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A multi-stage stochastic programming model for the unit commitment of conventional and virtual power plants bidding in the day-ahead and ancillary services markets

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HIGHLIGHTS

- A stochastic model for the optimal operation of virtual power plants is developed.
- The scenario tree contains both market and renewable generation scenarios.
- An ad-hoc decomposition method drastically reduces the computational time.
- Despite optimal solution, PV generation is partially curtailed.
- Cogeneration plant can effectively participate in more markets.

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ABSTRACT

As more uncontrollable renewable energy sources are present in the power generation portfolio, the need of more detailed and reliable tools for the optimal operation of energy systems has increased in the last years. This work presents a multi-stage stochastic Mixed Integer Linear Program with binary recourse for optimizing the day-ahead unit commitment of power plants and virtual power plants operating in the day-ahead and ancillary services markets. Scenarios reproduce the uncertainty of the ancillary services market requests, and production of photovoltaic panels. A novel decomposition algorithm is proposed to tackle the challenging multistage stochastic program. The methodology is tested on three types of large power plants: a natural gas-fired combined cycle, a combined heat and power combined cycle with thermal storage, and a virtual power plant integrating a combined cycle with battery and photovoltaic fields. Compared to the typical deterministic unit commitment approach, the proposed stochastic optimization approach allows to increase the revenues of the conventional power plant up to 13.58% and, for the combined heat and power and virtual power plant case, it allows finding a feasible and efficient operational scheduling.

1. Introduction

Due to the continuous increase in electricity demand and the rapid spread of intermittent renewable sources, the management and control of the electric grid has become increasingly complex and difficult. Furthermore, the progressive shift towards intermittent renewable sources has increased the relevance of the ancillary service markets [1], capacity markets [2], and spinning reserve [3] in terms of energy flows and revenues for the power plant. For example, according to [4] in 2019 (pre-covid), the majority of the Italian combined cycles reached only 2850 equivalent hours on average (very low value, denoting that most of the time the power plant was not operating or operating at low loads) and obtained 85 % of the total revenues from the ancillary service market (called "Mercato dei Servizi di Dispacciamento" (MSD)). Indeed, Italy is the EU country with one of the largest share of intermittent renewables with a total installed capacity of about 35 GW (generating 15 % of the electricity peak demand) which relegates many fossil-fired power plants to the grid balancing markets.

For this reason, today the short-term operational optimization of

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Nomenclature

Abbreviations

ACF	Autocorrelation Function
ASM	Ancillary Services Market
BESS	Battery Energy Storage System
BM	Balancing Market
CC	Combined Cycle
CCHP	Combined Cooling Heat and Power
CHP	Combined Heat and Power
COE	Cost of Electricity
DAM	Day Ahead Market
DOF	Degree Of Freedom
EBGL	Electricity Balancing Guideline
EVPI	Expected Value of Perfect Information
GTCC	Gas Turbine Combined Cycle
IDM	Intra Day Market
LDC	Load Duration Curve
MES	Multi Energy System
MILP	Mixed Integer Linear Programming
MSD	Mercato dei Servizi di Dispacciamento
NG	Natural Gas
O&M	Operation & Maintenance
OF	Objective Function
OPEX	Operational Expenditure
PACF	Partial Autocorrelation Function
PV	Photovoltaic
RO	Robust Optimization
SMILP	Stochastic Mixed Integer Linear Programming
SO	Stochastic Optimization
SOC	State of Charge
SOGL	System Operation Guideline
TESS	Thermal Energy Storage Systems
TSO	Transmission System Operator
UC	Unit Commitment
VPP	Virtual Power Plant
VSS	Value of the Stochastic Solution

Sets

$\mathscr{T}$	Set of timestep
$\mathscr{T}_{ASM_i}$	Subset of timesteps belonging to the i-th session of ASM
$\mathscr{S}c$	Set of scenarios
$\mathscr{G}$	Set of the types of energy associated to demands, generation and/or storage units: {EE, Heat}
$\mathscr{M}$	Set of conventional generation units
$\mathscr{E}\ell$	Subset of electricity generation units, $\mathscr{E}\ell \subseteq \mathscr{M}$
$\mathscr{M}_{2D}$	Subset of 2 degrees of freedom units, $\mathscr{M}_{2D} \subseteq \mathscr{M}$
$\mathscr{E}\mathscr{S}$	Set of energy storage units
$\mathscr{V}_m$	Set of vertices of the performance maps for 2DoF machines

Binary variables

$z^{DAM}_{sc,t}, z^{ASM}_{sc,t}$	Binary var. denoting the participation to the DAM/ASM in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in [0;1]$
$z^{cc}_{sc,t}$	Binary var. indicating whether at least one dispatchable generation unit $m \in \mathscr{M}$ is on in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in [0;1]$
$z_{m,sc,t}$	Binary on/off variable of dispatchable unit $m \in \mathscr{M}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in [0;1]$ (1 if unit is on, 0 if unit is off)
$\delta^{SU}_{sc,t}$	Binary variable associated to the start-up revenue in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in [0;1]$ (1 if the start-up revenue is obtained, 0 otherwise)
$\delta^{Pen}_{sc,t}$	Binary variable associated to the start-up penalty in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in [0;1]$ (1 when the unit starts-up and the penalty is assigned, 0 otherwise)
$\delta^{on}_{m,sc,t}$	Binary start-up variable of the machine $m \in \mathscr{M}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in [0;1]$ (1 if unit m starts up at time t, 0 otherwise)
$\delta^{off}_{m,sc,t}$	Binary shut-down variable of the machine $m \in \mathscr{M}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in [0;1]$ (1 if unit m shuts down at time t, 0 otherwise)

Continuous variables

$In_{m,sc,t}$	Average fuel power input [MW] consumed by the machine $m \in \mathscr{M}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in \mathbb{R}^+$
$\omega_{m,v,sc,t}$	Weight associated to vertex $v \in \mathscr{V}_m$ of the performance map of machine $m \in \mathscr{M}_{2D}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in [0,1]$
$Out_{m,g,sc,t}$	Average power output [MW] produced by the machine $m \in \mathscr{M}$ of output $g \in \mathscr{G}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in \mathbb{R}^+$
$Out^{DAM}_{sc,t}$	Average power [MW] offered on the DAM in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in \mathbb{R}^+$
$Out^{ASM}_{sc,t}$	Average power [MW] offered on the ASM in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in \mathbb{R}^+$
$SOC_{es,sc,t}$	State of charge [MWh] of the energy storage technology $es \in \mathscr{E}\mathscr{S}$ in scenario $sc \in \mathscr{S}c$ at the end timestep $t \in \mathscr{T}$, $\in \mathbb{R}^+$
$sp^{net}_{es,sc,t}$	Average net power exchange [MW] of the energy storage technology $es \in \mathscr{E}\mathscr{S}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in \mathbb{R}^+$
$sp^{ch}_{es,sc,t}$	Average charge power [MW] of the energy storage technology $es \in \mathscr{E}\mathscr{S}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in \mathbb{R}^+$
$sp^{disch}_{es,sc,t}$	Average discharge power [MW] of the energy storage technology $es \in \mathscr{E}\mathscr{S}$ in scenario $sc \in \mathscr{S}c$ at time $t \in \mathscr{T}$, $\in \mathbb{R}^+$

Parameters

Φ^{Opex}_{sc}	Total operational costs for scenario sc [€]
c^{NG}	Natural gas cost [€/MWh]
c^{SU}	Start-up revenue of the GTCC [€/start-up]
c^{TP}_{es}	Throughput O&M cost of the energy storage es [€/MWh]
$c^{O\&M}_m$	Operation and maintenance cost of the dispatchable generator m [€/MWh]
$c^{start-up}_m$	Start-up costs of the dispatchable generator m [€/start-up]
$Demand^{Heat}_t$	24-h profile of district heating demand [MW]
dt	Timestep duration [hours]
DT^{min}_m	Minimum down-time of unit m
$k^i_{sc',sc''}$	Scenario linking parameter equal to 1 if scenarios sc' and sc'' share the same node of the scenario tree in the *i-th* ASM session.
$k^i_{m,g}$	Linear coefficient of operational map for 1 DOF dispatchable unit m of output power $g \in G$
$V_{m,v,In}$	Vertex v of the convex polygon operational for 2 DOF dispatchable unit m of the input [MW]
$V_{m,v,g}$	Vertex v of the convex polygon operational for 2 DOF dispatchable unit m of output power $g \in G$ [MW]
$P^{ASM}_{sc,t}$	24-h profile of the maximum accepted quantity in the ASM for scenario sc [MW]
p_{sc}	Probability of the scenario sc
PUN_t	24 h-profile of the electricity price in the Day-Ahead Market [€/MWh]
$PV_{sc,t}$	24 h-profile of the maximum PV generation in scenario sc [MW]

$RD_{m,g}^{lim}$	Ramp-down limit under nominal operating condition of the machine m for output power $g \in G$ [MW/dt]
$RU_{m,g}^{lim}$	Ramp-up limit under nominal operating condition of the machine m for output power $g \in G$ [MW/dt]
$SD_{m,g}^{lim}$	Downward ramping limit during shutdown phase of the machine m for output power $g \in G$ [MW/dt]
$SU_{m,g}^{lim}$	Upward ramping limit during start-up phase of the machine m for output power $g \in G$ [MW/dt]
$rev_{sc,t}^{ASM}$	24 h-profile of the electricity price in the Ancillary-Services Market for scenario sc [€/MWh]
$size_{plant}$	Size of GTCC [MW]
UT_{m}^{min}	Minimum up-time of unit m

dispatchable power plants (fossil-fired power plants, hydroelectric power plants with reservoir, intermittent renewable-based power plants with energy storages, and aggregated units like virtual power plants) should be performed taking into account not only the day-ahead market but also all the grid balancing markets. The short-term approaches available in literature for power plants operating in the electricity markets can be classified into two main categories:

1. Approaches which optimize the plant scheduling (on/off and loads for each hour/quarter of hour) directly considering the forecasted electricity prices. This type of approach is suitable for price takers power plants (i.e., the bid of the power plant does not influence or has a little influence on the market clearing price) operating in the electricity markets with clearing prices (i.e., if the bid is accepted, the power plant receives the market clearing price and not the bid price, as it occurs in most European Day Ahead Markets). In this case, the power plant scheduling can be optimized using the forecasts of clearing prices of the electricity market while the bid price (to offer to the day ahead market) can be determined looking at the variable operating costs of the power plant (the bid must cover the variable operating costs in order to have a positive marginal revenue).
2. Approaches which optimize the bidding curve of the power plant to be offered to the electricity markets. These approaches are typically used for power plants which are not price takers (i.e., being large or strategic units, their offer influences the final clearing price) or are able to exercise market power for pay-as-bid electricity markets (the electricity generated is paid to the power plant at the price originally offered in the bid, as in most European Ancillary Service Markets due to particular security conditions of the electric power system, such as, for example, congestions or voltage regulation needs). In order to maximize the revenues for the power plant, the optimization approach needs to take into account the plant operational cost (i.e., the plant scheduling) as well as the statistical correlation between bid price and accepted quantity (energy) and /or the effects of the power plant bid on the market.

In the following sub-sections, the most relevant literature review related to the two approaches is presented, together with the motivation, contribution and structure of the work.

1.1. Relevant literature

The scheduling problem related to the first category of approaches abovementioned can be accurately formulated as a Mixed Inter Linear Program (MILP), including all the main technical constraints of the power plant such as ramping limitations, start-up/shut-down time, minimum up-time, start-up trajectories, start-up costs, operating modes changes [5]. Such MILP-based approach has been extended for the short-term scheduling optimization of Combined Heat-and-Power (CHP) power plants using the convex-hull representation of the operating map (see the works by Lahdelma and Hakonen [6,7]), or the piecewise linear 1-D and 2-D approximation of the operating maps [8]. The linearity of the formulation allows taking into account of the major uncertain data (e.g., electricity price, heating demand for CHP units) in a computationally efficient way with the robust optimization (RO) theory [9] and stochastic programming [10]. Indeed, thanks to the linearity of the problem and the duality theory, it is possible to reformulate the robust optimization problem into a large-scale MILP [11] or decompose the large scale stochastic program into smaller problems (using, e.g., Lagrangian decomposition or Benders decomposition). Moreover, the computational effectiveness of today's MILP solvers allows extending the problem to multiple dispatchable power plants aggregated within a virtual power plant [12 13], microgrid [14] or multi-energy system [15]. Already several approaches have addressed the effect of the uncertainty of the heating demand and intermittent renewable production with robust and stochastic optimization (SO) techniques: examples are the affine adjustable robust optimization MILP model proposed in [16] to tackle the uncertainty of the heating/electricity demand and renewable production, the adaptive robust approach proposed in [17], the two-stage stochastic program proposed in [18] for the energy and spinning-reserve optimization of microgrids and the stochastic program proposed in [19] to account for wind uncertainty on the optimal scheduling of a multi-energy system featuring wind generators, CHP units, a large heat pump and thermal storage.

On the other hand, very limited attention has been paid to the extension of these scheduling approaches (without bidding curve optimization) to co-optimize the participation to different electricity markets. Indeed, to the best of our knowledge, the main works are those by Al-Lawati et al. [20], Zhang et al. [21] and Jordehi et al. [22]. [20] proposed two sequential two-stage stochastic programs to optimize the scheduling of a price taker power plant participating in sequential markets (day-ahead, intraday, reserve, and balancing markets). [21] consider a robust approach to consider exogenous uncertainties associated with prices and wind production of a Virtual Power Plant (VPP), as well as endogenous uncertainties (which are decision-dependent) of real-time reserve requests. [22] proposed a scenario-based risk-adverse two-state stochastic program to take into account the uncertainty of pool prices in the optimal operation of a VPP participating in futures markets, pool markets and contracts with withdrawal penalty.

As far as the second category abovementioned is concerned (optimization of the bidding curve), several approaches have been proposed to take into account the different sequential electricity markets. For example, Mashhour and Moghaddas [23] addresses the bidding problem faced by a virtual power plant (VPP) in a joint market of energy and spinning reserve service with a non-equilibrium model based on the deterministic price-based unit commitment. The related nonlinear mixed-integer programming is solved with a genetic algorithm. Luo et al [24] proposed a stochastic bidding model to optimize the offers in the energy market and a model predictive control dispatch model to optimize the real-time operation. Liu et al. [25] proposed a hybrid stochastic/robust optimization model to minimize the expected net cost of microgrids. The uncertain intermittent renewables and day-ahead market prices are modelled via scenarios, while a robust optimization is used to limit the unbalanced power in the real-time market. Fu et al. [26] proposed a chance-constrained two-stage stochastic formulation to derive the bidding strategy for micro VPP to participate in the distribution level energy-reserve pool managed by a distribution system operator.

