Risk assessment of energy investment in the industrial framework – Uncertainty and Sensitivity analysis for energy design and operation optimisation

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Abstract

The industry is a crucial actor towards the energy transition with the possibility to adopt new energy strategies including a prosumer model. However, industries are struggling to adopt smart energy approaches, and initiatives supporting them should be improved. To enhance industrial participation in energy transition, it is required to assess the optimal energy infrastructure considering its economic advantages and associated risks. Up to date, the literature dealing with energy sizing optimisation does not consider the time evolution of parameters or the uncertainty linked to the energy framework. The objective of this paper is to fill this literature gap by proposing a novel complete methodology to optimise the design and operation of the energy infrastructure for its lifetime while assessing its uncertainty and risk through an uncertainty analysis, as well as to identify the inputs causing it by a two-stage sensitivity analysis. This framework is applied to a case study based on a real industrial manufacturing SME. The results indicate that the proposed methodology produces robust results in front of the present uncertainties, being energy price the one that causes most of it and thus the one more attention should be paid to when evaluating energy investment decisions.

Keywords

Energy investment, Optimal design, Prosumer, Uncertainty Analysis, Sensitivity Analysis

1. Introduction

1.1. Motivation

The industry is gaining an increasingly important role in the energy sector due to its possibility to adopt smart energy management strategies that can improve their productivity while creating flexibility in the energy market. The energy consumption, energy infrastructure, and the current Industry 4.0 revolution opportunities [1] place industrial entities as new actors in the energy market fundamental for market decarbonization [2]. Among industrial enterprises, SMEs represent more than 13% of total global energy consumption and account for more than half of the energy used in the industrial and commercial sectors, although they are under-researched in terms of their energy use [3]. Some scientific publications deal with energy efficiency improvements in the SME sector such as [4], where a study is done on energy efficiency drivers for industrial SMEs, or [5], where an information platform is presented to promote the usage of energy efficiency technologies. However, these studies deal only with efficiency improvement and, following the energy transition changes, it is necessary to adjust the latest trends and practices to SMEs framework [6], being the adoption of a prosumer model a key activity to incorporate in the sector.

SMEs could face the problem of having to invest in energy infrastructure due to equipment obsolesce or the existence of governmental, social and market pressures. For an industrial entity, this investment gives added value to the enterprises, supporting the achievement of their primary goal, which is its productivity. Industrial SMEs tend to select investments with short payback periods and

Nomenclature

Abbreviation	**Full description**
General Abbreviations	
CHP	Combined Heat and Power
EE	Elementary Effect
ESS	Energy Storage System
HP	Heat Pump
JC	Job Creation
LHS	Latin Hypercube Sampling
NPV	Net Present Value
O&M	Operation and Maintenance
OAT	One-At-a-Time
PDF	Probability Density Functions
PPA	Power Purchase Agreement
PV	Photovoltaic
RES	Renewable Energy Source
ROI	Return On Investment
RTP	Real-Time Pricing
SA	Sensitivity Analysis
SME	Small-and-Medium Enterprise
UA	Uncertainty Analysis
Energy infrastructure sizing and operation parameters	
P_{PV}	Power generated by the PV system [kW]
P_{CES}	Power at which the electrochemical storage is charged [kW]
P_{DES}	Power at which the electrochemical storage is discharged [kW]
P_{ED}	Electric power used by the electric to thermal equipment [kW]
P_{UG}	Power purchased from the utility grid [kW]
P_{FI}	Power injected to the utility grid [kW]
P_{CHP}	Electric power from the cogeneration system [kW]
P_{HP}	Electrical power used by the heat pump equipment [kW]
V_{CHP}	Gas used by the cogeneration system [kW]
Q_{CHP}	Thermal power from the cogeneration system [kW]
Q_{HP}	Thermal power from the heat pump [kW]
Q_{TL}	Thermal load [kW]
V_{BOI}	Gas power used by the boiler system [kW]
Q_{BOI}	Output power from the boiler [kW]
Q_{CTS}	Power at which the thermal storage is charged [kW]
Q_{DTS}	Power at which the thermal storage is discharged [kW]
η_{PV}	Efficiency of the connexion with the PV system [%]
η_{CES}	Charge efficiency of the electrochemical storage [%]
η_{DS}	Discharge efficiency of the electrochemical storage [%]
η_{ED}	Efficiency of the connexion with the electrical demand [%]
η_{UG}	Efficiency of the connexion with the utility grid [%]
η_{CHPe}	Cogeneration electrical efficiency [%]
η_{CHPth}	Cogeneration thermal efficiency [%]
η_{HP}	Efficiency of the heat pump [%]
η_{BOI}	Efficiency of the boiler [%]
η_{CTS}	Charge efficiency of the thermal storage [%]
η_{DTS}	Discharge efficiency of the thermal storage [%]
η_{TL}	Efficiency of the connexion with the thermal load [%]
$C_{O\&M,PV}$	PV O&M costs [€/kW-year]
$C_{O\&M,ES}$	Electro-chemical ESS O&M costs [€/kW-year]
$C_{O\&M,CHP}$	CHP O&M costs [€/kW-year]
$C_{O\&M,TES}$	Thermal ESS O&M costs [€/kW-year]
$C_{O\&M,HP}$	Heat Pump O&M costs [€/kW-year]
C_{UG}	Electricity price [€/kWh]
C_G	Gas price [€/kWh]
C_{FI}	Feed-in tariff [€/kWh]
C_{GHG}	Emissions costs [€/tCO_2]
Uncertainty Analysis and Sensitivity Analysis parameters	
Δ	Morris step
E	Expected value
p	Number of levels at which the PDF is divided in the Morris method
r	Number of trajectories created for the Morris method
S_i	First-order Sobol index for parameter i
S_{Ti}	Second-order Sobol index for parameter i
μ_i^*	Morris index for parameter i
V	Variance

favourable economic, environmental and social parameters and; once the investment has been made, the infrastructure is maintained in operation until another relevant event occurs that requires a new investment, thus exploiting the equipment for its whole lifetime [7]. When upgrading the energy infrastructure, it may be beneficial to evaluate the possibility of adopting smart energy management strategies such as a prosumer model. However, the intrinsic characteristics of industrial SMEs are not compatible with standard prosumer approaches, and specific investment selection strategies are required for them. Moreover, as exposed in the analysis performed in [8] considering investment trends in firms during the last years, entities tend to intuitively invest less if the uncertainty in the energy market increases. Therefore, as important expenses are to be performed, it is crucial to optimise not only the plant design and operation for the expected lifetime of the equipment but also to evaluate the risk of these actions according to the uncertain ranges and probabilities of the inputs. For this reason, the renovation of energy equipment has to consider the current and future feasibility of the decided energy solutions maximising the return of investment while evaluating the risk associated with the decision.

The optimisation of the energy design and sizing has been treated extensively in the literature. Many energy infrastructure and equipment sizing studies, such as [9], focus on islanded mode. Few studies consider a connection with the utility grid. This is the case of [10], where a hybrid energy system is proposed for an industrial area performing the optimisation separately for each month of the year and without analysing prosumer capabilities. Following the same line, in [11] a grid-connected photovoltaic system is sized parametrically, while in [12] an approach to select the sizes and locations of energy sources is performed with the objective to evaluate possible future energy expansions. In all the mentioned studies, the energy equipment sizing is optimised for a single year, omitting the time evolution of parameters and without calculating the value of the investment along its lifetime. Also, all input variables are treated as deterministic, not evaluating the uncertainty created by them. Overlooking the time evolution of parameters and the uncertainty can lead to a suboptimal and unexpected result, representing a risk for entities performing the investment activity. Recently, a study has been published where an optimisation model for long-term, multi-stage planning of a general decentralized multi-energy system is exposed without analysing uncertainties [13]. In this work, the optimal investment is addressed from a multi-stage point of view, distributing the investment over years and performing retrofitting. This strategy could be suitable for urban planning applicable to big governmental entities or districts where buildings are added in multiple phases but is not suitable for SMEs due to their investment characteristics. Also, despite multiple years are evaluated to perform the investment at different points in time, the considered parameters are discretized and considered constant during the year. This fact discerns from reality, as input parameters are subject to important seasonal and hourly variations [14]. This is especially true for the industrial sector, where the production is maintained constant during week-days and is diminished during weekends to perform minor activities such as adopting new plant configurations and maintenance [15], making it essential for industrial SMEs to consider continuous weekly operation to capture production and costs patterns and properly size their energy infrastructure.

To evaluate the real risk related to energy investments, it is essential to understand the value of the investment, the uncertainty in the design problem output and the inputs that cause it. Thus, when evaluating the optimal decision for an energy investment to be performed in an industrial SME, the complete lifetime of the energy infrastructure should be analysed considering continuous costs and production patterns. Also, a complete Uncertainty Analysis (UA) has to be done to properly analyse the risk linked to the investment and its robustness, and Sensitivity Analysis (SA) is required to identify the parameters that cause this risk. This identification allows SMEs to decide if they put an effort on better defining the most critical factors, thus reducing the epistemic uncertainty and the investment risk; and also provides them with a framework to identify the points in time at which the investment perspectives are better due to a clearer evolution of these key parameters.

Therefore, in this paper, a methodological framework is proposed to support SMEs in the optimisation of their energy infrastructure considering its whole lifetime together with weekly production and market operation cycles; as well as applying UA and SA. Considering the existing structure and investment strategies of industrial SMEs as well as the current changing market structure, the proposed methodology supposes a novelty in the decision-making process performed by these entities. The outputs of the methodology have important implications, allowing smart energy investment decisions, providing risk awareness, and identifying hotspots related to the economic, environmental, and social activities of the enterprise which helps industrial SMEs to take realistic energetic and financial decisions.

1.2. Relevant literature discussion

Up to date, some studies have been presented where uncertainty is addressed for energy infrastructures design and operation. In most of them, the uncertainty is analysed employing uniquely a basic SA to evaluate the variation of the output of the system according to a set of selected inputs. This is the case of [16], where an energy system for rural electrification is optimised and a SA is done. In this study, the proposed SA methodology is not clear and the inputs' uncertainties studied are selected subjectively, not presenting their probability distributions. Similarly, in [17] a set of pre-defined system combinations are evaluated and their sensitivity in front of different parameters is performed, without providing details on the methodology. In [18], a hybrid system is optimized employing commercial software and a SA is done. In this case, it is mentioned that the SA is carried out changing only one parameter at a time once. This procedure is also followed in [19], where a trigeneration system is optimised considering the variation of load and energy carriers prices through analysing potential occurrence scenarios. The one-at-a-time (OAT) strategy employed in these studies, where each input parameter is modified in an isolated manner while the others remain the same, is common in the literature due to its ease of implementation and logic analysis of results. The OAT approach has also been used in [20], where the optimal design of a stand-alone hybrid energy system for a rural area is addressed. In this study, the configuration of the system is pre-stated and a SA based on scenarios is conducted to appreciate the influence of environmental policy on the total system cost. Similarly, in [21] a techno-economic analysis of a standalone hybrid energy system is carried out and a SA through OAT strategy is conducted to see the effects of costs of energy in the system economic performance, while in [22] four hybrid power system scenarios for a household application are tested and a SA is done employing three wind speeds and solar radiation possibilities. In none of these works, however, the probabilities of the analysed uncertain inputs are considered. Moreover, the performed SA strategies do not provide the required insights to properly evaluate the output statistically, as they only consider a small number of scenarios and the interrelation of different energy inputs is overlooked. A slightly different approach is presented in [23], where an OAT methodology is carried out employing several samples performed on a uniform distribution, expanding the results of considering only few scenarios. However, the use of uniform distributions is a simplification of the reality, as it is common to have specific scenarios with higher probability of occurrence rather than intervals where the probability of all values is equal [24]. Therefore, the employment of uniform distributions limits the capacity of obtaining suitable insights for the investment problem faced by industrial SMEs.

