Optimal integrated sizing and operation of a CHP system with Monte Carlo risk analysis for long-term uncertainty in energy demands

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Abstract

In this study a probabilistic approach for optimal sizing of cogeneration systems under long-term uncertainty in energy demand is proposed. A dynamic simulation framework for detailed modeling of the energy system is defined, consisting in both traditional and optimal operational strategies evaluation. A two-stage stochastic optimization algorithm is developed, adopting Monte Carlo method for the definition of a multi-objective optimization problem. An Italian hospital facility has been used as a case study and a gas internal combustion engine is considered for the cogeneration unit. The results reveal that the influence of uncertainties on both optimal size and annual total cost is significant. Optimal size obtained with the traditional deterministic approach are found to be sub-optimal (up to 30% larger) and the predicted annual cost saving is always lower when accounting for uncertainties. Pareto frontiers of different CHP configurations are presented and show the effectiveness of the proposed method as a useful tool for risk management and focused decision-making, as tradeoffs between system efficiency and system robustness.

Keywords

Combined Heat and Power

Optimization

Uncertainty

Monte Carlo method

Multi-objective
Decision-making

1. Introduction

Cogeneration is the simultaneous production of electric energy and useful heat. Combined Heat and Power (CHP) plants haven been shown to be a reliable, competitive and less polluting alternative to separate generation. The European Union has promoted the use of high-efficiency cogeneration as a measure to save primary energy, avoid electric network losses, reduce emissions, namely greenhouse gases, and improve the security of energy supply [1]. CHP technology is considered an essential means of achieving the European 20% energy efficiency target by 2020 [2].

The energy, environmental and economic performances of CHP systems are strongly influenced by prime mover selection, equipment capacity and operational strategy. Undersizing and oversizing of CHP plants are frequent and do not allow the full exploitation of the energy saving of such systems [3]. For this reason, in recent years, many studies have focused on appropriate CHP system design methods [4]. Multi-objective optimization approaches for designing cogeneration systems have been developed both for residential [5] and for large-scale building energy systems [6]. The importance of integrated sizing and operational strategy methods for optimal selection of cogeneration systems has been explicitly addressed [7,8].

Different optimization techniques have been used over the years to identify the optimal design of polygeneration systems [9]. Arcuri et al. [10] presented a Mixed Integer Linear Programming (MILP) model for the determination of the design and the running conditions of a trigeneration plant for a hospital complex. Guo et al. [11] carried out a two-stage optimal planning and design method for Combined Cooling Heat and Power (CCHP) microgrid system, using both genetic algorithm and MILP algorithm techniques. Elsido et al. [12] and Arcuri et al. [13] proposed Mixed-Integer Non-Linear Programming (MINLP) models for determining the most profitable synthesis, design, and annual scheduling of CHP systems.

Other works have focused on the optimal exploitation of the CHP potential in existing plants. Franco and Versace [14] defined the optimal operational strategy of a cogeneration plant connected to a District Heating System. Li et al. [15] analyzed the effect of optimized operational strategy on a CCHP system for office and residential buildings. Bischi et al. [16], Ortiga et al. [17] and Ünal et al. [18] investigated the optimal operating schedule of CCHP systems, with a given design.

Many of these studies [6,11] have clearly indicated the importance of considering, in future research, the effect of uncertainties in CHP optimal design. Such a task is very challenging, but it is worthwhile for gaining accurate and robust results. In fact, it is well-known how intrinsic uncertainties affecting Distributed Energy Systems (DES), such as energy demands, fuel price fluctuations, regulation, and so on, might undermine the potential profit of such systems [19]. In this regard, several approaches of optimization under uncertainty have been employed, such as general sensitivity analysis [20,21], sensitivity analysis in mathematical programming [22], fuzzy programming [23,24], dynamic programming [25], robust optimization [19], and stochastic programming [26]. Each of these studies focused on specific types of uncertainties and energy systems. Yokoama and Ito [27] proposed a robust optimal design method, through a case study on a cogeneration system, considering uncertain energy demand of a single representative day. Akbari et al. [28] focused on designing a multi-technology distributed energy system in a neighborhood, under demand uncertainty concerning data insufficiency. Momen et al. [29] provided a Monte Carlo method applied to a gas-turbine-based cogeneration system, considering uncertainties in economic parameters. Mavrotas et al. [30] dealt with risk management for uncertainty in fuel costs and discount rate, by means of the combined use of Monte Carlo simulation and MILP algorithm. Li et al. [31] optimized a building CCHP system, considering fluctuations in the hourly energy demands.

In the mentioned studies, long-term uncertainties in energy demand are ignored and typical load year data are considered for the whole lifetime of CHP systems. However, fluctuations in energy demand over the years may be significant and their effect on overall performance and optimal sizing must be specifically evaluated.

The main purpose and novelty of this study is therefore to accurately investigate the effect of long-term uncertainties in energy demand on CHP systems. For this purpose, an original optimal integrated sizing and operational strategy methodology is defined, which takes analytically into account uncertainties in energy demand. More specifically, this study provides a probabilistic methodology for risk analysis, based on the simulation of the entire life-cycle of the cogeneration project. Such an approach allows to highlight shortcomings and inaccuracies of usual deterministic methods. Moreover, the adopted methodological framework provides results in the form of probability distributions, thus providing fruitful and complete information to decision-makers.

The remainder of the paper is organized as follows. In Section 2 the methodological framework is presented in detail. An essential description of the case study follows in Section 3. Section 4 contains a detailed analysis of the results, while the last section contains concluding remarks.

2. Methodology

In pursuit of the above-mentioned goals, a specific methodological framework has been developed. Three main tools have been employed: the dynamic simulation based on a full mathematical model of the system, the so-called Monte Carlo sampling Method, and an optimization algorithm.

2.1 System Simulation

It is commonly accepted that an extensive and accurate analysis of a CHP unit requires a detailed simulation of the energy system [32]. In fact, preliminary sizing methods, such as the load duration curve, are useful only for assessing orders of magnitude of the project and cannot fully embrace the complexity of a CHP system. Multiple time-varying loads, part-load performances, simultaneous energy balances and various economical features make any rule-of-thumb approach inaccurate. Furthermore, the importance of considering electrical and thermal load fluctuations instead of mean values is recognized [33].