1.2. Motivation and contribution

As previously mentioned, the uncertain nature of the parameters involved in the problem require the adoption of optimization approaches able to take this into account. In particular, the random behavior of both the non-dispatchable generation sources and the quantities accepted in the ASM would require a stochastic (scenario-based) approach. However, in some markets (like the Italian one) multiple ASM bidding session takes place during the day, and the influence of the decisions on each stage is propagated into the following ones. Therefore, multiple decision stages must be considered in the model, leading to the need of formulating a multi-stage stochastic program model. In addition, an ad-hoc methodology for the generation of the scenario tree must be designed, with the aim of creating the most representative set of scenarios onto which the power plant will operate.

This motivates the contributions of this work, that are the following:

1. An ad-hoc scenario generation approach based on historical data where each scenario is characterized by expected ASM accepted quantities and maximum available intermittent renewable generation profiles (solar photovoltaic),
2. A stochastic model to optimize the day-ahead scheduling of conventional dispatchable power plants, CHP power plants and virtual power plants (aggregating dispatchable units with intermittent renewable sources and energy storages) which participate to Day-Ahead Market (DAM) with clearing price and the Ancillary Services Markets (ASM) where the pay as bid rule is adopted in accordance with the Italian "Mercato dei Servizi di Dispacciamento" rules,
3. A novel temporal decomposition algorithm to solve the multistage stochastic model within limited computational times.

Compared to previous works based on two-stage stochastic models (see ref. [19;21]), the proposed approach reproduces the sequential sessions of the markets (DAM and ASM sessions, neglecting the Intraday market) in an accurate way using a multi-stage stochastic program model. This allows to take into account the conditional dependence of the decision variables and uncertain parameters among the different stages. This aspect cannot be considered with two-stage approaches, resulting in a far from optimal solution or even incompatible to the TSO needs.

Although the model here proposed is developed taking into consideration the specific rules of the Italian electricity market, it is necessary to point out that the approach described below has general validity and it can be applied in any liberalized market. For example, European countries are now characterized by a completely integrated DAM, while ASM rules integration are still in progress. Although not yet completed, significant progress has been made at European level to obtain a univocal definition of the ancillary services and their characterization from a technical point of view. In particular, two guidelines have been published by ENTSO-e in 2017 which are of interest for market integration: the Electricity Balancing Guideline (EBGL) [27] and the System Operation Guideline (SOGL) [28] which define the basis for a common definition of ancillary services and for the exchange of ancillary services between transmission system operators (TSOs).

Finally, the model is applied considering the Italian ASM and DAM and data collected for a real combined cycle power plant. Tests are repeated considering a combined cycle power plant, a CHP power plant with thermal energy storage and a VPP integrating a combined cycle with a battery and solar photovoltaics (PV) fields.

1.3. Paper structure

The paper is organized as follows:

1. the Italian Electricity Market is described in Section 2, showing the different market sessions happening throughout the day and in the day-ahead;
2. the most important aspects of the operational problem to solve are shown in Section 3, where the Problem Statement is presented;
3. the proposed methodology developed to tackle the operational problem is shown in detail in Section 4. Here the approach used for the scenario tree generation, the mathematical formulation describing the model and the decomposition algorithm are presented;
4. the different test cases are presented in Section 5, showing the plant characteristics and most important parameters;
5. Results related to each case study are shown in Section 6, showing the operational and economical metrics related to the optimal solution found, and comparing the outcome of the decomposition algorithm with respect to the one of the complete model;
6. Finally, conclusion remarks are discussed in Section 7.

2. Italian electricity market

The Italian DAM and ASM are characterized by seven main sessions:

- DAM (day ahead market session), occurring on the day ahead (D-1), in which the power plant bids 24 energy quantities (MWh_{el}), one per each hour of the day. If accepted by the TSO, the resulting profile represents the amount of energy the power plant is committed to provide during its operation in the following day. This market is integrated into the European DAM and it is solved by the European Power Exchanges adopting the EUPHEMIA algorithm [29].
- In the MSD, the Italian TSO (Terna S.p.A.) acts as a central counterparty and accepted offers are remunerated at the price offered (pay-as-bid). The MSD consists of a scheduling substage (ex-ante MSD) and Balancing Market (MB). The ex-ante MSD and MB take place in multiple sessions, as provided in the dispatching rules. The ex-ante MSD consists of six scheduling substages: MSD1, MSD2, MSD3, MSD4, MSD5 and MSD6. Before the September 2021, these six ASM sessions occur every-four hours of the operating day D. After September 2021, the distribution in the day of these 6 MSD sessions has been modified (while still maintaining a structure based on 6 sessions) to harmonize and integrate the Italian Intraday Market with the XBID platform [30].
- In this paper, the authors adopt the original structure of the ASM because the market data in the pre-covid pandemic period are used and processed. Therefore, for consistency with the input data, this paper refers to the structure of the MSD prior to the reform at the end of 2021. In any case, this modification has no impact on the proposed algorithm. In each ASM session the operator is invited to update the quantities offered for ancillary service purposes for the remaining hours of the day. The amount bid are the maximum quantities that the operator is willing to sell to the TSO for providing ancillary services. In light of these ASM sessions (and, for VPP with PV fields, also considering accurate intraday PV forecasts [31]), the power plant can adapt the amount of energy offered as the uncertain parameters unveil during day D.

As a consequence, from the point of view of the power plant operator, there are seven decision stages:

- S_0 (stage 0): after receiving the day-ahead forecasts of RES production and DAM clearing prices, the operational decisions related to the DAM committed quantities are taken and fixed,
- S_1-S_6 (stages 1–6): these are the decision stages related to the ASM and are taken after S_0. With the exception of S_1 (happening in D-1 since it refers to the ASM quantities offered from 00:00 am to 4:00 am), decision stages S_2 to S_6 happen all in sequence during day D. As it can be seen in Fig. 1, right after the end of one session ASM1, the TSO communicates the accepted quantities for the next four hours to the plant operator (midnight to 4:00 am). During this time, the operator has the chance to update the ASM offer for the remaining hours of the day. Before the end of ASM2 (4:00 am), decision of stage

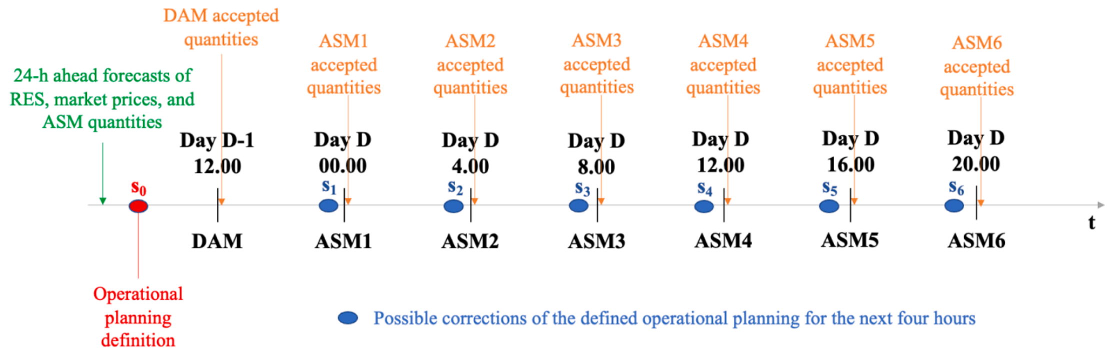


Fig. 1. Scheme of the different market sessions and key decision points of the power plant operator (before September 2021).

S_2 must be sent to the TSO for updating the bid referred to the current session.

The participation of both markets for the maximization of the revenues must consider an optimal balance between the quantities offered in both. In fact, while the quantities offered in the DAM are always remunerated (if bid with a price lower than the clearing one), there is no guarantee that the energy bids in the ASM will be called by the TSO (quantities are paid *only if* the power plant is asked to provide ancillary services). Therefore, a feasible power plant scheduling ensuring an optimal combination of DAM and ASM quantities must be carefully evaluated by considering the uncertainty related to the acceptance of these last ones and the expected prices.

3. Problem statement

Given the abovementioned description, in this work the general operation planning problem can be stated as follows:

Given:

- The set of available generation and storage units included in the VPP with their size/capacity, linearized performance curves/maps and technical operational limits (ramping, rate, minimum up time etc.),
- The historical data of the offers made by the power plant (in terms of prices and quantities) and accepted in the ASM in each hour of the day,
- The historical data of the PV production forecast and errors compared to the actual PV production profile,
- The day-ahead hourly forecast of PV production (relevant for VPP design including PV panels) for each scenario, $PV_{sc,t}$,
- The expected electricity selling price profile for both on the Ancillary Services Market ($rev^{ASM}_{sc,t}$) and Day Ahead Market (PUN_t) for the next day,
- Day ahead forecast of the heat demand (relevant only for CHP plants), $Demand^{Heat}_t$.

Determine:

- The day-ahead commitment decisions: on/off statuses of the units (commitment decisions), $z_{m,sc,t}$, and their electricity and heating loads for each hour of the following day, $Out_{m,g,sc,t}$,
- The real-time corrections of commitment decisions: possible corrections of loads and possible corrections of on/off status (only for quick-start units),
- The Battery charge/discharge profile, $sp^{net}_{es,sc,t}$,
- The 24-hour electricity power profiles to be submitted in the DAM ($Out^{DAM}_{sc,t}$) and all the ASM sessions ($Out^{ASM}_{sc,t}$) which maximizes the expected profit of the VPP considering the uncertainty affecting the accepted quantities in the ASM and the uncertainty (error) of PV production forecasts.

Subject to the following constraints:

- Dispatchable generation units' operational constrains (ramping limits, minimum up-/down-time, performance curve/map),
- Storage operational constraints,
- Maximum PV generation,
- Electricity and heating (just for CHP case) energy balances,
- Start-up and reserve constraints.

It is worth noting that among the power plant revenues, we also consider the so-called "start-up revenues". Introduced in the Italian electricity market in 2011, they aim to compensate each unprogrammed start-up the operator must perform for providing ancillary services to the power system following a request from the TSO. This revenue is assigned to all the thermoelectric power plants that have to deviate from the programmed schedule by switching on the plant so to sell on the ASM [32].

4. Methodology

The decision process previously described and shown in Fig. 1 is characterized by the presence of multiple possible choices of ASM and DAM quantities. The search of an optimal solution able to maximize the revenues must consider the uncertain behavior of the ASM accepted quantities in the different session of the day, as well as the PV forecasting error (for the VPP case). Therefore, in this work we tackle the problem with a multi-period multi-stage stochastic program featuring 7 stages (S_0 to S_6 as mentioned in the previous section), each one characterized by 4 time periods of one hour. In the model, exogenous uncertain factors are considered (they are independent from the problem decisions), and they are taken into account by defining multiple scenarios for each problem stage. Thus, a scenario tree is generated indicating the dependence between the different stages.

As it can be seen in Fig. 2, the scenario tree is characterized by a limited number of nodes per each level. Each level represents the decision stage, and each node represent a possible four-hour scenario featuring both the uncertain parameters and the decision variables. At each level, every node is linked to a "parent" node (related to the previous decision stage) and to a number of "children" nodes (linked to the next stage) equal to the number of branches. Each "children" node will inherit the same parameters and decisions of those past timesteps belonging to the "parent" node, while retaining an independent solution with respect to the other nodes of the same level. For example, by considering Fig. 2, each node of the tree's second level (Stage 1) feature three different "children" nodes (three tree branches per node) in the next stage. Thus, the resulting eight-hour scenarios defined for the first two ASM stages are nine (Stage 2). The first three ("ASM2 a, a-*b*-c") will feature the same 4-hour uncertain parameters profiles related to the first stage "parent" node ("ASM1 a"), as well as the decision variables. The same can be said for the children nodes of "ASM1 b" and "ASM1 c".

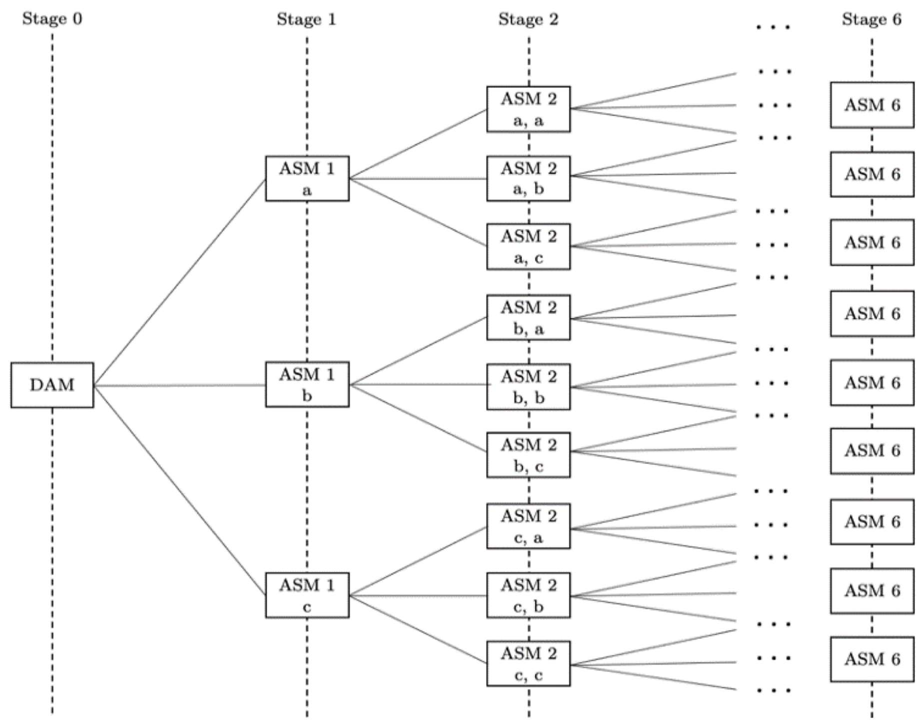


Fig. 2. Multi-period multi-stage scenarios tree.