Few studies with improved SA strategies have been published, such as [25], where a SA is applied for zero/low energy buildings aiming to obtain the design parameters that affect the performance. In this case, the SA is formed by a two-stage approach, using global and local methods as the first and second stage, respectively. However, in this analysis a UA is not performed and thus despite sensitivity is addressed to evaluate the inputs that most affect the performance, the output uncertainty is not known. In [26], UA and SA are both performed for the optimal design of a distributed energy system to supply energy to a tertiary demand. The objective is the minimisation of total system cost while meeting CO_2 emissions restrictions. The UA is performed using the Monte Carlo simulation while the SA consisted of a two-step global SA. Despite the existence of different market prognosis, the uncertainty linked to energy market costs is modelled as uniform, without considering the higher probability of some scenarios above others. Furthermore, in all the above studies the proposed optimisation models employ only one year as a representative time frame, simplifying the decision-making process and not evaluating the time evolution of parameters. According to [27], the fact of solving this optimisation problem using single "typical-year" approaches produces results that become suboptimal after a short time due to the changing framework where the energy systems are integrated. In this same line, the proposed inputs' probability distribution functions are static, i.e., they do not vary with time. This characterization does not evaluate the future costs probabilities and simplifies their consideration. This uncertainty handling is methodologically erroneous and does not enable to obtain a realistic framework for energy investment analysis.

Therefore, there is a gap in the literature regarding the optimisation and analysis of energy investments over time and the uncertainty linked to it which has to be filled to support industrial SMEs in energy investment decisions. In the following paragraphs, suitable techniques employed for uncertainty assessment in other research fields are reviewed to be able to propose the most correct methodological framework for its application in the prosumer energy investment problem of industrial SMEs.

The uncertain parameters that influence the investment decision can be characterized through different strategies, such as scenarios, numerical ranges or Probability Density Functions (PDF). The latter is more suitable for the problem presented here, as it enables the application of sophisticated methods that provide robust results [28]. To perform the UA, a method that generates samples according to these PDFs allows obtaining a reliable output for energy systems [29]. Although Monte Carlo is a commonly used statistical sampling method [30], its high computational cost suggests the employment of quasi-random sampling methods such as the Latin Hypercube Sampling (LHS), which provides results efficiently at a low computational cost [31] and has been proved to perform well in energy models [32].

Once the uncertainty in the output is known, the risk becomes more tangible for investors, although it is convenient to perform a SA to know the inputs that cause most of this uncertainty. Among other approaches, statistical global SA methods are the ones that provide the most model insights [28]. Due to the complexity of the optimisation problem and its high computational cost, a two-stage SA methodology is considered for the study here presented. The first stage aims at reducing problem dimensionality, identifying and discarding less influential inputs through a screening technique. Among the different screening techniques for energy models, the Morris method is the most suitable one as it does not require hypotheses regarding the nature of the model and thus can be applied to a wide range of problems [33]. The second stage of the SA methodology is selected to be formed by a statistical variance-based global SA method, applicable to non-monotonic and non-linear models [34]. Among the variance-based methods, the Sobol method presents robust results and allows for a suitable sample size to capture the behaviour of the problem [35]. The combination of Morris and Sobol has already been used in the literature to assess complex uncertain problems, such as in [36]; and has been proved to provide results efficiently while quantifying the sensitivity effectively.

1.3. Contributions

After analysing the literature and the most suitable tools for assessing the energy investment uncertainty, a design and operation optimisation methodology considering the lifetime of the equipment and performing a UA based on LHS and a two-stage SA formed by the Morris and Sobol methods is proposed in this paper. Considering the existing structure and investment strategies of industrial SMEs as well as the current changing market structure, the proposed methodology supposes a novelty in the decision-making process performed by these entities. The outputs of the methodology, which is designed to suit the industrial SMEs requirements, have important implications, allowing smart energy investment decisions, providing risk awareness, and identifying hotspots related to the economic, environmental, and social activities of the enterprise. Given the current managerial system of industrial SMEs, the adoption of this methodology forms a suitable, robust and efficient framework and provides SMEs with a different point of view that enables better asset planning, resulting in a competitive advantage.

The main contributions of this work to the state of the art can be summarized as:

- Optimisation of energy investments considering equipment operation over its lifetime which evaluates the production and energy market weekly cycles, hourly operation, and economic, environmental and social implications.
- Continuous probabilistic uncertainty characterization of optimisation's inputs over the expected lifetime of energy equipment.
- Energy system investment uncertainty quantification for risk acknowledgement of the upgraded infrastructure over time.

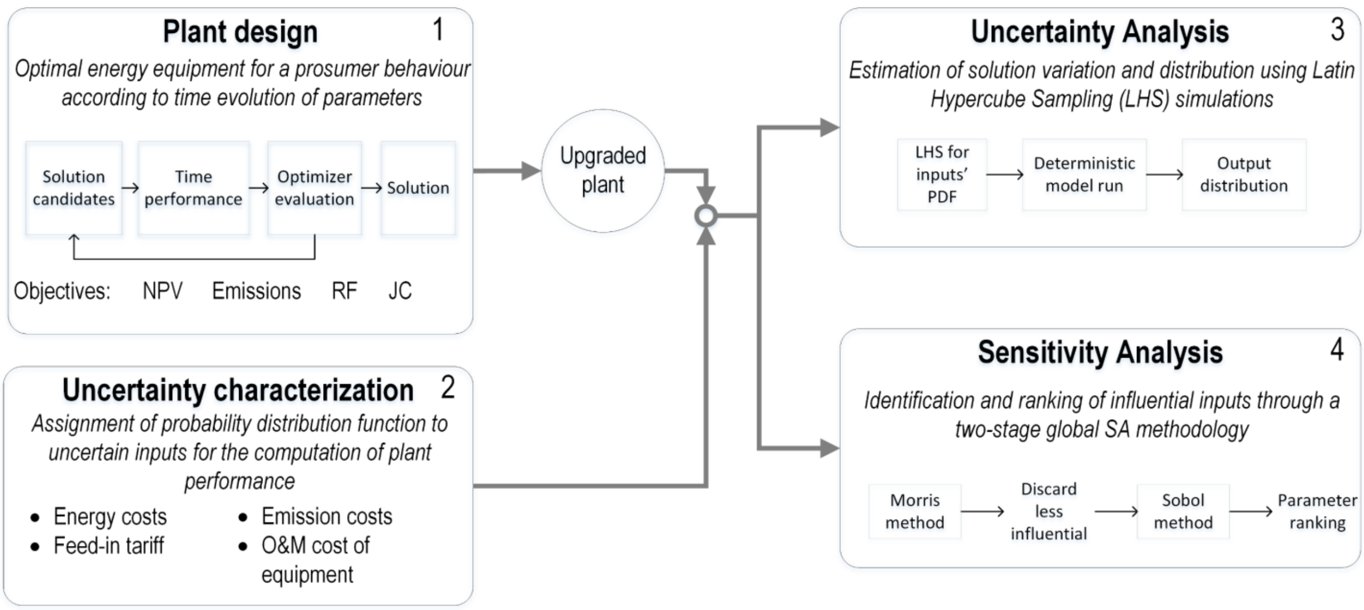

Figure 1: Workflow for investment optimisation and risk assessment

- Identification of the main inputs that influence the output uncertainty in the energy investment decisions through sensitivity analysis.

The paper is organized as follows. First of all, the studied problem is presented in section 2. This problem definition section includes the explanation of the methodology and techniques employed, as well as the characterization of the uncertainty in the inputs. Secondly, in section 3, the case study at which the exposed methodology is applied is shown, which is based on a real remanufacturing industrial SME. Then, the results of the optimisation, UA and SA are shown in section 4, where a discussion is also performed. Lastly, the conclusions of the study are presented in section 6.

2. Problem definition

The objectives of industrial SMEs willing to upgrade their energy infrastructure are the reduction of costs, the maximization of investment's return, the compliance with the legislation, the support to the green transition and the contribution to the progress of the local community. The methodology that is applied in this paper to properly evaluate the investment performed by SMEs in energy equipment is depicted in Figure 1, which considers the performance of the upgraded infrastructure acting as a prosumer along the lifetime of the equipment as well as the assessment of risks and the identification of key inputs causing uncertainty.

The first stage of this methodology, labelled in Figure 1 as box number 1, is the deterministic optimisation of the investment to upgrade the energy infrastructure of the SME considering its benefits over time. In the literature, most studies addressing energy sizing optimisations including renewable energy sources (RES) have as unique objective economic profit maximisation or cost minimisation, such as [37], although some of them also consider environmental and social implications. From these, the most common approach is to combine economic objectives with environmental ones, including emissions either as a constraint or as an objective. This is the case of, for example, [38], where a small hybrid power system is sized minimising costs and the resultant emission factor from the generated energy. The incorporation of social criteria in these sizing studies is often overlooked due to the difficulty of their measurement [39] and the moderate implications that the resultant system has in the local community. However, the decisions taken by industrial SMEs have a great social impact since these entities are closer to the local community, both geographically and in a social proximity manner. For these reasons, it is beneficial in the long term for the SME to include social objectives in the energy investment optimisation problem.

Given the characteristics of the studied problem, economic, environmental and social criteria are included in the optimisation function to reach a solution that is not only suitable from an economic profit point of view but that also contributes to the long-term continuity of the SME and the acceptance of the solution by the society. The economic parameter is represented through the maximisation of the Net Present Value (NPV), which is a measure employed when assessing the profitability of projects in enterprises [39]. Emissions are included in the objective function for its minimisation, and the social field is considered through the incorporation of the Renewable Factor (RF) and Job Creation (JC). RF measures the amount of load covered by RES [40] and enables to evaluate local community content with the energy solution, as it is common that the community accepts energy infrastructures where renewable sources cover the load [41], whereas JC is understood as the employment generated per equipment for their installation and maintenance services [42]. Also, restrictions such as maximum Return on Investment (ROI) specified by the investor and maximum emissions allowable are considered.

This energy equipment sizing optimisation procedure performed in this first stage of the methodology provides the optimal energy equipment and capacities to install as well as their energy, economic and environmental performance. To evaluate the risks associated with the investment and the most influential parameters, UA and SA are performed. For this, and as exposed in the second box of the methodology shown in Figure 1, the uncertainty in the input is characterized. The parameters considered as uncertain are those not under the control of the enterprise or that can change unexpectedly within some range. In this case, these are electrical energy costs, gas energy cost, selling price of electricity, emissions costs and operation and maintenance costs of equipment. With a PDF assigned to each of them and the upgraded plant model, it is possible to perform the UA and SA. The UA, which has to be carried out before the SA, uses LHS simulations to obtain input samples and repeatedly runs the deterministic plant model. Although in this methodological stage the selected energy equipment does not change, its hypothetical operation varies considering the different evolution of input parameters obtained through LHS. Thus, in the deterministic model run under the UA, the operation of the equipment is computed again for the considered inputs. With this process, the output distribution is obtained, making it possible to evaluate the robustness of the solution and the minimum expectable profit. Then, the SA is done through a two-stage global system, which enables to identify and rank the inputs that influence the most the uncertainty of the output obtained through the UA. This provides information about where efforts should be focused on when seeking additional framework data if the robustness of the solution wants to be improved.

The proposed methodological workflow is suitable for its application to industrial SMEs, with peak power ranging from dozens of kW to units of MW [43] and specific electricity and thermal consumption of 1.449 kJ/€ and 4.512kJ/€, respectively, concerning the value-added [44]. In Figure 2, the energy infrastructure of a typical SME is exposed. In bold lines, the original plant or "reference plant" existent before the investment purchases electricity to satisfy electrical demand and has a boiler to fulfil thermal demand. For the optimisation procedure to upgrade the energy infrastructure of the SME, the inclusion of equipment undergoing growing adoption and reducing its costs as well as equipment enabling the interconnection of the thermal and the electrical sides is considered. This equipment is formed by RES, in this case, photovoltaic (PV); electrochemical Energy Storage System (ESS), thermal ESS, Combined Heat and Power (CHP) units and electrical to thermal equipment, such as Heat Pumps (HP). In this paper, the considered lifetime of the energy upgrade is of 15 years.

In the following sections, details are provided regarding the optimisation procedure, the inputs' uncertainty characterization and the UA and SA techniques employed.

