Renewable microgrids covering the heat and electricity needs of industrial parks

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Abstract

The industrial sector, undoubtably, has a key role to play in the reduction of global greenhouse gas (GHG) emissions. However, the diversity of processes involved, coupled with the uncertainties around the affordability and the reliability of climate-neutral solutions, make decarbonization in the industrial sphere a complex challenge. They could enable industries to reduce part of their GHG emissions by using climate neutral alternatives, ensure the resiliency of factories to future climate change impacts, and represent an economic opportunity, by deploying profitable and efficient energy management actions. However, many questions remain on how to best implement microgrids from both a technical and financial perspective. Obviously, from an investment perspective, minimalizing the overall size of the grid is essential as this prevents extraneous investment in unnecessary and costly capacity. In this paper we address some of the technical and economic questions on grid sizing. We present an optimal sizing methodology for heat and power microgrids. These grids were composed of solar PV panels, Li-ion batteries, and a biogas fired CHP unit. We go onto assess the financial, environmental and resiliency potential of the solution and use a multi-factor optimization (considering both economic and technical factors) to address the problem. A case study renewable microgrid was designed based on a real-life dataset of an industrial park, located in the UK and used to show significant carbon footprint reductions through the implementation of our model.

Introduction

The industrial sector plays a significant role in GHG emissions: in 2016, the sector accounted for 29.4 % of total GHG emissions in the world, of which 24.2 % came of energy use and 5.2 % from direct industry processes (Our World In Data, 2021). Systemic actions are required, but technological, political, and economic hurdles remain to actively decarbonize the sector.

The diversity of processes and technologies undertaken among industrial subsectors complexifies the development of adequate solutions (Cooper and Hammond, 2018). Nevertheless, a wide range of solutions has been created to tackle the deep decarbonization of the industrial sector, from fuel switching to renewable electrification (Change Committee (CCC), 2020). The case of hydrogen demonstrates one of the crucial point delaying the ramp-up of the sector. Hydrogen is a technically mature technology enabling the decarbonization of parts of industrial subsectors. It could also be easier to implement thanks to the retrofitting potential of natural gas-fired technologies, especially for high heat appliances. In steel manufacturing for example, hydrogen can be used directly, as a reductant, to replace coal-based blast furnaces (Climate Change Committee (CCC), 2020). Nevertheless, the success of its development in the industrial sector is incumbent to the creation of hydrogen supply chains, which requires political and corporate investments and partnerships and management of the extra costs that this would bring to a globally competitive market.

The energy system transformation within the industrial sector requires solutions simultaneously covering environmental, economic and energy reliability issues. Renewable microgrids could be one of the most promising answers, as creating a renewable solution, technically and economically adapted to the industrial park needs, possibly accelerating the decarbonization of the sector. Energy reliability is a key factor for industries, as an interruption in energy supply impacts the company's profitability. Replacing fossil fuel solutions with intermittent renewable energy solutions may jeopardize the operation of an industry. Power cuts create direct economic losses, by stopping the production process in industries, but also indirect costs, such as additional cost to secure energy access or psychological impact during failure times (Shuai *et al.*, 2018). Moreover, the reliability of the energy system is at stake all over the globe, as climate change events are intensifying, and the energy system is transforming due to the shift from carbon-intensive technologies to intermittent renewables. Furthermore, climate change could impact energy consumption and production patterns, and eventually cause power cuts (Schaeffer *et al.*, 2012). The high penetration of renewables, coupled with the shutdown of load-following generation and a slow development of short-term and long-term storage expose the energy system to power shortages in case of extraordinary climate events. The recent natural hazards in California and Texas have shown how unprepared energy systems could be, and how exposed industries were to these events (Maanvi Singh, 2021). Furthermore, the adoption of energy efficiency and renewable energy solutions for industries is often difficult. Techno-economic barriers and a lack of internal resources often prevent companies from adopting solutions to decarbonize their business. Policies and regulations, availability of funds and capital intensity of investments are the three main factors influencing renewable investors. Moreover, energy consumption represents an important part of production costs in industrial processes, and companies are interested in reducing price volatility and cost. In Europe, over all industrial sectors energy cost represents up to 10% of total production cost, and for energy-intensive industries such as pulp or paper, cement, or iron, it can exceed 10% (European Commission, 2020).

Renewable based microgrids could decarbonize the industries energy mix, provide high reliability thanks to the ability to operate in an islanding mode of operation during power cuts, and decrease the price of energy (WBCSD, 2017). Low carbon microgrids, formed of a combination of renewable electricity and heat generation technologies, storage, and an energy management system, may enable industries to reach their environmental targets with local fossil fuel generation or back-up units replaced by solar, wind or bioenergy solutions. Microgrids allow colocation of supply with consumption, allowing self-reliability and security of supply to commercial and industrial companies (WBCSD, 2017). Also through choices of industry functions that may be prioritized in the links to the microgrid may allow critical functions to be linked to the microgrid, preventing the industry's operation to be negatively impacted by natural hazards and power cuts. Finally, renewable microgrids could represent an economic opportunity, thanks to the use of mature renewable technologies: the falling cost of solar PV, wind turbines and storage, combined with existing political support mechanisms, providing a cheaper and less risky solution to industrial energy demand when compared to hydrogen or continued fossil fuel usage in combination with carbon capture and storage. Moreover, microgrids enable profitable and efficient energy management policies: for example, on-site storage can reduce and shift peak demand charges, reducing the overall energy cost. It could be argued that microgrids remain capital intensive, however, financial mechanisms have been developed for mature renewable technologies, and higher cost visibility is established on the long-term compared to diesel or natural gas fired solutions, as these feedstocks price are more volatile over time (WBCSD, 2017). Lastly, renewable microgrids could represent an external revenue stream for industries: excess electricity generated could be sold on the grid; support services could be provided to the grid, such as local frequency regulation. Alongside this in a scenario of increased carbon taxation, local renewable microgrids may reduce the tax burden on the companies that implement these types of energy system. (WBCSD, 2017).