While ASM decision stages are dependent to the previous one, the DAM decisions are taken once-for-all in the day-ahead. Hence, every scenario (for each node from S_1 to S_6) will feature the same DAM decision. In other words, once decided the 24-hour DAM profile at Stage 0, every ASM decision will be made by considering the already committed DAM quantities for those hours relative to the considered ASM session.

The already mentioned description is schematically presented in Fig. 3. As it can be seen, in the day ahead (Stage 0) the decisions for the quantities bid in the DAM are made (Out_t^{DAM}, $\forall t \in [1; 24]$). Under the assumption that the power plant participates to the market as a price taker and full acceptance of DAM quantities by the TSO, these are fixed for day D, providing a boundary condition for the next ASM sessions. Every four hours, a ASM bidding profile is submitted to the TSO, deciding the plant operational scheduling consequently. With the example of session ASM1, and by referring to both Fig. 2 and Fig. 3, given t the timesteps of the day belonging to considered market session ($t \in [1; 4]$) and sc the scenario linked to a particular tree node (for this case “a”, “b” and “c”), $Out_{``a",t}^{ASM1}$ (sc=“a”) refers to the ASM bidding quantity at time t relative to node “ASM1 a” in the scenario tree. The decisions made in this session, together with the already committed quantities in the DAM for the same timesteps of the day, define the operation of the dispatchable units (namely the fuel input $In_{m,``a",t}^{ASM1}$ and the convex combination weights $\omega_{m,v,``a",t}^{ASM1}$ (if CHP) of unit m) and the storage net power exchange $sp_{es,``a",t}^{net,ASM1}$ and state-of-charge $SOC_{es,``a",t}^{ASM1}$ (if present).

The methodology proposed in this work for tackling the described problem consists in mainly-three steps: (1) designing the tools for the creation of the scenario tree needed (definition of conditional probability distributions, scenario generation and reduction); (2) creating a

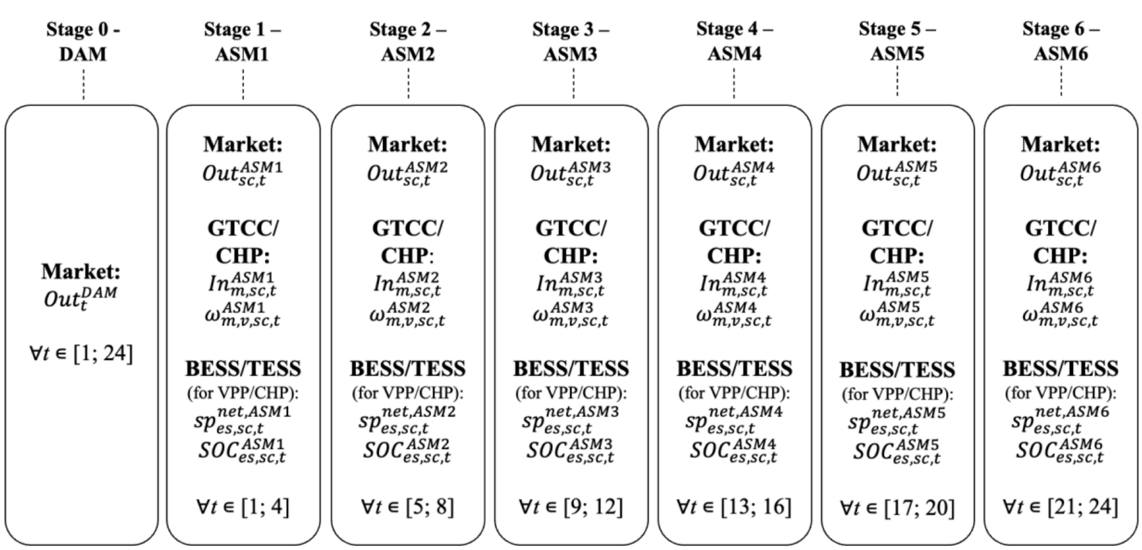


Fig. 3. Scheme of the optimization variables associated with each stage of the multistage multiperiod stochastic program.

multi-period multi-stage stochastic problem able to carefully describe the market dynamics by including the different DAM and ASM sessions, as well as start-up revenues; (3) developing custom solution approaches for improving the computational time while obtaining a close-to-optimal solution.

4.1. Scenario tree generation

The scenario tree of the multi-period multi-stage stochastic integer program have been defined using a scenario generation and reduction algorithm based on a conditional probability distribution derived from historical data. In this way, all the scenarios and the dependency between the decision variables of nodes with common roots are described.

In this study, the uncertain data profiles are the accepted maximum quantity in the ASM and the hourly day-ahead PV generation forecast (for those plants comprising such energy source). Two different procedures were developed, one to generate scenarios for the maximum accepted quantity in the ASM (used for conventional power plants without PV) and another one to generate scenarios of both ASM and PV production (for VPP).

In this section, a general description of the procedures developed to generate the scenario trees is provided, whereas the results of the analysis will be presented in Section 5.

4.1.1. Scenarios for conventional power plants without PV

The construction of the scenarios tree can be summarized in the following steps:

1 Data acquisition from DAM and ASM databases,
2 Data cleaning to remove outliers and compromised data,
3 Feature selection to identify the factors influencing the ASM maximum accepted quantities,
4 Construction of the matrices describing the conditional probability distributions,
5 Scenario tree generation and reduction.

After having collected the data, a feature engineering operation was performed. This refers to the analysis of data aimed at extracting features that enables the model to better predict the targeted variables. For this reason, a time series analysis has been performed on the parameters that most likely could affect the accepted ASM offers (e.g., electricity demand and PV production). To perform this analysis, all the non-stationary features (trends, seasonality, etc.) have been removed by means of the classical additive decomposition [33] to allow the investigation the correlation that could have been useful in the construction of the conditional-probability matrices.

From the collected data resulted that important lag features were present in the time series, and that the average amount of the electricity sold in a session of the ASM was strongly dependent on the average amount sold in the previous sessions. For this reason, the conditional probability distributions were built considering this correlation. Each probability distribution describes the probability that a four-hour profile bid characterized by a specific average value is accepted. The evaluation of such probability distributions follows these steps:

1 All the four-hour bids per each day of the available past data are collected and divided according to the different market sessions,
2 For each four-hour profile, the average value is calculated, and a discretization step is set,
3 For every set of values belonging to a certain ASM session, subsets are created by filtering on the basis of previous average ASM session value (e.g. subset of all the values whose preceding session value lies in a certain range),
4 For every subset, it is counted how many times the average accepted quantities belong to the different discrete ranges,
5 By dividing by the number of elements in the subset, the discrete probability distribution is found, which is conditional to the value of the average ASM quantity of the previous session.

The construction of the scenario tree comes from the adoption of a roulette-wheel approach featuring the already mentioned conditional probability distributions, and the use of k-medoids clustering algorithm. The generation of the tree is characterized by the following steps:

1 An initial condition on the average value of the last ASM session of the previous day is given as starting point (needed for the conditional probability distributions),
2 For each node of the considered tree level, 10′000 extractions are made from the conditional probability distribution, given the ASM value of the parent node. These ones are average ASM values used for the creation of the four-hour profiles relative to the considered nodes,
3 To reduce the number branches of each node (thus reducing the size of the scenario tree), k-medoids is applied for the identification of the k most representative profiles among those ones generated. In this way, the tree reduction is achieved by lowering the number of branches in each node from 10^4 to k,
4 Steps 2 and 3 are repeated for every node of every level, sequentially.

It is worth noting that the generated scenarios in each node of the tree (ASM session) are four-hour profiles featuring 4 elements equal to the extracted ASM average value. By appending the values of each node (following the node dependency described by scenario tree) the overall 24-hour ASM scenario are obtained. Each scenario, associated to a certain probability of realization, represents the maximum amount of electricity that the TSO is expected to buy. Finally, the prices associated to each discrete range of ASM bid quantities (expressed in €/MWh_{el}) are calculated as the average of the recorded accepted prices belonging to that specific range.

4.1.2. Scenarios for VPP with PV

For the Virtual Power Plant scenario generation, a different clustering method has been applied as the uncertainty coming from the PV production had to be considered. For the PV, an accurate forecast of the available energy has been evaluated by means of a physical hybrid artificial neural network developed by Ogliari et al. [31] that used the Clear Sky Irradiance and historical data to derive the power output profile from the PV power plant. For this reason, a conditional-probability matrix has been built to relate the Clear Sky Irradiance and the prediction errors (defined as the deviation between the forecast and the real data) related to one and two steps ahead, with the PV output power.

To bind the two sources of uncertainty into a single scenario, the following procedure has been adopted:

1 An initial condition on the average value of the last ASM session of the previous day is given (initial condition for PV generation is zero since at midnight),
2 For each node of the considered level of the tree, 10′000 extractions from the ASM and PV generation probability distributions are made. Each extraction consists in the generation of two four-hour ASM and PV generation profiles,
3 The two four-element vectors of each extraction are normalized according to their maximum and put together to for eight-element vectors,
4 Scenario tree reduction is applied on each node of the current level to reduce the number of branches. As before, this is done by using the k-medoids clustering algorithm reducing each children node in the following level of the tree from 10′000 to k,
5 The resulting k representative vectors of each parent node are de-normalized, separated and stored,

6 The steps 2 to 5 are repeated for the nodes of the next levels, sequentially.

While the ASM scenarios in each node are generated by extracting the average ASM value, four PV generation extractions are made so to get a four-element variable PV generation profile. Again, by appending the vectors belonging to each node according to the dependencies of the scenario tree, all the 24-hour scenarios are created for both the PV generation and ASM quantities. A summary of the steps performed for the ASM-PV scenario generation has been reported in Fig. 4.

4.1.3. Scenario tree analysis and features

One of the most critical issues about solving multistage stochastic programs is to find a reliable representation of the uncertain parameters by means of a scenario tree. Ideally, an infinite (very large) number of scenarios is needed to cover all the possible parameters realizations and thus have a complete knowledge of the uncertain parameters. However, this would make the problem computationally intractable. For this reason, a limited number of scenarios is generated based on a scenario-tree whose structure (number of branches per node) is decided a-priori (Fig. 2). In theory, this structure is the one that make the scenario tree "stable" [34], namely the one that provides the smallest number of scenarios such that the problem optimal solution does not change by considering any other larger tree.

To discover the minimum number of scenarios that makes the tree stable, it is required to solve the multi-stage problem to optimality over many different tree structures, requiring a very long time (even weeks) given the computational complexity of the problem (see Section 5 for computational time of this work). For this reason, it has been decided to exploit two particular features of the dataset as metric to evaluate the reliability of the scenario tree in terms of contained information: the probability of having no accepted quantity in the ASM (null scenarios) and the yearly Load Duration Curves (LDC) of the generated scenarios. Therefore, following the procedure mentioned in 4.1.1, different scenario trees were generated, differing by the number of node branches. The results of the calculations performed to generate the scenario tree that is provided as input to the optimization problem ae reported in Section 5.

4.2. Multi-stage stochastic MILP model

The multistage stochastic model is formulated using a scenario-based formulation [10], where all the operational variables and constraints are indexed for every timestep of every possible scenario. Each scenario features a fixed profile of PV forecast ($PV_{sc,t}$) and maximum expected accepted quantities in the ASM ($P^{ASM}_{sc,t}$). Non-anticipativity constraints are then added (see Section 4.2.8) to link variables of the different scenarios so to be consistent with the dependencies of the nodes belonging to adjacent levels of the scenario tree.

The decision variables of the problem are the following:

- On/off status $z_{m,sc,t}$ of every dispatchable unit m (e.g., GTCC) at any time t of every scenario sc, as well as the start-up and shut-down flaggers ($\delta^{on}_{m,sc,t}$ and $\delta^{off}_{m,sc,t}$ respectively) defining the first moment when the units have been turned on or off, for each timestep belonging to stage S_1 to S_6;
- Average fuel consumption power $In_{m,sc,t}$, average electricity generation power $Out_{m,EE,sc,t}$, average heat generation power $Out_{m,Heat,sc,t}$ and convex combination variables $\omega_{m,v,sc,t}$ (if CHP), for each timestep t belonging to stage S_1 to S_6;
- Storages average charge power $sp^{ch}_{es,sc,t}$, discharge power $sp^{disch}_{es,sc,t}$, net power exchange $sp^{net}_{es,sc,t}$, and state-of-charge $SOC_{es,sc,t}$ of storage unit es for each timestep t belonging to stage S_1 to S_6;
- Total average power quantities $Out^{DAM}_{sc,t}$ and $Out^{ASM}_{sc,t}$ bid by the power plant in the DAM and ASM respectively. Decisions on the 24 quantities to bid in the DAM are taken at stage S_0, while decisions on the quantities to bid in each session of the ASM are made from stage S_1 to stage S_6;
- Binary variables $z^{DAM}_{sc,t}$ and $z^{ASM}_{sc,t}$ for monitoring the bidding status of the power plant (if bidding on DAM and/or ASM), so to assess if

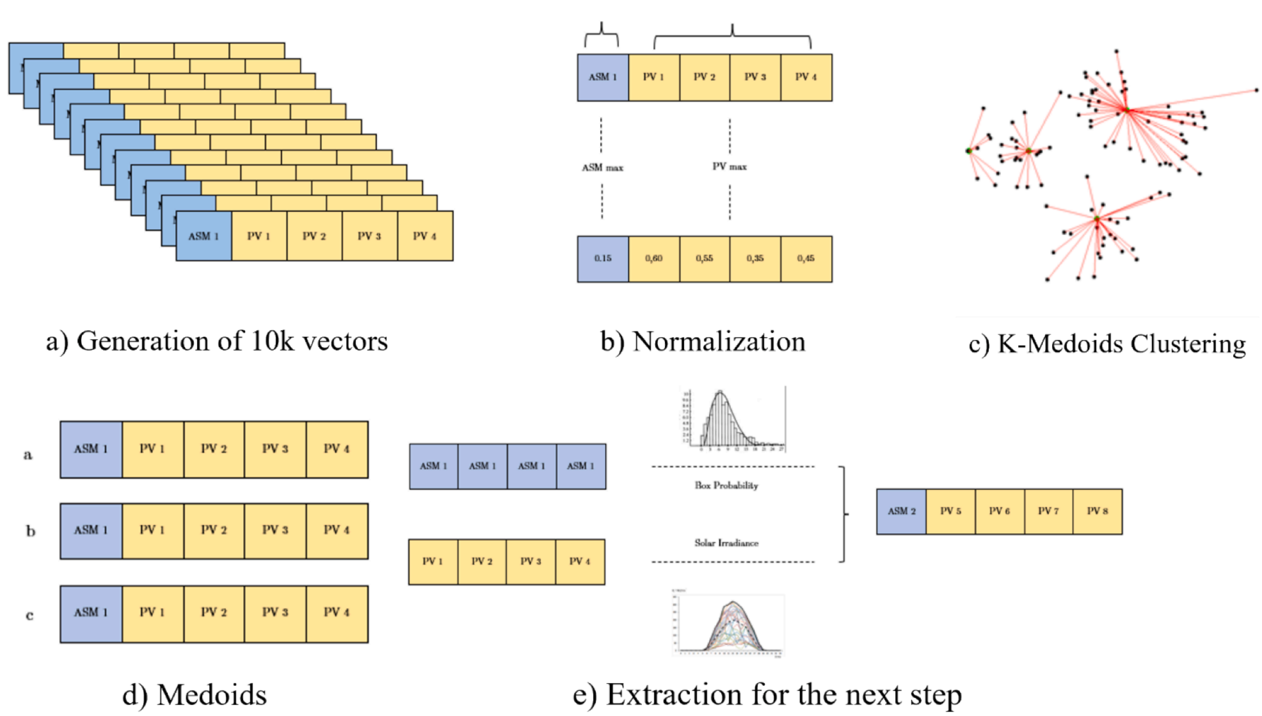


Fig. 4. Clustering schematic for VPP – a) Step1: Generation of the 10.000 sample vectors; b) Normalization of the vectors with respect to PV_{max} and $ASM_{s,\ max}$; c) K-medoids clustering of the sample; d) Medoids; e) Extraction of the next step.

minimum requirement needed to get the start-up revenue are attained (variables of each timestep belonging to stage S_1 to S_6).

