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# Optimal design of an Aggregated Energy System with N-1 reliability

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## ABSTRACT

This work presents a two-stage stochastic Mixed Integer Linear Programming model for the optimization of the design of an aggregated energy system (AES) (i.e., multi-energy systems, microgrids, energy districts, etc.) serving a university campus featuring electricity and heating demands. The off-grid system design is obtained by considering a set of representative periods for both demands by means of a carefully modified k-medoids algorithm. N-1 reliability is also considered in the model, by introducing the concept of "break-down scenarios" that allows the solution of the problem to be able to meet the user demands for every possible contingency in which one of the AES's units fails. The effect of including N-1 reliability in the model is then showed by comparing the optimal design obtained by considering such approach against one with no break-down scenarios.

**Keywords:** multi-energy systems, microgrid, optimization, MILP, stochastic programming, reliability.

## NONMENCLATURE

| | |
|---|---|
| *Abbreviations* | |
| AES | Aggregated Energy System |
| BESS | Battery Energy Storage System |
| CAPEX | Investment costs |
| CC | Compression Chiller |
| COE | Cost of Electricity |
| CHP | Energy Proceedings |
| EE | Electricity |
| HP | Heat Pump |
| MES | Multi-Energy System |
| MILP | Mixed-Integer Linear Programming |
| NG | Natural Gas |
| OPEX | Operational costs |
| PV | Photovoltaic panels |
| TAC | Total Annual Cost |
| TESS | Thermal Energy Storage System |
| *Sets* | |
| $U$ | Set of the installable dispatchable units |
| $J$ | Set of the available machines' slots |
| $K$ | Set of the representative periods |
| $T$ | Set of the timesteps within a period |
| $BDS$ | Set of the Break-Down Scenarios |
| *Variables* | |
| $z_{u,j,k,t}$ | 1 if variable of unit *u* installed in slot *j*, during representative periods *k*, at time *t* is online, zero otherwise. |

## 1. INTRODUCTION

In the last two decades an increasing industrial and scientific interest in aggregated energy systems (AES) has been shown. These are energy systems integrating and operating dispatchable generation and storage units, as well as intermittent renewable energy sources in a synergic way. These kinds of systems are able to serve users characterized by one or more energy demands (e.g. heat and electricity), while being economically completive and less carbon intensive than traditional solutions. In literature such aggregated energy systems are called microgrids, energy districts or Multi-Energy Systems (MES). An example of aggregated energy system coproducing electricity, heating and cooling power can be seen in Fig. 1. Despite the economic convenience of an AES, its design is particularly challenging since it must account for the operational constraints and part-load performance of the units. Moreover, for different applications (e.g., hospitals, schools, chemical processes like refineries, off-grid villages/islands, military camps, etc.) it is necessary to guarantee a high reliability level (namely the ability of the system to operate under stated conditions for a specified periods of time) on one or more energy services. For example, the heating and electric power demand of a hospital must be met also during maintenance or failure of one or more AES generation units. Similarly, the heating demand of a grid-connected school should always be met throughout the winter season despite any contingency. This reliability requirement leads to the need of installing multiple redundant units with a substantial increase in capital cost.

This work proposes a MILP model and decomposition algorithm for the optimal design of AES with reliability requirements. In particular, the MILP model include the "N-1 reliability" requirement of the AES: at any time and day of the year, the optimized design can meet the user's thermal and electrical demand even if one of the N installed units is not available for the whole day (under maintenance or out of service).

The model developed in this work can handle AES with energy storages and any type of units (combined heat and power units, heat pumps, etc.) without the need of including ad hoc constraints.

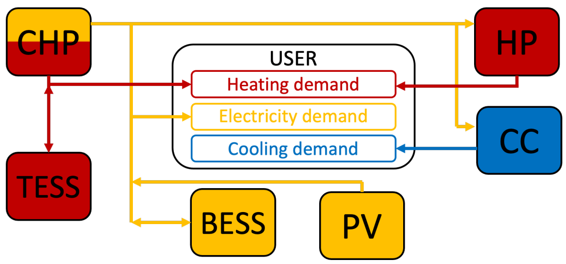


Fig. 1 An example of MES serving a user with multiple energy demands.

## 2. PROBLEM STATEMENT

The problem can be formulated as follows.