Therefore, we suggest that renewable microgrids can play a significant role in the decarbonization of the industrial sector. However, few studies have been focused on the investigation of the techno-economic and environmental effects of renewable microgrids. This paper, therefore, aims to develop a holistic approach to evaluating the techno-economic and environmental feasibility of heat and power microgrids. The major innovations and contributions of this study include: 1) developing a method to assess the energy requirement of the industrial park; 2) developing an optimal sizing method for renewable microgrids, composed of solar PV, batteries, biogas-fired combined heat and power (CHP) units and boilers to provide reliable energy demands; 3) developing a systemic method to quantify the financial and environmental effects of renewable microgrids for the industrial sector.

The rest of this paper is organized as follows: a description of the methodology will be conducted, followed by a real data-based case study, which objective will be to study the technical feasibility, and the environmental and financial opportunity of a renewable microgrid for an industrial park. The results are discussed, and further improvements and applications will be proposed for this study.

Methodology

To determine the scale and composition of the microgrid required and the economic impacts of its adoption a multistep process is followed which is described in Figure 1. First, the heat and power consumption patterns of the industry are estimated and analysed. Microgrids are a demand-side management technology therefore a clear understanding of the electrical and heat inputs is required. Initially, the algorithm collects and analyses the heat and power load curves of an industrial park with the desired constituent occupants. Then, based on the heat and power consumption patterns acquired or generated, the microgrid is optimally sized based on techno-economic and environmental strategies. The objective of the optimization process is to decrease the carbon intensity of the industry energy mix, measured in gCO_2/kWh and to optimize the cost and operation of the microgrid. Finally, the result of the optimal sizing and operation of the microgrid is transferred to financial

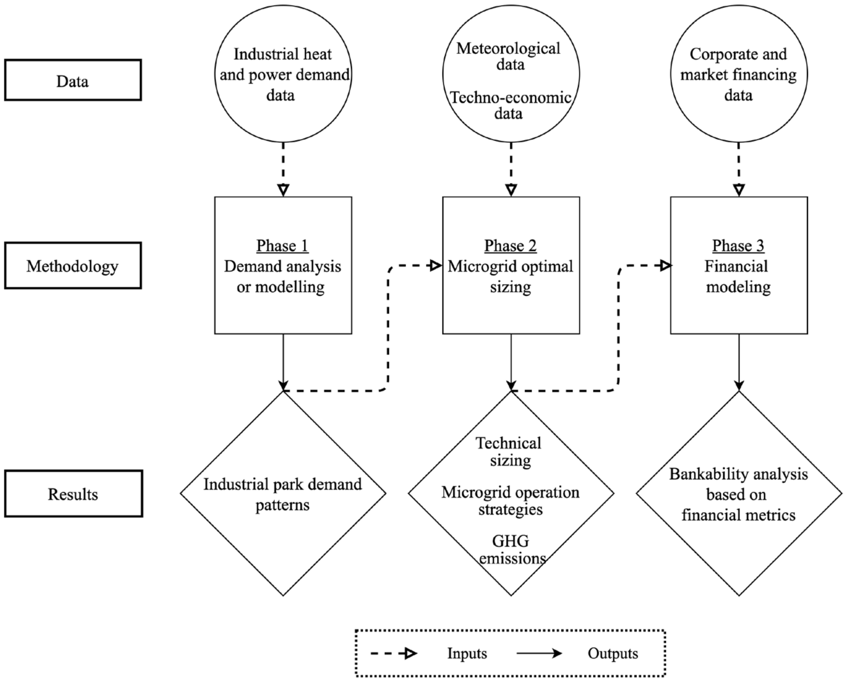

Figure 1. Description of the inputs, outputs, and phases of the methodology.

factors. The capital (CAPEX) and operation (OPEX) expenditures of the renewable generation and storage technologies, combined with the consumed electricity and biogas define the project cost and financial metrics.

DATA ANALYSIS

Key data required to optimally develop renewable microgrids is the local energy consumption data. However, access to energy consumption data of industrial parks can be challenging. Therefore, a Python model was created for this study, to generate the hourly energy demand patterns of an industrial park depending on two types of datasets (Figure 2). The first one regroups the metadata of 12 000 businesses collected by smart meters in Great Britain within the Energy Demand Research Project. The second is from energy consumption data collected by Veolia[1] from industrial parks in the UK, Slovakia and the United States.

The model[2] creates a simulated industrial park by combining the energy consumption patterns of different sub industry types based on business type metadata. The user defines the expected industrial park, by providing the type of industries, the quantity of each type of industry, and the interval of yearly average and maximum energy consumption of each unit of the park. This enables the end-user to create homogeneous industrial parks for example, by picking industries within the same consumption range. The individual energy consumption of each business is added, creating the total energy consumption pattern of the industrial park. As an example, a park has been created by combining the consumption patterns of a brewery, a small manufacturing company and a chemical company. The benefits from this approach is that developers can study the impacts of the industrial park size, the diversity of industries within the park or the most promising businesses to develop a renewable microgrid. Furthermore, if the user already has access to existing industrial park data , the model skips this step and simply analyses the energy consumption patterns on a seasonal basis and processes the data to use it in the microgrid sizing model.

The computational times for the sizing optimization calculations is determined by a combination of the problem size and granularity of data used. Therefore, using input data reduction techniques can help to gain time during the solving process. Based on a simplified use of Fahy et al. monthly peak preservation approach, average seasonal energy consumption load curves are generated from the hourly data (Fahy *et al.*, 2019). Finally, the generated data will be exported in a CSV file to be used in the microgrid sizing algorithm.

OPTIMAL MICROGRID SIZING

The microgrid is a combination of energy generation, storage, and distribution assets, as presented in Figure 3. In this study, it is composed of solar PV generation, Li-ion storage batteries and a CHP unit, which is composed of a biogas turbine and a heat recovery boiler, a cooler or a heat boiler depending on applications, and a connection to the power grid. This microgrid can provide energy in electric or thermal form, in islanding or off-grid mode.