For these reasons, a CHP simulation, based on hourly averaged values for load representation, should be adopted [34]. This approach allows several key factors to be considered, such as part-load efficiency, load factor lower bound, hourly time-dependent prices for purchasing and selling electricity, actual operational hours, different operational strategies. In such a way, comprehensive system performances and a detailed CHP operational scheduling can be obtained.

In fact, CHP systems can be run by several possible operational strategies. The two most common forms of operational strategies are: *Following the electric load* (FEL) and *Following the thermal load* (FTL). Nevertheless, these traditional strategies might not guarantee the best performance of the systems and optimal operating strategies have therefore been investigated in the last few years. [35,36]. Obviously, the adopted operational strategy can significantly influence the optimal sizing of the CHP system [7] and, consequently, it is essential to opt for an integrated methodology, which simulates all the possible operational strategies.

2.2 Monte Carlo Method

Uncertainty in model variables and parameters can considerably undermine the accuracy of the results and may lead to erroneous conclusions. Uncertainty in energy load demand plays a key role in the analysis and design of a cogeneration system [27,37,38]. Not only is an accurate estimate of the energy demand frequently difficult to provide, but also evolution and change in loads are likely to occur. In fact, economic analyses concerning CHP installations should deal with a multi-year time horizon, corresponding to the lifetime of the system, which is generally up to 20 years. During such a period, fluctuations in energy demand are highly probable and may be significant.

For the above-mentioned reasons, it is necessary to consider uncertainty associated with the energy input data and evaluate its propagation to the results, in the framework of a risk analysis approach. For this purpose, Monte Carlo Method (MCM) is adopted; indeed, Monte Carlo simulation technique is a state-of-the-art methodology in risk analysis and can be employed within the context of risk management of distributed energy infrastructures [39].

MCM is a family of numerical methods capable of solving mathematical problems by means of simulation with random variables. Given a deterministic model $y = f(\boldsymbol{x})$, with k input data $(x_1, \dots, x_i, \dots, x_k)$, MCM operates under the following steps.

1. To assign a probability density function (pdf_i) to each model input data x_i. It is also possible to specify a correlation between the various input data.
2. To generate N possible values for each input data, by means of random samples of its probability density function.
3. To combine the random samples to get N input vectors. If the input data are not correlated, samples can be combined in any order.
4. To perform the simulation of the model N times, one for each input vector. In such a way, a vector of results is provided, and an input-output mapping of the model is defined, within the input space of the input pdf_i.
5. The set of N values of the output data $(y_1, \dots, y_j, \dots, y_N)$ defines the probability density function of the result of the simulation.

The application of the MCM provides a detailed insight into the probability distribution of the target variable [40], allowing the calculation of typical statistical indicators, such as the mean value, the standard deviation, the skewness, the n-th percentile, the cumulative risk of negative values, etc. This additional information can offer a critical support to decision-makers, providing a probabilistic scenario and guaranteeing a robust decision.

A significant element in MCM is the number N of simulations to be performed to get accurate results. In fact, the uncertainty in the statistics obtained by the probability density function of the results drops as N increases. Given a certain confidence level, the margin of error usually decreases as $\sqrt{\mathrm{D}/\mathrm{N}}$, where D is a constant depending on the different variant of the applied MCM [40].

2.3 Optimization

A detailed optimization procedure, concerning both the long and short-term time frames, has been purposely developed and is described as follows.

2.3.1 The objective function

The optimization problem consists in the determination of the integrated CHP size and scheduling that meet the energy demand with the lowest possible cost. To evaluate the performance of the system, an annual cost saving index performance is defined. It is the annual cost saving with respect to the separate-production energy cost, which represents the reference energy system cost. In the separate-production energy system scenario, the thermal demand is met by a traditional natural gas-fired boiler and the electric demand is covered by the national electrical grid. In such a scenario, the only costs to be accounted for are based on the prices of purchased gas and electric energy required to meet the energy demand:

$$AC_{SP} = \sum_{i=1}^{8760} c_F^i \; F_{boi,SP}^i + \sum_{i=1}^{8760} c_{PEG} \; E_{p,SP}^i \tag{1}$$

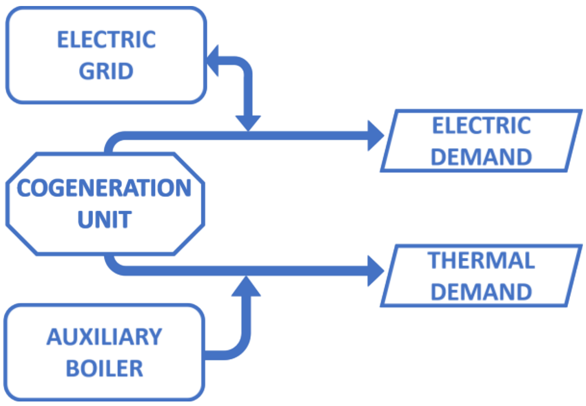

Fig. 1 Schematic representation of the Combined Heat and Power system

In the CHP system scenario (illustrated in Fig. 1), the thermal demand is met partly by the CHP heat production and partly by the gas-fired boiler, and the electric demand is covered partly by the CHP electric production and partly by the national electrical grid. Therefore, the economic features to be accounted for are: the purchased natural gas price, both for the boiler and the CHP units, the price for purchasing electricity by the grid, the income for selling electricity to the grid, the cogeneration unit investment cost, and the cogeneration unit maintenance cost.

$$AC_{CHP} = \sum_{i=1}^{8760} c_F^i \, F_{boi,CHP}^i + \sum_{i=1}^{8760} c_{PEG} \, E_{p,CHP}^i - \sum_{i=1}^{8760} c_{SEG} E_{s,CHP}^i + \sum_{i=1}^{8760} c_F^i \, F_{cgu,CHP}^i + C_{I,cgu} + C_{M,cgu} \tag{2}$$

It should be noted that both the separate-production and the CHP system costs are annual, which means they represent the cost needed to meet the energy demand of the reference year. The cogeneration unit investment cost is considered equally distributed over every year of its design lifetime.