*Given:*

- The catalogue of energy conversion and storage technologies (e.g. thermal energy storage, CHP engine, PV panels, etc.), their available sizes (continuous), their part-load performance maps and operational limits (e.g., min-max load, ramp-up limit, start-up time, etc.), their investment and operating costs,
- The user's electricity and heating demand profiles

*Determine optimal AES design (i.e., selection of the energy technologies and their sizes) that minimizes the Total Annual Cost (TAC), subject to the following constraints (to be met at any time and any day of the year, even in case of fault of one AES unit (N-1 reliability):*

- Operational limits (ramping, performance curve, minimum up-/down-time, charge/discharge efficiency)
- Electricity and heating energy balances.

## 3. METHODOLOGY AND ASSUMPTIONS

The optimization methodology consists in three main steps: (1) finding the representative operational periods, (2) formulating the two-stage stochastic MILP model featuring N-1 reliability (3) developing an ad hoc bi-level decomposition method for the solution of the problem.

### *3.1 Representative operational periods*

The optimized MES design must consider the operation of the system across the lifetime/year. Since co-optimizing the design and hourly operation for the whole year would yield to excessive computational time, it is necessary to identify a few representative days. In this study, the most representative days are obtained by means of a modified version of the k-MILP [1] clustering algorithm. This clustering approach can identify at the same time $N_T$ "typical" and $N_A$ "atypical/extreme" days (24 hours). In this work, we considered 6 typical and 6 atypical days. Among the "atypical" ones, two feature the yearly peak demand of Heat and EE respectively (Ex2 and Ex6, Fig. 4), and one the minimum PV generation integral (Ex5). The other three extreme periods are the three remaining most "atypical" (i.e., different from the typical days) days of the year.

### *3.2 MILP model and N-1 reliability*

The MILP model developed for this study is a two-stage stochastic MILP with design variables in the first stage and operational variables in the second stage. Each typical and atypical day is considered as a scenario. The MILP shares many of the design and operational constraints reported in [2], while the ramping limits as well as minimum up-/down-time constraints can be found in [3]. In this study, a catalogue of different technology is considered, each one with continuous size and size-dependent performance (as in [2]). Each technology is associated to $N_U$ slots allocated in the design superstructure, in such a way it is possible to install at most $N_U$ units of the same type (see Fig. 2 showing a case with 6 slots, 2 for ICE1, 1 for ICE2, 2 for HPs and 1 for boilers).

The N-1 reliability is forced by adding to the stochastic MILP the "break down scenarios" (BDSs): for each typical and atypical day *k*, there are $N_S$ BDSs where one slot (i.e., unit allocated in the slot) is not available (fault or under maintenance for the whole day). Thus, if the index *k* denotes the typical/atypical day and the index *j* denotes the slot, these BDSs can be indicated with the notation $BDS_{k,j}$. In addition to the $N_S$x($N_A$+$N_T$) BDS scenarios, the stochastic program contains ($N_A$+$N_T$) scenarios without failure where all the units of the slots are available. Therefore, the stochastic MILP contains ($N_S$+1)x($N_D$+ $N_T$) scenarios.

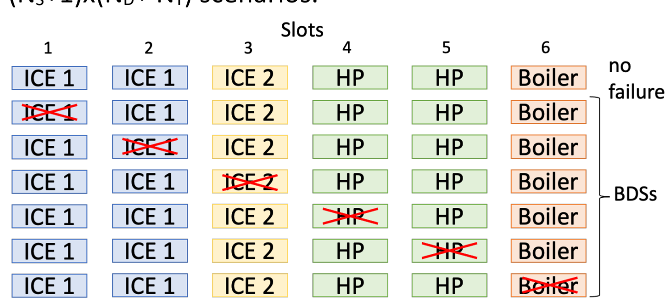


Fig. 2 Design super structure showing the number of machine slots available per technology. How BDSs model the N-1 reliability is also shown.