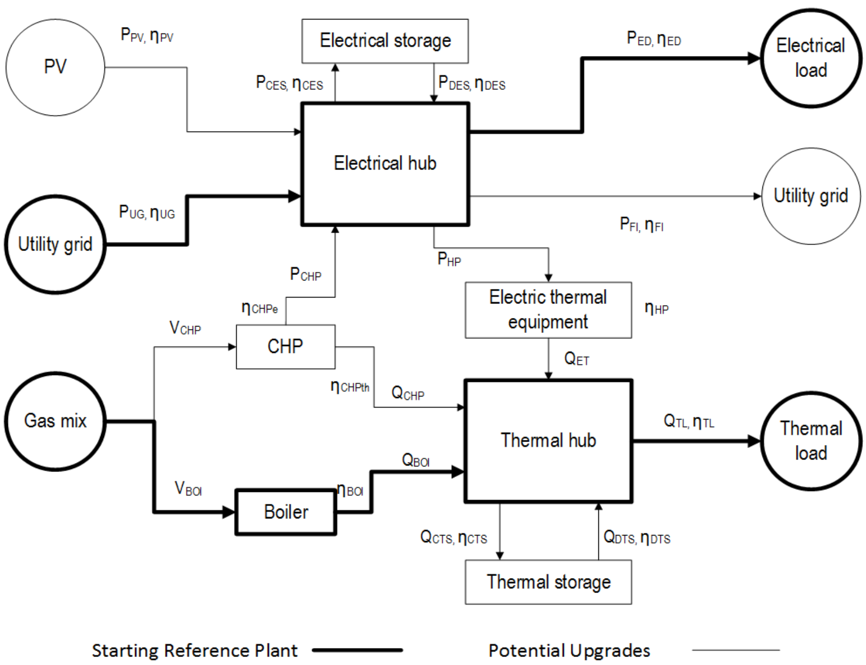

Figure 2: Energy infrastructure of a typical industrial SME and potential upgrade

2.1. Energy sizing optimisation

The optimisation aims to select the investment to upgrade the energy infrastructure of the SME for improving its competitiveness, considering economic, environmental and social parameters as well as the adoption of a prosumer energy behaviour. A deterministic model of the plant is constructed and a two-stage procedure is applied to optimize both the energy equipment and their operation over their lifetime. This formulation requires the specification of two sets of constraints. On the one hand, constraints related to the design, which can include maximum equipment size, maximum emissions and maximum investment and time for ROI. On the other hand, operation constraints regarding the energy flow inside the resultant plant. These include electrical and thermal hub equilibriums, energy exchange constraints, storage constraints, and fulfilment of equipment power capacity thresholds.

The flowchart of the optimisation procedure can be seen in Figure 3. First of all, SME parameters, investment constraints, and information of RES generation, energy market and demand are obtained. Four seasonal representative weeks per year are selected along the considered time horizon, which are used to obtain the expected costs and benefits per year. Once all the information is loaded, the optimal operation of the reference or starting plant before the investment is obtained, computing the total operation cost along the optimisation horizon, i.e. 15 years. This optimisation is solved through linear programming in an hourly format minimising the weekly cost. The total operating costs along the optimisation horizon are used as the reference value for plant sizing optimisation, which is solved in the next block.

For the sizing optimisation, the operation of the energy infrastructure along time is also considered. This optimisation employs a Direct Search approach that works with a set of candidates and evaluates their suitability. The selected candidates, which are the equipment to install and their capacities, should fulfil the constraints regarding maximum investment and plant restrictions, such as maximum space available. If so, the energy flows are verified and the operation

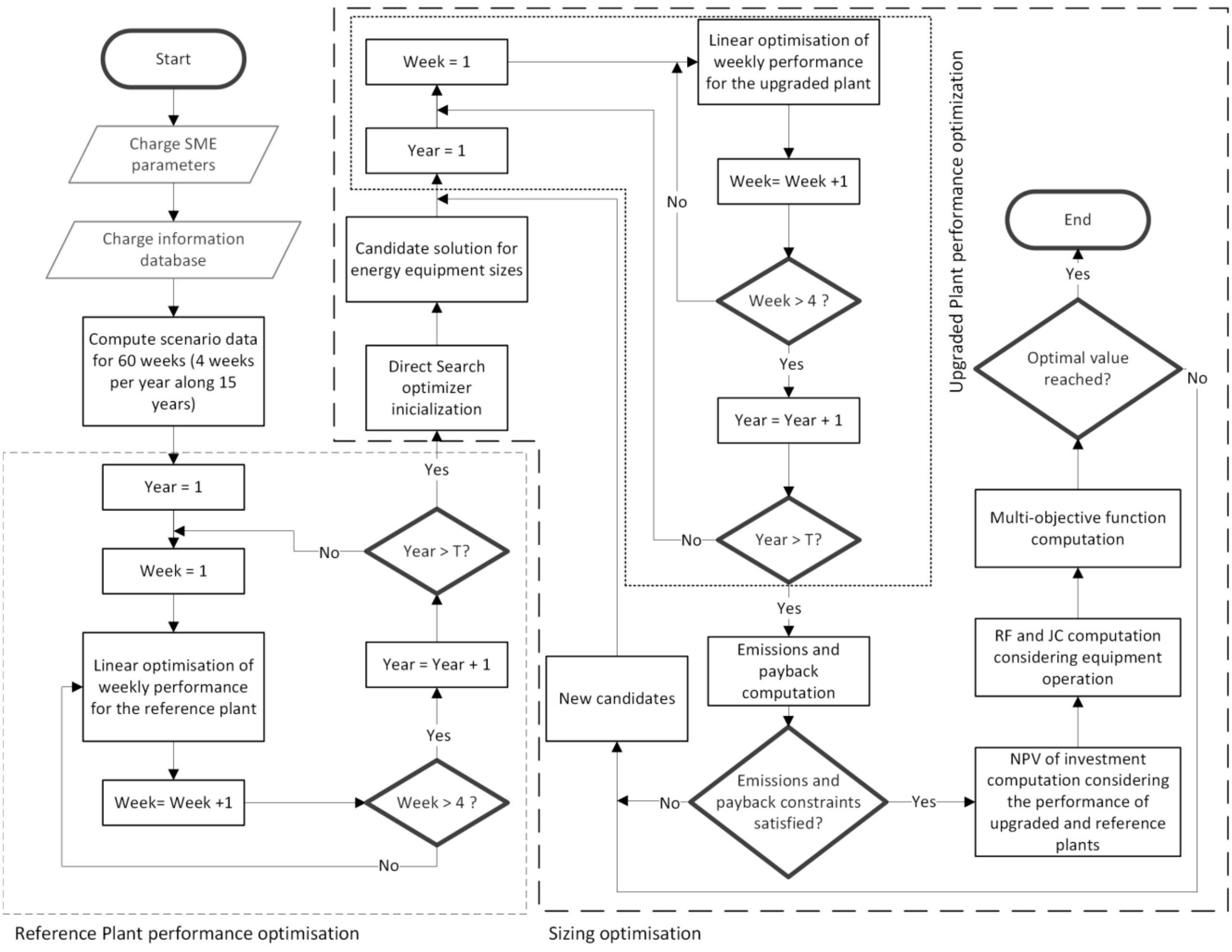

Figure 3: Flowchart of the energy sizing optimisation process

Uncertain parameter	Symbol	2020 PDF	2035 PDF
PV O&M costs	$C_{O\&M,PV}$	Nakagami (16,53; 43,69)	Nakagami (16,55; 21,39)
Electro-chemical ESS O&M costs	$C_{O\&M,ES}$	Weibull (9,07; 4,01)	Weibull (5,14; 3,25)
CHP O&M costs	$C_{O\&M,CHP}$	IG (36,6; 1.772)	IG (36,6; 1.772)
Thermal ESS O&M costs	$C_{O\&M,TES}$	Normal (0,26; $0{,}5^2$)	Normal (0,26; $0{,}5^2$)
Heat Pump O&M costs	$C_{O\&M,HP}$	IG (5,56; 12,36)	IG (5,56; 12,36)
Electricity price	C_{UG}	Nakagami (0,885; 10,14)	Nakagami (0,885; 10,14)
Gas price	C_G	Weibull (1,44; 3,11)	Weibull (1,44; 3,11)
Feed-in tariff	C_{FI}	U ($0{,}8C_{UG}$; $0{,}9C_{UG}$)	U ($0{,}8C_{UG}$; $0{,}9C_{UG}$)
Emissions costs	C_{GHG}	Nakagami (0,824; 20,03)	Nakagami (0,824; 20,03)

Table 1: Summary of PDFs for uncertain inputs

optimised. This operation optimisation is mathematically identical to that of the reference plant, although it is exposed separately in the diagram for the sake of readability. Once the operation optimisation is completed, ROI and emissions are computed and it is verified if their constraints are fulfilled. If so, the cost-benefit per year is obtained by comparing the performance of the upgraded plant with that of the reference plant and the NPV is computed. Then, bearing in mind the operation of the equipment, the RF is computed considering the total energy generated by the PV system and the load of the SME over the considered time horizon. JC is also evaluated following the guidelines provided in [45], using the total energy generated by generation and transformer equipment and the capacity of storage systems to compute the full-time jobs created over the expected lifetime of the new energy infrastructure. Once all the economic, environmental and social criteria values are obtained, they are normalised and included in a single weighted objective function. After its computation, a new set of solution candidates are created until the sizing optimizer reaches the optimal value.

This procedure enables to consider economic, energy, environmental, and social aspects in the investment and operation of the industrial plant and adjusts today's decision considering the forecasted changes in the external market over the lifetime of the equipment. For details on the mathematical formulation of the optimisation problem, please refer to Appendix A.

2.2. Uncertainty characterization

The inputs considered as deterministic in the optimisation stage are inherently uncertain. To evaluate the uncertainty of the computed NPV, it is indispensable to consider their uncertainty. In this section, these inputs are analysed and their uncertainty is evaluated and characterized. A summary of the obtained PDFs for each of the parameters can be seen in Table 2.

2.2.1. Operation and maintenance of equipment

The distribution of the Operation and Maintenance (O&M) costs is studied for the PV system, the CHP, the electrochemical ESS, the thermal ESS and the HP system. To do so, a literature search has been performed to gather values for these parameters and PDFs are fitted to the obtained data. The most suitable PDF is selected according to the goodness of the fit, evaluated using the likelihood function. For the same maintenance services, the O&M costs can vary due to the existence of additional services which do not affect the maintenance itself or due to external market causes. In this paper, this initial uncertainty is considered to improve the accuracy of the obtained results.

For the PV system, data collected from O&M contracts are obtained from [46]. The obtained data resembles a normal distribution with a positive skew, being the Nakagami distribution the one that shows better performance. In Figure 4, the histogram of the values and the Nakagami distribution are exposed. These values correspond to the year 2020 and are likely to decrease in upcoming years due to the growing practice and the economy of scale that the PV sector is experiencing. For this reason, PDFs are created for each year along the lifetime of the equipment, adjusting the initial distribution to the expected tendency exposed in studies [46–48], and decreasing the costs up to 30%.

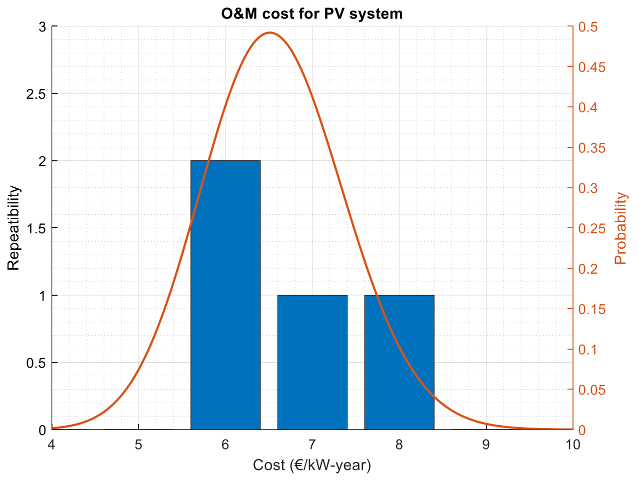

Figure 4: Histogram and PDF for the 2020 O&M cost of the PV system

Electrochemical ESSs are also undergoing technological developments that will decrease their economic costs. Despite that for power system stability and high energy capacity storage lead batteries are being used nowadays [49], there is a trend to implement more efficient technologies such as the Li-ion battery for smart energy management applications. The current O&M costs of Li-ion batteries lay around 8€/kW-year [50–52], which is forecasted to be reduced between 40% and 50% in the upcoming years [53,54]. In this case, the Weibull distribution is the most suitable, which is modified along the years according to the specified decrease range. In Figure 5, the values obtained for the O&M and the fitted PDF for 2020 is exposed.

