios; in other words,~~.~~ It can be argued that, the remuneration attributed to the thermal and electric load, influences the optimization strategy of SLSQP.

In the first scenario, where the two hybrid microgrids are interconnected, ~~FC-CHP~~PEMFC-CHP is the main ~~generation unit~~ thermal and electric generation unit in conjunction with WT. The actual LCOEs, (resulting after the optimization of the operations), indicated in ~~T~~table [5], highlight that the strategy deployed by SLSQP at each time-step, is appropriate. PEMFC-CHP returns, a cost of energy lower than utility grid (GRID). Therefore, when all the available power generated by RES is provided, then it becomes more convenient produce the additional required energy with the hybrid ~~power source~~fuel cell. Indeed PEMFC-CHP is able to generate electric energy at most economic way but also is capable to produce thermal energy, and water without any additional cost. The PEMFC-CHP and RES in MG_A are fulfilling not only the internal energy demand (ED) of thermal and electric loads and water. Their power sources are also able to deliver energy services (thru both MGs) and electric energy sellback to the grid utility. This happens, by transferring large amounts of thermal and electric energy from MG_A to MG_B (ITCEL_sellback,— ITCTH_sellback of MG_A in ~~T~~table [4]). The flows of energy among the interconnections is incentived by the price structures described in ~~T~~table [2]. In this example, the prices for energy interflows are in favor of— MG_A. In other words, the backbones of electric and -thermal energy among MGs are substituting the role of large energy storages transferring energy instead of deferring it,– at most economic conditions.

The second scenario (N~~n~~ot_~~-I~~interconnected~~ MGs~~) shows a different configuration and approaches to satisfy the energy demand. In MG_A the energy is mainly ~~produced~~dispatched with~~ FC-CHP~~ PEMFC-CHP in combination with WT.

Compared to scenario dealing with interconnected MGs,~~,~~ ~~here~~hither~~,~~ the contributions of RESs (namely WT and ST) are equivalent to PEMFC-CHP. ~~Here, t~~The exceeding thermal energy that is not used and can not be transferred to the other MG, is stocked in large tanks (Tank_Boiler, Tank_ST) by heating water as storage medium; hence the stored energy can be used at a later time.

The load-exceeding available electric energy supplied by PEMFC-CHP is given in sellback to the utility grid. Thus, this optimized scenario does not consider large electric energy storage systems. The demand of energy for MG_B of this second scenarios is satisfied with an approach similar to a traditional power system. In fact, the main source of electricity is the grid utility. The electric energy is then converted into thermal energy with an electric boiler in combination with a heat pump.

In the third scenario both thermal and electric loads are powered solely by the utility grid and electric boilers. This is a typical actual electric system, where loads do have not a peer to peer interconnection to RES thru MGs. The economic impact of such dispatching strategy is indicated in ~~T~~table [6].

In conclusion, revenues of the interconnected scenario are higher than the other. In MG_A of this first scenario, 25% of the revenue stream is generated by the loads, 14% by water and 54% by sellback to the other MGs. In MG_B 57% of revenues comes from the loads and 39% to sellback to the utility grid. The sale strategy implemented by SLSQP, allows to obtain the highest revenue streams with the lowers initial capital investment (CAPEX) in interconnected scenario than in the not interconnected one. Consequently, the contribution margin, calculated by deducing the total costs is considerably higher when the two microgrids are interconnected.

These considerations are finally synthesized in ~~T~~table [7] with key financial ratios. The limited amount of investments involving the first scenario, leads to a very attractive IRR (54%) and a relevant amount for the NPV (calculated with discount rate at 5%). Actual LCOE resulting from the final calculation of CAPEX and OPEX as aggregation of DERs is much lower than actual grid purchase costs in Germany (source: Eurostat https://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics). Payback (years to recuperate from operations in form of cash inflow– the total amount invested) calculated for these MGs is less than two years. In the other scenarios the return of investments is null and— the cost-profit structure of the business leads– to negative NPV. Finally, it should be noted that the RES fraction (calculated as ratio between the energy generated by the RES and the load consumptions-) in the interconnected MGs, results only 6% of the entire generated energy. However, if ~~we add also~~ the fraction of the on-site hydrogen productioned ~~ed~~ ~~on-site~~is added and ~~We~~moreover, it is -assumed that the further hydrogen demand is sourced by large wind and solar farms (green hydrogen), the contribution of RES goes almost– to 100%.

These simulations demonstrate that optimization strategies implemented via SLSQP algorithm in hybrid interconnected microgrids leads to a very attractive IRR, short term paybacks while contributing to strengthen the resilience of power systems. Optimal configurations of hybrid DERs in multiple microgrids, can operate at lower LCOE than current tariff offered today from the utilities. Thus, interconnected hybrid microgrids with SLSQP optimization techniques makes renewable and distributed energy resources outcompeting. They are a viable route to foster the transition to the low carbon energy paradigm and they can strand investments in fossil fuel generation.

6. Conclusions

This ~~paper~~work introduces an optimization method based on Sequential Least Squares Programming (SLSQP) to secure the best economic performances of interconnected hybrid microgrids. The algorithm minimizes every time-step a piecewise-linear convex objective function that incorporates the weighted contributions in terms of costs and revenues of distributed generators, loads, and microgrid interconnections. The nominal LCOE are the weight for the costs and the nominal LSOE are the weight for the revenues components of the objective function. Thermal and electric energy balances are the nonlinear constraint functions. The SLSQP algorithm finds in an efficient manner every iteration, the global solution of this nonlinear constrained convex optimization problem. The optimizer is embedded into a techno-economic model designed to shape dynamically the boundaries of the objective function. Moreover, the algorithm— computes— the— states of DERs and at the end, it returns the actual values of the key financial ratios. The proposed techno-economic model starts with the manipulation of climate datasets by combining FFT function with the IFFT. The objective is to achieve an accurate extrapolation of reanalyzed climate datasets issued by ECMWF over the project lifetime. A further method to identify linear correlations among coupled datasets has been investigated and hence a polynomial regressor has been implemented to predict temperature from solar radiation with less computing resources. The climate datasets feed the stochastic models forecasting renewable thermal and electric generation. A further stochastic model based on Gauss Markov function has been introduced to simulate hybrid loads profiles. Similarly, load shedding and load shifting has been implemented to simulate energy demand response to disturbances of the main grid. The proposed tool has proved to be very effective in simulating innovative business scenarios in which multiple revenue streams are generated from the sales of energy to end users, from further sales to the other energy networks and from deliveries of energy services to the grid utility. In particular, the techno-economic simulator has been used to analyze the financial performances of three different scenarios and it demonstrates the economic advantages of interconnected hybrid microgrids operated with SLSQP algorithm. This optimal scenario is compared to an alternative configuration of two not connected microgrids and another scenario where the loads are solely powered by the grid utility. All these simulations deal with both thermal and electric loads profiles of household communities located nearby the city of Bremen. With a payback within two years and an internal rate of return at 65%, the first scenario brings to a levelized cost of energy of 0,14 €/kWh. This value lead also to the conclusion that interconnected hybrid MG can operate at costs that are lower than a current typical utility tariff if an adequate mechanism of remuneration among prosumers and the utility grid is provided. Thus, the results of this work demonstrate that these energy systems can be very competitive option against the actual centralized large power networks.