$$C_{I,CGU} = {C_{TI,CGU}}\Big/{DLT_{CGU}} \tag{3}$$

Therefore, the optimization problem consists in the maximization of the annual cost saving percentage:

$$\max\{ACSP\} = \max\left\{\left(\frac{AC_{SP} - AC_{CHP}}{AC_{SP}}\right)\%\right\}. \tag{4}$$

2.3.2 Decision variables, demand constraints, capacity constraints, balance equations, operational strategy rules

As already indicated, three different operational strategies are considered: FEL, FTL and minimum cost (MC) operational strategy. For the FEL and the FTL, the only decision variable is the Co-Generation Unit capacity P_{cgu}, for the design optimization. Instead, five additional decision variables, for the MC operational strategy of the *i*-th hour, are defined as follows: $E_{cgu}^i, Q_{cgu}^i, Q_{boi}^i, E_p^i, E_s^i$. In case the simulated operational strategy is either the FEL or the FTL, these operational decision variables are univocally identified by the constraint equations and there is no need for optimization tools.

Demand constraints are defined as follows:

$$E_{CGU}^{i} + E_{p}^{i} - E_{s}^{i} - E_{d}^{i} = 0 \tag{5}$$

$$Q_{CGU}^{i} + Q_{boi}^{i} - Q_{d}^{i} = 0 \tag{6}$$

$$E_{p}^{i} E_{s}^{i} = 0 \tag{7}$$

where $i = 1,2,\dots,8760$. Equation (7) states that in the *i*-th timestep electricity is either sold or purchased.

Capacity constraints are defined as follows:

$$E_{CGU}^{i} - P_{CGU} t \delta_{CGU}^{i} \leq 0 \tag{8}$$

$$E_{CGU}^{i} - P_{CGU,min} t \delta_{CGU}^{i} \geq 0 \tag{9}$$

where $i = 1,2,\dots,8760$, and δ_{CGU}^{i} is a binary variable equal to 1 when the cogeneration unit is on and equal to 0 when it is off.

The following balance equations are considered.

$$F_{CGU}^{i} - {E_{CGU}^{i}}/{\eta_{E,CGU}^{i}} = 0 \tag{10}$$

$$Q_{CGU}^{i} - E_{CGU}^{i} \frac{\eta_{Q,CGU}^{i}}{\eta_{E,CGU}^{i}} = 0 \tag{11}$$

$$F_{boi}^{i} - {Q_{boi}^{i}}/{\eta_{boi}^{i}} = 0 \tag{12}$$

where $i = 1,2,\dots,8760$.

Different operation rules must be additionally implemented for each operational strategy. For the FEL:

$$E_s^i = 0 \tag{13}$$

$$E_p^i = 0, \qquad unless\ P_{CGU}t - E_d^i < 0 \tag{14}$$

where $i = 1,2,\dots,8760$.

For the FTL:

$$Q_{boi}^i = 0, \qquad unless\ P_{CGU}t\frac{\eta_{Q,CGU}^i}{\eta_{E,CGU}^i} - Q_d^i < 0 \tag{15}$$

where $i = 1,2,\dots,8760$.

For the MC:

$$\min\left\{\sum_{i=1}^{8760} c_{F,CHP}^i\ F_{boi,CHP}^i + \sum_{i=1}^{8760} c_{PEG,CHP}\ E_{p,CHP}^i - \sum_{i=1}^{8760} c_{SEG,CHP} E_{s,CHP}^i + \right. \\ \left. + \sum_{i=1}^{8760} c_{F,CHP}^i\ F_{CGU,CHP}^i\right\} \tag{16}$$

where $i = 1,2,\dots,8760$. The 5 decision variables of the operational strategy optimization problem are related to each other by means of Equations (5), (6), (7), and (11). Therefore, there is only one degree of freedom for the minimization.

2.3.3 Monte Carlo simulation and multi-objective optimization criteria

As previously indicated, the MCM consists in a high number of repeated random samples. For each sample a complete year simulation of the system must be run. This procedure allows to consider the whole life of the plant, in terms of energy demand fluctuations, even if an annual index performance is considered. Because of the MCM application, however, the objective function ACSP is not just a single value for each design configuration and operational strategy but is a probability distribution function. Consequently, the definition of a multi-objective optimization criterion is suggested [41]. Such a criterion can represent statistic information contained in the probability density function that are relevant to the selection of the CHP system. For these purposes, we propose to adopt the following two indicators: the expected value $ACSP_{EV}$ and the 2.5-th percentile $ACSP_{2.5th\,\%ile}$. The expected value of a random variable is the average value of the probability distribution and represents the average performance of the system. On the other hand, the 2.5-th percentile indicates the worst-case scenario. In fact, it is the ACSP value above which 97.5% of the values will occur. Therefore, a Pareto frontier of potentially optimal solutions will be obtained, so that decision-makers will be able to make appropriate tradeoffs within this set of solutions.

2.3.4 Solution Method

To solve this problem, we implemented a two-stage optimization algorithm in MATLAB environment:

- Stage 1: Design Optimization (for the selection of the optimal CHP size);
- Stage 2: Operational Strategy Optimization (for the determination of the optimal unit commitment).

The complete optimization procedure is summarized in the diagram set forth in Fig. 2.