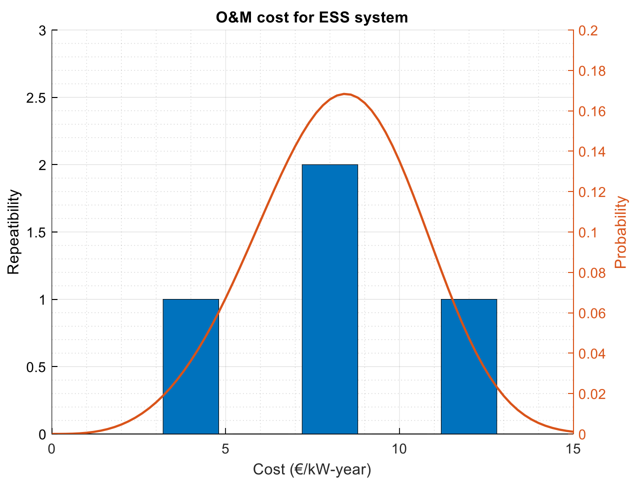

Figure 5: Histogram and PDF for the 2020 O&M cost of the electrochemical ESS

Regarding the rest of the systems, although they are still not widely included in smart grids, they have a considerable maturity level and their O&M costs are not likely to decrease in the near future [55]. Thus, their probability distribution will be kept constant along the considered time horizon. For CHP, O&M values are between 30€/kW-yr and 45€/kW-yr, and follow an Inverse Gaussian distribution, as exposed in Figure 6. In the case of the thermal ESS, sensible heat energy storage is considered due to its stability and its current use in industrial sites [56,57]. The O&M cost of these systems has a mean value of 0,26€ct/kW and a small variance [58]. This uncertainty is represented as a Normal PDF, as shown in Figure 7. HPs O&M costs range from 2,5€/kW-yr to 9€/kW-yr [14,59]. The Inverse Gaussian is the distribution function most suitable in this case. The histogram and the fitted PDF are shown in Figure 8.

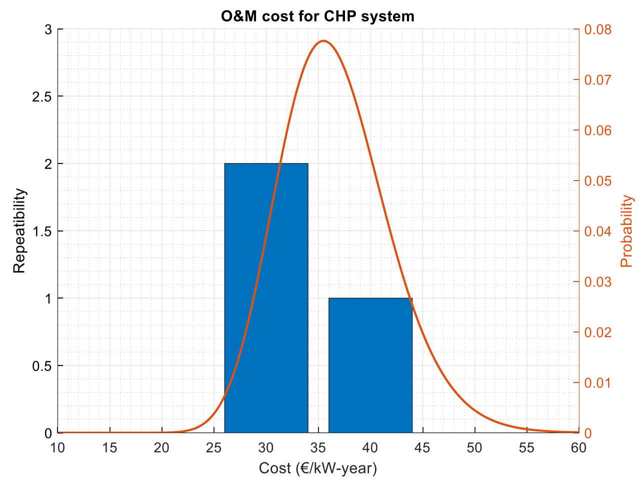

Figure 6: Histogram and PDF for the O&M cost of the CHP system

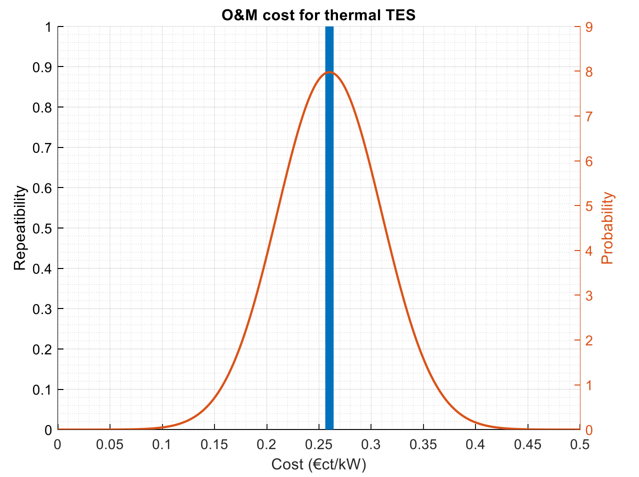

Figure 7: Histogram and PDF for the O&M cost of the thermal ESS

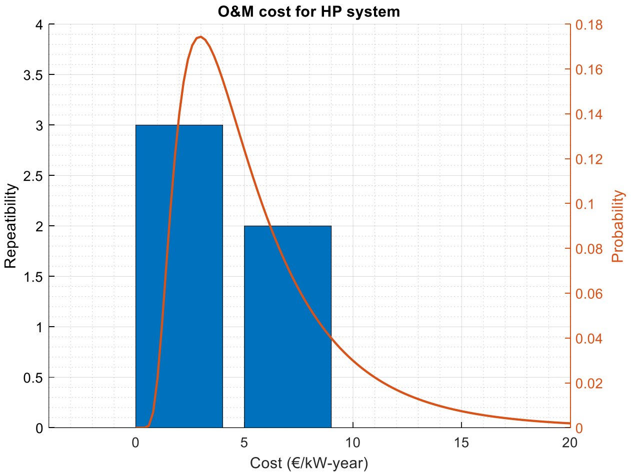

Figure 8: Histogram and PDF for the O&M costs of the HP system

2.2.2. Energy price

In this section, the uncertainty associated with the cost of electricity and gas during the lifetime of the energy equipment is evaluated.

In many countries, there are two main types of electrical tariffs: tariffs where the price is fixed and agreed with the supplier, and tariffs regulated by the energy market or governmental entities which include price variability. To enhance the employment of renewable energy sources, fixed price tariffs are increasingly reflected as power purchase agreements (PPAs) between energy consumers and renewable energy producers [60]. PPAs are performance-based contracts that aim to create a risk-controlled agreement for the purchase and sale of energy, and which typically last between 7 and 10 years. To enable the proliferation of PPAs, it is required to allocated RES at a considerable scale and therefore tendering schemes are being implemented. However, this strategy currently reduces the diversity of actors and presents a disadvantage for the participation of SMEs and private individuals in the renewable energy market [61], being big entities the ones primarily benefiting from these contracts.

In [62], it is argued that to promote a competitive inclusion of smart energy management strategies including renewable energy sources, the most efficient pricing strategy would be for the electricity price to vary in real-time and reflect wholesale market dynamism market. This is also defended in [63], where electricity supply dynamic pricing is presented as a key strategy to enhance the flexibility of consumers. The energy transition is currently opening the path to the purchase of electricity following dynamic cost patterns reflecting wholesale market behaviour [64]. In fact, the European Directive 2019/944 [65] developed in the framework of the Clean Energy Package defines the "dynamic electricity price contract" as an electricity supply contract between a supplier and a final customer that reflects the price at the spot market or at the day-ahead market at intervals at least equal to the market settlement frequency. These flexible tariffs are already been implemented and have been studied in the literature, evaluating also its suitability for prosumer SMEs. In [66], an industrial SME with a PV system is analysed in which a variable price tariff of two bands per day changing in a monthly manner is applied. A dynamic price strategy is also employed in [67] to surpass the technical and economic barriers that exist for SMEs applying novel energy management strategies, and a case study based on a bakery industrial SME is developed to check its suitability. Similarly, the economic benefits of installing new energy equipment in a medium-scale facility are studied in [68]. In this case, a real-time pricing (RTP) scheme is chosen based on the energy prices at the wholesale market.

In this study, given the prosumer energy model that the industrial SME is transforming to and the ongoing green transition, as well as the impacts of the energy behaviour in the local community and environment, it is chosen to employ an RTP tariff, considering hourly changing electricity price according to the wholesale market while including the applicable taxes and levies as done in [68]. This electricity price is forecasted to increase yearly, on average, between 0,79% and 4,82% until 2035 [26,69,70]. In Figure 9, the forecasted scenarios are exposed considering an average starting price of 47,68€/MWh [14].

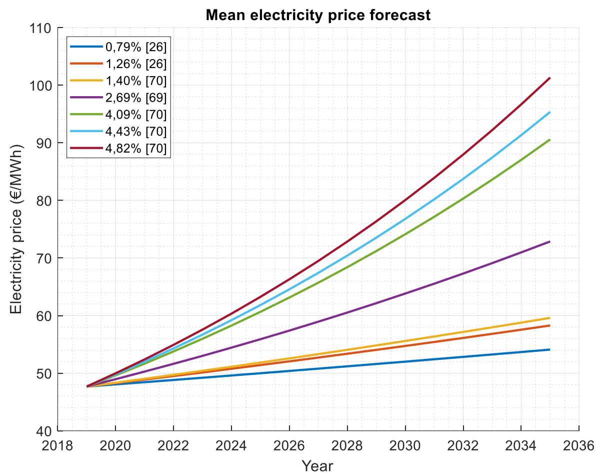

Figure 9: Electricity price forecast up to 2035

To capture the uncertainty of electricity price and obtain realistic time evolutions when sampling the PDFs, the energy price scenarios are translated into yearly percentage increases, enabling to obtain the electricity price based on previous year values. The most suitable distribution is the Nakagami one, which is exposed in Figure 10.

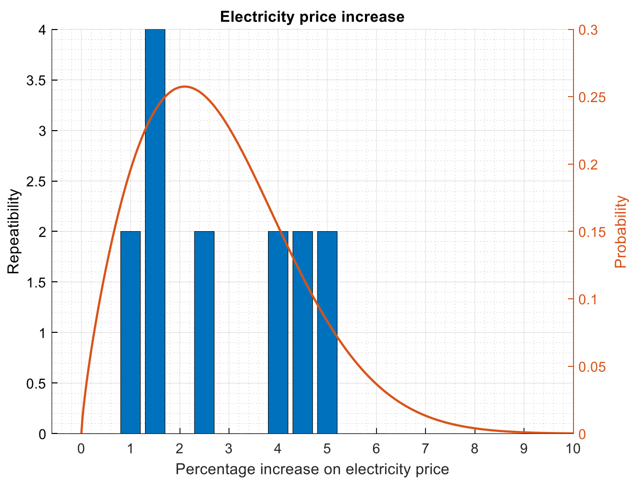

Figure 10: PDF of the electricity price increase

Regarding gas costs, tariffs do not differentiate the time of use and thus constant hourly prices are considered. The forecasting yearly increment of gas price lays between 0,65% and 1,81% until 2035 [70,71]. The forecasted scenarios, with a starting price in 2019 of 30,8€/MWh [72], are exposed in Figure 11. As with electricity, a PDF is generated based on the yearly percentage increase. The most suitable distribution is the Weibull, which is exposed in Figure 12.

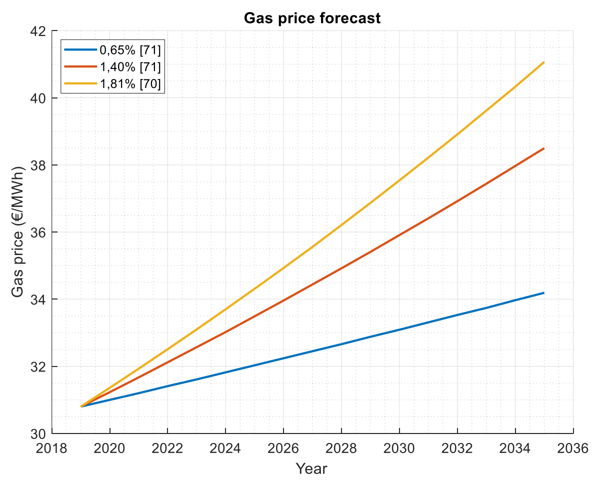

Figure 11: Gas price forecast up to 2035

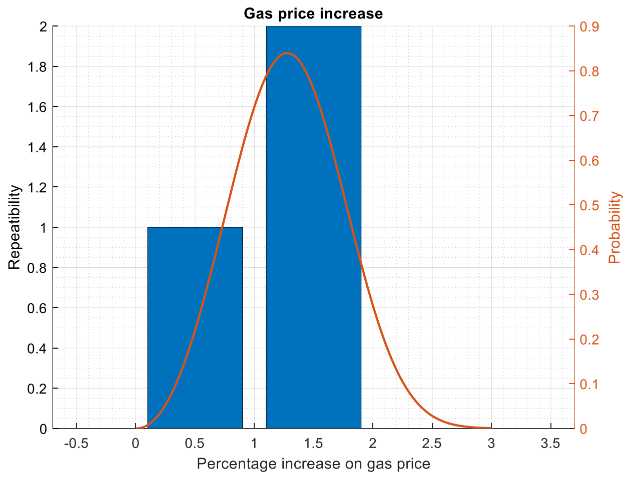

Figure 12: PDF of the gas price increase

The exposed energy costs and predictions do not consider the presence of taxes and levies. To obtain realistic final cost values, taxes of 40,7% and 20% are applied to electricity and gas price, respectively [73].