Since the BDSs are defined a priori (they do not depend on the optimization outcome), each scenario $BDS_{k,j}$ includes constraints which turs off whichever unit is installed in slot *j* for each typical/atypical day *k*: This takes the following mathematical form:

$$z_{u,j,k,t} = 0 \qquad \forall u \in U, \forall t \in T \tag{1}$$

Finally, the objective function to be minimized is the total annual cost, sum of annualized capital (CAPEX) and operating (OPEX) costs.

$$\mathrm{TAC} = \mathrm{CAPEX} * \mathrm{CCR} + \sum_k w_k \mathrm{OPEX}_k + \sum_{k,j} w_{\mathrm{BDS}_{k,j}} \mathrm{OPEX}_{\mathrm{BDS}_{k,j}} \tag{2}$$

with $w_k$ and $w_{\mathrm{BDS}_{k,j}}$ the probabilities of the scenarios. For the days without failure, such probability is essentially proportional to the number of occurrences of the typical and atypical days in the year (outcome of the clustering). On the other hand, $w_{\mathrm{BDS}_{k,j}}$ is the probability of failure of whichever unit installed in slot *j*. In this work, we consider that in all $N_S$ BDSs are equally probable, featuring a probability equal to $1/N_S$ (11.1%). It is worth noting that such low probability has a small influence on the objective function. Instead, the BDSs have a large effect on the constraints since operation of the AES must be guaranteed in all of them.

If the N-1 reliability is excessively conservative, it is also possible to adapt the formulation to limit the probability of unmet demand to a certain percentage (e.g., 2%).

### *3.3 Bi-level decomposition*

The two-stage stochastic program features a large number of variable and constraints due to the addition of the BDSs. Tackling it with a standard MILP solver requires days of computational time also on workstations. In order to find a close-to-optimal solution in practical computational time, we used a modified version of the Iyer-Grossmann bi-level decomposition [4]. The basic idea is to first solve (at the upper level) the design problem with relaxed operation (i.e., relaxing the on/off binary variables). Then, for fixed design, the operational problem (lower level, or subproblem) is solved for the different scenarios. The value of objective function (TAC) is evaluated, and the upper-level solution is evaluated again by adding one or more cuts (i.e., a constraint which excludes the previously found design solution with the aim of exploring another one). The algorithm differs from the original one by the addition of an integer and sub-set cut in the case when the solution coming from the design problem at the current iteration is the same found by the operational subproblem in the previous one. This avoids exploring previously found solutions and thus improve the overall run time. The algorithm stops if the TAC does not improve after 20 consecutive iterations or if the gap between the upper level and lower-level objective functions is below a certain tolerance.

## 4. CASE STUDY AND RESULTS

The above-mentioned methodology is applied to find the optimal design of a Multi-Energy System serving an academic campus with heating and electricity demand. The peak demands are approximately 7.5 $MW_{th}$ and 2.5 $MW_{el}$ respectively. The catalogue of possible energy technologies and performance parameters are in Table 1, with the number of available machines slots defining the superstructure of the problem. The NG cost is assumed to be equal to 33.2 €/$MWh_{LHV}$ (the average value in 2019 in Italy) [5].

The optimal design is evaluated for three different cases: a “nominal” case where no BDSs are considered, a “N-1” case where BDSs are considered just for the “typical” periods and a “N-1 extreme” case where BDSs are also considered in the “extreme” periods. In this way, the effect of considering the N-1 reliability in the model is assessed. In addition, the “N-1 extreme” case represents the worst-case scenario where machines failures are expected to happen also in the few days of the year characterized by the most challenging conditions, thus providing a very robust solution.

The results of the optimization problem were obtained with workstation featuring an Intel® i9-10980XE CPU (16 cores) and 64 GB of RAM. The bi-level decomposition stops when the percentage gap between LB and UB is lower than 1%. The design and operational problems were solved with Gurobi 9.5 [6].

### *4.1 Bi-level decomposition performance*

The MILP model used for the evaluation of the optimal design is challenging to solve, featuring up to 953435 continuous variables, 388846 binary variables and 2705996 constraints for the “N-1 extreme” case. By solving the model as a monolithic MILP, the computational complexity and size of the problem does not allow to achieve a gap lower than 5% after more than 24 hours.

By adopting the decomposition algorithm previously introduced, the computational time needed to get the optimal design reduces significantly. In fact, for the “nominal” case 17 minutes are needed (22 iterations), for the “N-1” case the run time was 6 hours and 32 minutes (15 iterations), while for the “N-1 extreme” case the total execution took 11 hours and 11 minutes (18 iterations). By looking at these numbers, it can be seen how the inclusion in N-1 reliability in the model significantly impacts the computational time.