The sizing methodology is based on a multi-objective optimization approach. The optimization model computes the solution of an objective function, which is defined by variables that are characterized by a set of constraints: the model will compute the capacities of the assets required to cover the heat and power needs of the industrial park in view of multiple objectives. The first objective is to reduce the cost of the project; the second to decrease the GHG emissions. The two objectives are linked to the price of carbon, which financially incentiv-

1. https://www.veolia.com

2. https://github.com/Eflamm29420/Renewable-microgrids-covering-the-heat-and-electricity-needs-of-industrial-parks-1.git Tool 1 - Electrical park VF.

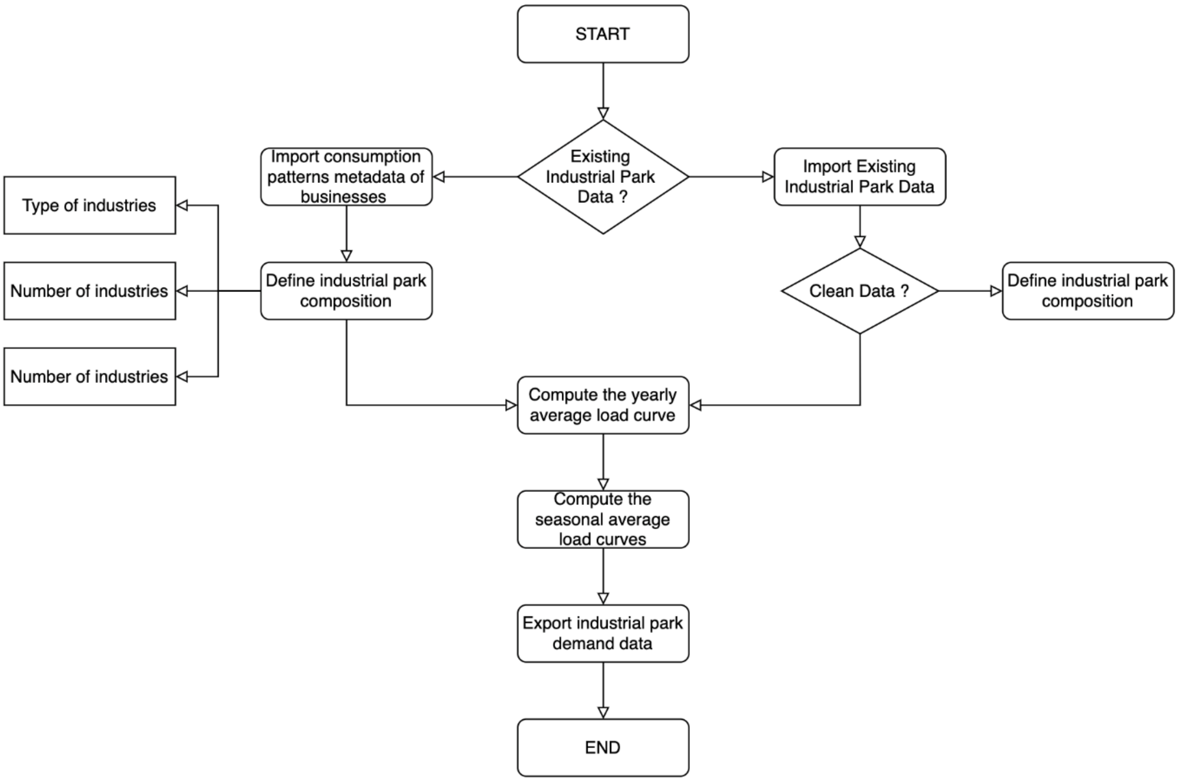

Figure 2. Decision tree of data analysing and editing model.

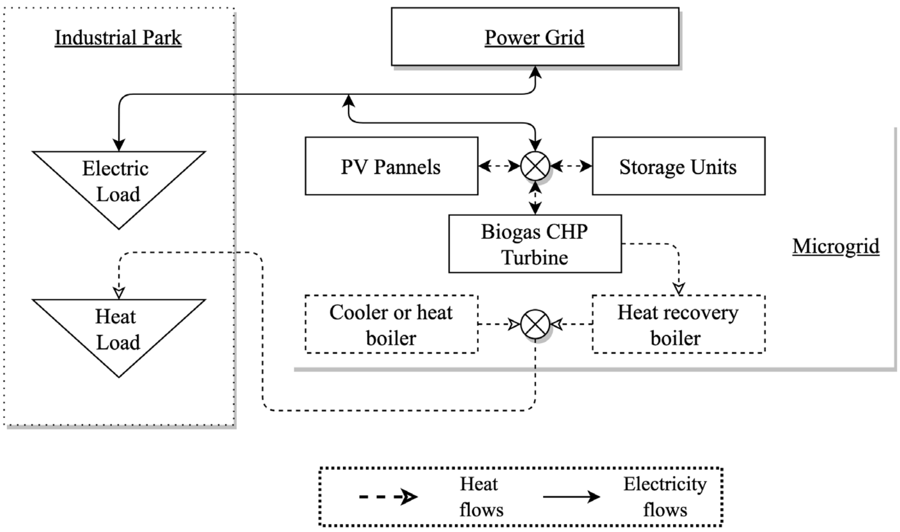

Figure 3. Microgrid system.

izes businesses to decarbonize their energy mix. Finally, a solver will be used to iteratively compute the asset capacities. The methodology is based on the combination of three optimization methodologies: the works of Yang et al. on optimal sizing of solar PV panels, wind turbines and CHP (Yang, Pei and Qi, 2012); the concept of thermal load tracking introduced by Aluisio et al. during its study on optimal sizing of a solar PV, wind turbine, BESS and CHP based microgrid (Aluisio *et al.*, 2017); finally, the methodology of Blake and al. which compared the costs and emissions of various microgrid operations modes (Blake and O'Sullivan, 2018).