2.2.3. Feed-in tariff

When an SME faces the decision of upgrading its energy infrastructure, it may be beneficial to consider the incorporation of new business models involving an active role in the energy market. For this reason, it is crucial to consider a feed-in tariff that enables the delivery of energy to the utility grid at a specified cost. There are three types of feed-in tariffs [74]. The first type is the percentage-based, which establishes the price of the energy sold as a percentage of the energy price at the same moment in the wholesale market. The second type are the fixed price tariffs, where the price is stated by the government and remains independent from the market, and the third type are the premium tariffs, which offer a price above the electricity price at the market at the same time. For the case studied in this paper, the most suitable approach is the employment of a feed-in tariff with dynamic prices, being these prices a percentage of the ones at the wholesale market [75]. This enhances the generation of energy at peak times and the purchase of energy at valley times, helping to decongest the electrical grid while creating a profit for the consumer. This percentage can vary due to political reasons. In this paper, the range of 80% to 90% of the wholesale market price is considered [76], modelled through a uniform distribution.

2.2.4. Emissions costs

Emissions are growing in importance due to their influence on global warming. In 2019, most countries with implemented emission trading schemes dealt with costs below 30€/ tCO_2 [77]. In this paper, the average European case is considered, with emission costs of 25€/ tCO_2 in 2019. This cost is forecasted to yearly increase as depicted in Figure 13, being the values obtained from [54,78]. This distribution is also captured by evaluating the yearly percentage increases. The Nakagami distribution is employed, which can be seen in Figure 14.

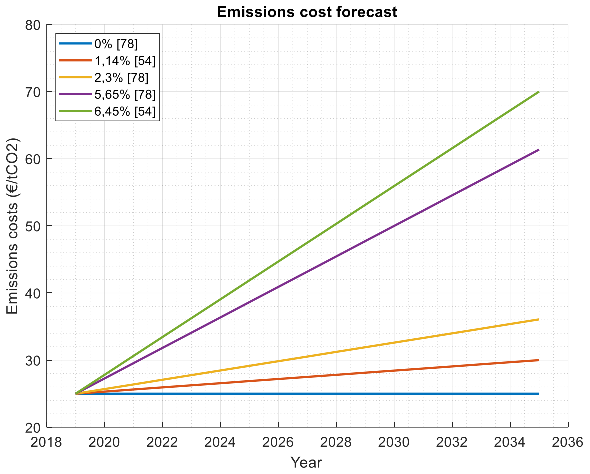

Figure 13: Emissions cost forecast up to 2035

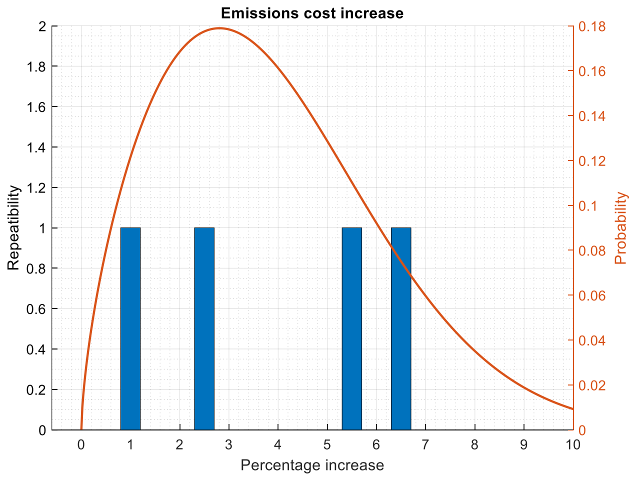

Figure 14: PDF of the emission cost at 2035

2.3. Uncertainty Analysis

In order to obtain the output distribution and the risk associated with the selected investment, a UA is performed. To do so, N samples are generated for each of the PDFs presented in the previous section using the LHS technique, a probabilistic procedure that divides the variable range into intervals with equal probability and selects one random sample within each interval. Combining randomly the samples generated, N scenarios are obtained [79]. These are introduced into the deterministic plant model, where the optimal operation of the equipment is computed considering the evaluated inputs. Then, the output is calculated for each of the scenarios, obtaining its uncertainty. In this paper, 9 uncertain inputs are evaluated. Considering their variation over the studied horizon, a total of 135 PDFs have to be sampled. For complex energy systems like this, 1000 samples per PDF is a suitable value to obtain an accurate and representative result that enables the study of the uncertainty in the output [25].

2.4. Sensitivity Analysis

With the output uncertainty obtained, it is possible to evaluate the risk of the investment decision. Once this uncertainty has been assessed, a SA is performed to identify the inputs of the system that cause most of it. A two-stage methodology is applied in this paper. In the first stage, the Morris method is used to reduce the dimensionality while, in the second stage, the Sobol method is applied to obtain the parameters ranking.

The Morris method is a global approach that can be considered as an extension of local OAT techniques which enables to discriminate the less influential inputs with a small sample size and low computational cost [80]. The uncertainty range of all the inputs is divided into p levels. Then, r base vectors are obtained from sampling one random level per uncertain input. These base vectors are recommended to be between 4 and 10 [81] and serve as the starting point for the creation of trajectories, which enable to analyse the influence of the inputs in the output. In this paper, each uncertain parameter is divided into $p = 11$ levels; and $r = 10$ trajectories are evaluated. In each trajectory, the inputs' values are increased or decreased a step Δ in a consecutive manner. The Elementary Effect (EE) of input x_i in the trajectory can be computed as:

$$EE_i = \frac{f(x_1, \dots, x_i + \Delta, \dots x_k) - f(x_1, \dots, x_i, \dots x_k)}{\Delta} \quad (1)$$

Where f represents the deterministic model. To ensure a desirable symmetric treatment of inputs [82], it is convenient to employ a value of p even and a step value of:

$$\Delta = \frac{p}{2(p-1)} \quad (2)$$

With the EE obtained, it is possible to rank parameters through the index μ_i^*:

$$\mu_i^* = \frac{1}{r} \sum_{j=1}^{r} |EE_i| \quad (3)$$

Following the procedure exposed, the total number of model evaluations is 380.

Once the less influential inputs are discarded, the Sobol method is applied, which aims to calculate two metrics per parameter named first-order Sobol index and total-order Sobol index. These metrics indicate the portion of the output variance that is explained by a parameter alone and the portion of the output variance that is explained by a parameter and its interactions with others [26].

On the one hand, the first-order index of the parameter x_i is defined as:

$$S_i = \frac{V_{x_i}\left(E_{X_{\sim i}}(Y|x_i)\right)}{V(Y)} \tag{4}$$

Where Y is the output of the system, $V(Y)$ is its total variance and $E_{X_{\sim i}}(Y|x_i)$ is the mean value of Y considering the variation of all model inputs except x_i, which remains fixed. This term is evaluated for all values of x_i, and its variance computed, which is expressed by the term V_{x_i}. On the other hand, the total-order index is defined as:

$$S_{Ti} = \frac{E_{X_{\sim i}}\left(V_{x_i}(Y|x_{\sim i})\right)}{V(Y)} \tag{5}$$

Where $V_{x_i}(Y|x_{\sim i})$ is the variance of the output over all the possible values of x_i when the rest of the inputs are fixed. This variance is computed for all the values of the inputs, which is represented by the $E_{X_{\sim i}}$ term. To compute the Sobol indices for complex energy problems considering the entire distribution of inputs, repeatedly running the model is required. To minimise the computational cost while maintaining the method robustness, the best practices exposed in [83] are employed, which are based on scenarios sampling and matrix combinations. In this paper, the number of primary scenarios created is 5.000, requiring a total number of model evaluations of 30.000. An overview of this computation strategy can be consulted in Appendix B.

3. Case study

In this section, a case study based on a real SME manufacturing industry related to the automotive sector is presented. The plant considered presents an

Figure 15: Electrical and thermal demands of the case study plant

annual electrical and thermal demand of 386MWh and 779MWh, respectively. The representative weeks selected to perform the sizing study are exposed in Figure 16. The total operation cost of the energy infrastructure of the plant, including energy purchase, emissions and equipment maintenance during the considered time horizon is 23.116.000€. This industrial SME is considering to perform an energy upgrade in which it would be possible to install a PV system, thermal ESS, electrochemical ESS, CHP and HP.

For the energy sizing optimisation, deterministic inputs are employed, which are formed by the expected values of the uncertain parameters exposed in the previous section and that are shown in Table 2. Apart from these values and other restrictions related to energy equipment operation, constraints that can be imposed by the enterprise are also considered and exposed in Table 3. Other information used as input can be consulted in Appendix C.

Input	2020 value	2035 value
$C_{O\&M,PV}$ (€/kW-yr)	6,56	4,70
$C_{O\&M,ES}$(€/kW-yr)	8,22	4,78
$C_{O\&M,CHP}$(€/kW-yr)	36,6	36,6
$C_{O\&M,TES}$(c€/kW-yr)	0,26	0,26
$C_{O\&M,HP}$(€/kW-yr)	5,56	5,56
C_{UG}(€/MWh)	47,68	70,0
C_G (€/MWh)	30,8	36,9
C_{FI} (€/MWh)	40,5	59,5
C_{GHG} (€/tCO_2)	25,0	42,5

Table 2: Deterministic inputs for the case study

Constraint	Value
Maximum investment	800.000€
Area to install PV	6.000m^2
Maximum payback time	6 years
Maximum emissions at final year	300tCO_2

Table 3: Constraints specified by the enterprise

4. Results and discussion

4.1. Deterministic energy sizing

The results of the deterministic energy sizing problem can be seen in Table 4. Through the proposed energy sizing optimisation strategy, the equipment to include in the upgraded energy infrastructure of the industrial SME is formed by a PV system, a thermal ESS and a CHP system. Although electrochemical ESS and HP were also considered for installation, the characteristics of the industrial load together with the cost, social and environmental parameters of the equipment led to an optimal solution in which these are not included. In Table 4, it is possible to observe that the initial investment required to upgrade the energy infrastructure of the plant is quickly recovered and its value is multiplied almost by 10, reaching a final NPV of 5,078M€, which represents a 22% of the total operation cost of the initial plant, leading to a considerable energy saving and economic benefit. As the optimisation has been performed considering also environmental and social parameters, the resultant energy infrastructure represents a trade-off solution bearing in mind the different interests of the SME. Therefore, the energy investment does not only provide profit for the enterprise in economic terms but is also a good option considering the long-term strategy of the SME related to economic and social implications.

Parameter	Value
Initial investment	530.920€
PV Area	6.000m^2
Thermal Storage Size	465kWh
Cogeneration Size	123kWe
NPV	5.078.900 €
Payback time	4 years
Emissions at the final year	210tCO_2
RF on electrical load	0,43
Job Creation	5,34 full-time jobs

Table 4: Results of the deterministic optimisation

It is worth mentioning that the optimal energy infrastructure found by the algorithm depends on the constraints specified by the enterprise. To exemplify this, in Table 5 the results of the optimisation for the same industrial plant but with a maximum investment of 400.000€ are exposed. It can be seen that, through forcing a smaller investment, the PV and the thermal storage are maintained, whereas the CHP size is reduced. This is due to the fact that PV positively affects all the criteria and the thermal storage has low costs, whereas CHP has a high capital cost and there already exist a boiler system in the industrial plant to fulfil thermal demand. Nonetheless, the installed capacity of the CHP and the thermal storage still enable an interconnection between both the thermal and the electrical sides of the plant, enhancing a smart energy management strategy that improves the prosumer behaviour, as seen in the equipment operation analysis performed in upcoming paragraphs.