Table 1 Most relevant parameters considered for the different technologies in this study.

| | | Dispatchable conversion technologies | | | | |
|---|---|---|---|---|---|---|
| | | ICE1 | ICE2 | ICE3 | HP | Boiler |
| Available machine slots | | 3 | 2 | 1 | 2 | 1 |
| Input | | NG | NG | NG | EE | NG |
| Output | | EE, Heat | EE, Heat | EE, Heat | Heat | Heat |
| Size range | EE | 50-200 $kW_{el}$ | 200-1434 $kW_{el}$ | 1500-3949 $kW_{el}$ | - | - |
| | Heat | 79-263 $kW_{th}$ | 276-1626 $kW_{th}$ | 1447-3461 $kW_{th}$ | 351-35100 $kW_{th}$ | 94-47200 $kW_{th}$ |
| $\eta_I$ [%] | EE | 33.8-37.2 | 37-41.7 | 43.6-45.8 | - | - |
| COP [-] | Heat | 53.4-48.9 | 51-47.2 | 42-40.2 | 351 | 94.4 |
| Capital cost [€/$kW_{out}$] | | 649-627 €/$kW_{el}$ | 627-398 €/$kW_{el}$ | 396-366 €/$kW_{el}$ | 723-177 €/$kW_{th}$ | 84-50 €/$kW_{th}$ |

| | Non-dispatchable technologies | | Storage technologies |
|---|---|---|---|
| | PV | | TESS |
| Specific investment cost | 800 €/$kW_{el,inst}$ | Specific investment cost | 400 €/$kWh_{th}$ |
| | | Charge/discharge efficiency | 95% |
| | | Self-discharge | 1%/h |

Table 2 Optimal design for the different cases considered.

| | | Nominal | N-1 | N-1 extreme |
|---|---|---|---|---|
| ICE3 | EE [$kW_{el}$] | 1517 | 1517 | 1782 |
| | Heat [$kW_{th}$] | 1462 | 1462 | 1680 |
| ICE2 (1) | EE [$kW_{el}$] | 425 | 1229 | 1101 |
| | Heat [$kW_{th}$] | 522 | 1401 | 1262 |
| ICE2 (2) | EE [$kW_{el}$] | - | 428 | 1016 |
| | Heat [$kW_{th}$] | - | 542 | 1264 |
| HP | Heat [$kW_{th}$] | - | 2843 | 3475 |
| Boiler | Heat [$kW_{th}$] | 5692 | 3691 | 4626 |
| TESS | Heat [$kWh_{th}$] | 631 | 1772 | 1934 |
| PV | EE [$kW_{el}$] | 1820 | 1820 | 2091 |

### *4.2 Optimal designs comparison.*

The optimal designs for the three considered cases are presented in Table 2. For the "nominal" case, the optimal design corresponds to the installment of ICE3, one ICE2, a Boiler, a TESS and PV panels. This design represents the solution with the minimum cost, under the optimistic assumption that no unit can go out of service. In the "N-1" case the BDSs are considered just for the "typical" periods. By considering the contingency in which at most, but certainly, one unit fails, the design changes. One additional ICE2 is installed, as well as a HP. The same design, but with increased sizes, can be found in "N-1 extreme". The reason behind this change in the design is certainly related to the contingency described by the BDSs. This can be easily understood by looking at Table 3, where the yearly operating hours for each unit is represented, for each BDSs. "N-0" is the scenario where no failure occurs, while "N-X" is the scenario where unit "X" is considered out of service. By looking Table 3 and Fig. 3, it can be understood that for the "nominal" case most of the EE demands is met by the PV during the day, while ICEs are operated mostly at night or to help meeting the demand when the PV generation is low. On the other hand, the Boiler operates in support of the ICEs, especially to cover the peaks of Heat demand.

When looking at the cases when N-1 reliability is considered, similar conclusions can be made. At first, the reason why the number of operating hours of the unit that is supposed to be out of service in each BDS (e.g. ICE3 in N-ICE3) is different than zero for the "N-1" case, is because the scenario simulates the failure of the unit for all the "typical days" but the extreme ones. By looking at the "N-0" scenario, the HP mainly assist the ICEs for helping to meet the Heat demand, while the Boiler is used just for peaking. The number of operating hours of the Boiler substantially increases for the BDS where the HP is down (N-HP), to cover the lack of Heat generation. Regarding the ICEs, an additional ICE2 is installed both to cover the reduced EE and Heat generation occurring when one other ICE is offline and when the HP is out of service.