Objective function

The generation, storage and distribution assets forming the microgrid are defined inputs for the optimization problem: input variables, decision variables and constants are associated to each asset to determine its technical, economic, and environmental parameters. These variables are also describing the generation and storage behaviour of the grid, the interaction between the assets within the microgrid and with the grid.

The objective function is formed of three cost subsegments: capital expenditure, operation and maintenance costs, and the environmental cost linked to the carbon tax applied to the car-

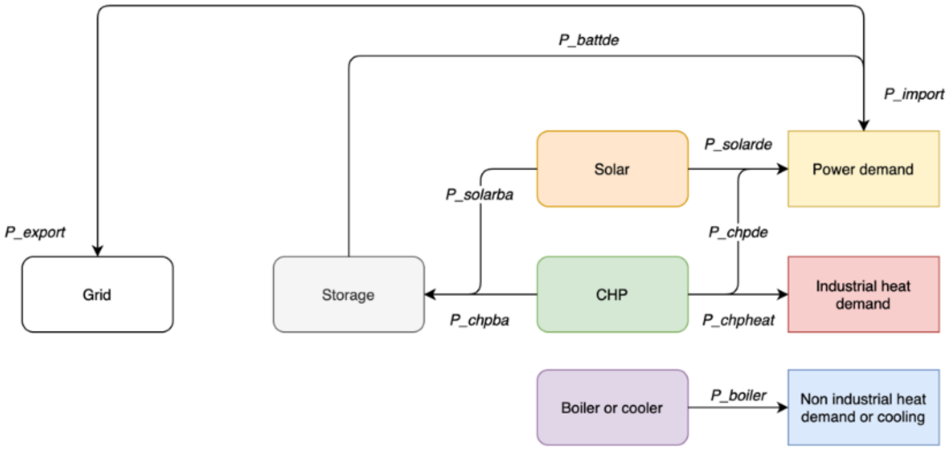

Figure 4. Microgrid set up and energy flow variables.

bon intensity of the microgrid system, as presented in equation (1). Microgrid sizing implies long-term and short-term operation scheduling. Therefore, the optimization model integrates the long-term and short-term costs during the microgrid project lifetime.

$$min\, f = C_{capex} + C_{opex} + C_{carbon} \quad (1)$$

$$C_{capex} = \sum_{1}^{T} k_{technology} * S_{technology} \quad (2)$$

$$C_{opex} = \sum_{1}^{T} opex_{technology} * P_{technology} \quad (3)$$

$$C_{carbon} = \sum_{1}^{T} CO2_{technology} * CO2_{price} * P_{technology} \quad (4)$$

In equation (2) $k_{technology}$ represents the depreciation of the technology, embodying the CAPEX during the project lifetime; $S_{technology}$ represents the capacity of each technology; $opex_{technology}$ the operation and maintenance cost; $P_{technology}$ is the energy generated by the technology on an hourly basis. Finally, $CO_{2technology*}CO_{2price}$ represents the cost of carbon due to each microgrid component operation.

Definition of constraints: sizing and operation hypothesis of the microgrid

To define the constraints on the optimization variables, two hypothesis were adopted, establishing an operation mode for the renewable microgrid. The first hypothesis is that the CHP unit will be operated in thermal load tracking. As introduced by Aluisio et al., the CHP unit is sized to follow the behaviour of a dedicated thermal load (Aluisio *et al.*, 2017). The hypothesis was made in this study that the heating unit of the CHP will be sized based on the behaviour of the industrial heat demand, and that the remaining heat demand will be supported by the boiler or the cooler. This assumption sets a constraint on the electrical generation unit of the CHP, simplifying the sizing. The second hypothesis is the electricity balance of constraint, which links the power variables in the system, as presented on the flow chart in Figure 4. The total electricity demand equals the sum of the electricity generated by the PV panels, the electricity generation unit of the CHP, the difference between the electricity imported and exported from the grid, and the electricity stored in the battery.

The optimization problem will search for solutions in dedicated intervals. Therefore, boundaries must be set to the variables. Except the variable linked with the export of electricity towards the grid, all variables are set as positive. Then, a maximum value is set by the user during the algorithm process to reduce the size of the search interval.

Optimization algorithm model[3]

The theoretical optimization model has been defined and adapted to our case study by studying the energy flows within the microgrid. Solving this optimization problem will require an algorithm strategy, as presented in Figure 5. After importing and analysing the data, the algorithm will find the most energy-intensive day for the microgrid infrastructure. It was defined that this day will be the one where the difference between the electricity demand and the electric output of the CHP is the highest. This definition implies that during this day the needs in solar PV generation, grid importation and electricity storage will be at their peak. A first sizing of the microgrid will be realized, without taking storage into account. The objective of this step is to analyse a different operation mode of the microgrid and define the parameters intervals. For example, the maximum charge and discharge value will be computed thanks to the maximum energy imported and exported from the grid during the period. This limit will prevent the algorithm to increase the PV and battery size indefinitely to sell electricity into the grid in the second sizing step. Then, based on the sizing intervals defined by the first step, storage will be introduced in the sizing to reduce the cost of energy and the GHG emissions of the microgrid. This step will define the final capacity sizing of the components of the microgrid. Finally, the sizing will be tested for the rest of the year, enabling a study of the microgrid effectiveness and performance on a seasonal basis. This optimal sizing strategy is based on the combination of two academic approaches. First, Balke et al. analysed the sizing and emissions of a microgrid in various operation modes (grid only; grid and

3. https://github.com/Eflamm29420/Renewable-microgrids-covering-the-heat-and-electricity-needs-of-industrial-parks-1.git Tool 2 – Smart Parc UK–Copy 1.