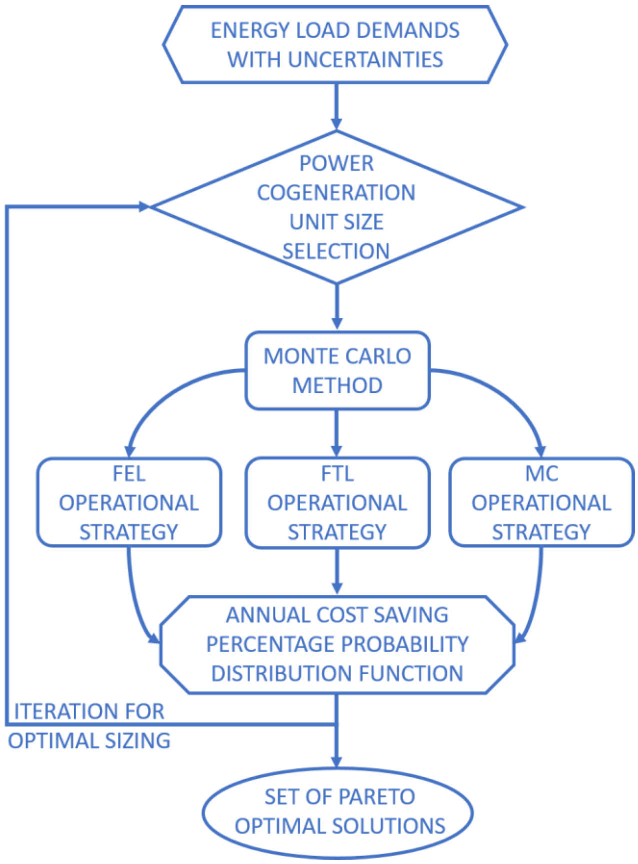

Fig. 2 Optimization procedure

The Design Optimization consists in the dynamic simulation of potentially available cogeneration units with discrete sizes, for each given operational strategy. The comparison between the annual cost savings of several sizes makes it possible to determine the optimal design. The choice of a discrete selection of sizes is taken in view of the difficulty in finding commercially available CHP gas engines with sizes exactly corresponding to optimal numerical solutions [42,43]. For each selected size, MCM is applied, performing repeated random simulation samples for each operational strategy. In the event the simulated operational strategy is either the FEL or the FTL, there is no need for further optimization algorithms, since those strategies can be easily implemented.

Conversely, when the performance under optimal unit commitment is investigated, the Operational Strategy Optimization is required to determine the optimal management of the cogeneration unit. This optimization algorithm is aimed at identifying, for each simulated timestep, the optimal load factor of the CHP unit that minimizes the overall annual cost saving. For this purpose, several optimization techniques have been used over the years, such as mathematical programming, genetic algorithms, and other methods [4,9]. Usually, these algorithms investigate the entire feasible region, considering a single optimization problem for the whole-time domain (e.g. one year), thus requiring high computational cost. Nevertheless, for the energy system under consideration, the overall optimum coincides with the sum of optimums of every single timestep. We can use the so-called "greedy" approach because the physical system has no "memory" of the previous timesteps. Therefore, the overall problem was split into 8760 subproblems, one for each hourly timestep, and a low computational-cost algorithm, compatible with the high number of simulations required for the MCM, was specifically written. In this way, the problem size for each simulated year is reduced from N_L^8760 to $N_L \times 8760$, where N_L is the number of the feasible discrete intervals of the CGU load factor L.

3. Case study application

The case study used for testing the methodology refers to an operative Italian hospital facility. It is a 500-bed hospital, with a total volume of 230,000 m^3. Generally, hospital facilities are particularly suitable to be powered by CHP systems, because of high and constant loads during the year [3].

This paragraph summarizes the primary features of the energy system under investigation and the load demand of the case study.

3.1 The energy system: technical and economic characterization

In this section, models and features adopted for the components of the simulated energy system are illustrated.

3.1.1 Cogeneration unit

The cogeneration unit (CGU) consists in an internal combustion engine (ICE) fueled by natural gas. ICEs are the most commonly used prime movers for medium scale (100-5000 kW) CHP applications [36]. The considered nominal electric power capacities P_{cgu} go from 600 kW to 1600 kW, with discrete intervals of 100 kW.

The model for the CGU has been taken from [44]. Therefore, the power capacity lower bound is equal to 50% of the nominal power capacity and part-load efficiencies are considered according to the following relations:

$$\eta_{E,CGU} = \eta_{E,CGU,nom}(1.1260\ L - 0.1260\ ) \tag{17}$$

$$\eta_{H,CGU} = \eta_{Q,cguCGU,nom}(0.8253\ L + 0.1747) \tag{18}$$

where the load factor is defined as $L = F_{CGU} \cdot \eta_{E,CGU,nom}/P_{CGU}$. Table 1 reports nominal efficiencies and the corresponding heat-to-power ratio of the CGU.

Table 1

Cogeneration unit main specifications

Parameters	Value
$\eta_{E,CGU,nom}$	38.5%
$\eta_{Q,CGU,nom}$	34.4%
HPR_{nom}	0.894

The unitary cost of internal combustion engines is significantly influenced by the “scale effect”. For this reason, a relationship of the CGU cost with respect to size has been considered, based on [45]:

$$C_{TI,CGU} = 15460\ P_{CGU}^{0.7247} \tag{19}$$

where $C_{TI,CGU}$ must be expressed in € and P_{cgu} in kW.

The design lifetime of the CGU has been considered equal to 20 years, identical for all the accounted sizes; such a duration for cogeneration system projects is commonly accepted [46].

The engine maintenance cost per unit of electric kWh produced, as a function of the nominal power capacity, has also been considered, based on [45]. Therefore, the annual maintenance cost is defined as:

$$C_{M,CGU} = \sum_{i=1}^{8760} E_{CGU}^{i}\ 0.05604\ P_{CGU}^{0.1638} \tag{20}$$

where $C_{M,CGU}$ must be expressed in €, E_{CGU}^{i} in kWh, and P_{CGU} in kW.

3.1.2 Boiler

The nominal power capacity of the natural gas boiler has been considered such as to cover any thermal demand, for each different configuration and operational strategy.

It has been modeled with a constant efficiency, with reference to [20]:

$$\eta_{boi} = 0.9 \tag{21}$$

Both the boiler and the cogeneration unit are fed by natural gas; the fuel cost per unit of thermal energy, on the lower heating value basis, is:

$$c_F = 0.04\ €/kWh \tag{22}$$

3.1.2 Electric grid

The electric grid allows for both the sale and the purchase of electric energy. The prices for purchasing and selling electricity have been considered as constant values:

$$c_{PEG} = 0.15\ €/kWh \tag{23}$$

$$c_{SEG} = 0.05\ €/kWh \tag{24}$$

3.2 Energy load demand

As illustrated above, hourly-averaged values have been adopted for representing the energy load demands. Fig. 3 shows the load duration curves of the electric and thermal demands of the hospital. This data has been obtained from 12 typical days, corresponding to 4 typical weeks. For every week, representing significant seasonal weather periods, one weekday and two weekend days (Saturday and Sunday) have been considered.