Parameter	Value
Initial investment	400.000€
PV Area	6.000m^2
Thermal Storage Size	480kWh
Cogeneration Size	64kWe
NPV	4.964.400 €
Payback time	4 years
Emissions at the final year	210tCO_2
RF on electrical load	0,29
Job Creation	4,43 full-time jobs

Table 5: Optimisation results considering different economic constraints

Bearing in mind the demand of the industrial plant exposed in Figure 16 and the energy infrastructure optimally obtained and shown in Table 4, the operation of the resultant energy infrastructure as a prosumer is here analysed. The operation of the selected energy equipment is exposed in Figure 16 for the summer week and in Figure 17 for the winter week, both corresponding to the final evaluation year. In these figures it is possible to appreciate the electricity generated by both the PV and the CHP systems, as well as the thermal power generated by the boiler and the charge and discharge cycles of the thermal ESS. It can be appreciated that, in the summer season, as thermal demand is generally lower than in winter season, the boiler system is used only as back-up for peak-power moments and the thermal ESS is employed to store excess thermal energy from the CHP system. In contrast, in the winter season the boiler has a more active role and thermal storage is rarely used as almost all power is employed to cover demand.

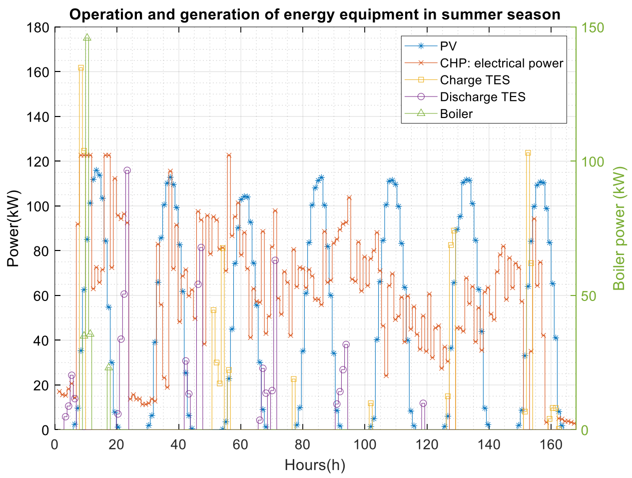

Figure 16: Power operation and generation of the energy equipment selected for the summer week.

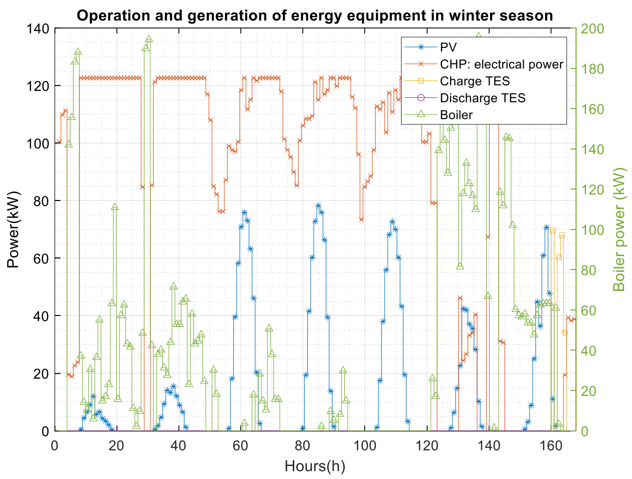

Figure 17: Power operation and generation of the energy equipment selected for the winter week.

With this operation, the total energy generated and consumed in the electrical and thermal sides for summer and winter weeks are exposed in Figure 18, Figure 19, Figure 22 and Figure 23. It can be seen that the electrical demand is covered through a combination of the CHP and the PV system in both seasons, and that excess electrical energy is present in the system. Electricity directly purchased from the utility grid is also employed, although it is not directly exposed here. For the thermal side, it is possible to appreciate that, in summer, almost all demand power is covered by the CHP system while in the winter, the CHP works most of the time at near maximum capacity and the boiler is employed to completely fulfil demand requirements.

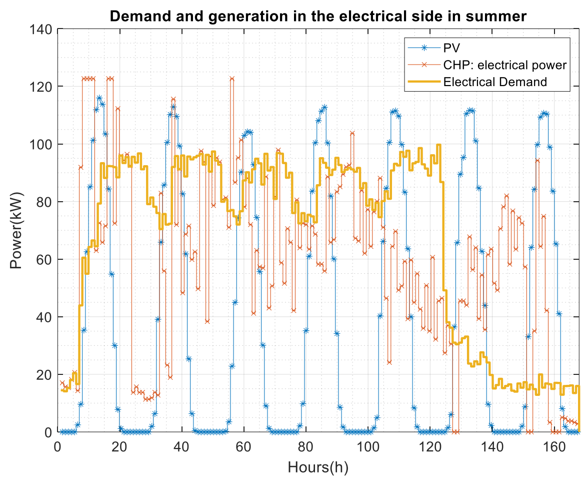

Figure 18: Electrical demand and generation for the summer week.

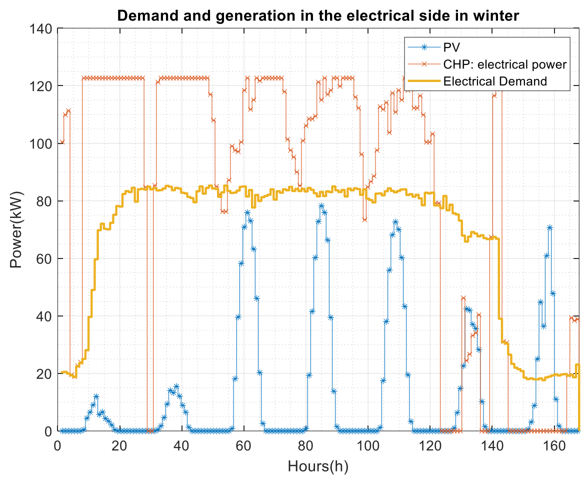

Figure 19: Electrical demand and generation for the winter week

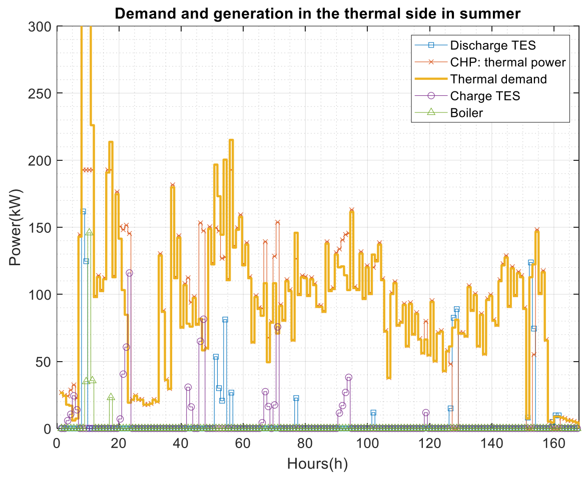

Figure 20: Thermal demand and generation for the summer week

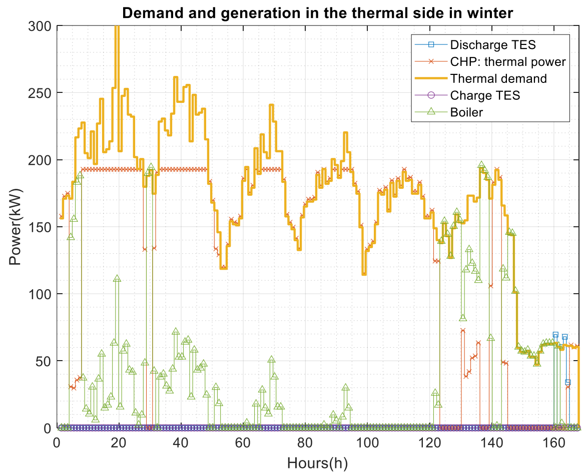

Figure 21: Thermal demand and generation for the winter week

The exposed energy equipment behaviour has been computed considering a prosumer model. This obtained energy exchange is shown for the two analysed seasons in Figure 22 and Figure 23. For the summer case, a combination of CHP, PV and electricity bought at low prices is employed to fulfil electrical demand. When the electricity price for feed-in is high, electrical energy coming from both the PV and the CHP is injected into the utility grid. This happens for example at hour 10, when the price of electricity is high and although electrical demand is also high there is surplus electrical power that is sold to the utility grid. The decision of employing CHP electrical power to fulfil electrical demand and also to sell it to the utility grid is a consequence of the difference between energy carriers and emissions costs. Most of the time, the added cost of gas and emissions is lower than the cost of electricity. Therefore, it is profitable to burn gas and employ the electrical energy coming from the CHP to fulfil electrical demand and to sell it to the utility grid. As the thermal demand is considerably higher than the electrical demand, the CHP thermal power, linked to the CHP electrical power, is directly used to cover internal thermal load. As the thermal demand is considerably higher than the electrical demand, the CHP thermal power, linked to the CHP electrical power, is directly used to cover internal thermal load. If the desired CHP electrical operation and corresponding CHP thermal production exceed the required thermal power, thermal storage enters into action and absorbs the surpluses of thermal power to provide it at later times where thermal demand is higher. An example of this performance can be seen at hour 45, when the electricity price is high, electrical demand is also high, but PV generation is low. To reduce the electricity purchased from the utility grid, electrical demand from the CHP system is used. However, thermal demand is relatively low and thus more thermal power is generated than used. For this reason, the thermal ESS stores this surplus and delivers it later, in hour 55, where there is a small peak of thermal power. Where important thermal power peak occurs in this season, the boiler is also employed.

In the winter season, the thermal demand is higher than in summer and the electrical demand is more stable and lower. For this reason, the CHP operates most working hours at maximum capacity. In this case, the boiler takes a more active role, as it is employed to support the CHP in meeting thermal demand. Regarding the electrical demand, it is fulfilled by the energy generated from the CHP and the PV system, minimising the energy purchase and selling the surpluses. In case of electricity costs being remarkably low, as happens on weekend days, the operation regime of the CHP is lowered down and electricity is purchased and employed to fulfil electrical demand, using the boilers to meet the thermal demand at that moment.

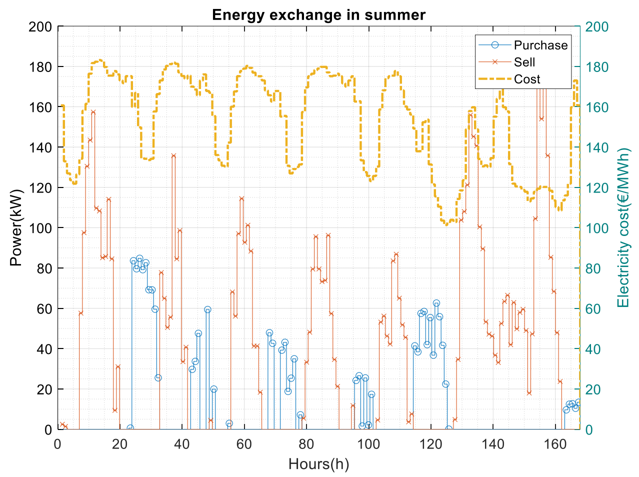

Figure 22: Exchange of energy with the utility grid for the summer week.

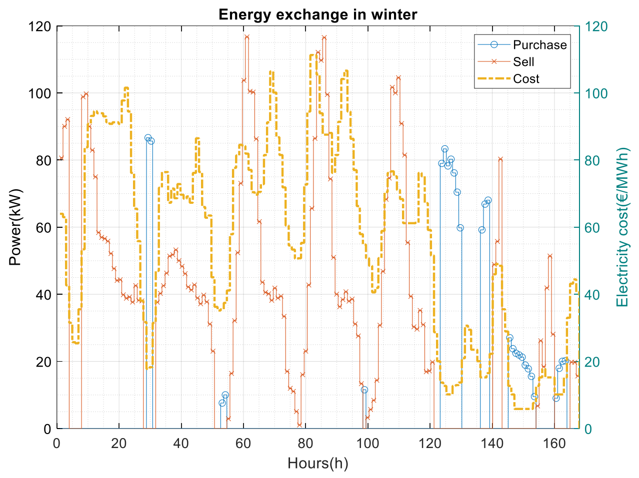

Figure 23: Exchange of energy with the utility grid for the winter week.