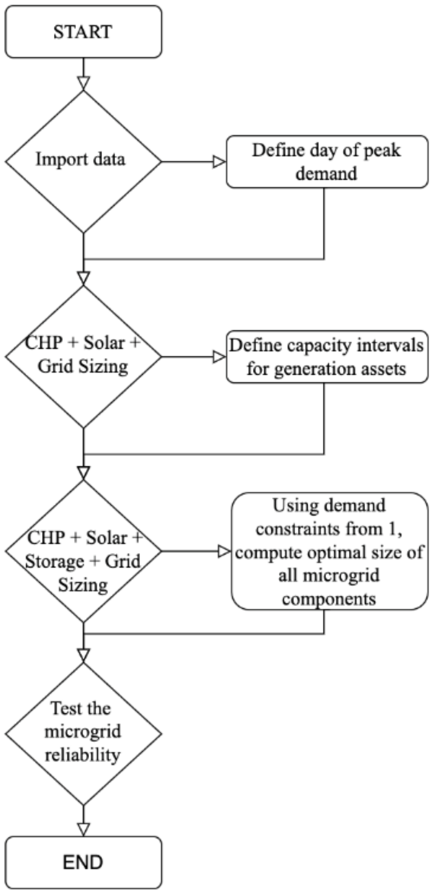

Figure 5. Optimization algorithm model.

wind turbines; grid, wind turbines and CHP…) (Blake and O'Sullivan, 2018). Then, Fahy et al. demonstrated that using a seasonal approach (monthly approach in their case) could reduce the optimization time and still provide reliable sizing results (Fahy *et al.*, 2019).

FINANCIAL MODELLING

The financial modelling of the microgrid needs to be based on a business model: estimating the bankability of the microgrid requires a definition of revenue streams and capital structures. Then, the Energy-as-a-Service (EaaS) was chosen for this case study. It operates as a PPA agreement: the microgrid host sends recurring payments to the microgrid owners, without participating in the capital expenditures. Therefore, the financial burden should be borne by the microgrid owner, Veolia[4] in our case study. Nevertheless, to spread the financial expenditures across different shareholders, third-party microgrid ownership could be adopted. A special purpose vehicle should be created for the microgrid project. The project will be financed through equity and debt. Veolia, as the owner, developer, and distributor of the microgrid, could pair up with investors such as infrastructure investment funds, development banks, or other industrial partners and share the ownership of the microgrid with this third-party. Moreover, the capital structure should be a mix of debt and equity. The recurring payment of the microgrid customer will cover the debt repayment, delaying over time the financial burden of capital expenditures. Based on the microgrid sizing and the business model defined earlier, financial metrics will be computed to estimate the profitability and solvency of the microgrid design. . The project Net Present Value (NPV), Internal Rate of Return (IRR), Debt Service Coverage Ratio (DSCR) and Weighted Average Cost of Capital (WACC) will indicate how bankable the solutions are.

Case study and discussion

Herein we outline some case studies based on our methodology. The case studies are based on real-life data provided by the industrial partner with the industrial parks based in the UK. The case study will first examine the inputs of project, such as energy demand, prices, the renewable generation available the location and then the economic sizing of the microgrid will be conducted. The result of the sizing will then be analysed thanks to a financial model.

INPUT DATA ANALYSIS: DEMAND, PRICES, AND RENEWABLE GENERATION

The data provided by the industrial partner covers industrial parks with heat and power demands. To gather the required data for the microgrid sizing, a questionnaire was sent to Veolia's business units to ask for specific data: it was asked to provide hourly heat and power consumption data, and that the industrial and non-industrial processes were distinguished. The industrial partner provided data for an industrial park in the UK. No additional location was provided; therefore, it has been decided that the location of the park will be in Oxford, Southeast England. Moreover, no additional information was provided on the type of business, the industrial processes used and the seasonality of the firm business.

This industrial park for the UK is composed of four types of energy consumption vectors: electricity demand, cooling demand, steam demand, and low temperature or pressure heat water (LTHW). To supply this heterogeneous energy demand, a combined cooling, heating and power (CCHP) solution was adopted: a cooling chiller will be added to the electricity generation and heat recovery system. Therefore, it was assumed that the LTHW and steam energy demand will be summed and analysed together; moreover, the cooling demand will be analysed and sized on its own. The demand data was recorded for one full year, enabling a seasonal analysis of the data (Figure 6, Figure 7, Figure 8).

First, the electricity demand capacity averages 10.2 MW, and peaks at 16.0 MW. The total daily electricity demand averages at 244.6 MWh. Moreover, the spring and summer periods are more electricity intensive than the winter and autumn periods. For example, the winter and autumn consumption have lower minimums at 2:00 pm than the spring and summer periods. Nevertheless, the winter electricity consumption outperforms the other seasons from 7:00 pm to 11:00 pm (Figure 6).

Second, the heat demand, combining the building heating and industrial heating demand, has an average capacity of 9.4 MW, and peaks at 14.8 MW. The total daily heat demand averages at 226.7 MWh. Moreover, the first insight from the heat demand analysis is that the total heat demand has its minimum at 2:00 pm, resulting in a decrease in heat demand between 12:00 am and 2:00 pm. It could be explained by a de-

4. https://www.veolia.com

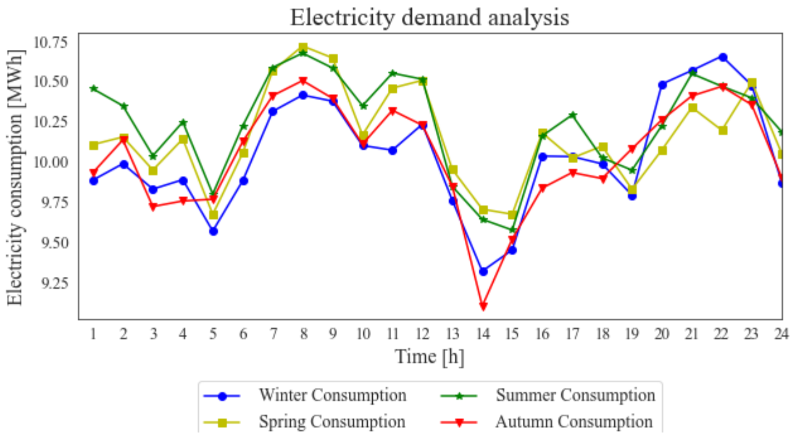

Figure 6. Electricity seasonal demand variation of the UK park.