The uncertainty in the annual energy load demand has been considered through normal distributions. A 20% relative standard deviation has been employed for both electric and thermal demands. Such a value is consistent with the 8-consecutive-year data of energy demand, measured in the test case hospital.

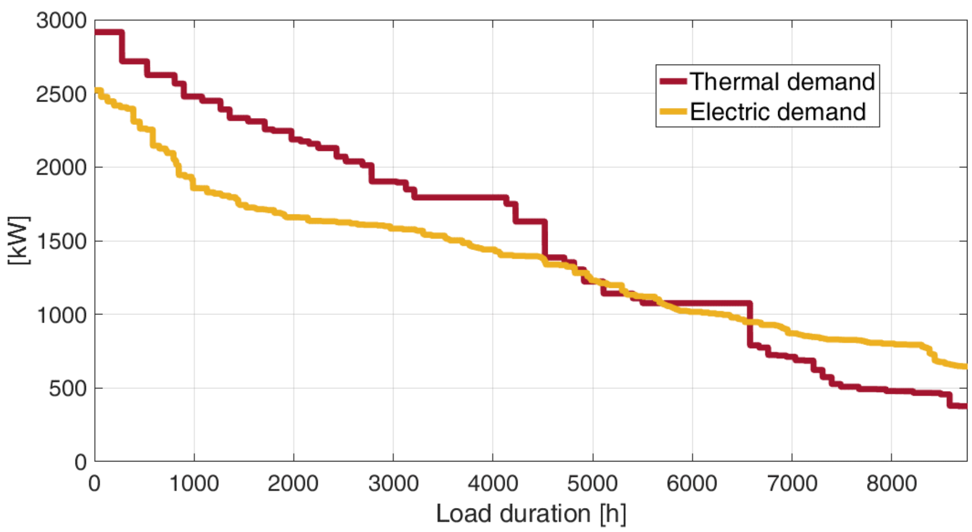

Fig. 3 Electric and thermal demands: load duration curves

4. Results and discussion

The simulation results for all the potential CGU sizes and operational strategies are shown in this section. 300,000 simulations were performed for each combination of design configuration and operational strategy, so that reliable results and limited uncertainty in the output indicators could be obtained.

Figs. 4 and 5 show typical examples of how the simulated energy system works and what kind of detailed outputs are available from the simulations. Fig. 4 shows how the electric demand is met in 72 consecutive hours; Fig. 5 shows the same kind of result, for the thermal demand.

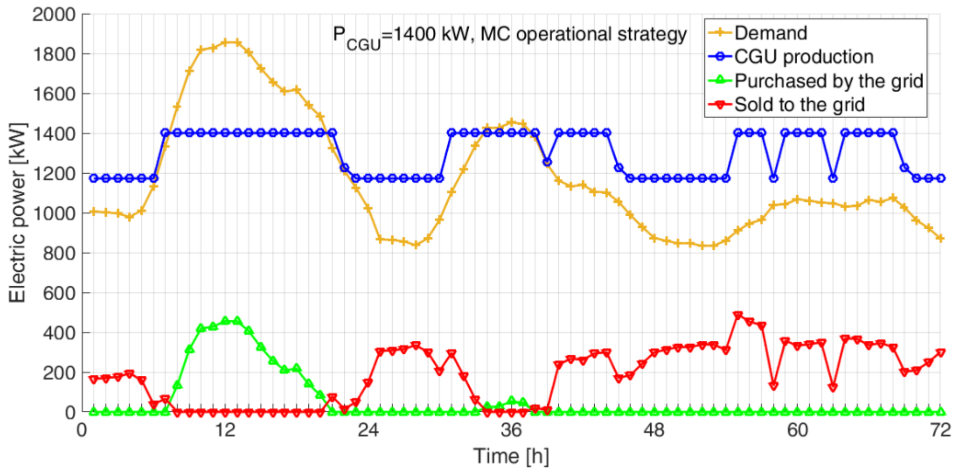

Fig. 4 Example of simulation output: electric power

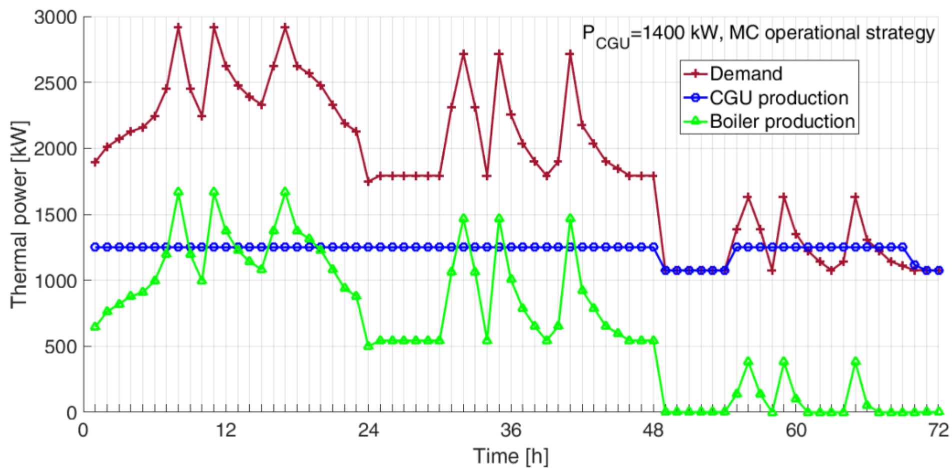

Fig. 5 Example of simulation output: thermal power

In Figs. 6 and 7, examples of the results obtained by the MCM are displayed. Fig. 6 is a demonstration of one of the probability distribution functions of the annual cost, obtained for a certain CHP size and operational strategy. Fig. 7, instead, shows the same results in the form of annual cost saving percentage. In both figures, the vertical dotted line represents the deterministic value of the index, which corresponds to the simulation result obtained with the most probable (i.e. deterministic) values of the input data. From these quantitative examples, the importance of assessing the effect of uncertainties and their propagations to the results is evident. Another interesting consideration arising from these examples is the asymmetry of the probability distribution function of the annual cost, despite the symmetry of the input random variables. This aspect, due to the non-linearity of the model $y = f(\boldsymbol{x})$, further reinforces the need for a probabilistic approach.

