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Research paper

Quantitative and qualitative risk-informed energy investment for industrial companies

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A B S T R A C T

In the ongoing energy transition, small and medium-sized industrial companies are making energy equipment investments due to the obsolescence of their current equipment as well as social, political and market pressures. These firms typically choose investments with low risk exposure based on a combination of criteria that are not always quantifiable. However, published studies on energy investment to date have not been suitable for industrial SMEs because they do not assess the value of the investment over time, ignore the qualitative aspects of decision-making, and do not consider uncertainties. To fill this gap in the literature, this paper proposes a methodology that considers both quantitative and qualitative parameters and risks over time through an extended two-stage risk-informed approach. The proposed methodology includes fuzzy and statistical techniques for evaluating both qualitative and quantitative parameters, as well as their uncertainties, at the time of decision-making and over the investment lifetime. Fuzzy logic is used in the first stage of the optimisation process to measure qualitative parameters and their uncertainty, while quantitative parameters are expressed using probability density functions to account for their uncertainty and measure the quantitative risk assumed by the investor. This methodology is applied to a case study involving a real industrial SME, and the results show that considering both quantitative and qualitative parameters and uncertainties in the optimisation process leads to a more balanced consideration of economic, environmental and social criteria and reduces the variability of the outcome compared to economic-only approaches that do not account for risks. Specifically, the case study shows that considering these parameters and uncertainties resulted in a 15.7% reduction in the size of the cogeneration system due to its environmental and social impacts, and 4.2% reduction in the variability of the economic result.

1. Introduction

The energy sector is undergoing a paradigm shift towards a system that ensures energy supply while preserving sustainability. This transition requires the reduction of greenhouse gas (GHG) emissions through, among others, the incorporation of Renewable Energy Sources (RES), increased penetration of distributed energy resources, and active participation of actors in the energy market. Among these actors, consumers are expected to play a key role by becoming active prosumers rather than passive users. Currently, industrial consumers account for 37% of global energy use and produce 24% of total emissions (IEA, 2020). Industrial small-and-medium enterprises (SMEs) are particularly significant in terms of energy consumption, as they use more than half of the energy in industrial and commercial sectors (Fawcett and Hampton, 2020), being critical for the green transformation (Özbuğday et al., 2020). However, these enterprises are generally under-researched and face more difficulties than larger entities in adopting new energy strategies (Kakran and Chanana, 2018). SMEs may need or be required to upgrade their energy infrastructure by incorporating RES and flexibility due to the obsolescence of their equipment and as a result of the current Industry 5.0 revolution, which aims to renew industries and make them more future-proof, resilient, sustainable and human-centred (Cotta et al., 2021). SMEs tend to prefer investments with short payback periods, favourable economic, environmental and social parameters, low exposure to risks and such that the infrastructure is maintained in operation for its whole lifetime once it is upgraded (Gveroski and Risteska, 2017). However, energy investments are inherently linked to risks arising from uncertainty both in quantitative parameters, whose exact value over time is unknown, and qualitative parameters, which reflect subjective preferences and opinions. In the current changing situation, where public perception is increasingly important and the energy market is becoming more volatile, these risks inhibit investments and firms' innovation activity (Alaali, 2020). To facilitate these actions in industrial SMEs, this paper addresses their energy

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Nomenclature

General Abbreviations

AHP	Analytical Hierarchy Process
CHP	Combined Heat and Power
CVaR	Conditional-Value-at-Risk
DS	Direct Search
EES	Electrochemical Energy Storage
FIS	Fuzzy Inference System
HP	Heat Pump
JC	Job Creation
LHS	Latin Hypercube Sampling
MF	Membership Function
NPV	Net Present Value
O&M	Operation and Maintenance
PDF	Probability Density Functions
PV	Photovoltaic
RES	Renewable Energy Source
RF	Renewable Factor
SA	Sensitivity Analysis
SME	Small-and-Medium Enterprise
TES	Thermal Energy Storage
UA	Uncertainty Analysis
VaR	Value at Risk

Energy infrastructure sizing and operation parameters

P	Electrical power
Q	Thermal power
η	Efficiency
C	Economic cost
QC	Qualitative cost
Cap	Capacity of energy storage
RC	Charge ratio of energy storage
RD	Discharge ratio of energy storage
SD	Self-discharge ratio of energy storage
E	Energy stored in energy storage system
I	Cash flow
r	Hurdle rate
W	Weeks per year analysed
W_Y	Total weeks per year
A	Area
w	Weight assigned to a decision parameter
VAR_{level}	Probability level for computing the VaR
$E(x)$	Expected value of x

Subscripts and superscripts

max	Maximum capacity of equipment
min	Minimum capacity of equipment
j	Time instant considered for operation's optimisation
i	Optimisation year
0	Instant when decision is taken
T	Expected lifetime of energy infrastructure
PV	PV system
ES	Electrochemical energy storage
CES	Charge EES
DES	Discharge EES
ED	Electrical demand
UG	Utility Grid
FI	Feed-in
CHP	Cogeneration system
CHP_e	Electrical side of the CHP system
CHP_{th}	Thermal side of the CHP system
TL	Thermal Load
BOI	Boiler
TS	Thermal energy storage
CTS	Charge TES
DTS	Discharge TES
g	Gas from the grid
GHG	Greenhouse gases
$O\&M$	Operation & Maintenance
ref	Hypothetic case without investment
JC	Job Creation
nom	Nominal power
ec	Economic parameter
so	Social parameter
en	Environmental parameter
ql	Qualitative parameter
qt	Quantitative parameter
$norm$	Normalised value

investment problem by considering quantitative and qualitative parameters and uncertainties over the expected lifetime of the upgraded infrastructure.

Most current studies on energy investment do no considering uncertainties in their optimisation processes. For example, Li et al. (2022) optimise a hybrid to minimise cost and maximise performance, but without considering risks or uncertainties. Some papers do analyse energy investment uncertainty, but only after obtaining the solution, rather than optimising with regards to uncertainties. Mavromatidis et al. (2018) carry out Uncertainty Analysis (UA) and Sensitivity Analysis (SA) to evaluate the effect of uncertain input values on the year cost performance of a multi-carrier energy system. Similarly, Solangi et al. (2019) analyse several strategies for sustainable energy planning and conduct a SA to evaluate the robustness of the obtained solution, Qiao et al. (2022) address the risks of renewable energy projects investment without optimising the investment, and Liu et al. (2022) perform a SA on the design of a nearly zero-energy community. These approaches provide investors with information about the risk assumed when investing, but do not propose an adaptation strategy for unacceptable risk levels or incorporate uncertainty and risk analysis into the optimisation problem.

The literature on energy investment optimisation that considers risks within the decision-making problem is scarce. Chen et al. (2016) develop an optimisation model for regional energy systems, which includes degrees of fulfilment for the uncertain constraints, providing decision-makers with alternatives under different violation parameters. Afzali et al. (2020) address an optimal energy system by minimising total annual cost while limiting average worst-case emissions. Both of these studies do not consider risk as an optimisation objective, but rather as a limitation, creating a strategy that is robust in the face of uncertainties. While robust optimisation provides a simple framework for dealing with uncertainty, it is conservative and trades off system performance for robustness (Lekvan et al., 2021). Another strategy commonly employed in the literature to consider uncertainty is two-stage stochastic optimisation, in which the decision parameters are selected in the first stage and all possible scenario realisations are considered in the second stage, optimising the mean resultant value. This approach is used in Pickering and Choudhary (2019), which applies a two-stage stochastic model to a district energy system optimisation under uncertainty on the demand side, in Tian et al. (2021), which employs two-stage stochastic search for the optimal sizing and placement of energy storage, and in Wang et al. (2022), where this technique is used to optimise thermal storage under wind uncertainty. While two-stage stochastic methods do incorporate uncertainty in the optimisation problem, they do so from a risk-neutral perspective, not providing a clear measure of the risk taken by the investor (Noyan, 2012). Li et al. (2020) present an improved method including a risk-aversion strategy, in which the planning of an integrated energy system is done by incorporating Conditional-Value-at-Risk (CVaR) as part of the objective function. Following the same approach, Xie et al. (2021) propose a sizing methodology that assesses risk through the computation of the mean variance, and Mu et al. (2022) also use CVaR to optimise a community energy system considering uncertain demand. These studies express risk using quantitative-only approaches that focus mainly on economic parameters. Few of the aforementioned studies consider other objectives such as environmental or social ones, and when these are considered, they use quantifiable parameters as criteria. Zhang et al. (2022b) create an index covering techno-economic, financial and social-environmental benefits, though they only use measurable criteria, and Gao (2022) includes social utility in the optimisation problem as a combination of the value of price and quantity of energy delivered by the sized system. In contrast, Zhang et al. (2022a) consider policy support not as a criterion but as an input parameter, creating policy scenarios that the quantitative optimisation model runs on, without including policy support in the optimisation itself. However, quantitative-only optimisation models are insufficient for energy sizing problems because there are decision and uncertainty dimensions that should be addressed through qualitative approaches, which can equal or dominate quantitative ones (Pye et al., 2018). Therefore, it is essential to incorporate qualitative considerations in energy investment decision-making (Bhardwaj et al., 2019), which improves the evaluation of uncertainty and the competitiveness of the enterprise, resulting in significant positive outcomes (Cornejo-Cañamares et al., 2021).