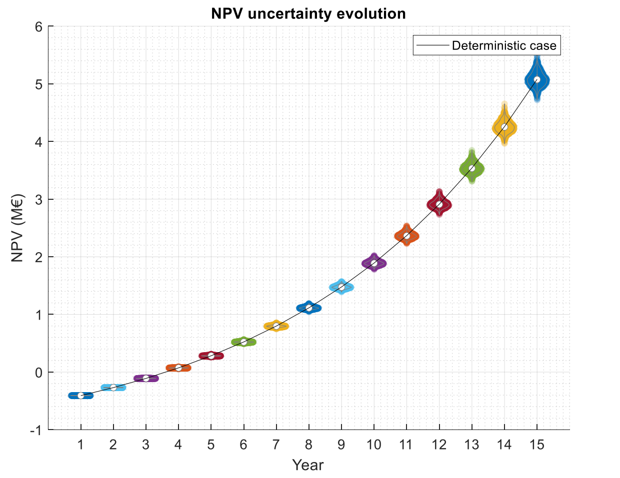

Figure 24: Uncertainty evolution of NPV along the lifetime of the energy equipment.

4.2. Uncertainty Analysis

The results of the UA showing the evolution of the uncertainty of the NPV are exposed in Figure 24 while the final NPV uncertainty is shown in Figure 25 together with the fitted PDF, which in this case is an Inverse Gaussian with parameters (5,08; 8.869). The mean final value is 5.082.200€, slightly higher than the obtained in the deterministic case due to the change in equipment operation, which is improved in some of the cases, being the expected final profit higher than the deterministic one. It can be seen that the uncertainty on the value of the investment increases with time following the same pattern as the exposed by the uncertainty in prices related to energy and emissions. For its final value, the NPV presents a standard deviation of 121.700€, which means that there is a 68% chance that the final value lays around 2,4% of the mean value and a 95% of probabilities that the final value lays around 4,8% of the mean value. These results expose that, despite the uncertainty existent in the input parameters, the proposed optimisation methodology provides robust results which creates a benefit for the industrial enterprise with an acceptable risk level.

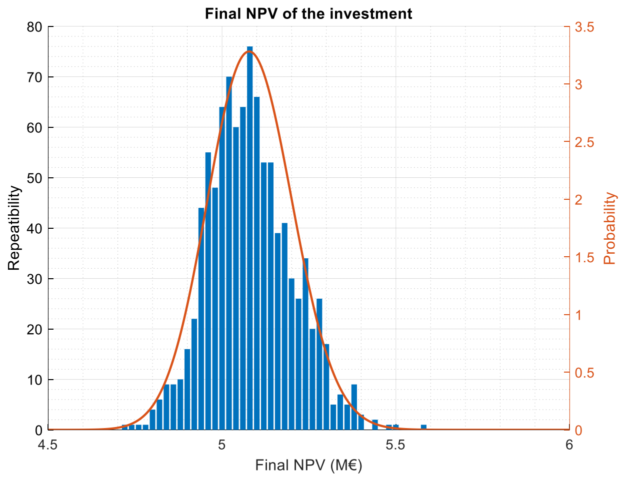

Figure 25: Final NPV uncertainty and fitted PDF.

4.3. Sensitivity Analysis

4.3.1. First stage: Morris method

As the objective of this first stage is to discard the less influential inputs, all the inputs exposed in section 2.2 are considered. The results of the Morris SA are exposed in Figure 26.

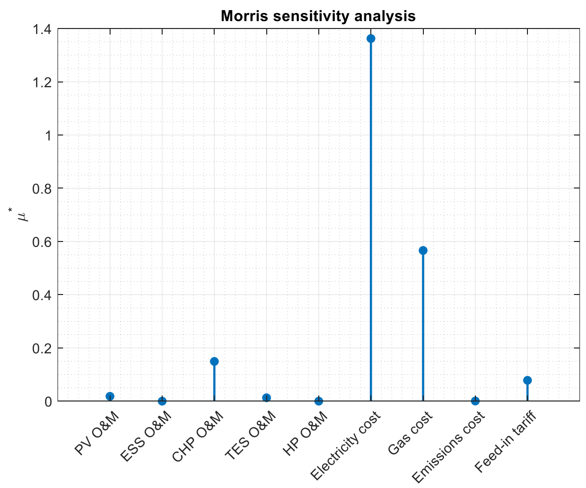

Figure 26: Morris SA results.

The obtained results show five parameters having almost no influence on the output uncertainty, which endorse the methodology employed to perform this evaluation as they can be clearly identified and erased from further analysis. The O&M cost of the PV, ESS, TES and HP systems can be considered as deterministic as they are inconsequential in terms of output variance. Also, and although the uncertainty in the output increases with time as the uncertainty in emissions costs do, the results expose that these costs have a negligible influence due to their low value in front of that of the energy carriers. By eliminating the mentioned O&M costs and the cost of emissions at this point of the evaluation, the computational effort in the second stage of the SA is reduced 54% while maintaining the uncertain information intact.

4.3.2. Second stage: Sobol method

The results of the Sobol analysis are exposed in Figure 27, in which the y-axis is presented on a logarithmic scale.

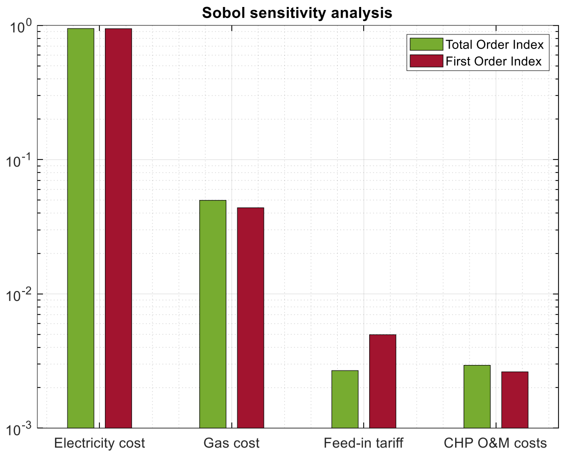

Figure 27: Sobol SA parameter ranking results.

It can be observed that the input that has the main influence in the final NPV uncertainty is the cost of electrical energy, being the influence of the cost of gas more than 10 times lower and the influence of the feed-in tariff and the O&M costs negligible.

The dependence of the performance of energy equipment on energy prices was also exposed in [26], where the sensitivity of the single-year economic performance of an energy system was studied. Being the cost of energy carriers the inputs that cause most of the uncertainty, the demand profile together with the framework and boundary conditions applied determine which of them has a predominant role. For instance, in [26], the selling price of electricity was maintained independent from the cost of electricity, not enhancing to exchange energy with the utility grid at the most interesting time intervals, and a more restrictive CO_2 emissions cap was applied, which affected the performance of the CHP to supply power to the electrical demand and utility grid. Consequently, electricity cost became a minor factor of uncertainty and gas cost the major influencer.

Apart from claiming the importance of the energy price in the investment uncertainty, the results obtained here also justify mathematically the firms' investment tendencies found in [8], in which it was appreciated, through a statistical analysis based on historical information, that enterprises tend to invest less if the uncertainty in the energy market increases.

5. Conclusions

This paper presents a methodology to optimise the investment in energy equipment for prosumer industrial SMEs considering its operation along time and assessing the risk this action supposes together with the inputs that influence the most. The energy infrastructure is optimised considering the time evolution of energy carriers and operation costs. This sizing optimisation includes also the operation optimisation of the plant over the lifetime of the newly installed equipment, which is performed based on a weekly horizon to take into account production and energy market patterns. The proposed optimisation procedure enables to compute the net present value of the investment as well as the environmental and social implications that the upgraded energy infrastructure has, therefore supporting industrial SMEs to obtain the solution that best suits their interests. The risk linked to this energy investment is also evaluated to enrich the investment procedure typically followed by SMEs given their managerial and financial characteristics. To do so, the upgraded energy infrastructure is analysed under uncertain scenarios through an Uncertainty Analysis (UA). This UA enables to compute the statistical final expected value of the investment as well as its deviation, exposing the probability of the outcome to be within a certain range and thus the risk that the enterprise is facing when performing the investment. To complete the risk analysis, Sensitivity Analysis (SA) is also performed. In order to have reliable results in an efficient manner, the employed SA combines Morris and Sobol methods and identifies the most influential parameters. This SA provides industrial SMEs with information regarding the inputs that influence the most the risks of the investment, being possible for them to locate efforts in better defining these inputs to reduce the risk. A case study has been developed in which it has been possible to appreciate the economic, social and environmental benefits for enterprises upgrading their energy infrastructure and adopting prosumer behaviour. The proposed optimisation approach provides robust results and a risk analysis that allows a more informed investment by industrial SMEs. These results are of high utility for industrial entities when upgrading their energy infrastructure, exposing their suitability to adopt a prosumer behaviour and providing a framework to further support their energy investment decision process.

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Appendix A. Energy optimisation problem formulation

A.I. Reference Plant performance optimisation

- Constraints:
    - Electrical hub equilibrium:

$$P_{UG,ref}\eta_{UG} = \frac{P_{EL}}{\eta_{EL}} \tag{6}$$

Where $P_{UG,ref}$ is the energy purchased by the reference plant, P_{EL} the power required by the electrical demand and η_{UG} and η_{EL} the efficiencies of connexion with the utility grid and the demand.

- Thermal hub equilibrium

$$V_{BOI,ref}\eta_{BOI} = Q_{BOI,ref} = \frac{Q_{TL}}{\eta_{TL}} \tag{7}$$

Where $V_{BOI,ref}$ is the gas consumption by the boiler at the reference plant, $Q_{BOI,ref}$ the heat produced by the boiler, Q_{TL} the thermal demand, η_{BOI} the boiler efficiency and η_{TL} the connexion efficiency with the thermal demand.

- Energy exchange:

$$0 \leq P_{UG,ref} \leq E_{max} \tag{8}$$

$$0 \leq V_{BOI,ref} \leq V_{gmax} \tag{9}$$

$$0 \leq Q_{BOI,ref} \leq Q_{BOI,max} \tag{10}$$

Where E_{max}, V_{gmax} and $Q_{BOI,max}$ are the maximum power thresholds in the utility grid, gas grid and also in the boiler.

- Objective function:

$$f_{weekly,ref} = \sum_{j=1}^{N} P_{UG,ref,j}C_{UG,i,j} + Q_{BOI,ref,j}C_{BOI} + V_{BOI,ref,j}(C_{G,i} + F_{gGHG}C_{GHG,i}) \tag{11}$$

Where *j* represents the hour considered and *i* the year under evaluation. This computation is performed for the different weeks along the yeas of the optimisation horizon. C_{UG} is the cost to purchase energy from the utility grid, C_{BOI} is the cost for using the boiler, C_G is the cost to purchase gas, F_{gGHG} is the emission factor of the purchased gas and C_{GHG} the cost of emissions.

A.II. Upgraded Plant performance optimisation

- Constraints:
  - Electrical hub equilibrium:

$$P_{PV}\eta_{PV} + P_{UG}\eta_{UG} + P_{CHP} + P_{DES}\eta_{DES} = \frac{P_{ED}}{\eta_{ED}} + P_{FI} + \frac{P_{CES}}{\eta_{CES}} + P_{HP} \tag{12}$$

Where P_{PV}, P_{UG}, P_{CHP}, P_{DES}, P_{FI}, P_{CES} and P_{HP} are the power from the PV system, from the utility grid, from the CHP, from the electrochemical ESS, to the utility grid, to the electrochemical ESS and the HP. η_{PV}, η_{UG}, η_{DES}, η_{ED}, η_{UG} and η_{CES} are the efficiencies of the connection with the PV system, the utility grid, the efficiency for discharging the ESS, the efficiency of the connexion with the demand, the utility grid and the efficiency of charging the ESS, respectively.