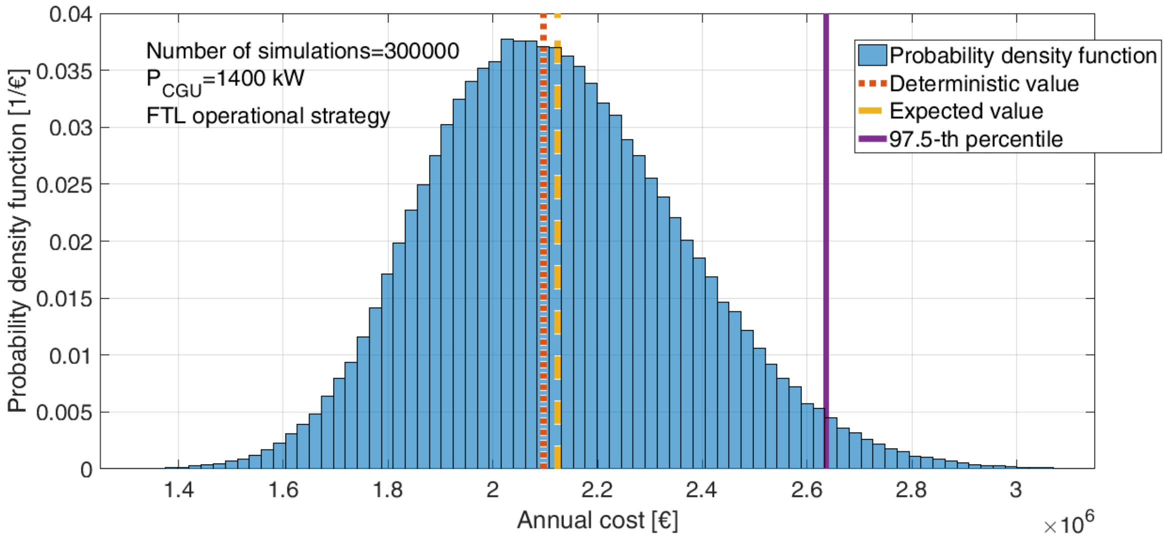

Fig. 6 Example of MCM result: annual cost probability density function

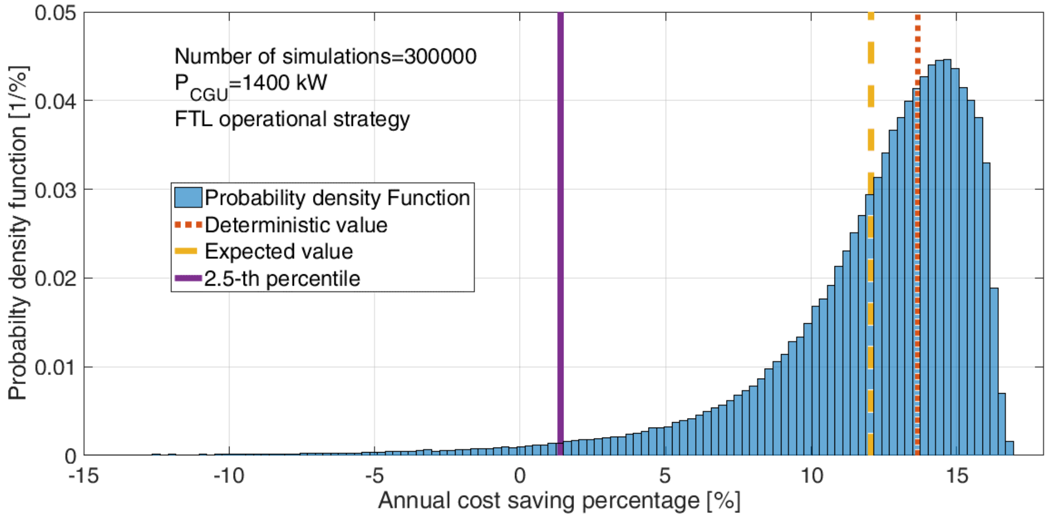

Fig. 7 Example of MCM result: annual cost saving percentage probability density function

Fig. 8 shows a comparison between deterministic and probabilistic results, for all the evaluated operational strategies. The probabilistic results are represented by means of the expected value for each configuration. The ACSP as a function of the CGU size is shown. As already highlighted, the main outcome is the numerical gap between the deterministic and the expected values. Moreover, in this case study, for all the three operational strategies, the expected value of the ACSP is always lower than the deterministic one, and the gap between these two indicators rises as the CHP size increases. The method clearly shows how demand uncertainties can significantly affect evaluation of CHP system performance; therefore, they should always be considered in a thorough analysis. More specifically, these results reveal that traditional deterministic approaches tend to overestimate the annual cost saving percentage. In fact, for all three simulated operational strategies, the best annual cost saving percentage, calculated by means of the deterministic method, is about 10% overestimated in comparison with the expected value of the probability density functions.