To date, qualitative parameters inside the decision-making process have been considered in the literature for non-energy optimisation problems. Boudreau et al. (2019) present a generic methodology for assets management decision-making that considers quantitative and qualitative factors, where the latter are crisply measured. Solangi et al. (2019) propose country energy planning strategies that use qualitative criteria, although they are not optimised. Harter et al. (2020) consider both quantitative and qualitative parameters for uncertainty assessment in the design of a building, although qualitative attributes are set as crisp numerical values without considering judgemental vagueness. More recently, Bishnoi and Chaturvedi (2022) propose an approach for the site selection of hybrid renewable installations that considers both quantitative and qualitative parameters, measuring the latter through crisp numbers specified by decision-makers. Even though these studies incorporate qualitative parameters, they do not account for the uncertainty linked to their subjective nature. Kaya et al. (2019) assess decision-making methodologies for energy policy making and present fuzzy set theory as a tool to express uncertainties inherently associated with human opinions. It is concluded that fuzzy set theory can be successfully used with multi-criteria optimisation problems to get a more sensitive, concrete and realistic result. However, although the non-energy approaches mentioned in this paragraph include qualitative parameters crisply or by proposing the use of fuzzy logic, they leave quantitative information in a background position, not creating a suitable framework for energy infrastructure optimisation.

In addition to the lack of a methodology that incorporates both quantitative and qualitative parameters and their uncertainties for energy investment decisions, most studies on this topic do not consider the lifetime value of the investment, but only its cost or profit over a shorter period. In the energy sizing studies described above, a time frame is specified, such as in Guo and Xiang (2022), where a set of typical days of a year are simulated to reveal the performance of the energy system. Thus, the suitability of the investment is evaluated based on a static time frame, simplifying the evolution of parameters and considering them constant for several years. This optimisation procedure does not reflect the current changing context and leads to suboptimal solutions that overestimate the performance of the selected energy infrastructure (Pecenak et al., 2019). Few of the most recently published papers incorporate a continuous-time framework for energy sizing problems. It is the case of Mavromatidis and Petkov (2021), which develop a model for multi-year, multi-location of energy sources. Petkov et al. (2022) present an upgrade of this model that includes the possibility of retrofitting the designed energy system, but does not provide a framework for design based on the probability of future events. Urbano et al. (2021a) perform the design of multi-carrier energy infrastructure considering the time evolution of parameters. UA and SA are carried out to acknowledge the risk and identify the most relevant parameters, but uncertainty is not incorporated into the optimisation problem. Bohlayer et al. (2021) consider energy carriers' price and investment costs uncertainties within the optimisation problem through a two-stage stochastic strategy. However, this two-stage stochastic strategy is risk-neutral as it optimises the expected value of the solution, not directly analysing the risk related to it.

In summary, existing methodologies for energy investment decision-making proposed up to date are incomplete and not suitable for industrial SMEs since:

- qualitative spectrum of the decision-making process, including qualitative parameters measurement and uncertainty assessment, is omitted;
- quantitative uncertainty is either neglected, analysed outside of the optimisation problem or included in the optimisation through a risk-neutral strategy; and
- energy parameters are most of the time considered static and time evolution and uncertainty growth is not evaluated.

To fill these gaps, a novel optimisation methodology is proposed in this paper. This methodology presents the following contributions to the state-of-the-art:

- Qualitative parameters and related uncertainty handling through a fuzzy logic approach, which enables their measurement considering uncertainty and improving crispy strategies used in the literature.
- Inclusion of risk-averse factors for energy infrastructure optimisation, which improves risk-neutral strategies.
- Investment optimisation considering combined quantitative and qualitative parameters, which contributes to the inclusion of qualitative parameters and improves the consideration of quantitative only approaches presented up to date in the literature for energy investment problems.
- Energy infrastructure operation optimisation considering dynamic quantitative and qualitative parameters over time, improving static approaches in which parameters and related uncertainty do not evolve over time.

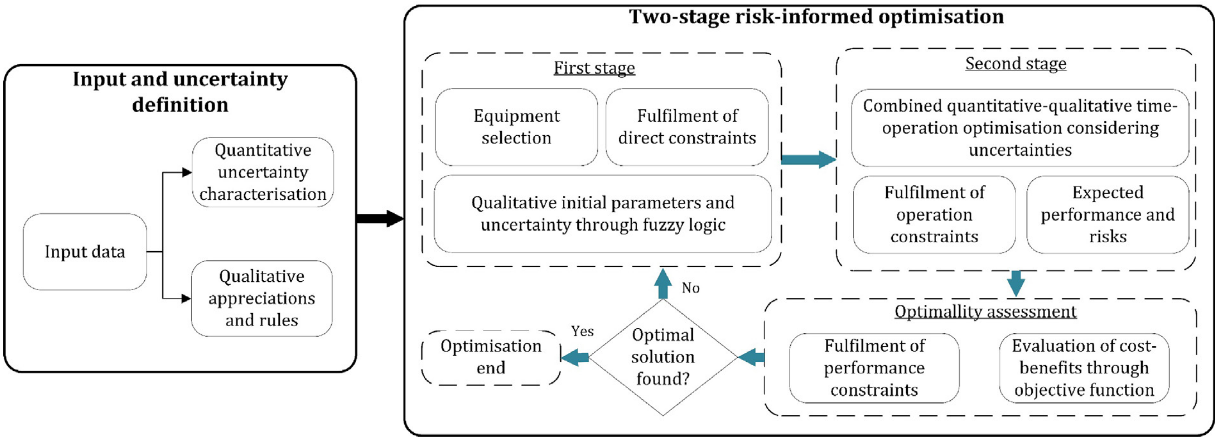

Fig. 1. Risk-informed energy-investment optimisation procedure.

The proposed complete methodology is therefore the main contribution outcome of this paper and is presented as an extended two-stage risk-informed optimisation. As stated above, this methodology considers both quantitative and qualitative parameters and their uncertainties at the moment of taking the decision and over the lifetime of the energy infrastructure.

Specifically, the equipment in which to invest is selected in the first stage of the optimisation and qualitative criteria are measured considering the uncertainty linked to them through fuzzy logic. In the second stage, the performance of the energy infrastructure is computed by optimising its operation over lifetime evaluating both quantitative and qualitative parameters together with their uncertainty through a risk-averse strategy. In this way, it is possible to optimise the energy investment by considering its quantitative and qualitative global performance as well as its risks. A practical case study based on a real manufacturing industrial SME is described to appreciate the effects of including quantitative criteria, qualitative criteria and risks in enterprises' decision-making process.

The paper is organised as follows: Section 2 describes the proposed optimisation methodology, Section 3 presents the case study, Section 4 discusses the results, and Section 5 offers the conclusions.

2. Methodology

The proposed methodology in this paper for optimising energy investment is illustrated in Fig. 1. The first step is to identify the input parameters and their uncertainty. The process then proceeds to a two-stage risk-informed optimisation. In the first stage, the equipment is selected through an optimiser, and direct constraints such as allowable investment and available space for installations are checked. Then, qualitative parameters such as ecological impact and administration alignment are evaluated. Given their subjective nature, the uncertainty associated with these parameters is considered using a fuzzy logic approach. The operation of the selected energy infrastructure is then optimised for its lifetime, taking into account both quantitative and qualitative costs and the associated uncertainty. Operation constraints are checked, and the expected performance and risks of the energy infrastructure are calculated. With this information, the costs and benefits of the upgraded energy infrastructure are evaluated using the selected criteria. In this stage, the fulfilment of constraints imposed by the company such as maximum payback or minimum return on investment, is verified. If the optimiser meets its stopping criteria, the process ends here. Otherwise, another possible energy equipment solution is analysed.

2.1. Input data and uncertainty characterisation

The input data required to address the energy investment problem depends on the characteristics of the potential energy infrastructure as well as on the criteria that the enterprise wants to consider for taking the decision. These data can be divided into two types: quantitative and qualitative.

2.1.1. Qualitative data

Qualitative data is necessary for making decisions, but it cannot be measured quantitatively. Its value is determined by an expert or decision-maker based on their knowledge of, for example, the industry context and the governmental framework (Peng et al., 2019). The subjectivity of qualitative parameters introduce uncertainty, and treating them as precise numbers can lead to loss of information. To include this uncertainty in energy investment optimisations Fuzzy logic can be used (Srivastava and Bisht, 2019) to evaluate the *probability* and *impact* of the energy infrastructure on the relevant qualitative perceptions (Brocal et al., 2019). In the studied problem, *impact* refers to the potential effect that of the qualitative perception on the performance of the energy infrastructure, while *probability* measures the likelihood of is the impact occurring (Nieto-Morote and Ruz-Vila, 2011). Both *impact* and *probability* depend on the mix of technologies chosen for upgrading the energy infrastructure, as well as on their social, environmental and technical influences. To consider all these factors and determine a measure of the qualitative perception that includes uncertainty, the fuzzy system illustrated in Fig. 2 is proposed. The capacities of the selected technologies are first fuzzified and membership functions (MFs) are assigned to them. *Probability* and *impact* are then calculated based on the rules set by decision-makers, and these *impact* and *probability* functions are aggregated to form a fuzzy set for the qualitative perception. This set is later defuzzified to provide an accurate representation of qualitative parameters that improves their treatment as crisp.