It is important to note that the proposed MILP model uses as variables the average power consumed or generated by the units in each time step (e,g, $Out_{m,g,sc,t}$ as MW). Therefore, the energy quantities related to the average power at each time interval are obtained by multiplying the variable by the timestep duration *dt*. In case of hourly timestep duration (as for this study), then the numerical values related to the average power and energy are exactly the same. On the other hand, the ramping limits of the units must be evaluated considering the average power and not the instantaneous power generated at the end of each time step.

The operational problem aims at defining the unit commitment (UC) and economic dispatch of the power plant by minimizing the total expected operational costs:

$$OF = min\left(\sum_{sc\in\mathscr{S}\mathfrak{c}} p_{sc}\cdot\Phi_{sc}^{Opex}\right) \tag{1}$$

Where:

$$\begin{aligned}\Phi_{sc}^{Opex} = \sum_{t\in\mathscr{T}}\Bigg[&c^{SU}\cdot\left(\delta_{sc,t}^{Pen} - \delta_{sc,t}^{SU}\right) - PUN_t\cdot Out_{sc,t}^{DAM}\cdot dt - rev_{sc,t}^{ASM}\cdot Out_{sc,t}^{ASM}\cdot dt + \sum_{m\in\mathscr{M}}\Big(c^{NG}\cdot In_{m,sc,t}\cdot dt\\ &+ c_m^{O\&M}\cdot Out_{m,EE,sc,t}\cdot dt + c_m^{start-up}\cdot\delta_{m,sc,t}^{on}\Big) + \sum_{es\in\mathscr{E}\mathscr{S}} c_{es}^{TP}\cdot sp_{es,sc,t}^{disch}\cdot dt\Bigg]\end{aligned} \tag{2}$$

The total operational costs Φ_{sc}^{Opex} associated to each scenario *sc* are given by the sum of four main components:

- $\sum_{t\in\mathscr{T}}[c^{SU}\cdot\left(\delta_{sc,t}^{Pen} - \delta_{sc,t}^{SU}\right) - PUN_t\cdot Out_{sc,t}^{DAM}\cdot dt - rev_{sc,t}^{ASM}\cdot Out_{sc,t}^{ASM}\cdot dt]$ represents the revenues coming from the start-up credit and from selling in the DAM and ASM ("negative costs"),
- $\sum_{t\in\mathscr{T}}[\sum_{m\in\mathscr{M}}\left(c^{NG}\cdot In_{m,sc,t}\cdot dt + c_m^{O\&M}\cdot Out_{m,EE,sc,t}\cdot dt + c_m^{start-up}\cdot\delta_{m,sc,t}^{on}\right)]$ is the sum of the costs related to natural gas consumption, operation and maintenance (O&M), and start-up,
- $\sum_{t\in\mathscr{T}}[\sum_{es\in\mathscr{E}\mathscr{S}} c_{es}^{TP}\cdot sp_{es,sc,t}^{disch}\cdot dt]$ the throughput-based storage O&M cost.

The main constraints to which the model is subjected are defined for each scenario and they can be summarized as follows:

- *Power balance constraints*: the overall power (electricity, heat) generated by the dispatchable and non-dispatchable units, and the power discharged by the storage, must always be equal to the power charging the storage and the quantities exported to the different electricity markets (just for the Electricity balance), or delivered to the thermal user (just for the Heat balance),
- *Maximum expected ASM quantities the TSO is willing to purchase:* the power plant is free to choose the amount of electricity to bid in the ASM up to a limit defined by the current scenario at any time of the day,
- *Performance curve of dispatchable generators* (units with one degree of freedom) [35],
- *Performance maps of CHP dispatchable generators* (units with two degrees of freedom, thus electricity and heat generation are controlled independently) [36]
- *Ramping limits:* each dispatchable generation unit must respect the ramping limits in the different operational phases [37] (in this work the ramping limits of the units are evaluated considering the average power and not the instantaneous power generated at the end of each time step),
- *Operational logic constraints*: the different operational binary variables (on–off, status, start-up and shut-down flagger) must be linked together to define the conditions under which a start-up or shut-down occurs, as well as whether or not the minimum up-/down-time are respected [38],
- *Storage dynamic constraints:* for each storage unit, the operational behaviour describing the charge and discharge power, as well as the evolution in time of the state-of-charge [39],
- *Start-up revenue constraints:* logic constraints that model the conditions under which the start-up revenue is awarded (see 4.2.7),
- *Reserve constraints:* at any time, the power plant must be able to ramp-up/-down of at least ± 6 % of the installed power to provide replacement reserve to the power system,
- *Non-anticipativity constraints:* constraints that ensure that the decisions, taken at a specific stage, depend only on the information revealed up to that stage, not on the data that will be realized in the future [10]. These are also needed to link the variables in each scenario to the different nodes/levels of the scenario tree.

4.2.1. Power balances and reserve

The maximum amount of electricity that the power plant operator is willing to bid in the ASM is equal to the maximum value that is expected to be awarded by the TSO in each considered scenario:

$$Out_{sc,t}^{ASM} \le P_{sc,t}^{ASM} \qquad \forall sc\in\mathscr{S}\mathfrak{c}, \forall t\in\mathscr{T} \tag{3}$$

In addition, the plant is required by the TSO to be able to increase its power output by the 6 % at any time (also known as "tertiary reserve" in the Italian electricity framework or replacement reserve):

$$\sum_{m\in\mathscr{E}\ell} Out_{m,EE,sc,t} \le 0.94\cdot size_{plant} \qquad \forall sc\in\mathscr{S}\mathfrak{c}, \forall t\in\mathscr{T} \tag{4}$$

In case a CHP plant is considered, the sum of the heating power generated by the Gas Turbine Combined Cycle (GTCC) units and the discharge of the Thermal Energy Storage systems must always meet the user demand:

$$\sum_{m\in\mathscr{M}_{2D}} Out_{m,Heat,sc,t} + sp_{TES,sc,t}^{net} = Demand_t^{Heat} \qquad \forall sc\in\mathscr{S}\mathfrak{c}, \forall t\in\mathscr{T} \tag{5}$$

Finally, the electricity balance for each timestep of the considered horizon links the power plant production with the quantities aimed to be sold on the DAM and ASM. Please note that the PV generation ($Out_{sc,t}^{PV}$, always lower or equal to the maximum generation available $PV_{sc,t}$) and storage net outputs ($sp_{BESS,sc,t}^{net}$) are present only for the Virtual Power Plant case.

$$Out_{sc,t}^{ASM} + Out_{sc,t}^{DAM} = \sum_{m\in\mathscr{E}\ell} Out_{m,EE,sc,t} + Out_{sc,t}^{PV} + sp_{BESS,sc,t}^{net} \qquad \forall sc\in\mathscr{S}\mathfrak{c}, \forall t\in\mathscr{T} \tag{6}$$

4.2.2. Dispatchable generators operational curve

The performance curve linking fuel consumption and electricity generation for dispatchable units characterized by one single degree of freedom can be linearized (see Fig. 5), taking the following expression:

$$Out_{m,EE,sc,t} = k_{m,EE}^1\cdot In_{m,sc,t} + k_{m,EE}^2\cdot z_{m,sc,t} \qquad \forall m\in\mathscr{M}, \forall sc\in\mathscr{S}\mathfrak{c}, \forall t\in\mathscr{T} \tag{7}$$

At any time, if the unit in online, the fuel consumption must always be bounded by the minimum and maximum operational limits:

$$In_{m,sc,t} \ge z_{m,sc,t}\cdot In_m^{min} \qquad \forall m\in\mathscr{M}, \forall sc\in\mathscr{S}\mathfrak{c}, \forall t\in\mathscr{T} \tag{8}$$

$$In_{m,sc,t} \le z_{m,sc,t}\cdot In_m^{max} \qquad \forall m\in\mathscr{M}, \forall sc\in\mathscr{S}\mathfrak{c}, \forall t\in\mathscr{T} \tag{9}$$

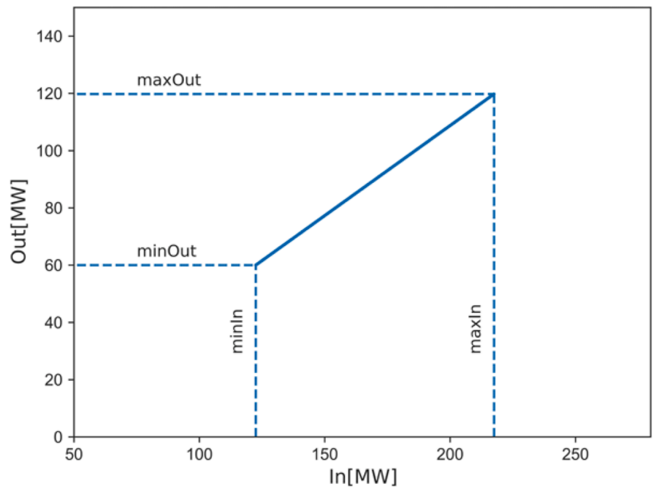


Fig. 5. Dispatchable generators characteristic curve.

4.2.3. CHP dispatchable generators operational map

CHP units are characterized by the generation of both electricity and heating. The operational map is modelled as a convex polygon with multiple vertexes (Fig. 6 represents the operational map used in one of the case studies of this work). Each vertex is characterized by a unique value of input fuel consumption, electricity, and heat generation efficiency. Therefore, each operating point in terms of fuel input and energy outputs can be expressed as the convex combination of the map's vertexes:

$$In_{m,sc,t} = \sum_{v\in\mathscr{V}_m} V_{m,v,In}\cdot\omega_{m,v,sc,t} \qquad \forall m \in \mathscr{M}_{2D}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{10}$$

$$Out_{m,g,sc,t} = \sum_{v\in\mathscr{V}_m} V_{m,v,g}\cdot\omega_{m,v,sc,t} \qquad \forall m \in \mathscr{M}_{2D}, \forall g \in \mathscr{G}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{11}$$

with $V_{m,v,In}$ and $V_{m,v,g}$ the values of the input fuel and energy output g related to the map's vertex v.

Then, at each time, the following constraint links the on/off status of the unit with the weights defining the operating point at time t of scenario sc:

$$\sum_{v\in\mathscr{V}_m} \omega_{m,v,sc,t} = z_{m,sc,t} \qquad \forall m \in \mathscr{M}_{2D}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{12}$$

Please note that Eq. (10)-(12) can be used for those cases where the operational map of the CHP unit can be approximated with a low error to a convex polygon (as for the case study considered in this work, see Section 5). For those cases where the CHP units are characterized by a non-convex performance maps, other formulations are present in literature able to convert them into convex regions (e.g., as proposed [7;40]).

4.2.4. Ramping limits

The constraints defining the upwards/downwards ramping limits during the start-up/shut-down phase and under nominal operation are here presented. These are defined for every output of the generation units:

$$Out_{m,g,sc,t} - Out_{m,g,sc,t-1} \le z_{m,sc,t-1}\cdot RU^{lim}_{m,g} + \left(1 - z_{m,sc,t-1}\right)\cdot SU^{lim}_{m,g} \qquad \forall m \in \mathscr{M}, \forall g \in \mathscr{G}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{13}$$

$$Out_{m,g,sc,t} - Out_{m,g,sc,t-1} \ge -z_{m,sc,t}\cdot RD^{lim}_{m,g} - \left(1 - z_{m,sc,t}\right)\cdot SD^{lim}_{m,g} \qquad \forall m \in \mathscr{M}, \forall g \in \mathscr{G}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{14}$$

With $RU^{lim}_{m,g}$ and $RD^{lim}_{m,g}$ defining the ramp-up and ramp-down limits of average power in each time step when in operation, $SU^{lim}_{m,g}$ the upward limit during the start-up phase of average power in each time step and $SD^{lim}_{m,g}$ the downward limit at shut-down.