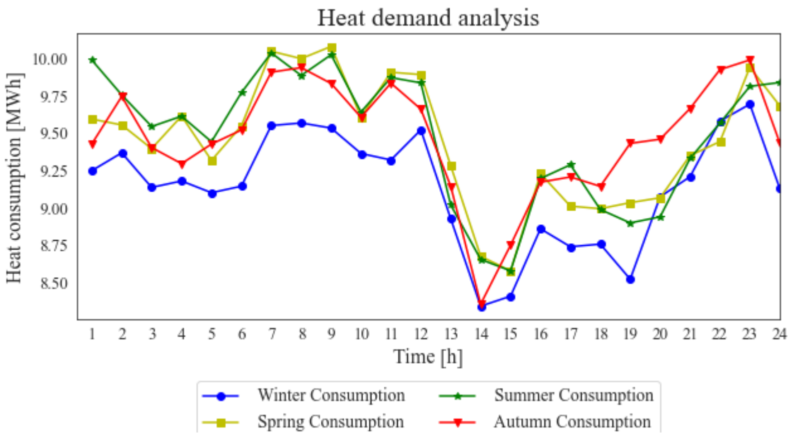

Figure 7. Heat seasonal demand variation of the UK park.

crease in activity during lunch break, which was also assessed on the electricity demand curves (Figure 6). Moreover, the seasonal variations during the other parts of the day could be explained by analysing the LTHW and Steam seasonal variations. It was assessed that the low winter heat demand and the high autumn heat demand were driven by the demand in Steam, representative of the industrial heat demand. On the other hand, the patterns of the LTHW demand, representative of the building heating demand, are almost the same within the four seasons, with higher demand in winter and autumn. Therefore, the seasonal heat demand variation could be explained by a seasonality in the industrial process and the company's business model.

Finally, the cooling demand average capacity reaches 1.8 MW and its peak reaches 3.6 MW. The total daily heat demand averages at 43.8 MWh. In contrary to the heat demand, the cooling demand peaks in the middle of the day. Moreover, the summer period is the most consuming period: it is due to higher demand for the cooling of the building. However, a share of the cooling demand may also be used in the industrial process, as we assess the same growth trend from 7:00 pm to 9:00 pm as in the steam and electricity load curves. The exception of autumn season could also be due to a seasonal variability of the industrial process. (Figure 8).

The electricity price used for this model is based on the Octopus Agile tariff of the South-eastern region. It is composed of a buying and selling electricity price, enabling the microgrid to sell the excess generation of electricity to the grid. On average, the price of electricity bought is USD13.5/MWh, and the price of reselling is USD7.4/MWh. The daily and seasonal average price variation analysis shows a daily volatility: the electricity buying and selling price peak between 3:00 pm and 8:00 pm.

MICROGRID SIZING

The optimization methodology was used based upon the input data presented in the previous section: the results of the techno-economic sizing will then be presented (Table 1). First, the heat demand peaked at 14.8 MW during the period. Therefore, it was decided that the size of the CHP unit will be 14.8 MW, to be able to always cover the heat demand of the industrial park, for energy security reasons. According to the same methodology, the cooling unit was sized at 3.6 MW.

Then, the solar PV panels and Li-ion batteries were optimally sized based on the methodology presented, resulting in respective capacities of 23.1 MW and 25.0 MW, as listed in Table 1.

Following this sizing, the microgrid operation will be discussed. Based on the methodology described earlier, the microgrid is working in heat load tracking mode when the energy

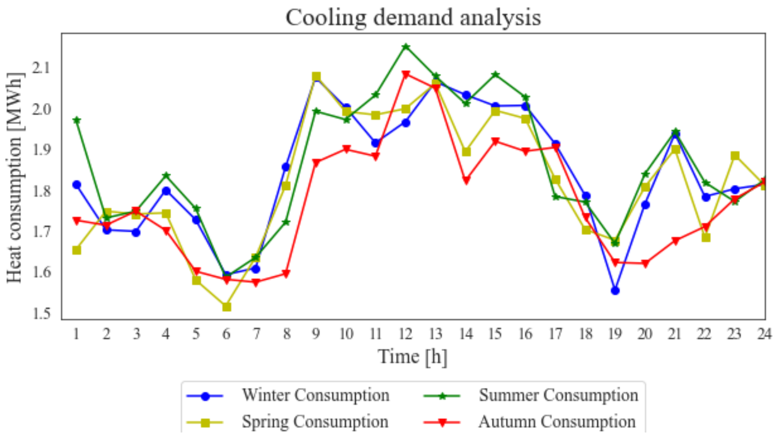

Figure 8. Cooling seasonal demand variation of the UK park.

Table 1. Microgrid sizing results for the UK park.

Sizing	Solar PV (MW)	BESS (MWh)	CHP (MW)	Cooler (MW)
Microgrid	23.1	25.0	14.8	3.6

demand is based on the thermal and electric vectors. The sizing of CHP and cooling unit based on the peak thermal demand ensures a reliable supply of energy, key to guaranteeing thermal energy security for the microgrid. However, this exogeneous sizing induces an oversizing of the CHP unit: the average CHP loading rate is 64.3 % during the year, and the CHP efficiency and fuel consumption is a function of the CHP loading rate, as demonstrated by the academic literature (Yang, Pei and Qi, 2012; Gu *et al.*, 2015). The CHP heat and power efficiency was considered at 100 % loading rate, demonstrating an opportunity for cost optimizing (DECC P2, 2013).