This analysis supports a non-exclusively quantitative process that incorporates qualitative parameters into the first stage of the optimisation, allowing the solution to be tailored to the company's interests. However, the socio-political framework is susceptible to changes, so these parameters should also be included in the second stage of the problem. To do this, decision-makers should analyse potential socio-political changes and assess how the employed technologies would impact investment performance in the new context, considering both positive and negative influences. This analysis reflects the alignment of the chosen technologies with the company's interest over time and can be translated into dynamic qualitative costs for inclusion

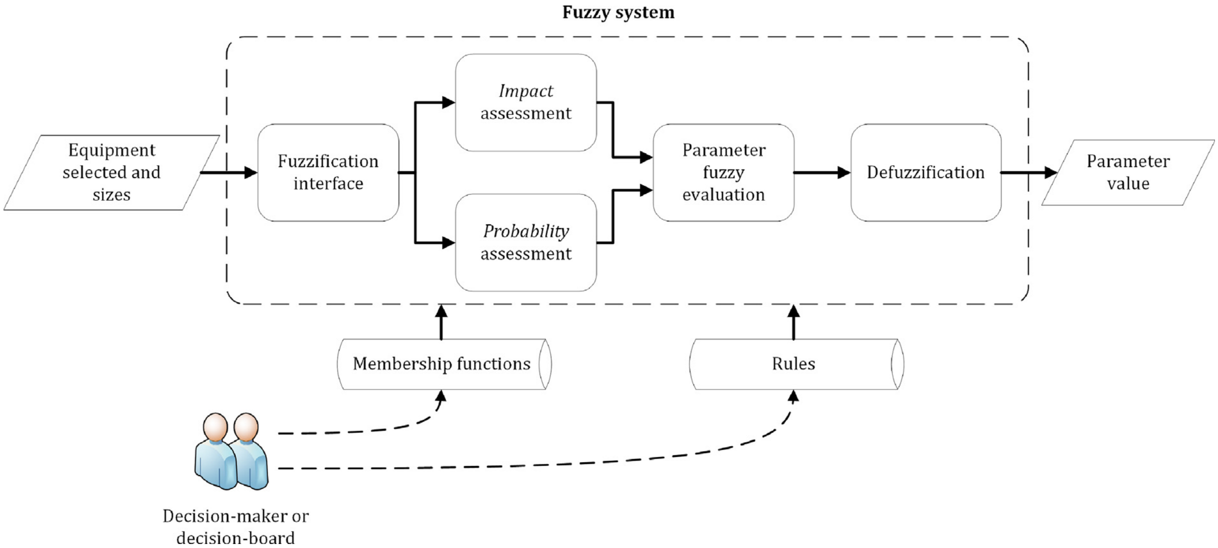

Fig. 2. Process flow for the assessment of qualitative criteria through a fuzzy approach.

in the operation optimisation, creating a strategy that is aware of qualitative factors. Since these dynamic costs are subject to vagueness, fuzzy logic is also used. To do this, technologies are evaluated individually to compute the cost of employing them and *probability* and *impact* values are assigned. The qualitative dynamic cost is then calculated using the same fuzzy methodology that is used for initial qualitative perceptions.

2.1.2. Quantitative data

Quantitative data is necessary to conduct a technical and economic analysis of the solution. To evaluate the investment's performance over time, it is important to consider their values and uncertainties. Quantitative data can also be characterised by *probability* and *impact*. On one hand, *probability* refers to the possible values that input parameters can take and how likely each value is. This probability can be represented using a range of discrete values or by assigning Probability Distribution Functions (PDF) (Borgonovo and Plischke, 2016). On the other hand, *impact* refers to the influence of the input values on the result or on the company's chosen criteria. To calculate *impact*, the company's criteria must be evaluated for each input, requiring sampling of the PDFs and solving the energy infrastructure performance optimisation problem for the resulting samples. Using a PDF assigned to uncertain quantitative parameters, a method like Latin Hypercube Sampling (LHS) that generates samples according to these probability distributions can provide a reliable output that captures the distribution across the entire variation range (Tran and Smith, 2018). LHS is selected in this study because it efficiently covers a broad range of the PDF at a relatively low computational cost (Kristensen and Petersen, 2016). Once uncertainty samples have been generated, *impact* is computed in the second stage of the optimisation problem.

2.2. Two-stage risk-informed optimisation

This section provides details on the two-stage risk-informed optimisation considering a standard industrial SME plant. This industrial plant purchases electricity directly from the utility grid to satisfy electrical demand and owns a boiler to transform chemical energy into thermal one. The candidate equipment to be included are: PV system, thermal energy storage (TES), electrochemical energy storage (EES), cogeneration (CHP), and heat pump (HP).

2.2.1. First-stage

In the first stage of the optimisation, a set of potential solutions made up of equipment capacities that could be installed in the company is obtained from a global optimiser. In this case, a derivative-free global optimisation algorithm called Direct Search (DS) is used because it can effectively handle complex, disconnect feasible areas and has been successful in front of practical problems (Lewis et al., 2000). After DS selects the potential solutions, their compliance with the company's constraints are checked. If they meet the constraints, initial qualitative parameters are computed by introducing the equipment in the proposed fuzzy system.

2.2.2. Second-stage

In the second stage of the process, shown in Fig. 3, the chosen equipment is used to optimise the operation of the infrastructure based on both quantitative and qualitative costs. First, data from previous stages is gathered and the first scenario is selected from the samples of uncertain quantitative inputs. The operation of the upgraded plant is then optimised for the investment lifetime, taking into account 7-day weeks over the course of several years to consider weekly energy patterns both in industrial demand and energy markets. Inputs are considered to vary with time in a representative time frame. Electricity cost, for example, varies in an hourly manner and presents an evolution between different weeks and years. To obtain realistic dispatching strategies, equipment degradation is also included in the optimisation problem. This stage evaluates a prosumer operation to consider the adoption of new roles arising in the energy market. To perform this optimisation, a mathematical model of the plant is needed. The model used in this research, which is based on the Energy Hub (EH) concept, allows to consider all energy equipment, energy carriers and their interconnectivity in a single entity, maximising the efficiency of the system (Mansouri et al., 2020). Urbano et al. (2021b) exposes the definition of the specific model used in this research article, its mathematical formulation and validation results. Inputs to the model include technical parameters and economic and qualitative costs, connexion efficiencies, and costs related to emissions and energy inputs such as electricity and gas. The model is formulated with all possible equipment in mind, with the capacity of each to be set to zero when they are not included in the analysed solution. For the standard industrial SME

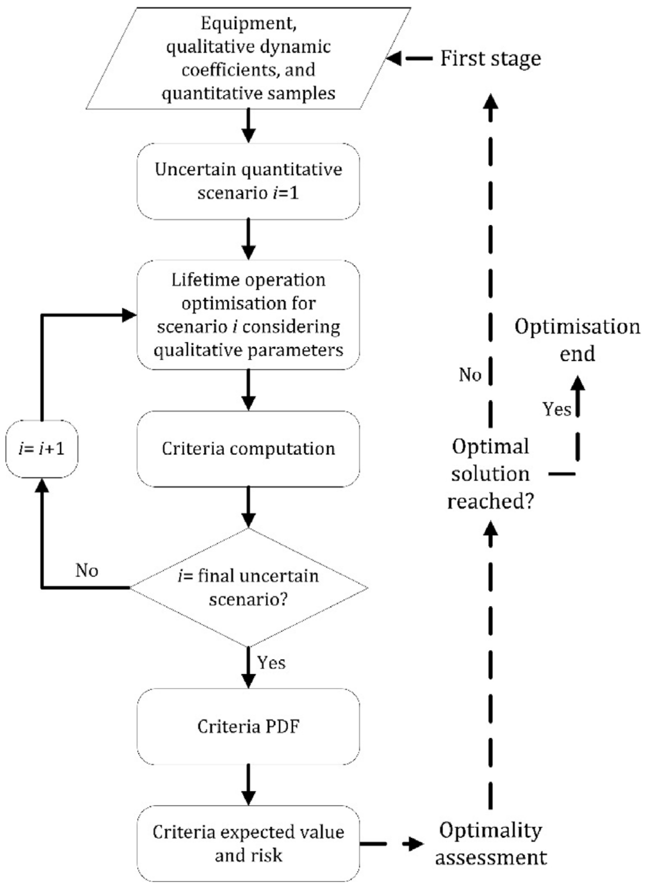

Fig. 3. Second-stage optimisation procedure.

described earlier the energy equilibrium for the electrical side is:

$$P_{PV}\eta_{PV}+P_{UG}\eta_{UG}+Q_{CHP}\frac{\eta_{CHPe}}{\eta_{CHPth}}+P_{DES}\eta_{DES}=\frac{P_{ED}}{\eta_{ED}}+P_{FI}+\frac{P_{CES}}{\eta_{CES}}+P_{HP} \quad (1)$$