4.2.5. Operational logic constraints

Logic constraints are needed to link the different binary variables of the dispatchable units and they are needed to define the conditions under which a certain event happens. The following constraints are needed to define whether the unit m starts up or shuts down at t.

$$\delta^{on}_{m,sc,t} - \delta^{off}_{m,sc,t} = z_{m,sc,t} - z_{m,sc,t-1} \qquad \forall m \in \mathscr{M}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{15}$$

Then, in every t the unit can only start up or shut down:

$$\delta^{on}_{m,sc,t} + \delta^{off}_{m,sc,t} \le 1 \forall m \in \mathscr{M}, \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{16}$$

Whenever the unit m starts up or shuts down, the minimum up and down time durations must be guaranteed for the following timesteps. These conditions are enforced by the following expressions:

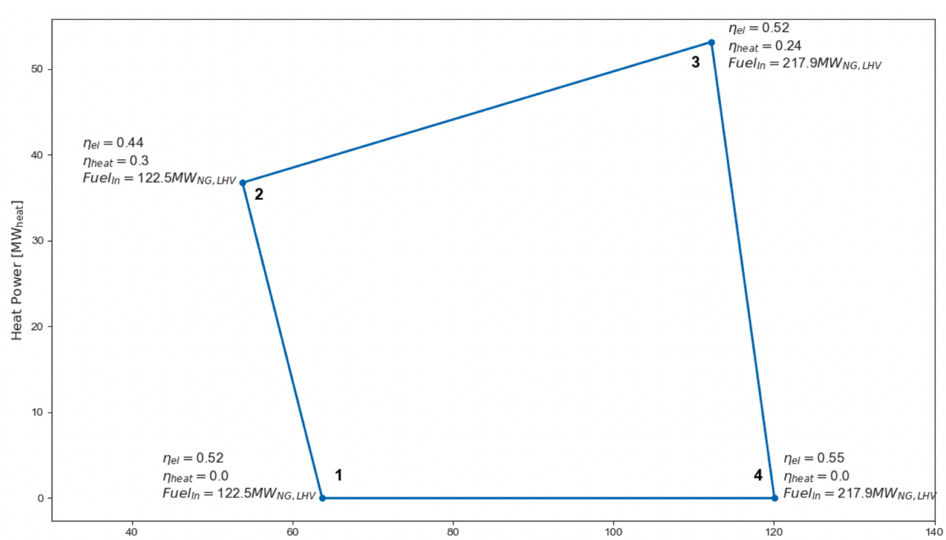


Fig. 6. Operating map of the CHP generator (CHP combined cycle).

$$\sum_{t-UT_m^{min}+1}^{t} \delta_{m,sc,t}^{on} \leq z_{m,sc,t} \qquad \forall m \in \mathscr{M}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in [UT_m^{min}, \mathscr{T}] \tag{17}$$

$$\sum_{t-DT_m^{min}+1}^{t} \delta_{m,sc,t}^{off} \leq 1 - z_{m,sc,t} \qquad \forall m \in \mathscr{M}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in [DT_m^{min}, \mathscr{T}] \tag{18}$$

Finally, in presence of two units of the same size (e.g. U1 and U2), priority constraints are introduced to break operational symmetries (unit 2 can only switch one if unit one is already operating):

$$\delta_{U2,sc,t}^{on} \leq z_{U1,sc,t} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{19}$$

4.2.6. Storage operational constraints

From a modelling point of view, thermal energy storage and batteries are approached adopting the same strategy. For both the technologies, the effective capacity available for operations has been considered, therefore a constraint on the minimum state of charge (SOC) is not necessary. In other words, in our model the condition with null SOC corresponds to the real case in which the charge level is equal to the minimum value allowed for a safe storage operation.

Given the above-mentioned assumptions, upper bounds on the maximum charge and discharge power, as well as the maximum storage capacity, are defined:

$$sp_{es,sc,t}^{disch} \leq P_{es}^{disch} \qquad \forall es \in \mathscr{ES}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{20}$$

$$sp_{es,sc,t}^{ch} \leq P_{es}^{ch} \qquad \forall es \in \mathscr{ES}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{21}$$

$$SOC_{es,sc,t} \leq SOC_{es}^{max} \qquad \forall es \in \mathscr{ES}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{22}$$

Then the net power flow from/to the storage is described by the real variable $sp_{es,sc,t}^{net}$, which takes into account the charge and discharge efficiencies:

$$sp_{es,sc,t}^{net} = sp_{es,sc,t}^{disch} \cdot \eta_{es}^{disch} - \frac{sp_{es,sc,t}^{ch}}{\eta_{es}^{ch}} \qquad \forall es \in \mathscr{ES}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{23}$$

The state-of-charge evolution in time is then defined by the following constraint, which describes the SOC of the storage at the end of t by taking into account the self-discharge of the unit by means of η_{es}^{SD}:

$$SOC_{es,sc,t} = SOC_{es,sc,t-1} \cdot \eta_{es}^{SD} + \left(sp_{es,sc,t}^{ch} - sp_{es,sc,t}^{disch}\right) \cdot dt \qquad \forall es \in \mathscr{ES}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{24}$$

4.2.7. Start-up revenues

In the Italian ASM, start-up revenues can be awarded *if and only if* the power plant is turned on (by switching on at least one dispatchable generation unit) specifically to provide ancillary services (its schedule in the DAM does not foresee any start up during the day, but the power plant is asked to operate in the ASM from a shutdown status). These conditions can be translated into two logical propositions, as shown below in Eq. (25):

$$\bigvee_m \delta_{m,sc,t}^{on} \wedge \neg z_{sc,t}^{DAM} \wedge \neg z_{sc,t-1}^{cc} \Leftrightarrow \delta_{sc,t}^{SU} \qquad \forall m \in \mathscr{M}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{25}$$

with $\delta_{m,sc,t}^{on}$ considered as "true" in case the unit m is switched-on at timestep t of scenario sc, $z_{sc,t}^{DAM}$ associated to whether the entire power plant is selling electricity in the DAM, $z_{sc,t-1}^{cc}$ the variable defining if at least one dispatchable unit is online at *t-1* of *sc*, and $\delta_{sc,t}^{SU}$ associated to the start-up revenue award.

An additional condition must be considered to avoid excessive remuneration in the model: no credit is paid if the plant is selling in the DAM at *t and* it was selling in the ASM at *t-1*. In fact, if the operational schedule is set to export a committed DAM quantity at *t*, a start-up is already programmed to happen. However, given Eq. (25), the condition for awarding the start-up revenue in case of being called by the TSO for providing ancillary service at *t-1* (thus anticipating of one hour the already programmed start-up) is respected. Nevertheless, the current regulation does not allow any remuneration for the anticipation of an already programmed start-up, and thus this must be corrected. By introducing $\delta_{sc,t}^{Penalty}$, which, when active, introduces a penalty cost in the objective function equal to the absolute value of the start-up revenue, the actual awarded revenue in the objective function is equal to $c^{SU} \cdot \left(\delta_{sc,t}^{Pen} - \delta_{sc,t}^{SU}\right)$. As a result, the logical proposition describing the condition under which $\delta_{sc,t}^{Penalty}$ is active is the following:

$$z_{sc,t-1}^{ASM} \wedge z_{sc,t}^{DAM} \Rightarrow \delta_{sc,t}^{Penalty} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{26}$$

Eq. (25) and (26) can be translated into mathematical constraints by means of the rules of Disjunctive Programming [41]. Therefore, Eq. (25) translates to:

$$z_{sc,t}^{DAM} + z_{sc,t-1}^{cc} - \delta_{m,sc,t}^{on} + \delta_{sc,t}^{SU} \geq 0 \qquad \forall m \in \mathscr{M}, \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{27}$$

$$\delta_{sc,t}^{SU} + z_{sc,t-1}^{cc} \leq 1 \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{28}$$

$$\sum_{m \in \mathscr{M}} \delta_{m,sc,t}^{on} \geq \delta_{sc,t}^{SU} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{29}$$

$$\delta_{sc,t}^{SU} + z_{sc,t}^{DAM} \leq 1 \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{30}$$

While Eq. (26) translates to:

$$\delta_{sc,t}^{Pen} \geq z_{sc,t-1}^{ASM} + z_{sc,t}^{DAM} - 1 \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{31}$$

Then, the binary variable $z_{sc,t}^{cc}$ is equal to 1 if at least one plant's CCGT is on-line, 0 if they are all shut-down.

$$z_{sc,t}^{cc} \geq z_{m,sc,t} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{32}$$

$$z_{sc,t}^{cc} \leq \sum_{m \in \mathscr{M}} z_{m,sc,t} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{33}$$

Finally, the relationships between the power plant's quantities bid in the DAM and ASM, and the relative binary variables indicating if the plant is willing to operate in these markets, are here presented:

$$Out_{sc,t}^{DAM} \geq z_{sc,t}^{DAM} \cdot Out_{plant}^{min} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{34}$$

$$Out_{sc,t}^{DAM} \leq z_{sc,t}^{DAM} \cdot size_{plant} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{35}$$

$$Out_{sc,t}^{ASM} \geq z_{sc,t}^{ASM} \cdot Out_{plant}^{min} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{36}$$

$$Out_{sc,t}^{ASM} \leq z_{sc,t}^{ASM} \cdot size_{plant} \qquad \forall sc \in \mathscr{S}\mathfrak{c}, \forall t \in \mathscr{T} \tag{37}$$

with Out_{plant}^{min} is the minimum power that the plant can export to the grid (1 MW), and $size_{plant}$ the plant's total dispatchable installed power. These constraints also define the bounds of the maximum and minimum quantities that can be bid in the DAM and ASM.

4.2.8. Non-anticipativity constraints

Non-anticipativity constraints are necessary for every scenario-based stochastic programming model. They are used to ensure that the decisions taken at a specific stage depend only on the information revealed up to that stage, not on the data that will be realized in the future. They are the only constraints that link variables belonging to different scenarios and without them the problem would degenerate into a multitude of parallel deterministic problems with no share of information. In modelling terms, their addition makes relatively easy the formulation of the stochastic model starting from the scenario tree structure.

As it can be seen in Fig. 7 (left), which shows an extract of the scenario tree presented in Fig. 2, each level of the tree can have multiple nodes, each one inheriting the decisions and parameters of the "parent"

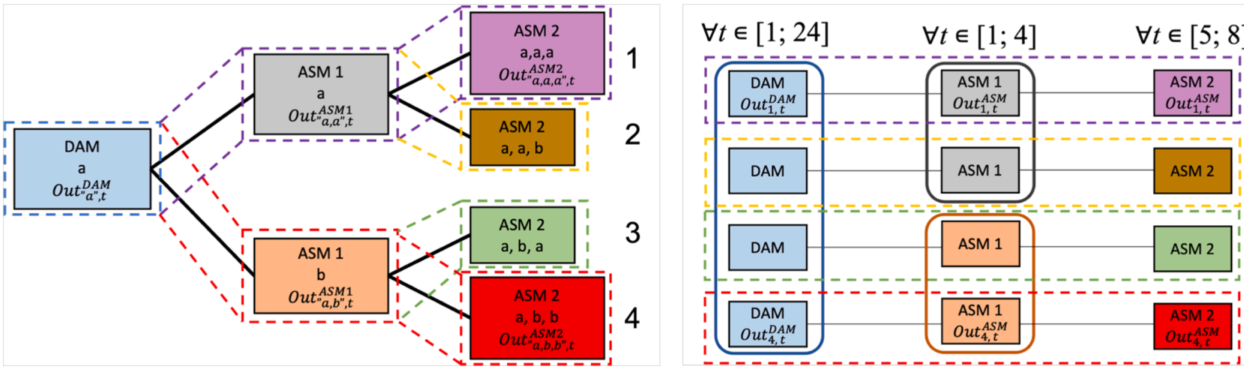


Fig. 7. Non-anticipativity constraints representation and link between a node-based and scenario-based model. The rounded rectangles (in the right image) represent the non anticipativity constraint forcing variables of different scenario to be equal each other for the considered timesteps.

nodes. The resulting four scenarios for ASM sessions 1 and 2 will be all influenced by the DAM decisions, while scenarios 1 and 2, as well as 3 and 4, share the same uncertain parameters and decisions concerning the timesteps of ASM1 (according to node parenthood). By considering a scenario-based model where all the variables are indexed for each scenario, the dependence with the parent nodes shown in the scenario tree is enforced by the following non-anticipativity constraints (schematically presented by the rounded rectangles in Fig. 7 (right)):

$$z^{DAM}_{sc',t} = z^{DAM}_{sc'',t} \cdot k^{i}_{sc',sc''} \qquad \forall sc', sc'' \in Sc, \forall t \in \mathcal{T}_{ASM_i}, \forall i \in ASM \tag{38}$$

$$z^{ASM}_{sc',t} = z^{ASM}_{sc'',t} \cdot k^{i}_{sc',sc''} \qquad \forall sc', sc'' \in Sc, \forall t \in \mathcal{T}_{ASM_i}, \forall i \in ASM \tag{39}$$

$$z_{m,sc',t} = z_{m,sc'',t} \cdot k^{i}_{sc',sc''} \qquad \forall m \in \mathcal{M}, \forall sc', sc'' \in Sc, \forall t \in \mathcal{T}_{ASM_i}, \forall i \in ASM \tag{40}$$

$$Out^{ASM}_{sc',t} = Out^{ASM}_{sc'',t} \cdot k^{i}_{sc',sc''} \qquad \forall sc', sc'' \in Sc, \forall t \in \mathcal{T}_{ASM_i}, \forall i \in ASM \tag{41}$$

$$SOC_{es,sc',t} = SOC_{es,sc'',t} \cdot k^{i}_{sc',sc''} \qquad \forall es \in \mathcal{ES}, \forall sc', sc'' \in Sc, \forall t \in \mathcal{T}_{ASM_i}, \forall i \in ASM \tag{42}$$

$$sp^{ch}_{es,sc',t} = sp^{ch}_{es,sc'',t} \cdot k^{i}_{sc',sc''} \qquad \forall es \in \mathcal{ES}, \forall sc', sc'' \in Sc, \forall t \in \mathcal{T}_{ASM_i}, \forall i \in ASM \tag{43}$$

$$sp^{disch}_{es,sc',t} = sp^{disch}_{es,sc'',t} \cdot k^{i}_{sc',sc''} \qquad \forall es \in \mathcal{ES}, \forall sc', sc'' \in Sc, \forall t \in \mathcal{T}_{ASM_i}, \forall i \in ASM \tag{44}$$

With ASM the set of the number of ASM sessions (one to six), $\mathcal{T}_{ASM_i}$ the subset of timesteps belonging to the *i-th* ASM session and $k^{i}_{sc',sc''}$ a parameter equal to one if scenarios sc' and sc'' share the same parent node in the scenario tree for the considered *i-th* ASM session, zero otherwise.