The economic impact of N-1 reliability, applied both on all representative days and just on the typical ones, can be seen both in Table 3 and Table *4*. At first it can be seen that the installment of bigger, more efficient ICEs (efficiency increases with the size), together with a HP that efficiently converts the EE generated by PV and ICEs into Heat, decreases the OPEX with respect to the "nominal" case. The increase in operational cost with respect to the "N-0" scenario is up to +5.4% and +4.9% when BDSs are considered. Despite the small difference in OPEX with the "nominal" case, the main difference is represented by the CAPEX term. In fact, the investment cost increase by +62.44% and +86.88% for the "N-1" and "N-1 extreme" cases respectively. This brings an increase in the TAC and COE of +16.63% and +23.05% for the same already cited cases.

Table 3 Yearly operating hours of each unit installed, for each considered case.

| **Operating hours [h]** | | ICE3 | ICE2 (1) | ICE2 (2) | HP | Boiler | OPEX [k€] |
|---|---|---|---|---|---|---|---|
| Nominal | | 6715 | 1499 | | | 1916 | 656.4 |
| N-1 | N-0 | 6870 | 14 | 1719 | 2132 | 118 | 632.3 |
| | N-ICE3 | 124 | 6760 | 2346 | 1371 | 591 | 666.5 |
| | N-ICE2 | 6870 | 14 | 1719 | 2132 | 118 | 632.3 |
| | N-ICE2 | 7431 | 788 | 43 | 2081 | 220 | 645.7 |
| | N-HP | 5600 | 1233 | 1257 | 120 | 1889 | 646.6 |
| | N-**Boiler** | 6870 | 57 | 1719 | 2175 | 32 | 632.4 |
| N-1 extreme | N-0 | 5468 | 1177 | 921 | 2081 | 13 | 625.8 |
| | N-ICE3 | 0 | 6694 | 2796 | 2081 | 18 | 656.5 |
| | N-ICE2 | 5468 | 0 | 2095 | 1885 | 113 | 626.4 |
| | N-ICE2 | 5469 | 2047 | 0 | 2081 | 19 | 628.1 |
| | N-HP | 4380 | 910 | 2082 | 0 | 1805 | 644.7 |
| | N-**Boiler** | 5461 | 1191 | 936 | 2081 | 0 | 626.0 |

Table 4 Cost figures for all considered cases.

| | **N** | **N-1** | **N-1 extreme** |
|---|---|---|---|
| CAPEX [k€/year] | 2766.43 | 4493.89 | 5169.88 |
| OPEX [k€/year] | 656.39 | 638.77 | 631.12 |
| TAC [k€/year] | 933.03 | 1088.16 | 1148.10 |
| COE [€/MWh$_{el}$] | 86.89 | 101.34 | 106.92 |

Finally, by considering the abovementioned cost of NG and an electricity purchasing cost of 89.5 €/MWh$_{el}$ [5], it can be estimated the TAC related to meeting the energy demands using boilers (95% efficiency) for heating and the grid for electricity. With a yearly heating and EE demand of 7.8 GWh$_{th}$ and 10.5 GWh$_{el}$ respectively, the overall TAC would be 1217.6 k€/year (assuming boilers with 95% efficiency). Under this condition, the adoption of a MES would bring down the yearly costs of about -23.4% when N-1 reliability is not considered in the design phase. If this is taken into account, saving of -10.6% and -5.7% would be expected for the N-1 approach is considered for just the typical days and for all representative periods respectively.

## 5. CONCLUSIONS

In the work the optimal design of a MES serving an academic campus is investigated. N-1 reliability is introduced by means of Break Down Scenarios, allowing the MES to meet the energy demands whenever at most one unit is out of service. The proposed methodology consists in the identification of typical and atypical periods of the year, the development of a MILP model