For thermal side, the equilibrium is:

$$Q_{CHP}+Q_{BOI}+Q_{DTS}\eta_{DTS}+P_{HP}\eta_{HP}=\frac{Q_{TL}}{\eta_{TL}}+\frac{Q_{CTS}}{\eta_{CTS}} \quad (2)$$

These equilibriums are subject to restrictions related to power exchange with external grids and to maximum capacity of equipment:

$$0 \le P_{UG} \le P_{UG,max} \quad (3)$$

$$0 \le P_{FI} \le P_{UG,max} \quad (4)$$

$$0 \le \frac{Q_{CHP}}{\eta_{CHPth}}+\frac{Q_{BOI}}{\eta_{BOI}} \le Q_{g,max} \quad (5)$$

$$0 \le Q_{BOI} \le Q_{BOI,max} \quad (6)$$

$$0 \le Q_{CHP} \le Q_{CHP,max} \quad (7)$$

$$0 \le P_{HP} \le P_{HP,max} \quad (8)$$

For the energy storage, restrictions include not only their charge and discharge ratios but also the energy stored. The formulation for the TES and EES is similar, and is described below:

$$0 \le Q_{CTS} \le RC_{TS} \times Cap_{TS} \quad (9)$$

$$0 \le Q_{DTS} \le RD_{TS} \times Cap_{TS} \quad (10)$$

$$E_{TS}^{j}=E_{TS}^{j-1}+\Delta t\left(Q_{CTS}-Q_{DTS}\right)-SD_{TS}E_{TS}^{j} \quad (11)$$

$$Cap_{TS,min} \le E_{TS}^{j} \le Cap_{TS} \quad (12)$$

With this mathematical model, it is possible to carry out the equipment's operation optimisation. As the proposed optimisation considers both quantitative and qualitative costs, the fitness function for this stage of the optimisation is:

$$\begin{aligned} f_{op}=\sum_{j=1}^{N} w_{ec}\Big(&P_{PV,j}C_{PV}+P_{UG,j}C_{UG,j}+C_{ES}\left(P_{CES,j}+P_{DES,j}\right)\\ &+P_{CHP,j}C_{CHP}+P_{HP,j}C_{HP}+Q_{BOI,j}C_{BOI}\\ &+\left(\frac{Q_{CHP,j}}{\eta_{CHPth}}+\frac{Q_{BOI,j}}{\eta_{BOI}}\right)\left(C_{G,j}+F_{g}C_{GHG,j}\right)\\ &+C_{TS}\left(Q_{CTS,j}+Q_{DTS,j}\right)-P_{FI,j}C_{FI,j}\Big)\\ &+w_{ql}\Big(P_{PV,j}QC_{PV}+QC_{ES}\left(P_{CES,j}+P_{DES,j}\right)\\ &+P_{CHP,j}QC_{CHP}+P_{HP,j}QC_{HP,j}+Q_{BOI,j}QC_{BOI}\\ &+QC_{TS}\left(Q_{CTS,j}+Q_{DTS,j}\right)\Big) \end{aligned} \quad (13)$$

This optimisation problem can be solved using linear programming, which allows for efficient determination the global minimum (Liberti, 2008). Once the operation for single scenario has been obtained, quantitative criteria of interest can be computed. One useful parameter for evaluating the performance of the energy infrastructure over time is the net present value (NPV), which takes into account various cash inflows and outflows for each year and converts them into current value, allowing for the assessment of the profitability of energy investments (Eriksson and Gray, 2017). The NPV is calculated by comparing the upgraded industrial plant to its hypothetical operation without any investment, using the following formula:

$$NPV=-I_0+\sum_{i=1}^{T}\frac{I_i}{(1-r)^i} \quad (14)$$

Cash flow are computed for the analysed weeks and extrapolated for years as:

$$\begin{aligned} I_i=\frac{W_Y}{W}\sum_{k=1}^{W}\Bigg(&\sum_{j=1}^{N}P_{FI,i,k,j}C_{FI,i,k,j}+\left(P_{UG,ref,i,k,j}-P_{UG,i,k,j}\right)C_{UG,i,k,j}\\ &+\left(\frac{Q_{BOI,ref,i,k,j}}{\eta_{BOI}}-\frac{Q_{CHP,i,k,j}}{\eta_{CHPth}}-\frac{Q_{BOI,i,j,k}}{\eta_{BOI}}\right)\left(C_{G,i}+F_gC_{GHG,i}\right)\Bigg)\\ &-\left(C_{O\&M,CHP}Q_{CHP,nom}+C_{O\&M,HP}Q_{HP,nom}+C_{O\&M,ES}Cap_{ES}\right.\\ &\left.+C_{O\&M,TS}Cap_{TS}+C_{O\&M,PV}A_{PV}P_{PV,nom}\right) \end{aligned} \quad (15)$$

Once the quantitative parameters are computed, another scenario including a different set of possible inputs is evaluated until all scenarios are covered. Then, the PDF of the quantitative parameters is obtained. This is used to compute their expected value and to evaluate the risk through CVaR, which enables to consider the complete outcome PDF avoiding undesirable profit distributions (Vahedipour-Dahraie et al., 2020). CVaR is computed as:

$$CVaR(x)=\frac{1}{1-VaR}\int_{-1}^{VaR_{level}} xp\,(x)\,dx \quad (16)$$

where $p\,(x)\,dx$ is the probability of the value x according to the PDF.

2.2.3. Optimality assessment

In this stage, the optimal equipment is determined based on the quantitative and qualitative criteria calculated in the optimisation process, which are combined in a single fitness function. The criteria can be combined through aggregation or multiplication. In this case, aggregation is used because it takes into account both positive and negative criteria and handles outliers better, limiting their influence on the final function value. The qualitative criteria evaluated in the first stage of the optimisation include their uncertain definition and risk in their value. In contrast, the quantitative criteria have two distinct measures: expected value and CVaR. In this paper, these values are unified into a single measure using the VaR level, which defines CVaR, as:

$$X_{measure\ with\ risk} = E\left(x\right) + VAR_{level}CVaR(x) \tag{17}$$

Once values for all criteria including their uncertainties are obtained, they are structured under the main decision-making criteria employed for investment evaluation in enterprises: economic, social and environmental (Hoogmartens et al., 2014). The main criteria are computed as the arithmetic means of the criteria under them. To avoid numerical illness, remove dimensions, and obtain a realistic measure of the criteria, all parameters are normalised previous to the balance. The mathematical formulation is, for the case of the economic criteria:

$$X_{ec} = \frac{\sum_{k=1}^{n} X_{ec,qt,norm,k} + \sum_{z=1}^{m} X_{ec,ql,norm,k}}{m+n} \tag{18}$$

where m is the number of qualitative sub-criteria and n is the number of quantitative sub-criteria. Main criteria are then incorporated into a single function reflecting the preferences of decision-makers. These preferences are obtained through the Analytical Hierarchy Process (AHP) (Saaty, 1987), which allows the consideration of subjective preferences in a robust manner (Roszkowska, 2013). The objective function is thus:

$$f = w_{ec}X_{ec} + w_{so}X_{so} + w_{en}X_{en} \tag{19}$$

This fitness function is computed and the global optimiser checks its stopping criteria, which can include result tolerance, number of iterations without improvement, optimisation time, etc. If the optimal solution has been reached, the optimiser finalises its operation. Otherwise, the result is returned to the first stage where new potential solutions are created and the process is repeated.

3. Case study

This section presents the application of the proposed methodology to a manufacturing SME from the automotive sector located in Spain. First, the industrial plant to which the methodology is applied is described. Then, both quantitative and qualitative input parameters are collected, which is an essential part of the proposed methodology for conducting optimisation with uncertainties. On one hand, the quantitative input factors and their uncertainties, which are used to calculate quantitative criteria and associated risks, are analysed statistically. On the other hand, the rules and membership functions of the fuzzy logic system are established to calculate the relevant qualitative criteria for the optimisation problem, as well as the qualitative costs of using technologies. Finally, decision preferences are evaluated using AHP and weights for the different decision criteria are obtained. With this data, the mathematical optimisation process described earlier can be run to obtain the results, which are discussed in Section 4.

3.1. SME industrial plant

The studied enterprise relies on a boiler to transform gas into thermal power and purchases electricity from the utility grid to meet the electrical load. Fig. 4 exemplifies the demand pattern for a typical winter week, exposing an important thermal demand which fluctuates with days and occupation and a more stable electrical demand. The enterprise is exploring the possibility to upgrade its energy infrastructure and transform into a prosumer by including increasingly adopted technologies. These technologies are: PV system, CHP system, HP and storage, both electrical (EES) and thermal (TES). The new equipment is foreseen to be kept in operation for the next 15 years. Equipment degradation considering this horizon is mainly present in PV and EES systems. For the case of PVs, a continuous performance loss of 0.8% per year is implemented (Jordan et al., 2015). For the ESS, the degradation appears as a loss of capacity instead of a loss of efficiency. In this paper, continuous degradation of 6% per year accumulated is applied (Carnovale and Li, 2020). Table 1 exposes the criteria that the enterprise considers important for taking the decision. From these criteria, NPV and GHG emissions can be computed quantitatively. In contrast, business continuity, ecological impact, social acceptance, and administration alignment are considered qualitatively. The energy investment should fulfil the set of constraints specified by the industrial SME that appear in Table 2 and which are related with maximum investment, maximum payback time, maximum emissions and are available for the installation of the PV system.