Finally, as already mentioned before, DAM decisions are taken once-for-all in the day ahead, and therefore are equally considered in each scenario as same for every scenario:

$$Out^{DAM}_{sc',t} = Out^{DAM}_{sc'',t} \qquad \forall sc', sc'' \in Sc, \forall t \in \mathcal{T} \tag{45}$$

4.3. Clustering-based sequential two-stage decomposition

As the number of decision variables increase, both because of the higher complexity of the power plant layout (e.g., multiple controllable units) and/or the additional number of uncertain parameters to deal with, the problem becomes harder to solve from a computational point of view. Also, the number of considered scenarios play a major role in the solution complexity. As a result, the computational time could reach values unsuitable for practical use. In fact, since the DAM bidding profile must be submitted to the TSO in the day ahead, the plant operator cannot accept the use of a tool requiring more than 24 h to run.

To improve the computational time, while providing a close-to-optimal solution, in this work we propose a novel decomposition method based on the idea of the Shrinking Horizon approach (as in [42;43]). The main idea behind the method is to solve the entire problem as a sequence of two-stage stochastic programming models, by exploiting the fact that the DAM decision is taken once-for-all in the day-ahead. For each two-stage problem, the scenarios are obtained by means of a clustering algorithm choosing the most representative ones from the scenario tree. The clustering method used is a modified k-medoids which takes not only vectors as input, but also weights associated to them. In this way, being the vectors the possible scenarios and the weights their probabilities of realization, the clusters' medoids represents the most representative profiles from a probability standpoint.

By considering a scenario tree composed by 7 levels and n branches per node (for a total of $m = n^6$), the proposed approach follows these steps:

1 Evaluation of k representative 24-hour ASM and PV (if present) scenarios, with $k \geq n$, from all the m scenarios of the tree,
2 Calculation of the optimal DAM solution by running a two-stage stochastic model based on the k scenarios. The DAM profile is saved and fixed for all the timesteps of the following iterations,
3 For each node of the second level of the tree (Stage 1), n representative scenarios from those belonging to its children nodes are evaluated. The resulting two-stage reduced tree will therefore feature n^2 scenarios,
4 Calculation of the optimal operational scheduling per each scenario, by considering fixed the DAM profile in each timestep as the one computed in Step 2. The solution related to the timesteps of ASM1 is saved and fixed for those scenarios featuring the same parent node in the next level (stage),
5 Steps 3 and 4 are repeated for the remaining levels (stages) of the tree. Therefore, given j the level of the tree, each two-stage model will feature n^j scenarios. For level 7 (Stage 6) the same original m scenarios are considered.

The decomposition algorithm is presented in Fig. 8. On the left, clustering is used to get the k most representative scenarios among all the ones in the scenario tree. Then, the optimal scheduling is obtained, and the DAM solution is saved. The following iteration of the algorithm can be seen in Fig. 8 (right). The DAM rectangle is red, indicating that the solution for such quantities has been fixed. All the scenarios featuring the same ASM1 profiles (namely all those ones described by the nodes with common root in level 1/Stage 2) are clustered, resulting in n^2 scenarios. Optimal scheduling is computed, and ASM1 quantities are saved and fixed for those scenarios linked to the same parent nodes

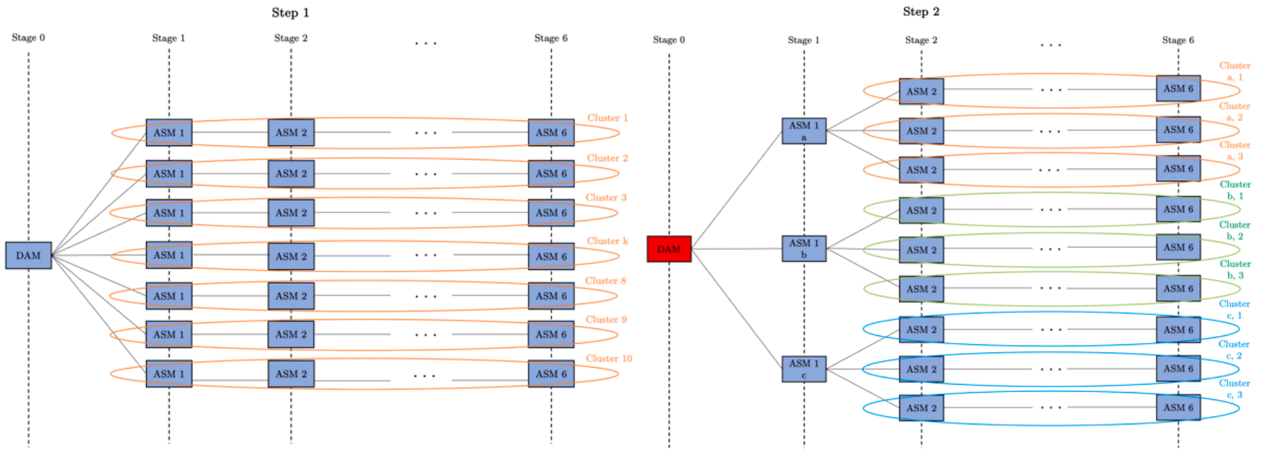


Fig. 8. Decomposition algorithm – Left: Step 1; Right: Step 2.

in the tree, in every next iteration. As a result, as the algorithm advances, the number of possible scenarios increases while the timesteps related to decision variables are reduced (since everything else is fixed). Please note that the reason why n is equal to the number of branches in the scenario tree is to avoid a mismatch between the number of representative scenarios in Stage 5 and the fixed number of Stage 6 (last stage).

The overall benefit of adopting such methodology lies on solving multiple two-stage stochastic problem, whose complexity is lower than the original multi-stage one. In particular, the combinatorial complexity of the models once the DAM profile is fixed reduces, further improving the overall run time. However, there are two downsides: (1) the final solution coming from this approach can be suboptimal and (2) fixing the DAM profile may lead to a condition of infeasibility for the following iterations. In fact, by considering representative scenarios instead of the full space of parameters, the degree of detail is decreased. As a result, the DAM decisions based on a limited number of scenarios may lead, once the uncertain parameters are revealed in the following iterations, to the impossibility to find an operational schedule able to provide the committed quantities to the market. This issue is present only when non-dispatchable energy sources (e.g. PV) are part of the VPP. In fact, given the fixed DAM profile, as new scenarios reveal, there might be the case where the sum of the PV generation and the total installed dispatchable power is not sufficient to cover the DAM quantities.

To mitigate this issue, the model can change its DAM commitments in the different iteration of the algorithm by lowering them. This change is penalized by associating a virtual cost characterized by a value three order of magnitude higher than the highest operational cost. In this way, the only reason why the DAM profile is changed is for feasibility reason, thus bringing little to no influence in the decision process and low impact on the computational time.

The flowchart shown in Fig. 9 represents all the different steps in the sequential decomposition approach presented. In case the DAM profile was updated in one of the iterations, such profile is saved. Then, the decomposition algorithm is launched a second time, skipping the first iteration, and fixing the updated DAM profile. In this way, the ASM quantities are evaluated in each session and under feasible boundary conditions.

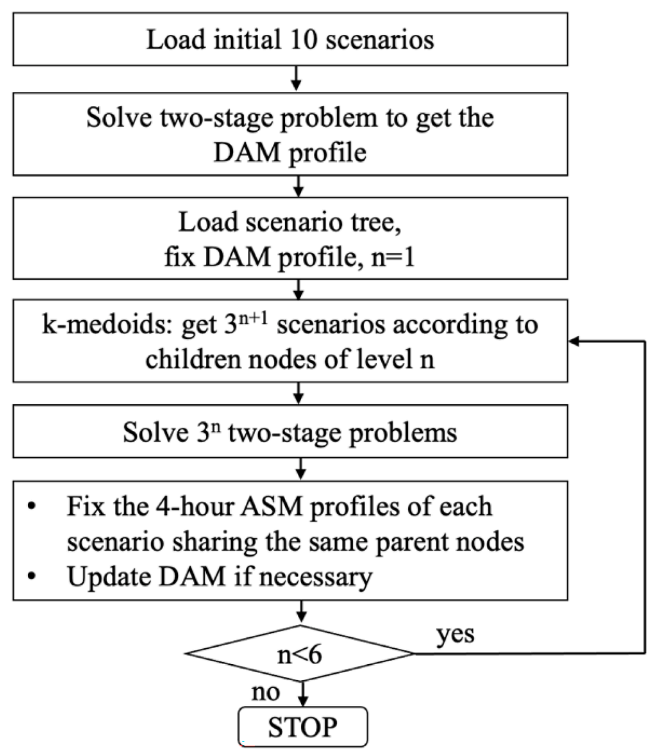


Fig. 9. DAM adjustment block diagram.

5. Test cases

In this work, three different case studies have been considered to test the abovementioned methodology: a “reference case” with two 120 MW_{el} Gas Turbine Combine Cycles (GTCC) units, a second case where the same units operate in CHP mode to serve a local user with the support of a Thermal Energy Storage System (TESS), and a “VPP case” where the two GTCCs operate in synergy with a PV field and a Battery Energy Storage System (BESS).

The first case study resembles the Marghera Azotati power plant, located near Venice, in the North of Italy. Since not publicly available, the part-load performance maps/curves of the two 1 + 1 GTCC units comes from literature [35].

Operational parameters (e.g., ramping limits) were taken by the datasheet of the GTCC with the closest size on the market. Moreover, all the historical ASM bids (both in prices and accepted quantities) of the Marghera Azotati power plant were downloaded respectively from [44,45]. In this way, the conditional probability distributions were evaluated for the creation of the scenario tree, following what shown in 4.1. The reason why this power plant was considered as case study is because reliable estimates of the operational parameters were available, and because the power plant operates almost always in the ASM. Therefore, the data used for the creation of the ASM scenarios are little to non-dependent on the interaction of the plant with other markets. In addition, by recreating the same boundary conditions, it is possible to assess whether the optimal solution coming from the proposed

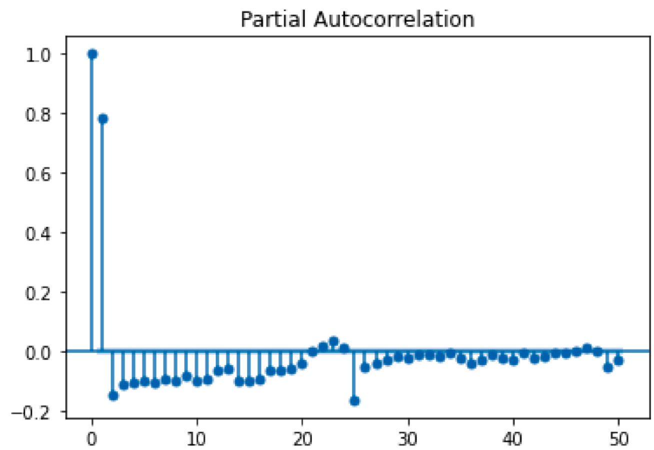


Fig. 10. ASM sold electricity partial autocorrelation.

methodology is in line with the current operational practice considered by the operator.

As mentioned in Section 4.1.1, a feature engineering operation has been performed on the collected data to quantify the influence that some parameters (e.g., electricity demand and PV production) could have on the predicted accepted offers in the ASM. After having removed all the sources of non-stationarity (i.e., trends, seasonality, etc.), the correlation between the residuals of the investigated time series has been evaluated using the Pearson's coefficient.

Since correlations between the energy demand in the day ahead market and the accepted offers in the Ancillary Service Market were not present (absolute value of the Pearson coefficient lower than 0.3) as well as the correlation with the overall production from PV power plants in the same geographic area of the investigated power plant, another analysis on the correlations between the lags of the accepted offers time series has been performed by means of the partial autocorrelation function (PACF) (Figs. 10 and 11).

For the VPP scenario generation, a conditional-probability matrix has been built to relate the Clear Sky Irradiance and the prediction errors (defined as the deviation between the forecast and the real data) related to one and two steps ahead, with the PV output power. The PACF for the PV production has been calculated showing correlation between the values with no lag and with lag 1 and 2.Table 1 and 2.

Lastly, the minimum number of scenarios that makes the tree stable has been found using the probability of having no accepted quantity in the ASM as metric to evaluate the stability of the scenario tree. As it can be seen in Table 3, for a number of branches per node equal to 4 (thus,

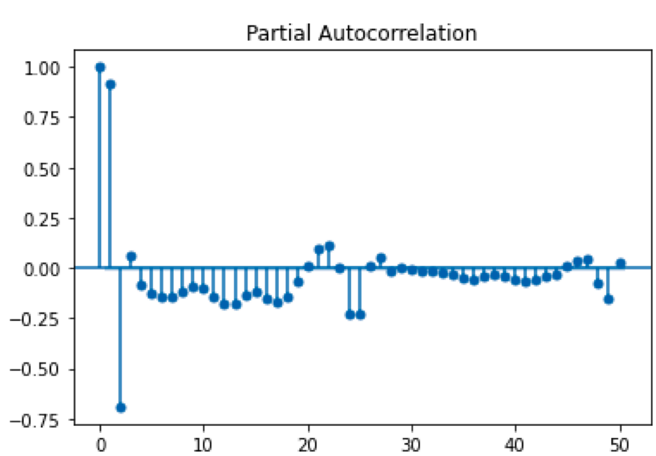


Fig. 11. PV production partial autocorrelation showing the correlation between the values with no lag and with lag 1 and 2.

Table 1
Pearson correlation coefficient.

Electricity demand vs Accepted Offers ASM	0.1075
Accepted Offers ASM vs PV production	−0.1410

Table 2
Partial autocorrelation function.

ASM partial autocorrelation function	0.7943

given 6 tree level, an overall number of scenarios equal to 4096), the probability of null scenarios is 40.29 %, close to the original value in the dataset of 40.8 %. Moreover, by increasing the size of the tree, no significant differences are noted from the point of view of this metric.