On the electricity part of the microgrid, a few trends can be assessed. During the critical day, the demand difference between the electricity generated by the CHP and the electricity demand, combined with the low solar capacity factor during this day, force the microgrid to import electricity. It is the highest grid electricity importation (27.5 % during this day) and no excess electricity is generated by the microgrid (Table 2). Nevertheless, the study of the electricity imports trends and the grid price volatility (the average buying price equals USD10.2/kWh and the standard deviation is around USD2.3/kWh) shows a price arbitrage behaviour from the system. At 1.am, the microgrids imports 7.5 MWh from the grid, to breach the gap between the electricity demand and the generation and to store 5 MWh in the BESS. The electricity stored will enable the system to operate without having to import electricity from the grid between 2:00 am and 3:00 am, when the electricity price increases from 60 % compared to 1:00 am. More generally, the microgrid imports and stores more electricity into the battery at night and in the morning (from 10:00 pm to 12:00 am), stores it, and reuses it during the peak price period (from 3:00 pm to 7:00 pm). Nevertheless, more advanced storage operation methodologies could be used to improve the profitability of the microgrid and prevent the microgrid from importing electricity during the high price periods (Xie *et al.*, 2017).

Then, the microgrid optimally sized was tested on the average heat and power demand values of the industrial park, to estimate the microgrid performance during these periods (Figure 10). The operation follows a similar trend during the 4 seasons: the microgrid benefits from the low energy tariffs at night (from 10:00 pm to 7:00 am depending on the seasons) to fill the gap between the electricity demand and the electricity generated by the CHP unit. The battery is charged until 3:00 pm at its maximum, before selling electricity into the grid during the high price period, demonstrating an ability to sell electricity in the right period. (Figure 10).

The seasonal analysis demonstrates that, without any constraints apart from electricity cost and CO_2 reduction, the microgrids relies on 89.8 % on-site energy generation, as only 10.2 % of its energy mix is provided by the grid. It demonstrates the economic and sustainability benefit from the solution, and implies a higher resilience towards power outages on the grid.

Finally, the environmental performance was assessed by measuring the carbon intensity of the energy generated by the microgrid (Table 2). The average yearly carbon intensity of the microgrid is 97.5 gCO_{2eq}/kWh, which represents a decrease of 62.2 % of the GHG emissions compared to the grid carbon intensity. The grid impact was computed by considering that the total electricity demand was supplied by the national grid, and the total thermal demand was supplied using natural gas generation. Therefore, the development of this microgrid prevented the emission of 30.2 $ktCO_2$ during the estimated period: with 18.3 $ktCO_2$ emitted, the microgrid solution designed by this methodology outperforms the most environmentally friendly solution internally studied by the industrial partner (26.2 $ktCO_2$).

FINANCIAL ANALYSIS

The bankability assessment of the microgrid will be based on a study of the financial performance of the project, and its solvency. First, the technical capacities and operation patterns defined by the optimal sizing are combined with the technologies CAPEX and OPEX. It results in CAPEX and OPEX breakdown. (Table 3)

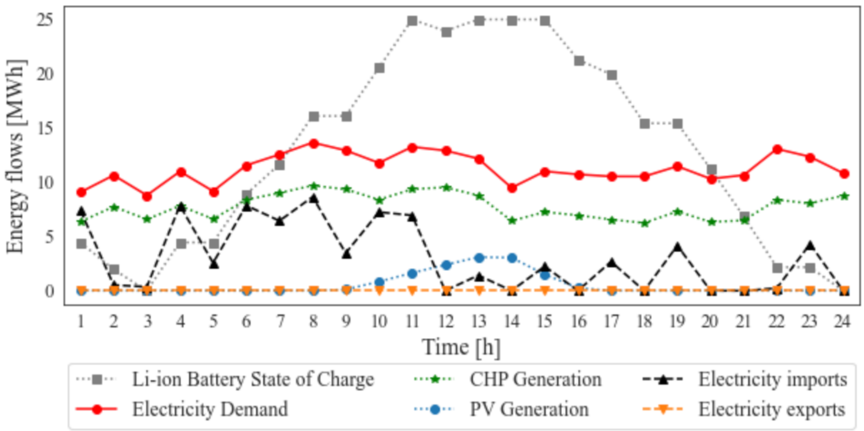

Figure 9. Microgrid operation during the critical day for the UK park.

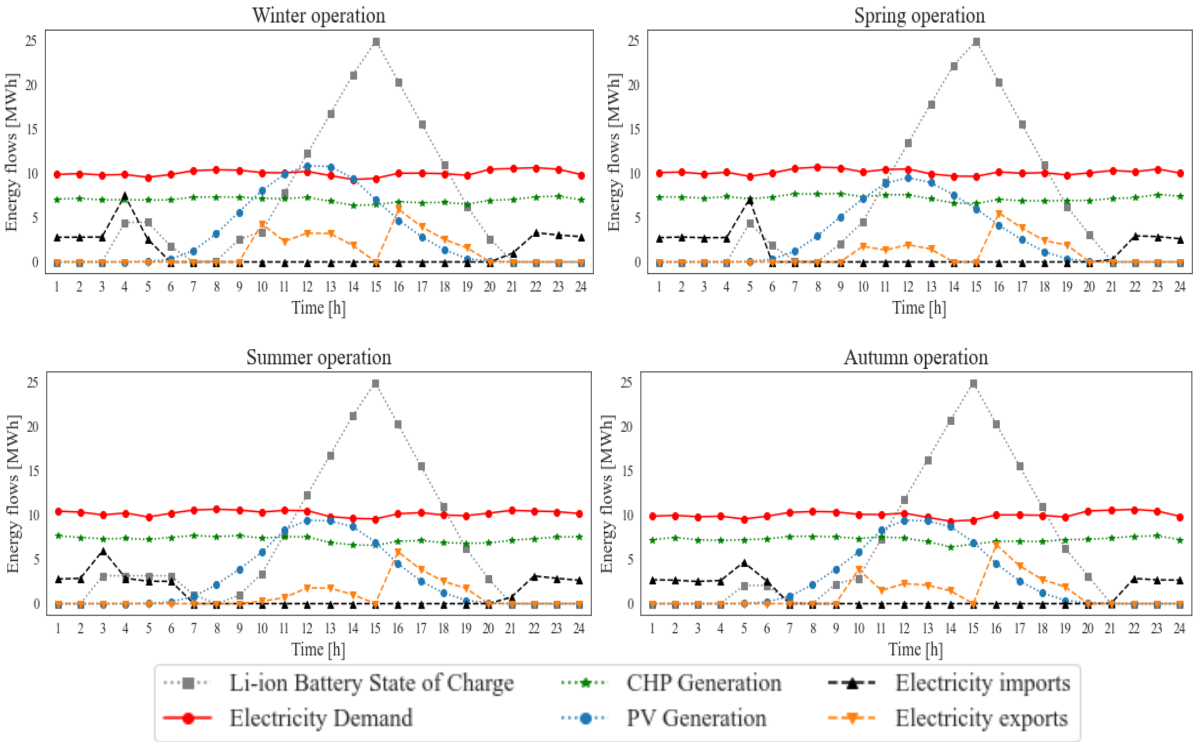

Figure 10. Microgrid seasonal operation for the UK park.