Table 1
Decision-making criteria the case study industrial SME.

Main criteria	Sub criteria
Economic	• NPV • Business continuity
Environmental	• GHG emissions • Ecological impact
Social	• Social acceptance • Administration alignment

Table 2
Energy investment constraints for the case study.

Constraint	Value
Maximum initial investment	1 000 000 €
Maximum time for the return of investment	6 years
Maximum emissions at year 15	300 tCO_2
Maximum area of the PV system	12 000 m^2

3.2. Quantitative data

The quantitative data required to carry out the optimisation include equipment parameters, operation and maintenance (O&M) costs, energy carriers' costs and connexion efficiencies. Although the evolution of all of these parameters is uncertain, only energy carriers' costs uncertainty affect significantly the performance of the energy infrastructure (Urbano et al., 2021a). Therefore, their uncertainty is incorporated in the optimisation process whereas the rest of the quantitative parameters are considered deterministic. The industrial SME under study employs two energy carriers: electricity and gas. Electricity price is forecasted to increase between 0.51% and 2.69% yearly (Afman et al., 2017; Comission, 2016; Zhou, 2021). Fig. 5 shows how these cost evolution scenarios can be fitted to the PDF which will be employed to obtain the samples that will serve as input for the optimisation problem. The PDF is selected according to the goodness of the fit measured through the loglikelihood function and is in this case an Inverse Gaussian distribution with parameters $\mu = 1.48$ $\lambda = 3.72$. For gas, today's cost is expected to vary in upcoming years between −2.19% and 1.4% (Zhou et al., 2019; Zhou, 2021). Fig. 6 shows these values together with the fitted Extreme Value PDF with parameters $\mu = 0.67$ $\sigma = 1.10$. Initial energy carrier's costs are obtained from wholesale markets in Spain, being of 90€/MWh (Omie, 2021) for electricity and 48€/MWh for gas (MIBGAS, 2021). Other quantitative data employed in the optimisation can be consulted in Appendix.

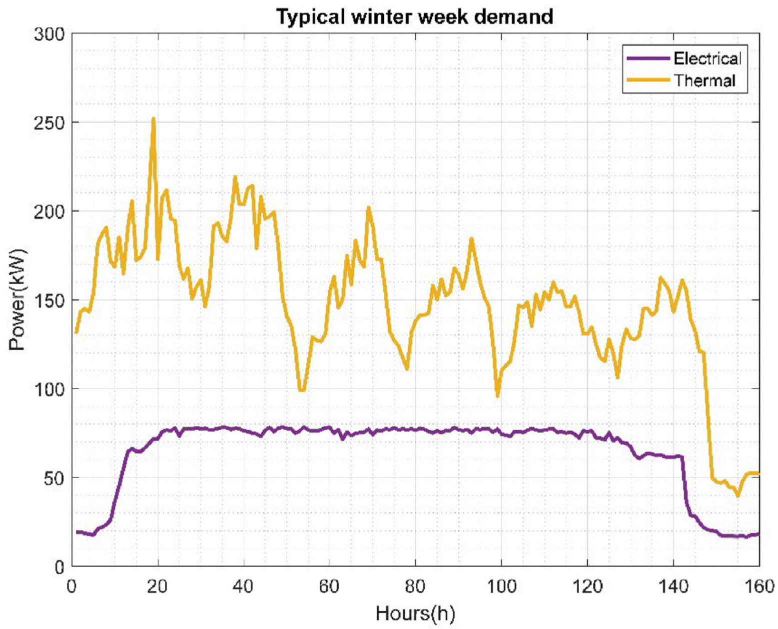

Fig. 4. Demand pattern of the industrial case study for a typical winter week.

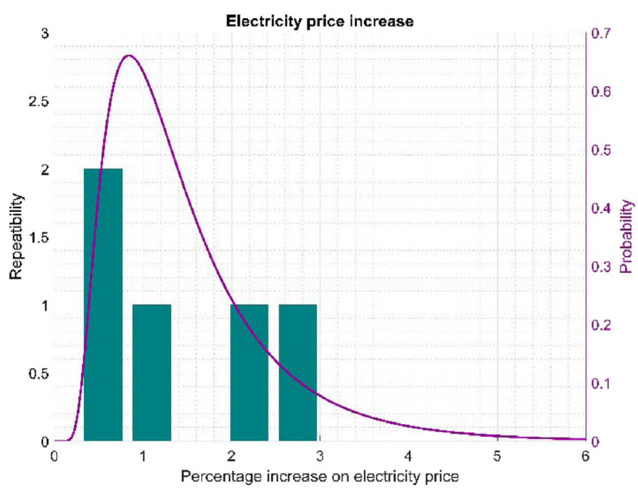

Fig. 5. Electricity price evolution uncertainty characterisation.

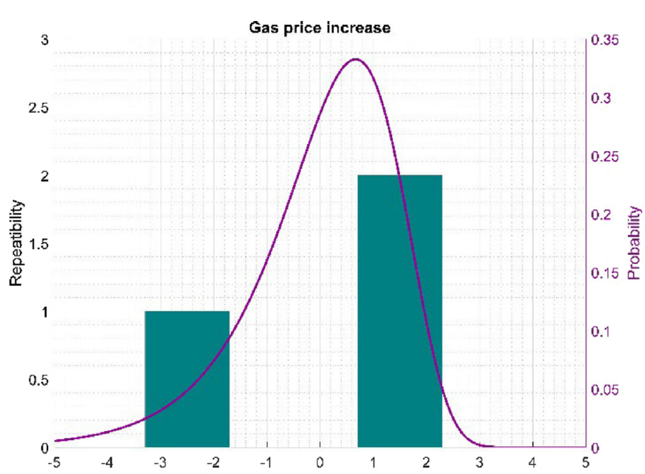

Fig. 6. Gas price evolution uncertainty characterisation..

3.3. Qualitative data

3.3.1. Initial perception

In the first stage of the optimisation, the qualitative criteria are computed according to the selected technologies. To do so, MFs and rules of the fuzzy system are defined. MFs represent imprecise information coming from human opinions and sentiments regarding energy equipment. To do so, the employment of Gaussian MFs is preferable as they describe the continuity of opinions better than other common types of MFs due to their smoothness and naturality (Abdar et al., 2020). MFs can be directly defined by decision-makers through their expertise in the field or obtained through opinion mining (Serrano-Guerrero et al., 2021). The process of opinion mining and definition of the most suitable MFs is out of the scope of this study and thus, for the sake of exposition, the MFs shown in Figs. 7 and 8 are assumed to suitably represent society's opinion for this case study. Fig. 7 expose the MFs for the analysis of the size of energy equipment and are in this case those of the PV system, although they are common to the rest of the equipment. Fig. 8, in contrast, expose the MFs for the evaluation of *impact* and *probability* that are needed to obtain the value of a qualitative perception through the fuzzy system.

Decision-makers also establish the rules to compute *impact* and *probability* for business continuity, administration alignment, social acceptance, and ecological impact. The rules are written in an *if–then* format and enable obtaining the output based on the set of provided inputs and the MFs — exposed in Fig. 8. These *if–then* rules, together with previously exposed MFs, enable the creation of a fuzzy surface, which represents the computation of the *impact* or the *probability* of a specific solution based on the inputs provided. The fuzzy method used to compute *impact* and *probability* employs max–min composition to consider all activated rules. Then, *probability* and *impact* resultant functions are aggregated through the max method and the resultant function defuzzified employing the centroid method. Fig. 9 shows the surface for *impact* on administration alignment according to different PV and CHP sizes. It can be seen that in this case, according to decision-makers, the solution is more aligned with the administration if it contains PV and it is less aligned with the administration if it contains a bigger size of CHP.

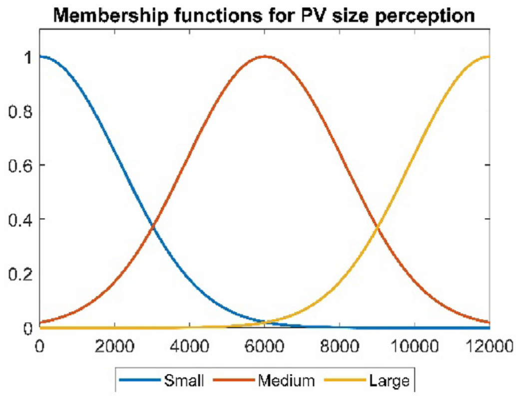

Fig. 7. MFs for the assessment of energy equipment size: PV system.

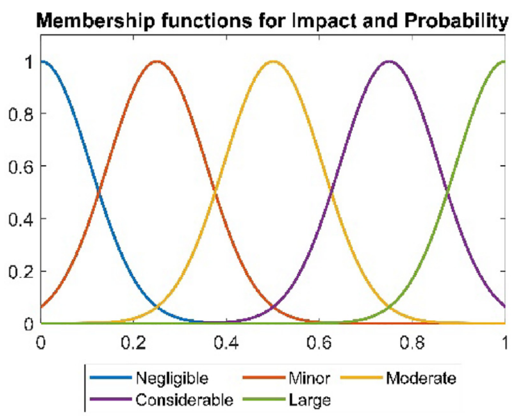

Fig. 8. MFs for the assessment of *impact* and *probability*.