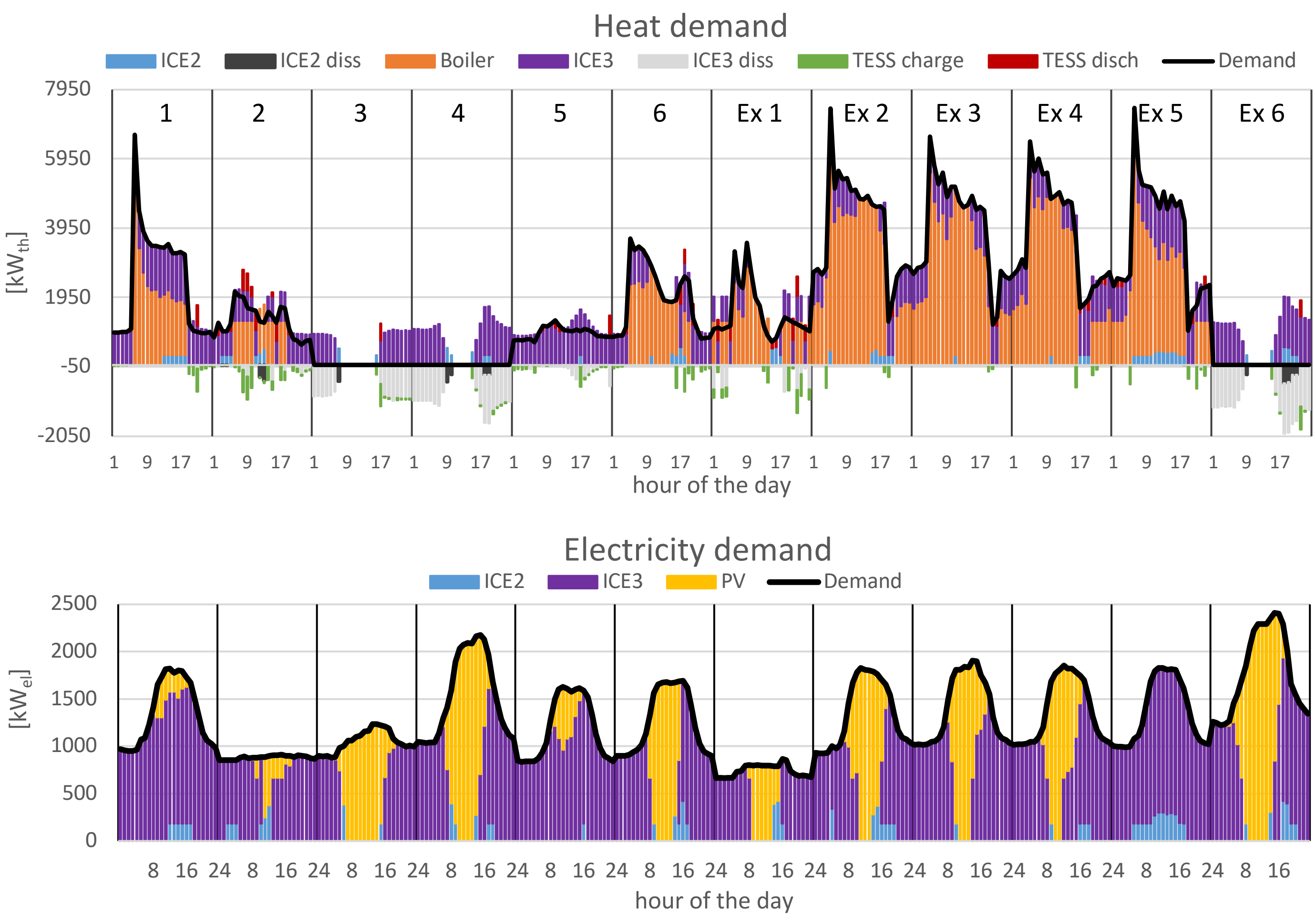


Fig. 3 Daily operation for the considered typical and extreme (Ex) periods when the optimal design for the "nominal" case is considered.

with N-1 reliability and the creation of a bi-level decomposition to find the optimal solution faster.

Results show the impact of considering BDSs on just the typical days, and both the typical and atypical ones. With respect to the nominal solution (without N-1 reliability), the design sees the addition of one ICE2 and one HP, as well as increased units' sizes (except for the boiler). The overall economic impact is mostly related to an increase in CAPEX, that bring up the TAC and COE. In fact, despite the small difference in OPEX between the "nominal" and the "N-1" and "N-1 extreme" cases, an increase in capex of +62.44% and +86.88% is seen for the already mentioned cases respectively. This is reflected in higher TAC values of +16.63% and +23.05%. Despite the rise in TAC, the adoption of a MES is economically more convenient that meeting the energy demands in a more conventional way (purchasing electricity from the grid and using boilers for heat generation). In fact, with respect to this last solution, even the more expensive MES design coming from the "N-1 extreme" case features a -5.7% lower TAC.

Additional effort must be done to validate this methodology, by applying it to different case studies where energy supply is critical (e.g. hospital, remote island, etc.). In addition, different MILP formulation based on similar approaches can be compared to assess for techno-economic assessment of the solutions.

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