The other metric affecting the scenario generation was the conditional probability discretization step. Different ones were considered and its effect on the yearly Load Duration Curve (LDC) and scenario tree null-scenario probability was investigated. Despite the insignificant effect of choosing different discretization steps on the overall null-scenario probability, different values of this metric produce relevant effect on the LDC. As it possible to see from Fig. 12 right, a discretization step of 40 MW better approximate the original LDC over the three years of available data with respect to a discretization step of 10 MW. For this reason, a 40 MW step was chosen during the evaluation of all ASM conditional probability distributions. Even if this result may appear counterintuitive (since it is expected that a thinner discretization should better capture the probability distribution), the reason is related to the number of available data in the dataset: considering a discretization step of 10 MW, the number of ranges in which the offers are discretized increases as well, and so the number of available data becomes insufficient to derive significant statistical information (since small occurrences are considered as noise).

Following the considerations presented in 4.1.3, the numbers of scenarios considered to perform the simulation was equal to 729. The adoption of such number comes from the trade-off in evaluating the stability of such tree in terms of the probability of having zero-offer scenarios, accuracy of parameters representation and expected computational complexity with respect to the available computing power. The final structure of the scenario-tree is shown in Fig. 2.

While the ASM bidding prices are scenario dependent, the price profile for the DAM quantities is defined as the clearing price profile. In such case, given the predictable nature of the clearing price values, the operator is assumed to be a price taker, hence being able to have all his DAM quantities accepted. The DAM price profile assumed for all the three case studies can be seen in Fig. 13 (we assume that the zonal price is approximate by the PUN, the national uniforme price that characterize the Italian DAM). This profile was obtained by considering the DAM clearing price for the years 2017–2019, normalizing each day by its maximum value, applying k-means clustering (k = 12) and taking the representative period of the larger cluster. In this way, the selected profile is the one whose shape is the most representative across multiple years. Then, the normalized profile is scaled so to have an average value of 60 €/MWh. Therefore, the resulting profile has a minimum and

Table 3
Null-scenarios probabilities for different trees.

# Scenarios	Clustering time [s]	Null-scenarios probability	Non-null scenarios probability
2ˆ6 = 64	449	60.82 %	39.18 %
3ˆ6 = 729	2581	46.07 %	53.93 %
4ˆ6 = 4096	8523	40.29 %	59.71 %
5ˆ6 = 15625	19,709	40.04 %	59.96 %
6ˆ6 = 46656	54,827	40.17 %	59.83 %

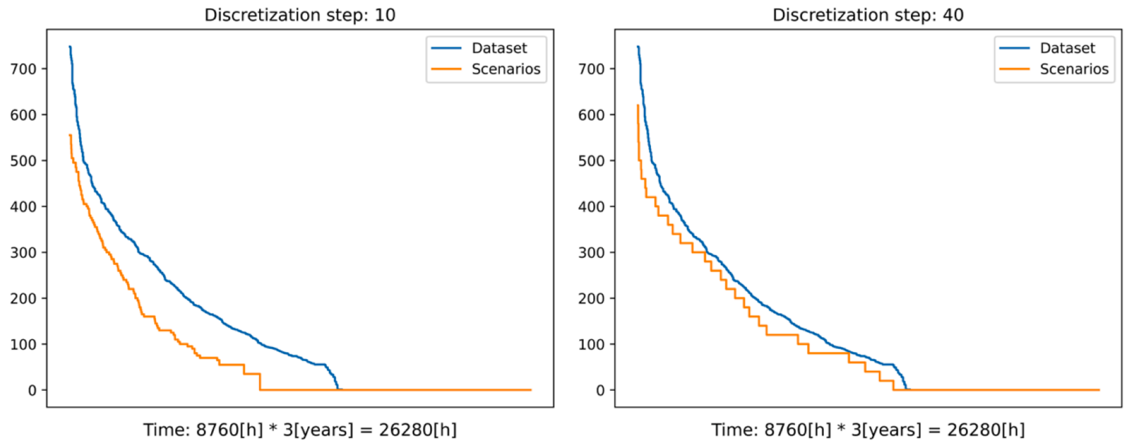


Fig. 12. Maximum accepted offers on ASM duration curves – Left: Discretization step = 10; Right: Discretization step = 40.

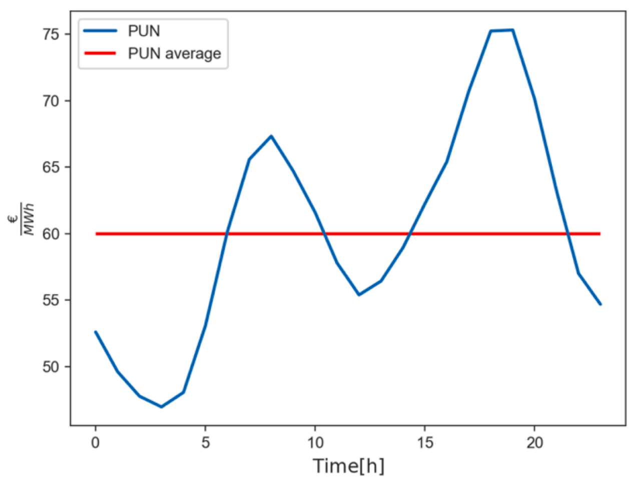


Fig. 13. DAM price profile considered for each case study.

maximum values of PUN equal to 46.97 and 75.32 €/MWh respectively.

A summary of all the parameters used in the different case studies can be found in Table 4.

5.1. Case 1 – GTCC (Reference case)

The reference configuration investigated resembles the Marghera Azotati's power plant. It consists of two 120 MW_{el} natural gas fired CCGTs, for a total installed power of 240 MW_{el}. Given the size, the single CCGT was assumed to be an AE64.3A® [46]. Each unit operates independently from the other, and the overall electricity generated by the plant can either be exported to the grid by selling it in either the DAM or ASM (Fig. 14).

5.2. Case 2 – CHP

The second case study considers the same couple of GTCC as for the previous case, although in CHP mode, with a total electrical and heating installed power of 119.9 MW_{el} and 52.3 MW_{th} respectively. In addition, the power plant is also equipped with a TESS and must meet the heating demand of a district heating network. The CHP unit is assumed to export heat by steam extraction and condensation from the turbine. As a consequence, the system has two degrees of freedom (the amount of fuel burned into the gas turbine and the opening position of the steam extraction valve from the turbine). The operating map of the units can be seen in Fig. 6, while the values of the vertexes are shown in Table 4. The operational map was evaluated by means of Thermoflex® [47 48] and then linearized, obtaining a mean square error of about 1 %.

The TESS has a nominal capacity of 70 MWh_{th} and its main purpose is to operate in support of the CHP units by peak shaving and load shifting. From a technological standpoint, it is a hot water tank heating up by means of the heat provided by the two CHP units. The TESS is assumed to have no loss during the charging phase, by considering it located nearby the power plant. In addition, it is also assumed that the delivery temperature of the TESS is always high enough (e.g. 80 °C) so to have a suitable temperature at the final user (e.g. new generation buildings with floor heating at 30 °C water temperature). Given the small size and the daily operational purposes (each charge discharge cycle happens within 24 h), the thermal losses at the wall are neglected. The overall plant layout can be seen in Fig. 15.

The power plant can export electricity to the grid and it is design to serve a local thermal user. The generated heat is assumed to be sent to a district heating network of a medium-sized city located in the North of Italy. The 24-hour profile (Fig. 16) has been measured from the network and scaled for confidentiality reasons. In contrast with the uncertain nature of the ASM accepted quantities, the heating demand profile forecast is here considered highly reliable, given its good predictability (the district heating network operator can predict the heat demand profile with a relative error below 5 %). In addition, the profile shows the winter day featuring the peak heating demand (peak at 70.43 MWh_{th} at hour 9, 578.52 MWh_{th} the total energy integral).

5.3. Case 3 – VPP

The last case study considers a possible VPP design based on the one presented in Case 1 (see Fig. 17). The two-GTCC power plant is equipped with a 100 MWh_{el} BESS and paired with a 100 MW_{el} PV field located in the surrounding area. The resulting aggregated power plant gives the possibility for each dispatchable, non-dispatch and storage units to bid in both the DAM and ASM. The optimal operation of such case study is considered for understanding the economic potential and the computational tractability. In fact, the increased number of variables and the presence of an additional uncertain parameter (PV generation), makes the problem harder to solve.

The battery was sized to store the peak PV generation, and also to support the GTCC for load shifting. A C-rate equal to 0.5 was considered so to provide a total discharge time of 2 hours.

6. Results and discussion

In this last part, the results of the simulations are presented. The model has been built in Pyomo (v5.7) [50,51] which is a Python-based, open-source optimization modelling framework with a diverse set of optimization capabilities. The resulting Stochastic MILP problem has

Table 4
Techno-economic parameters.

Market Parameter				
Natural gas cost	30 €/MWh			
DAM price range	47–75 €/MWh			
ASM price range	98–116 €/MWh			
Start-up revenue	65′160 €			
Combined Cycle (electrical power generation)				
Min/max nominal power	60–120 MW			
Performance curve parameters	$k^1_{m,EE} = 0.629\,[MWh_{el}/MWh_{NG,LHV}]$, $k^2_{m,EE} = -17.058[MWh_{el}]$			
Nominal efficiency	55 %			
Ramp up/down limit	117 MW/h			
Ramp-up limit at start-up	62 MW/h			
O&M cost	2 €/MWh			
Start-up cost	19′000 €			
CHP Combined Cycle (Map vertexes referred to Fig. 6)				
Vertex	1	2	3	4
Fuel consumption [$MW_{NG,LHV}$]	122.5	122.5	217.9	217.9
Electricity generation [MW_{el}] and efficiency [%]	63.7 | 52 %	53.9 | 44 %	113.3 | 52 %	119.9 | 55 %
Heating generation [MW_{th}] and efficiency [%]	0.0 | 0 %	36.8 | 30 %	52.3 | 24 %	0.0 | 0 %
Battery Energy Storage Systems				
Nominal capacity	100 MWh_{el}			
Nominal charge/ discharge power	50 MW (C-rate = 0.5)			
Charge/discharge efficiency	97 %			
Self-discharge	0.05 %/h			
Thermal Energy Storage System				
Nominal capacity	70 MWh_{th}			
PV field				
Nominal installed power	100 MW			
Efficiency (NOCT)	15.80 % [49]			

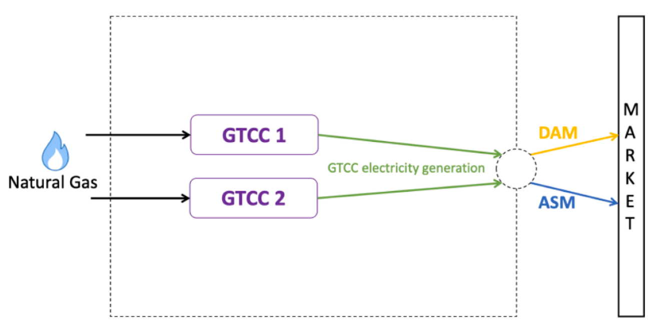


Fig. 14. Case 1 Plant layout.

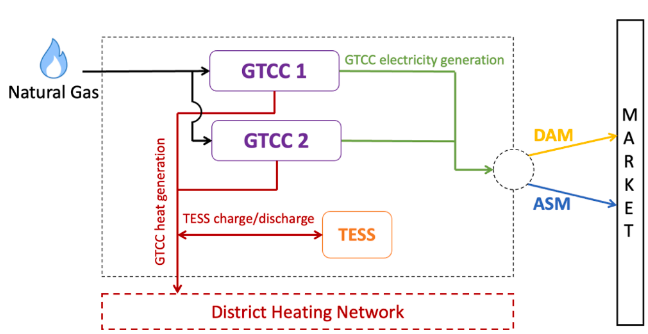


Fig. 15. Case 2 plant layout.

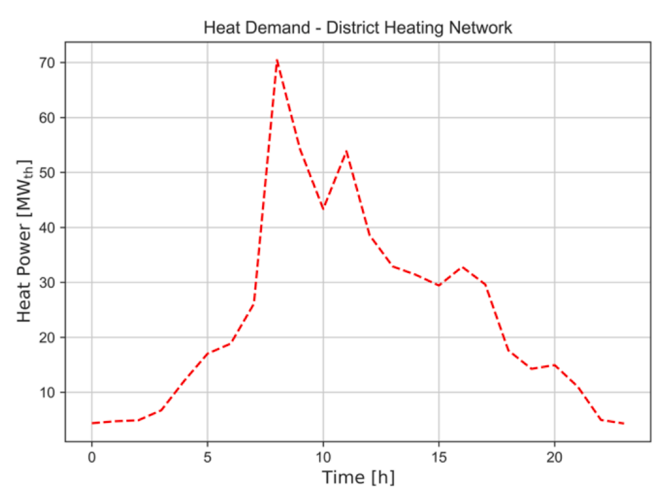


Fig. 16. Case 2 heat demand of the district heating network.

been solved by means of Gurobi Optimizer (v9.1.1) [52]. All the optimization runs have been performed on a workstation with a 2.2 GHz 6-core Intel Core i7 processor and 16 GB of RAM.

Before presenting the results, useful metrics are hereby shown for better understanding the advantage and usefulness of adopting a stochastic optimization approach. Two parameters are now introduced to quantify the value of the stochastic solution [53]: the EVPI (Expected Value of Perfect Information) and the VSS (Value of Stochastic Solution).

The EVPI represents the quantity that a decision maker is willing to

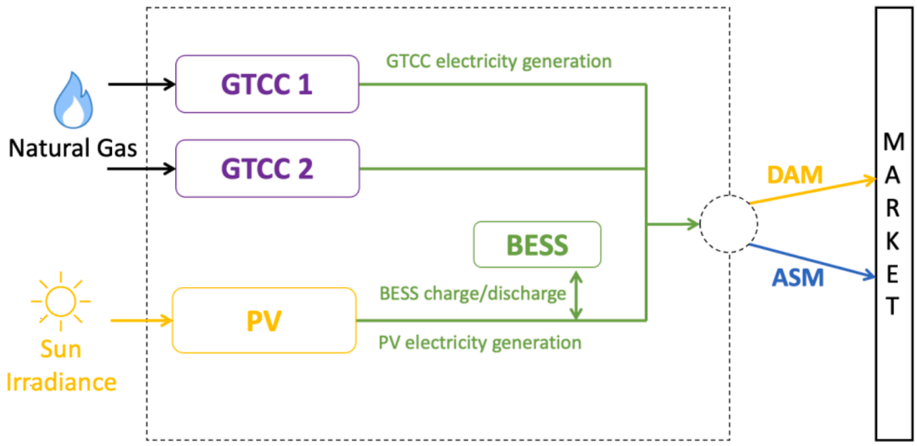


Fig. 17. Case 3 plant layout.

pay to obtain perfect information about the future and it is calculated as the difference between the objective function optimal value of the stochastic model and the one of the same model without non-anticipativity constraints.