Table 2. Microgrid operational and environmental performance.

Indicator	Winter	Spring	Summer	Autumn	Critical day	Grid
Share of grid importation	10.7%	9.9%	10.7%	9.6%	27.5%	100%
Excess generation	3.8%	3.9%	5.6%	5.2%	0%	0%
CHP Loading Rate	62.6%	64.8%	65%	64.9%	68.8%	0%
Cooling Unit Loading Rate	51.2%	50.6%	51.8%	49.3%	44.6%	0%
Carbon intensity (gCO_{2eq}/kWh)	96.3	97.6	98.5	97.8	116.0	258.2

Table 3. CAPEX and OPEX breakdown by microgrid component.

Technology	CAPEX (mUSD)	OPEX (mUSD)
PV	38.0	0.4
CHP	18.4	-
Engine	-	0.6
Fuel consumption	-	4.9
BESS	8.75	0.1
Grid	-	-0.1
Total	65.2	5.9

Table 4. Financial metrics assessing the project bankability.

Financial metric	Value
NPV	14.3 mUSD
IRR	11.4%
Payback period	8 years
LCOE	8.25 USD/MWh

The ability of the microgrid to generate economic value thanks to energy trading was assessed by computing the "grid OPEX". This value compares the imports and exports during the four seasons, computing the average cost of interacting with the grid. The negative value demonstrates that the microgrid ability to generate, store and sell electricity into the grid during the high price period, creates economic value. Then, the financial performance indicators are computed, based on a 20-year project and financial and economic inputs, and an 8.5 % WACC. IRENA estimates the WACC for renewable projects in OECD countries around 7.5 % (Agency, 2020); it was assumed that 100 basis points will be added to the WACC to account for the microgrid projects lack of maturity. Moreover, the price of energy sold will be a combination of the average buying price (13.5 USD/MWh) and the natural gas price for UK industries (4.1 USD/MWh): it results in a price of USD8.56/MWh. The financial metrics were computed and presented in Table 4. The project is profitable, as the NPV is positive, the IRR higher than the WACC, allowing the project CAPEX to be covered by the energy generation, without increasing the energy price: The LCOE of the project is 8.25 USD/MWh. Finally, the solvency of the microgrid will be assessed by the DSCR. The average DSCR of the project is 3.1x, meaning that the cash-flows generated account on average for 3.1 times the current debt obligations. Moreover, the minimum DSCR is 1.98x at the 11th year due to the lithium-ion batteries replacement. The industry minimum DSCR is around 1.35x, which shows the project creditworthiness.

In conclusion, the microgrid designed secures energy, decreases the environmental impact of the industrial activity and is bankable.

Conclusion and discussion

Renewable microgrids will play an important role in achieving the decarbonization of the industrial sector. It can be considered as a transitory solution, that will tackle the energy trilemma of the industrial sector. On-site microgrids will provide energy reliable energy access, decarbonize the industrial activity, and enable plant owners to secure a stable energy price.

This study presents a holistic methodology to analyse the techno-economic, environmental, and financial performance of a microgrid. Based on Veolia's data, a microgrid was designed. The solution combines 23.1 MW of solar PV panels, 25 MW of Li-ion batteries, 14.8 MW of CHP unit and 3.6 MW of cooling units. This microgrid enabled the industrial park to source locally energy supply at 89.8 % and decrease the GHG emissions by 62.2 % compared to the national grid by reaching a carbon intensity of 97.5 gCO_{2eq}/kWh. Lastly, the project is profitable and creditworthy, as the NPV reaches USD 14.3 million, the IRR 11,4 % and the average DSCR on the period is 3.1x.

Nevertheless, the scale-up of renewable microgrids depends on a reliable environment established by public authorities. Therefore, this methodology could help governments to assess the most promising sectors for microgrids developments, enabling an adapted help to launch the transformation. Business developers could also use the conclusion of this study. They have access to more precise and real data, in terms of electricity consumption, components prices and microgrid project costs. Therefore, they could study the economy of scale introduced by using many small and diverse renewable-based microgrids. The methodology could also be used on a metadata approach: the demand analysis tool could be used by business developers to create fictive industrial parks based on various industrial electrical and thermal demand. Business developers could then target the right subsectors and the right industrial park size to reach their projects hurdle rates.

In the future, our study could be extended in the following directions. First, the energy efficiency of CHP operation could be improved by adding heat storage solutions. The oversizing of the CHP, boiler and cooling units has led to low loading factors, impacting the system's efficiency. Then, agile energy management strategies could be adopted to improve the storage performance of the microgrid, enabling an improvement in the financial performance and reducing the importations from the grid. Moreover, some boundaries exist to this model. As the renewable microgrid consumes 98 GWh of biogas, it requires the creation of large infrastructures and robust supply chains. In the case of biogas scarcity, inducing high fuel prices, the bankability of the project could be jeopardized. A sensitivity analysis could be realized to assess how resilient is the microgrid to fuel price, interest rates or WACC variations. Future work could also focus on using different technologies, such as hydrogen, to cover the heating demand. Then, the resiliency of the microgrid operation could also be assessed by a sensitivity analysis. The current paper only analysed the operation during a critical day. For example, it could be interesting to study how the microgrid operates if the national grid is down for a few days, or if the electricity generated by the CHP and the solar panels are too low to cover the demand.

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