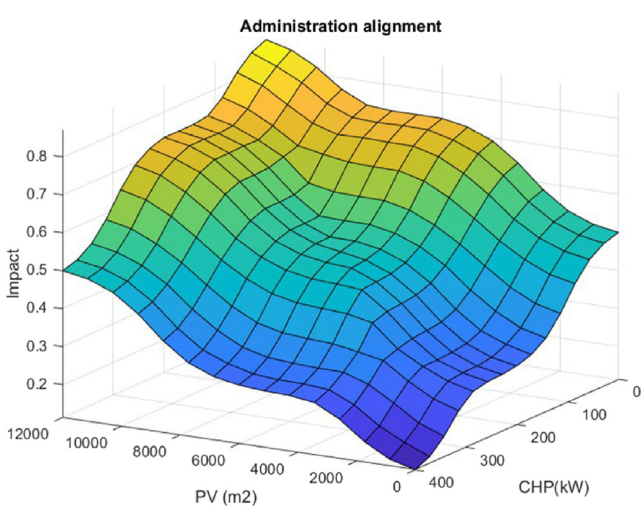

Fig. 9. Impact surface for administration alignment based on the size of the PV and CHP systems.

3.3.2. Continuous qualitative cost of technologies

Qualitative perceptions are also included in the second stage of the optimisation as the qualitative costs of employing a specific technology. To obtain this cost, decision-makers evaluate for 15 years of the investment's lifetime the *impact* and *probability* of the technology to contribute negatively to the specified qualitative criteria. *Impact* and *probability* are then incorporated into a fuzzy system which computes the cost. The MFs for these inputs and for the output are the same as exposed in Fig. 8, with the difference that the output's range is [0,0.1] to have the same magnitude order as the economic costs. In this case, the rules generated by decision-makers, depend only on two inputs and therefore can be expressed in a qualitative risk matrix. Table 3 expose the generated *if–then* rules for the case study analysed in a qualitative risk matrix, exposing which is the suitable output MF according to the input *impact* and *probability* MFs.

3.4. Decision preferences

The sub-criteria are structured under the main criteria as seen in Table 1. To obtain the criteria weights the Saaty method is followed in this case study, which concludes with Table 4. This table represent the Saaty comparison matrix and the resultant computed weights. For the case analysed, it can be seen that the predominant criterion is the economic one, followed by the environmental and the social, which are at an approximately equal level although being the social spectrum slightly of more interest for the enterprise than the environmental one. These weights serve to create the objective function which is used through the optimisation process.

4. Results and discussion

Table 5 shows the optimal energy infrastructure for this case study, as well as the results for a baseline optimisation that considers deterministic parameters and NPV as a single objective, to compare the proposed methodology with a common approach used in the literature. It can be seen that the PV system covers all available area as it positively impacts all criteria. In contrast, the CHP size and its operation are moderated in the proposed optimisation, while its size is larger in the baseline case. CHP is mainly used to meet thermal demand, contributing also to electrical one. In the proposed optimisation, the moderate use of CHP is a due to the emissions caused, the increasing qualitative cost of employing it – decreasing social acceptance and a high ecological impact – and the lack of alignment with the administration, as there are measures planned for reducing the installed capacity of CHP systems (Spanish Government, 2020). When qualitative criteria are not considered, the CHP system is 15.7% larger because it contributes positively to the economic performance of the enterprise. However, when qualitative criteria and risks are considered, its size is reduced due to its negative impacts on the environment, making it a riskier option given current social perceptions of gas-fired facilities and the trend towards moving away from them. Therefore, the benefits of incorporating quantitative and qualitative criteria and risks in the optimisation problem include a more complete understanding of the CHP system. Thermal storage is used to better align electrical and thermal demands and maximise the usefulness of CHP output. Regarding the HP system, it is not selected since the difference between electricity and gas costs makes it not economically viable, despite some favourable qualitative parameters. ESS are also excluded from the optimal infrastructure due to their current costs and ecological impact. The case study industrial plant has been optimised as a prosumer, interconnecting also the different equipment to maximise efficiency and security of supply. Fig. 10 shows the operation of the plant for a typical autumn week together with thermal and electrical demand. It can be seen that the energy generated by the PV system surpasses electrical demand and thus excess energy is present in the system which is sold to the utility grid. Another important finding is that the CHP system follows the thermal load except at some points in which it adapts its behaviour to better supplement electrical load. It is at these points in time where the thermal storage acts

Table 3
Qualitative risk matrix that express the *if–then* rules for the evaluation of technologies' qualitative cost.

		Probability				
		Large	Considerable	Moderate	Minor	Negligible
Impact	Large	Large	Large	Considerable	Considerable	Moderate
	Considerable	Large	Considerable	Considerable	Moderate	Moderate
	Moderate	Considerable	Considerable	Moderate	Moderate	Minor
	Minor	Considerable	Moderate	Moderate	Minor	Negligible
	Negligible	Moderate	Moderate	Minor	Negligible	Negligible

Table 4
Saaty pairwise comparison matrix and resultant criteria weights.

	Economic	Social	Environmental	Weight
Economic	1	5	5	**0.7089**
Social	1/5	1	2	**0.1786**
Environmental	1/5	1/2	1	**0.1125**

Table 5
Results of the optimisation.

Equipment	Optimal size	Baseline size
PV	12 000 m^2	12 000 m^2
Thermal storage	250 kWh	250 kWh
Cogeneration	118 kW	140 kW

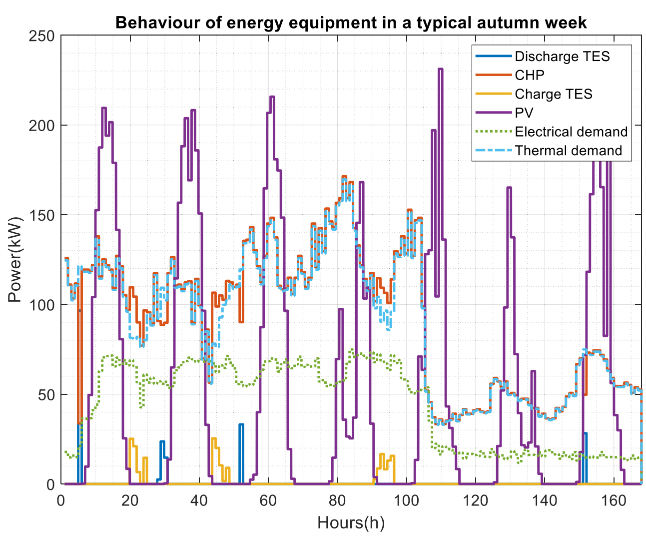

Fig. 10. Operation of the optimal energy infrastructure for a typical winter week.

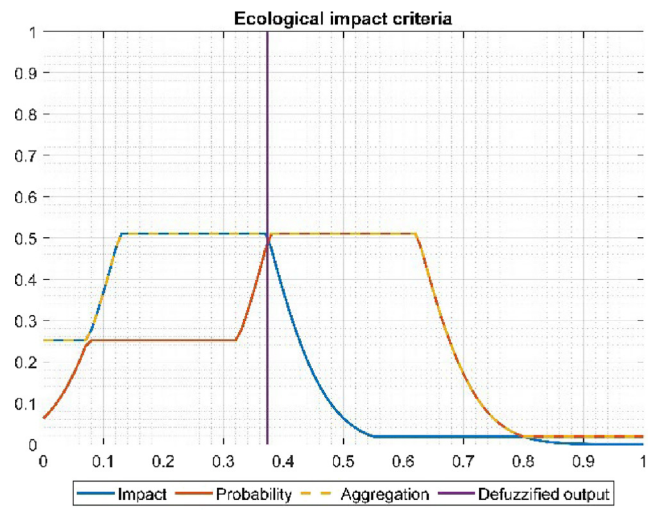

Fig. 11. Ecological impact criteria fuzzy computation: activated rules, min implication, max aggregation and defuzzification.

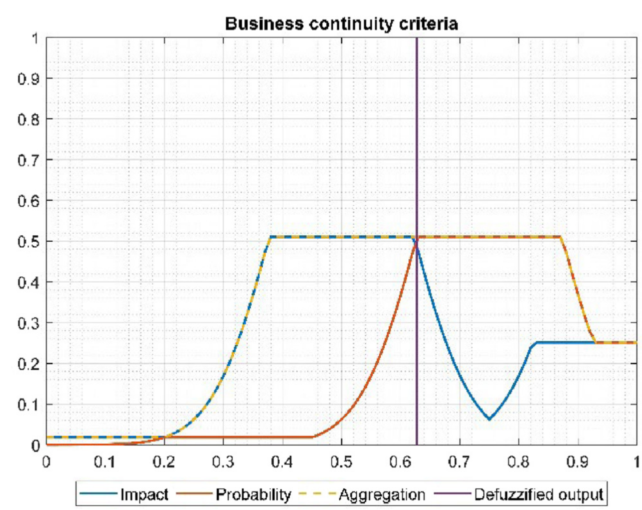

Fig. 12. Business continuity criteria fuzzy computation: activated rules, min implication, max aggregation and defuzzification.

and captures the excess thermal storage generated by the CHP or provides thermal power to thermal demand.