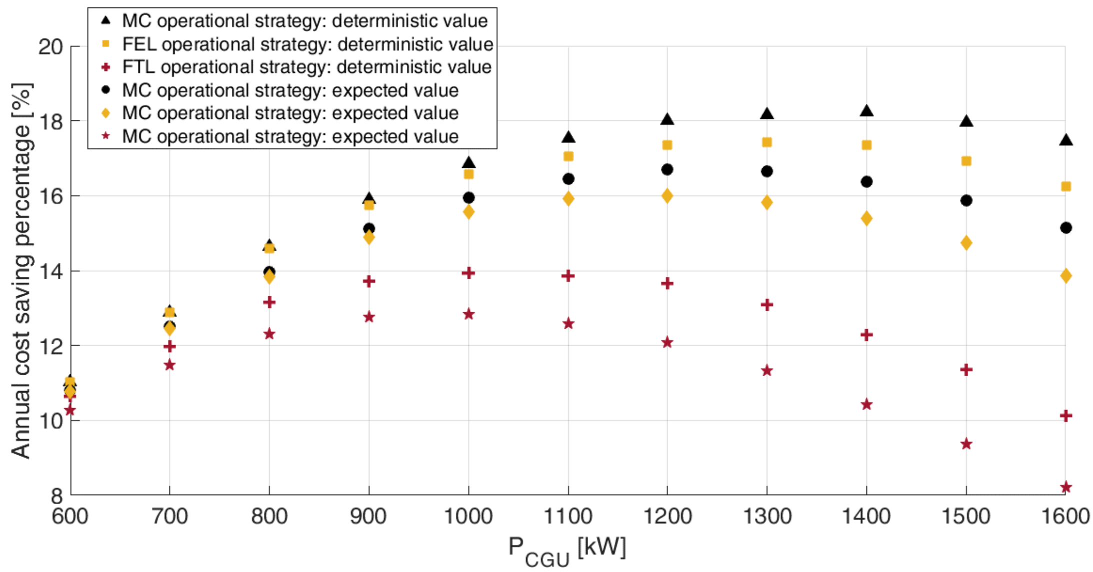

Fig. 8 ACSP for all the CGU sizes and operational strategies: a comparison between the deterministic and the expected value

Fig. 9 shows the $ACSP_{EV}$ against the $ACSP_{2.5th\ \%ile}$ values for all the evaluated CGU sizes and operational strategies. From this chart, it emerges that some solutions are clearly dominated by other more favorable solutions and shall be rejected for this reason. It should also be noted that some configurations can even entail a negative cost saving in the worst-case scenario (2.5-th percentile). The margin of error in the $ACSP_{EV}$ and in the $ACSP_{2.5th\ \%ile}$ values, with a confidence level of 95%, has been evaluated as $\frac{\sigma(\bar{X})}{\sqrt{N}} t_{0.025,N}$, where σ is the standard deviation, $\bar{X}$ is a sample of size N of a random variable (i.e. $ACSP_{EV}$ and $ACSP_{2.5th\ \%ile}$) and $t_{0.025,N}$ is the value on a t-distribution with N degrees of freedom for 0.025 right tail probability [47]. The maximum absolute margin of error in the $ACSP_{EV}$ and in the $ACSP_{2.5th\ \%ile}$ values is equal to 0.025% and 0.141%, respectively.

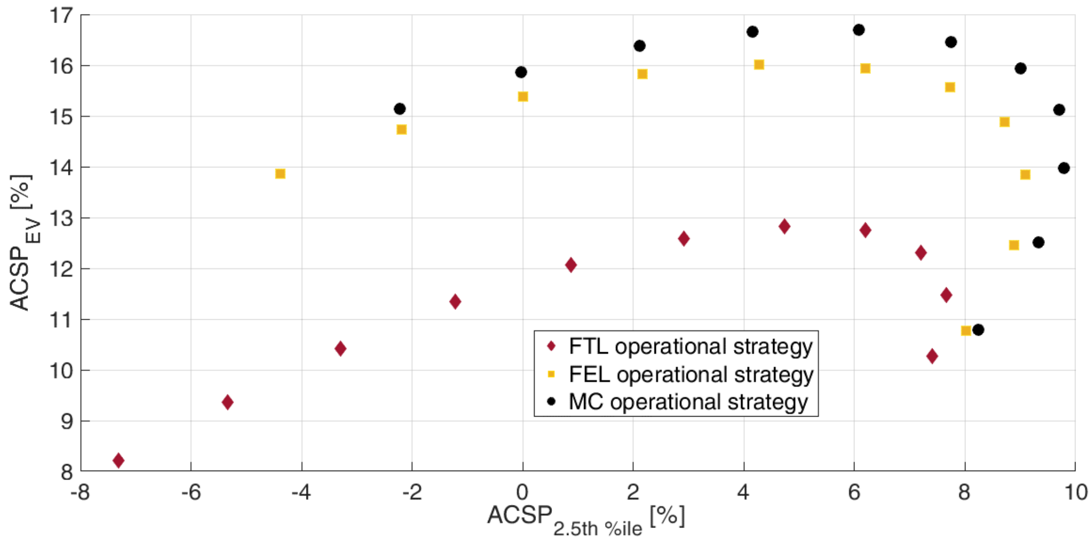

Fig. 9 ACSP$_{EV}$ vs. ACSP$_{2.5th\ \%ile}$ for all the CGU sizes and operational strategies

Finally, Pareto frontiers for each different operational strategy are shown in Figs. 10-12. All these CHP configurations are Pareto efficient with respect to the expected value and the 2.5-th percentile of the annual cost saving percentage. On these same graphics, the best deterministic solutions, namely the highest nominal cost saving solutions, are also represented.

Thanks to this representation, it is possible to evaluate which sizes are most likely to provide a higher profit, but with a greater risk, and which ones can guarantee an acceptable performance even in the worst-case scenario, at the expense of a lower expected value of the cost saving.

These charts clearly show the effect of energy demand uncertainties on the overall performance: both in the MC and in the FEL operational strategies, the optimal deterministic sizes are dominated solutions and shall be rejected.

Furthermore, it is clear how some configurations, despite being Pareto efficient, are reasonably going to be discarded: for example, in Fig. 10, the 800-kW solution provides a substantially lower $ACSP_{EV}$ value, compared to the 900-kW unit, but just a slightly higher $ACSP_{2.5th\ \%ile}$ value.