- Thermal hub equilibrium:

$$Q_{CHP} + Q_{BOI} + Q_{DTS}\eta_{DTS} + P_{HP}\eta_{HP} = \frac{Q_{TL}}{\eta_{TL}} + \frac{Q_{CTS}}{\eta_{CTS}} \tag{13}$$

Where Q_{CHP}, Q_{BOI}, Q_{DTS} and Q_{CTS} are the thermal power from the CHP, the boiler, the thermal ESS and the power to the thermal ESS. $\eta_{TL}$is the efficiency of the connexion with the thermal load and η_{DTS} and η_{CTS} are the efficiencies of discharging and charging the thermal storage.

- Energy exchange

$$0 \leq P_{UG} \leq E_{max} \tag{14}$$

$$0 \leq P_{UGS} \leq E_{max} \tag{15}$$

$$0 \leq V_{CHP} + V_{BOI} \leq V_{gmax} \tag{16}$$

Where E_{max} is the maximum exchange of power with the electrical grid and V_{gmax} the maximum for the gas grid.

- Energy storage.

The formulation is exposed for general energy storage, which is applied to both electrochemical and thermal storages.

$$0 \leq P_C \leq R_C \times Cap \tag{17}$$

$$0 \leq P_D \leq R_D \times Cap \tag{18}$$

$$E^t = E^{t-1} + \Delta t(Q_C - Q_D) - SDE^t \tag{19}$$

$$Cap_{min} \leq E^t \leq Cap \tag{20}$$

Where Cap is the capacity of the storage and R_C and R_D its charge and discharge ratios. E^t is the stored energy at the evaluated instant, E^{t-1} describes the energy stored in the previous instant while Δt is the time step. SD is the self-discharge ratio.

- Power capacity of energy equipment

$$0 \leq Q_{BOI} \leq Q_{BOI,max} \tag{21}$$

$$0 \leq P_{CHP} \leq P_{CHP,max} \tag{22}$$

$$0 \leq Q_{HP} \leq Q_{HP,max} \tag{23}$$

Where $Q_{BOI,max}$, $P_{CHP,max}$ and $Q_{HP,max}$ are the maximum power thresholds for the boiler, the CHP and the HP.

- Objective function:

$$\begin{aligned} f_{weekly} = \sum_{j=1}^{N} & P_{PV,j}C_{PV} + P_{UG,j}C_{UG,i} + C_{ES}\left(P_{CES,j} + P_{DES,j}\right) + P_{CHP,j}C_{CHP} + P_{HP,j}C_{HP} \\ & + Q_{BOI,j}C_{BOI} + \left(V_{CHP,j} + V_{BOI,j}\right)\left(C_{G,i} + F_{gGHG}C_{GHG,i}\right) \\ & + C_{TS}\left(Q_{CTS,j} + Q_{DTS,j}\right) - P_{FI,j}C_{FI,i} \end{aligned} \tag{24}$$

Where C_{PV}, C_{ES}, C_{CHP}, C_{HP}, C_{BOI} and C_{TS} are the LCOE of the PV system, the electrochemical storage, the CHP, the HP, the boiler and the thermal storage system.

A.III. Optimisation of energy equipment to install

- Constraints:
  - Equipment size:

$$A_{PV} \leq A_{PV,max} \tag{25}$$

$$\frac{C_{ES}}{\rho_{ES}} + \frac{C_{TS}}{\rho_{TS}} + \frac{P_{CHP,max}}{\rho_{CHP}} + \frac{Q_{HP,max}}{\rho_{HP}} \leq A_{int,max} \tag{26}$$

Where $A_{PV,max}$ is the maximum area for the installation of PV; ρ_{ES}, ρ_{TS}, ρ_{CHP} and ρ_{HP} are the energy and power densities of the electrochemical storage, the thermal storage, the CHP and the HP. $A_{int,max}$ is the maximum area available for the installation of internal energy equipment.

  - Initial investment

$$C_0 = A_{PV}C_{0,PV} + C_{ES}C_{0,ES} + C_{TS}C_{0,TS} + P_{CHP,max}C_{0,CHP} + Q_{HP,max}C_{0,HP} \leq C_{0,max} \tag{27}$$

Where C_0 is the initial investment and $C_{0,PV}$, $C_{0,ES}$, $C_{0,TS}$, $C_{0,CHP}$ and $C_{0,HP}$ are the initial costs of the PV system, electrochemical storage, thermal storage, cogeneration and HP, respectively. $C_{0,max}$ the maximum investment limit.

  - Emissions:

$$\begin{aligned} GHG_T = \frac{52}{4}\left(\sum_{k=1}^{4} GHG_{T,k}\right) = \frac{52}{4}\left(\sum_{k=1}^{4}\sum_{j=1}^{N} F_{gGHG}C_{GHG,T}\left(V_{CHPT,k,j} + V_{BOIT,k,j}\right)\right) \\ < GHG_{max,T} \end{aligned} \tag{28}$$

Where GHG_T are the total yearly greenhouse gas emissions for and $GHG_{max,T}$ the maximum emissions limit. The factor k represents the week of a year considered.

  - Payback

$$PB_t \equiv \left\{ i_{PB} \middle| \left(-C_0 + \sum_{i=1}^{i_{PB}} C(i) = 0 \right) \right\} \tag{29}$$

Where PB_t is the payback time and i represents the years evaluated.

- Objective: The objective function is composed by economic, environmental and social parameters included in a weighted and normalised manner.
  - Economic objective

The economic objective is the maximisation of the Net Present Value, which is computed as:

$$NPV = -C_0 + \sum_{i=1}^{T} \frac{C_i}{(1-r)^i} \tag{30}$$

Where C_i is the cash flow, or benefits minus cost, for the period i, and r is the hurdle rate.

To obtain the NPV, the computation of costs and benefits per year is required.

- Seasonal benefit minus cost (obtained through its representative week):

$$\begin{aligned} C_{season,i=} \sum_{j=1}^{N} P_{FI,j} C_{FI,i} + \left(P_{UG,ref,j} - P_{UG,j}\right) C_{UG,i} \\ + \left(V_{BOI,ref,j} - V_{CHP,j} - V_{BOI,j}\right)\left(C_{G,i} + F_{gGHG} C_{GHG,i}\right) \end{aligned} \tag{31}$$

- Benefits minus cost for the year *i:*

$$\begin{aligned} C_i = \frac{52}{4}\left(C_{spring,i} + C_{summer,i} + C_{autunm,i} + C_{winter,i}\right) \\ - \left(C_{O\&M,CHP} P_{CHP,max} + C_{O\&M,HP} Q_{HP,max} + C_{O\&M,ES} Cap_{ES} + C_{O\&M,TS} Cap_{TS} \right. \\ \left. + C_{O\&M,PV} A_{PV} P_{nom}\right) \end{aligned} \tag{32}$$

Where $C_{spring,i}$, $C_{summer,i}$, $C_{autumn,i}$ and $C_{winter,i}$ are the variable cash flow of the four representative weeks for the year i and $C_{O\&M,CHP}$, $C_{O\&M,HP}$, $C_{O\&M,ES}$, $C_{O\&M,TS}$ and $C_{O\&M,PV}$ are the yearly operation and maintenance costs per unit capacity of CHP, HP, electrochemical storage, thermal storage and PV system, respectively.

- Environmental objective
  Total emissions over the lifetime of the energy infrastructure.

$$GHG = \sum_{i=1}^{T} \frac{52}{4}\left(\sum_{k=1}^{4}\sum_{j=1}^{N} F_{gGHG} C_{GHG,i}\left(V_{CHPi,k,j} + V_{BOIi,k,j}\right)\right) \tag{33}$$

- Social objective
  The social objectives are represented by the RF and JC.
  - Renewable factor
    Ratio between the energy generated by the PV system and the total demand of the SME.

$$RF = \frac{\sum_{i=1}^{T}\sum_{k=1}^{4}\sum_{j=1}^{N} P_{PVi,k,j}}{\sum_{i=1}^{T}\sum_{k=1}^{4}\sum_{j=1}^{N}\left(P_{EDi,j,k} + Q_{TLi,j,k}\right)} \tag{34}$$

  - Job Creation
    Full-time jobs created through the upgrade of the energy infrastructure over its lifetime.

$$\begin{aligned} JC = PV_{JC} \sum_{i=1}^{T} \frac{52}{4} \sum_{k=1}^{4}\sum_{j=1}^{N} P_{PVi,k,j} + CHP_{JC} \sum_{i=1}^{T} \frac{52}{4} \sum_{k=1}^{4}\sum_{j=1}^{N} P_{CHPi,k,j} \\ + HP_{JC} \sum_{i=1}^{T} \frac{52}{4} \sum_{k=1}^{4}\sum_{j=1}^{N} P_{HPi,k,j} + ES_{JC} C_{ES} T + TS_{JC} C_{TS} T \end{aligned} \tag{35}$$

Where PV_{JC}, CHP_{JC}, HP_{JC}, ES_{JC}, and TS_{JC} are the job creation for the PV, CHP, HP, ES, and TS equipment, each represented in the units exposed in Table C.1.

- Multi-objective function
  The economic, environmental and social criteria are included in a single objective function:

$$f = w_{ec}NPV^{trans} + w_{en}GHG_{trans} + w_s(w_{s1}RF^{trans} + w_{s2}JC^{trans}) \tag{36}$$

Where w_{ec}, w_{en}, and w_s are the economic, environmental and social weights respectively, and w_{s1} and w_{s2} are the weights of the renewable factor and job creation inside the social dimension. As the criteria in the optimisation function present different units, their value is normalised to remove dimensions and balance magnitude differences [84]:

$$p^{trans} = \frac{p - p^0}{p_{max} - p^0} \tag{37}$$

Where p^{trans} is the normalised parameter which lays between 0 and 1, p is the measured value and p^0 and p_{max} are the minimum and maximum value achievable, respectively.

Appendix B. Sobol indices computation strategy

Starting from two different sampling matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ with rows equal to the number of simulations and columns equal to the number of considered uncertain inputs, the matrix $\boldsymbol{A}_{\boldsymbol{B}}^{(\boldsymbol{i})}$ is constructed for all factors with all the columns from $\boldsymbol{A}$ expect the *i*-th column, which is obtained from ***B*.** Then, the numerical estimators of the sensitivity indices are computed as:

$$V_{x_i}\left(E_{X_{\sim i}}(Y|x_i)\right) = \frac{1}{N}\sum_{j=1}^{N} f(\boldsymbol{B})_j \left(f\left(\boldsymbol{A}_{\boldsymbol{B}}^{(\boldsymbol{i})}\right)_j - f(\boldsymbol{A})_j\right) \tag{38}$$

$$E_{X_{\sim i}}\left(V_{x_i}(Y|x_{\sim i})\right) = \frac{1}{2N}\sum_{j=1}^{N} \left(f(\boldsymbol{A})_j - f\left(\boldsymbol{A}_{\boldsymbol{B}}^{(\boldsymbol{i})}\right)_j\right)^2 \tag{39}$$

Appendix C. Parameters employed for the optimisation

Parameter	Value
PV	
Initial cost	950 €/kW
LCOE	0.07 €/kWh
PV connexion efficiency	99%
Job creation	0.87 jobs/GWh
Electrochemical storage	
Initial cost	430 €/kWh
LCOE	0.06 €/kWh
Charge efficiency	94%
Discharge efficiency	94%
Charge ratio	0.5C
Discharge ratio	5C
Job creation	0.01 jobs/MWh- capacity
CHP	
Initial cost	3400 €/kWe
LCOE	0.042 €/kWeh

G2E efficiency	35%
G2T efficiency	55%
Job creation	0.31 jobs/GWh
HP	
Initial cost	700 €/kW
LCOE	0.076 €/kWh
COP	4.5
0.25	jobs/GWh
Thermal storage	
Initial cost	5 €/kWh
LCOE	0.0243 €/kWh
Charge efficiency	92%
Discharge efficiency	92%
Self-discharge	1%
Charge ratio	5C
Discharge ratio	0.25C
Job creation	0.01 jobs/MWh- capacity
Boiler	
LCOE	0.053 €/kWh
Efficiency	90%
Connexion efficiencies	99%
Objective function weights	
w_{ec}	0.65
w_{en}	0.20
w_s	0.15
ws_1	0.75
ws_2	0.25

Table C.1: Input values employed

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