To reach the exposed results, qualitative parameters are obtained through the initial fuzzy system, whose operation is exposed for ecological impact and business continuity in Figs. 11 and 12. In these figures, MFs for probability and impact are shown together with their aggregation and defuzzification. It can be seen that for both criteria two rules are activated for the computation of *impact* and *probability*, being all of them truncated following the *min* implication method and aggregated through the *max* method. The followed process enables the obtention of a final defuzzied value for the qualitative criteria which account for uncertainty and vagueness in judgements. Table 7 shows these values for all the qualitative criteria evaluated in the analysed case study. Qualitative costs of employing technologies over time, which are used in the second stage of the optimisation process to create a qualitative-aware operation strategy, are also computed through fuzzy logic and exposed in Table 6.

Aside from qualitative criteria, to reach the mentioned result the optimisation algorithm also computed quantitative criteria and related risks. Table 8 exposes NPV and GHG emissions' mean value, CVaR, and standard deviation both for the proposed optimisation and for the baseline case. These values have been obtained by sampling the input quantitative uncertain parameters and propagating them through the optimisation process, which generated different NPV and GHG emissions results which can be seen in Figs. 13 and 14. These results were used to statistically analyse the proposed solution, obtaining the VaR and CVaR as also shown in the figures.

The optimal energy investment obtained through the proposed methodology has a lover NPT compared to the baseline case. However, the proposed methodology balances different criteria and thus the obtained GHG emissions are lower than those

Table 6
Qualitative costs for employing energy equipment technologies. Values in €/kWh × 10^{-3}.

		Year														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Technology	PV	40.6	40.6	35.1	35.1	30.5	30.1	28.9	28.9	28.9	26.2	21.7	21.1	20.3	20.3	20.3
	CHP	55.0	59.4	59.4	59.4	59.4	69.5	72.5	72.4	72.0	74.2	74.3	74.3	74.3	76.3	80.0
	ESS	50.0	40.6	40.6	40.6	40.6	35.1	35.1	35.1	35.1	30.5	30.5	30.1	27.3	27.3	27.3
	HP	40.6	40.6	40.6	35.1	35.1	35.1	30.5	30.1	27.3	27.3	24.4	24.4	21.1	20.3	20.3
	TSS	40.6	40.6	35.1	38.4	35.1	35.1	32.1	30.4	28.9	27.3	24.9	24.4	20.5	21.1	21.1

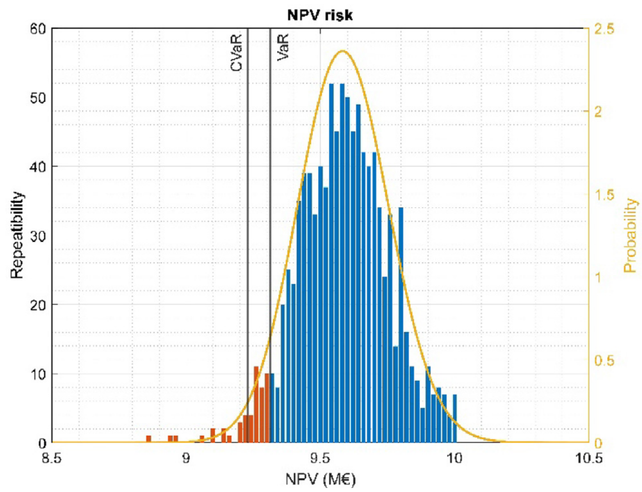

Fig. 13. NPV probability distribution function with obtained VaR and CVaR.

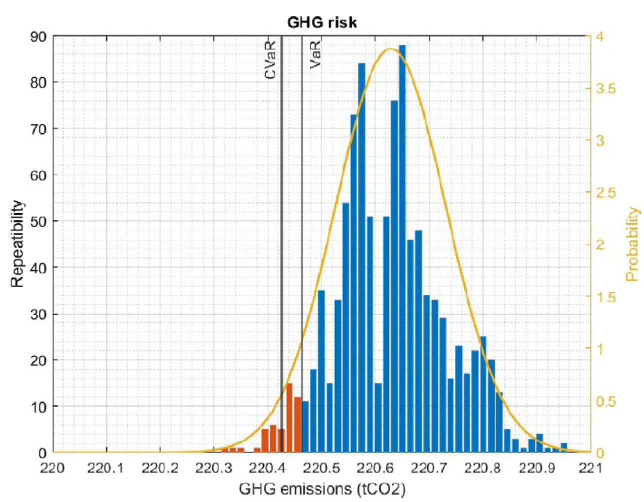

Fig. 14. GHG probability distribution function with obtained VaR and CVaR.

Table 7
Initial qualitative criteria evaluation: resultant defuzzified values for the obtained solution.

Qualitative criteria	Defuzzified value
Business continuity	0.6268
Ecological impact	0.3732
Social acceptance	0.7882
Administration alignment	0.4745

Table 8
Quantitative criteria values for the obtained solutions.

Parameter	Optimal value	Baseline value
NPV mean	9 586 600 €	9 617 900 €
NPV CVaR	9 228 400 €	9 247 800 €
NPV standard deviation	168 970 €	176 450 €
GHG mean	220 630 $kgCO_2$	220 776 $kgCO_2$
GHG CVaR	220 426 $kgCO_2$	220 579 $kgCO_2$
GHG standard deviation	103 $kgCO_2$	100 $kgCO_2$

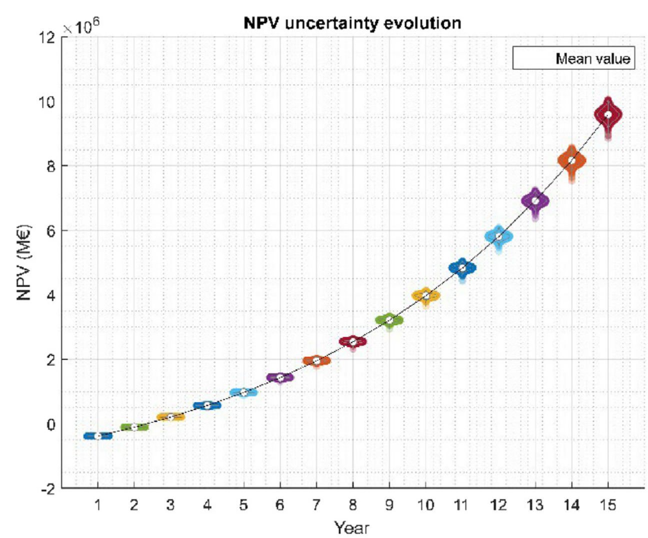

Fig. 15. NPV mean and NPV uncertainty evolution over investment lifetime.

of the baseline case. While there is still some variability in NPV and GHG, the proposed optimisation strategy reduces the CVaR and standard deviation of the quantitative criteria and thus the uncertainty in the investment outcome. In particular, the variability of the economic outcome is reduced by 4.2%. This variability is linked to the uncertainty of the input energy carriers, electricity and gas. Given the uncertainty in the evolution of these two energy sources, the quantitative criteria are also uncertain and their uncertainty grows exponentially over time, as shown in Fig. 15. Nonetheless, the proposed optimisation approach minimises this variability and the risk of quantitative outcomes are lower than in the baseline case, resulting in a more robust and resilient energy investment option.

Fig. 16 illustrates the final values of the economic, social, and environmental criteria used in the optimisation. Economic criteria have been prioritised followed by social and then environmental ones, reflecting the preferences of decision makers. Although economic criteria are the primary focus, their improvement has been conditioned by social and environmental criteria, reaching in a trade-off solution where economic criteria are maximised while social and environmental criteria also reach acceptable values. As the criteria include risks in both qualitative and quantitative parameters, the resulting optimal energy infrastructure represents a solution that minimises risk while achieving good performance across the spectrum of decision criteria.

The results of this case study demonstrate the benefits of using a two-stage risk-informed optimisation approach compared to a base case that only considers deterministic quantitative criteria.

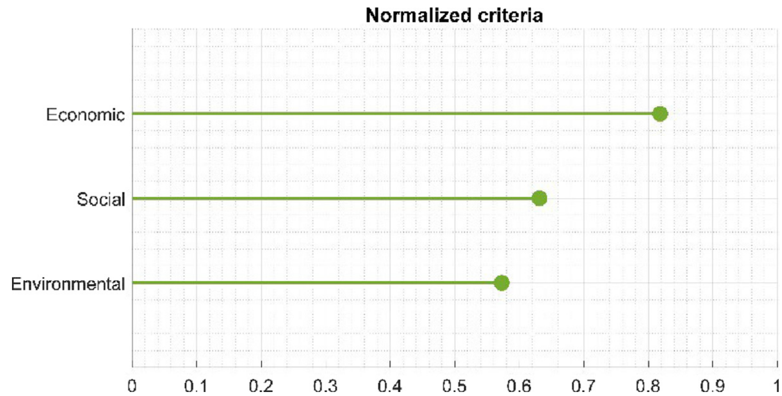

Fig. 16. Optimisation normalised criteria for the resultant energy investment.