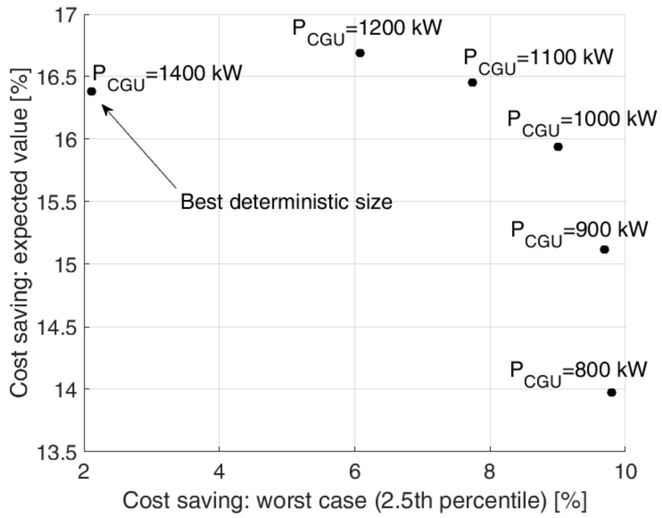

Fig. 10 MC operational strategy: Pareto frontier of CGU sizes

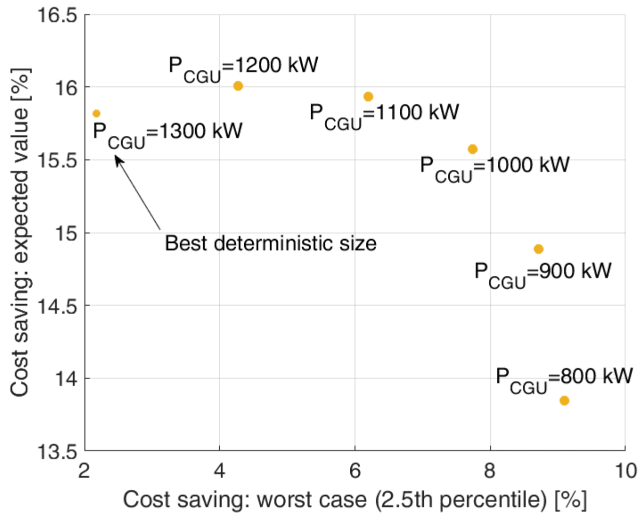

Fig. 11 FEL operational strategy: Pareto frontier of CGU sizes

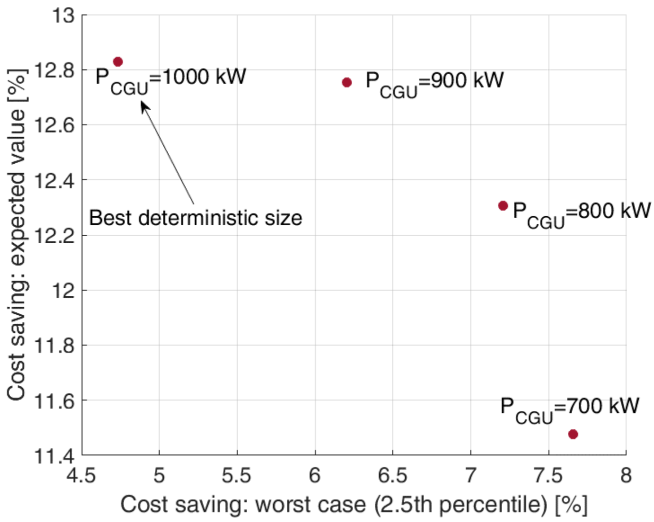

Fig. 12 FTL operational strategy: Pareto frontier of CGU sizes

By comparing the three different operational strategies, it turns out that, in the case study under examination, the FEL strategy always provides better performances than the FTL strategy. In addition, the optimal sizes are larger under the FEL strategy, compared to the optimal ones under the FTL strategy. This is mainly due to the low price of the electricity sold to the grid. Nevertheless, as expected, the MC operational strategy provides the best cost savings and largest optimal sizes.

Furthermore, smaller sizes turn out to be less risky and less unsure than the larger ones, since their performances are less affected by energy demand uncertainties. In any case, the probabilistic approach has clearly shown that the optimal sizes for the case study are significantly smaller than the optimal ones provided by the deterministic approach. For instance, under the MC operational strategy, the Pareto optimal CGU sizes are, on average, almost 30% smaller than the optimal deterministic ones.

5. Conclusions

In this study, we proposed an original methodology for optimal integrated sizing and operation of cogeneration systems under long-term uncertainty in energy demands. The suggested methodology consists of detailed simulations of the energy system under several operational strategies, a probabilistic analysis based on Monte Carlo method, and a two-stage optimization algorithm. Such an approach allows to analytically and accurately evaluate the effect of energy demand uncertainty and provides a useful tool for robust decision-making.

The application of the method has been demonstrated in a case study concerning the implementation of a CHP system for an Italian hospital. First, the influence of uncertainty in energy demands on both optimal cogeneration unit size and annual total cost has been shown. We have clearly highlighted the importance of considering such uncertainties in the evaluation of a CHP system. More specifically, we have shown how traditional deterministic methods tend to oversize cogeneration units and overestimate cost savings. In fact, disregarding long-term uncertainty in energy demand, the optimal size turns out to be about 30% larger and the annual cost saving is overestimated by approximately 10%. Moreover, the implementation of Monte Carlo method has allowed us to define a multi-objective optimization problem. This problem aims at maximizing the expected cost saving while minimizing the risk associated with energy demand uncertainty and can be useful for an accurate assessment of cogeneration plant performance. Pareto frontiers of different CHP configurations have been presented. The simulation results have highlighted that the smaller sizes are less affected by energy demand uncertainties than the larger ones, which, in turn, provide better performance in terms of expected values.

Future research may focus on: more complex polygeneration systems (modular cogeneration, energy storage and chillers), effect of combination of uncertainties in several parameters (energy demands at different time scales, fuel and electricity costs, design lifetime, and so on), analysis of correlation between uncertain parameters, and definition of other kinds of multiple criteria (environmental, energetic, exergetic indicators).

Nomenclature

Parameters

C	Unit cost, €/kWh
C	Cost, €
DLT	Design lifetime, years
t	Timestep, 1 h
η	Efficiency, dimensionless

Continuous variables

AC	Annual cost, €/year
$ACSP$	Annual cost saving percentage, %
E	Electric energy, kWh
F	Energy content of the consumed fuel, kWh
HPR	Heat-to-power ratio, dimensionless
L	Load factor, dimensionless
P	Electric power, kW
Q	Heat, kWh

Binary variables

δ	On-off state for cogeneration units

Subscripts

2.5th %ile	2.5-th percentile
boi	Boiler

CGU	Cogeneration unit
CHP	Combined heat and power production scenario
d	Demand
E	Electric
EV	Expected value
F	Fuel
I	Annualized investment
M	Annual maintenance
min	Minimum
nom	Nominal (L=1)
p	Purchased
PEG	Electricity purchased by the grid
Q	Thermal
s	Sold
SEG	Electricity sold to the grid
SP	Separate-production scenario
TI	Total investment

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