By including uncertainties and qualitative criteria in the optimisation process, it has been possible to identify and verify the advantages of this approach. These results can also be compared with those of other case studies and scenarios found in the literature to validate the proposed methodology. To this end, while there are no studies in the literature that examine all of the parameters considered in the proposed optimisation, we have used the following works as references: Liu et al. (2022), Bohlayer et al. (2021), Coppitters et al. (2020), Das et al. (2021) and Khan et al. (2021). These works represented important developments in the field and include segments of the methodology proposed here, allowing a comparison to be made between the results obtained. Specifically, the references mentioned can be divided into the following groups:

- Optimisation with posterior analysis of uncertainty: Liu et al. (2022)
- Optimisation considering uncertainty in quantitative parameters: Bohlayer et al. (2021) and Coppitters et al. (2020)
- Optimisation considering different economic, technical, environmental and social parameters (Das et al., 2021; Khan et al., 2021)

A comparison between the results obtained in these studies and those obtained here is presented in the following paragraphs. First, Liu et al. (2022) present an optimisation methodology for a hybrid energy system with the goal of minimising energy exchange with the grid, as well as emissions and system cost. They analyse various case studies, the results of which demonstrate the suitability of incorporating a photovoltaic system with energy storage, which is consistent with the findings of this study. After obtaining the solution, Liu et al. (2022) perform a SA to see the effect of electricity price on emissions and operating cost, increasing it from 40% to 160%. While a full statistical analysis and comparison cannot be conducted due to the small number of samples used in the SA, it can be seen that emissions vary from their average value between −22% and +39% and operational cost varies from −20% to +20%. By using the optimisation approach proposed in this paper, which takes uncertainties into account in the energy investment problem, these figures are significantly reduced. The variation of emissions ranges from −0.22% to +0.32% relative to their average value, and the net present value (NPV), which is calculated using operational cost, varies from −9% to +8%.

In contrast, Bohlayer et al. (2021) consider uncertainty within the optimisation problem by performing a two-stage stochastic optimisation. Their case study involves the energy supply system of an industrial complex in Germany. In this case, the total system cost has a standard deviation of 3%–10%, which is similar to the NPV standard deviation reported in this paper - 1.76% - and supports the benefits of incorporating uncertainties in the optimisation problem. Coppitters et al. (2020) also include uncertainties in the optimisation problem and further evaluated the impact of modifying the optimisation result on a non-economic objective: self-sufficiency. Coppitters et al. (2020) study the sizing of a PV system with energy storage and concluded that, if only economic performance is considered, the PV system without storage is the optimal choice with the lowest operating cost. However, if self-sufficiency and variability are taken into account as criteria, the inclusion of a battery in the resulting energy infrastructure leads to higher costs. The results of Coppitters et al. (2020) for the PV system without a battery show a standard deviation in cost of 18%–20% of the mean, which is reduced to 12.2% by incorporating a battery that supports the isolation of the system from electricity grid price uncertainty. These results are consistent with the findings of this paper, indicating the economic inappropriateness of including a battery, the significant effect of electricity price on system uncertainty, and the importance of criteria selection in the resulting energy infrastructure.

Finally, Das et al. (2021) optimise a hybrid renewable energy system to use excess energy generated to meet external electrical and thermal load demands and reached a similar conclusion regarding the battery system: the option with the lowest cost is the one with the least amount of battery installed. In contrast to previous research that has focused on quantitative parameters such as economics and the environment (emissions), Khan et al. (2021) develop a hybrid renewable energy system optimisation that also examines its techno-financial and social viability. The optimisation criteria included net present cost of the system, cost of energy, life cycle emissions, renewable energy penetration, unmet load, duty factor, human development index, particulate matter, and job creation. The resulting energy infrastructure was a combination of renewable energy sources, fossil fuel generators, and storage systems that balanced all of these criteria. The net present cost, which is directly related to the NPV, had a variability of 8% relative to its mean value, similar to the NPV variability, from −9% to +8%, of the methodology proposed in this study.

Through the analysis of the results and the comparison with other studies in the literature, it is possible to conclude that the proposed methodology is an improvement over incomplete methodologies that do not consider quantitative and qualitative factors and uncertainties simultaneously. The results of this paper are consistent with those in the literature, but offer greater precision and reliability due to the consideration of a larger number of parameters and real-world conditions in the decision-making process.

5. Conclusions

This paper has presented an extended two-stage optimisation methodology for the sizing of energy infrastructures for industrial SMEs. This methodology evaluates quantitative and qualitative criteria and risks affecting the investment, both at the time of decision-making and during the operation of the energy infrastructure. This approach is well-suited for industrial SMEs, as it considers a wide range of diverse and inherently different criteria and aims for long-term low-risk investments. Previous researches has either focused on quantitative or qualitative parameters, leaving the other spectrum aside, and most of them do not consider uncertainty or the investment performance over time. Therefore, the methodology presented in this paper fills a gap in the literature by providing a comprehensive and detailed methodology for the treatment of criteria and risks of interest for the energy investment.

In the proposed methodology, qualitative parameters dealing with subjective perceptions are calculated using a fuzzy system that evaluates the impact and probability of the decision on the analysed perceptions. Fuzzy logic is also used to determine the dynamic qualitative cost of using the energy equipment over time. These approaches allow for the incorporation of the uncertainty dimension in the measures of qualitative parameters. Risks for quantitative parameters are managed through a probabilistic approach, obtaining through the optimisation their expected value and CVaR. During the first stage of the optimisation, the energy infrastructure to be analysed is selected and qualitative criteria directly linked to it are calculated using the proposed fuzzy approach. In the second stage, the operation of the infrastructure is optimised by considering both quantitative and qualitative costs and associated uncertainties to determine expected values and risk measures. The suitability of the analysed energy infrastructure is assessed based on the preferences of decision-makers and the various criteria and risks, leading to a solution that recognises the overall performance of the investment across different decision-making spectrums. A case study has been conducted to examine the benefits of including quantitative and qualitative parameters and risks over time in the optimisation process. The energy infrastructure obtained through the proposed optimisation methodology has been compared with a baseline optimal infrastructure resulting from considering only an economic objective. The comparison reveals that including quantitative, qualitative and risk parameters in the optimisation process does indeed affect the resultant energy infrastructure. Without these criteria, equipment that is economically feasible but has the potential for significant negative social and environmental impacts may be chosen for installation. However, when qualitative criteria and risks are considered, the equipment is selected through a trade-off between different criteria, resulting in a solution that is overall less risky. Therefore, the selection of criteria is crucial and affects drastically the resultant solution of the optimisation problem. Additionally, even though the optimisation problem considers the economic, environmental, and social spectrums, the specific criteria selected to measure them, e.g. emissions or ecological impact for environmental criteria measurement, can alter the optimisation output by prioritising one outcome to another. The proposed optimisation approach also leads to a lower level of quantitative risk for the investor and a more robust and resilient energy investment option when uncertainties are considered.

This paper presents a new approach for helping industrial SMEs make energy investment decisions that enable them to adapt to changing energy conditions and improve their competitiveness. This approach can be used to solve generic asset investment problems, as it allows the consideration of various criteria and uncertainties in a problem in which there exists a model for the performance of the asset. To further develop this methodology, future research could focus on defining qualitative perceptions, determining the most relevant criteria for energy investment optimisation, and extending the methodology to include optimal energy equipment retrofitting.

CRediT authorship contribution statement

Eva M. Urbano: Conceptualization, Methodology, Software and models, Resources, Validation, Writing – original draft, Visualization, Funding acquisition. **Victor Martinez-Viol:** Software, Writing – review & editing, Visualization. **Konstantinos Kampouropoulos:** Conceptualization, Supervision, Writing – review & editing. **Luis Romeral:** Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix. Case study quantitative data

Parameter	Value
PV	
Initial cost	950 €/kW
LCOE	0.07 €/kWh
Initial O&M cost	6.56 €/kW-year
O&M cost variation	−2.3% per year
PV connexion efficiency	99%
Job creation	0.87 jobs/GWh
Electrochemical storage	
Initial cost	430 €/kWh
LCOE	0.06 €/kWh
Initial O&M cost	8.22 €/kW-year
O&M cost variation	−3.8% per year
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
O&M cost	36 €/kWe-year
G2E efficiency	35%
G2T efficiency	55%
Job creation	0.31 jobs/GWh

HP	
Initial cost	700 €/kW
LCOE	0.076 €/kWh
O&M cost	5.56 €/kW-year
COP	4.5
0.25	jobs/GWh
Thermal storage	
Initial cost	5 €/kWh
LCOE	0.0243 €/kWh
O&M cost	0.26 €ct/kW-year
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
O&M cost	70€/kW-year
Efficiency	90%
Connexion efficiencies	99%
Emissions	
Initial emissions cost	25 €/tCO_2
Increase ratio	3.9% per year
Feed-in tariff	0.85 of wholesale market price
Demand growth	1.5% per year

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