The VSS is a parameter that quantifies the advantage of using a stochastic programming approach with respect to a deterministic one. It is defined as the difference between the objective function optimal value of the stochastic model and a deterministic model considering averaged values. In case the optimal solution of the deterministic model with averaged uncertain parameters turns out to be unfeasible on any of the initial scenarios, the VSS cannot be evaluated. This is a clear sign that the problem can only be tackled by considering the uncertain nature of the parameters.

The economic analysis of the plant operation is done by considering the expected plant Cost of Electricity (COE) and the revenues coming from the start-ups, and by selling electricity in the DAM and ASM:

$$COE = \sum_{sc\in\mathscr{S}c} p_{sc}\cdot\left\{\frac{\sum_{t\in\mathscr{T}}\sum_{m\in\mathscr{M}} c^{NG} In_{m,sc,t}dt + c_m^{O\&M} Out_{m,EE,sc,t}dt + c_m^{start-up}\cdot\delta^{on}_{m,sc,t}}{\sum_{t\in\mathscr{T}}\sum_{m\in\mathscr{M}} Out_{m,EE,sc,t}dt}\right\} \tag{47}$$

$$Revenue^{MGP} = \sum_{t\in\mathscr{T}}\left[PUN_t\cdot Out_t^{DAM}\right] \tag{48}$$

$$Revenue^{MSD} = \sum_{sc\in\mathscr{S}c} p_{sc}\cdot\left\{\sum_{t\in\mathscr{T}}\left[rev^{ASM}_{sc,t}\cdot Out^{ASM}_{sc,t}\right]\right\} \tag{49}$$

$$Revenue^{start-up} = \sum_{sc\in\mathscr{S}c} p_{sc}\cdot\left\{\sum_{t\in\mathscr{T}}\left[c^{SU}\cdot\left(\delta^{Pen}_{sc,t} - \delta^{SU}_{sc,t}\right)\right]\right\} \tag{50}$$

Finally, for each case the power plant scheduling is presented, both in terms of expected ASM and DAM bidding profiles. Among all the different scenarios, the most representative are shown to present the scheduling of the different generation and storage units of the plant. The average ASM bidding curve and maximum expected ASM awarded quantities shown in the figures are calculated as follows:

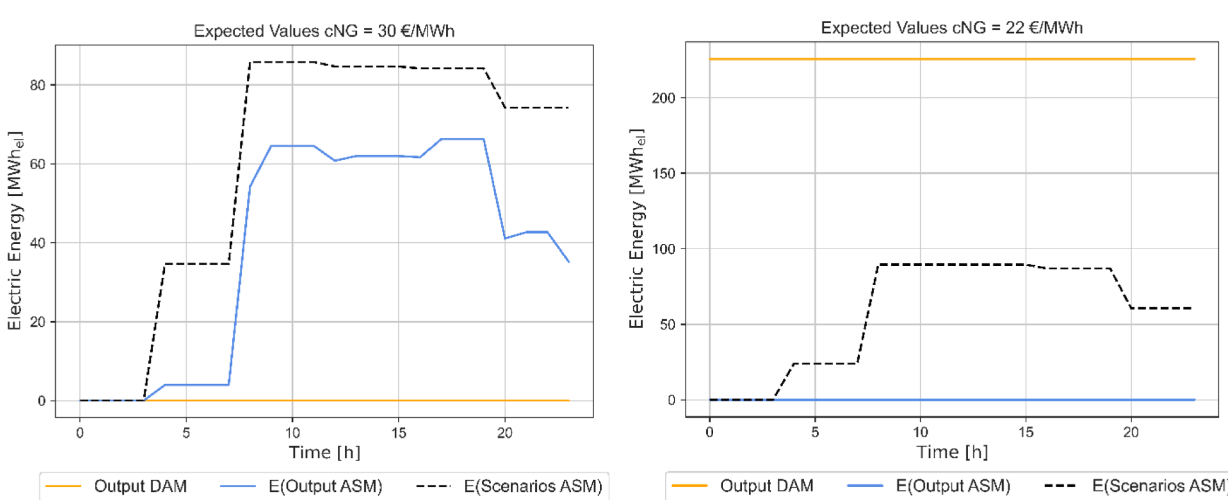


Fig. 18. Case 1 DAM and expected ASM bidding profiles. Left: $c_{NG} = 30€/MWh$; Rigth: $c_{NG} = 22€/MWh$.

Table 5
Case 1 economic analysis.

NG cost [€/MWh]	Bid quantities [MWh]		COE [€/MWh]			Cost [€]	Revenue [€]			
	DAM	E(ASM)	min	mean	max	OPEX	DAM	ASM	Start-up	Total
30	0	344.64	66.46	103.61	141.39	29,842	0	35,502	61,046	99,608
22	5414.40	0	42.27	42.27	42.27	228,841	324,864	0	0	324,864

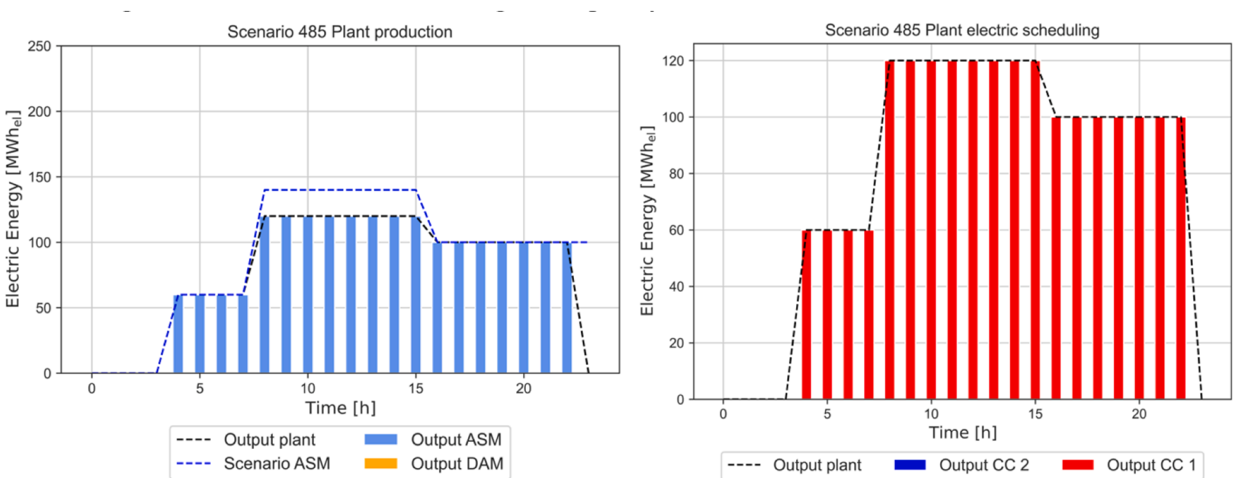


Fig. 19. Case 1 scenario 485, $c_{NG} = 30€/MWh$. Left: Plant production; Right: Electric scheduling.

$$E(Scenario_{ASM}[t]) = \sum_{sc\in\mathcal{S}c} P^{ASM}_{sc,t}\cdot p_{sc} \tag{51}$$

$$E(Out_{ASM}[t]) = \sum_{sc\in\mathcal{S}c} Out^{ASM}_{sc,t}\cdot p_{sc} \tag{52}$$

6.1. Combined cycle case study

In this case, the power plant is composed by two gas turbine combined cycles. Fig. 18 (left and right) shows the hourly profiles of the expected values related to the ASM and the bidding profile of the DAM for two natural gas prices (30 €/MWh left, 22 €/MWh on the right). In particular, the dashed black line represents the average profile coming from all the ASM scenarios, thus depicting the expected maximum ASM awarded quantities. Given the exact same set of scenarios, by changing the NG price the operational strategy completely shifts from selling just on one market to the other. This can be understood by looking at the DAM clearing price profile in Fig. 13 and the values in Table 5. The COE for the case with NG price at 30 €/MWh$_{NG}$ ranges, among all different scenarios, between 66.46 and 141.39 €/MWh$_{el}$. Since the DAM price is always below 75.32 €/MWh$_{el}$, the plant results non profitable for most of the hours of the day if bidding in this market. On the contrary, the ASM price ranges between 97.52 and 115.83 €/MWh$_{el}$, with an average value of 103.33 €/MWh$_{el}$ across all considered scenarios. Given the COE and ASM prices, it can be seen that bidding on this market is the preferred choice, especially considering the possibility to get the start-up revenue. This clearly explains why in Fig. 18 (left) the optimal solution features bids only on the ASM from 4:00 am (thus aiming at getting the start-up revenue).

An example of the daily operation for one of the considered scenarios can be seen in Fig. 19. Again, it can be noted that the power plant schedule to operate just one of the two GTCCs by bidding just in the ASM. The dashed blue line in Fig. 19 (left) represents the maximum expected ASM awarded quantities for this scenario. The dashed black

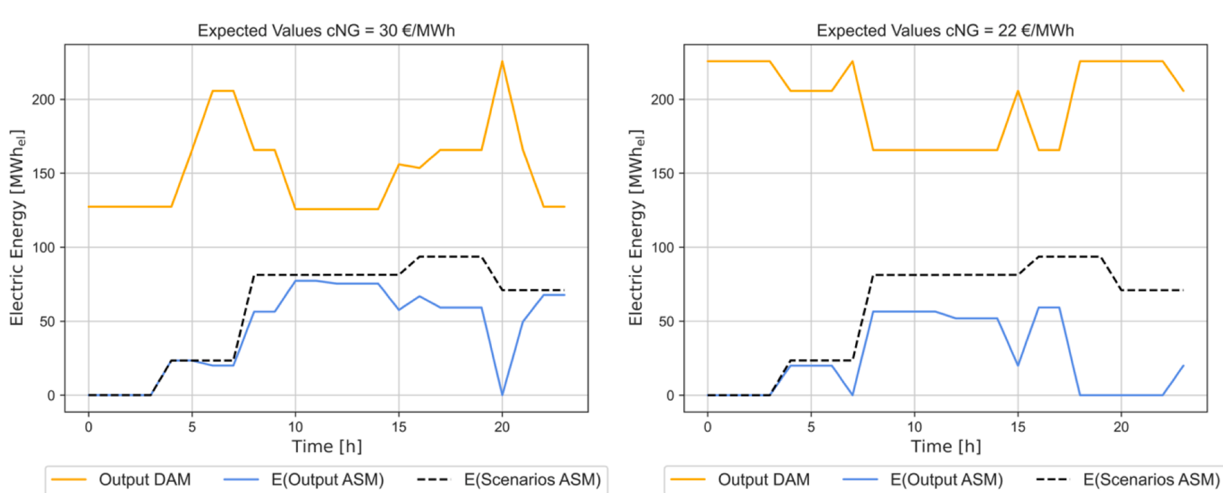
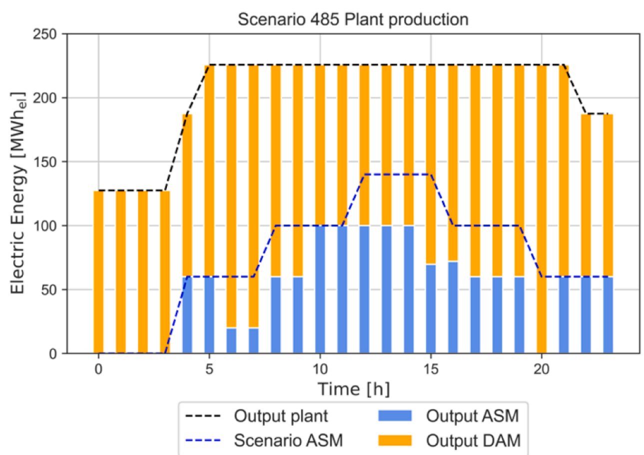


Fig. 20. Case 2 – Left: Expected Scheduling $c_{NG} = 30€/MWh$; Right: Expected Scheduling $c_{NG} = 22€/MWh$.



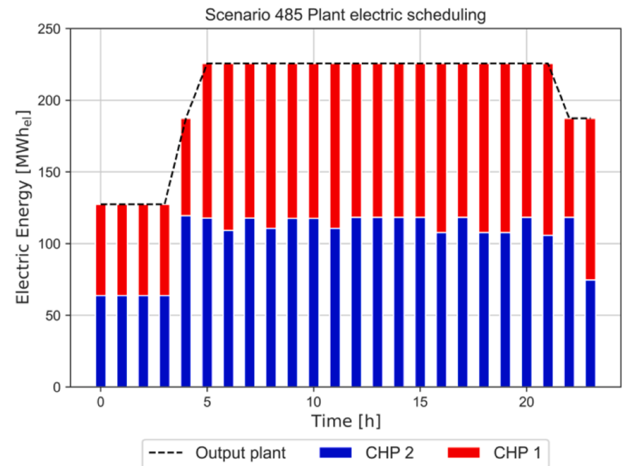


Fig. 21. Case 2 scenario 485, c_{NG} = 30€/MWh – Left: power plant electricity export; Right: power plant electricity scheduling.

line is the actual power plant electricity output, which reaches a peak value of 120 MWh, equal to the maximum production of one GTCC in one hour.

It is important to note that the optimal solution obtained for a NG price of 30 €/MWh$_{NG}$ are similar to most of the operational scheduling and bidding strategy of the Marghera Azotati power plant (which is the real plant from which the ASM historical data and operational parameters where taken) for year 2018. Such year featured an average DAM price of 61.31 €/MWh [54] and a NG price of 26.42 €/MWh [55], values similar to the values considered in this scenario. In fact, according to the publicly available data related to the Italian electricity market in 2018 [4], the power plant participated to the DAM for only 25 days in the year. On the contrary, it participated in the ASM 242 days.

When considering a different scenario with a lower NG final purchasing price (22 €/MWh$_{NG}$), the bidding strategy completely changes. By looking at Fig. 18 (right), it can be seen that the plant schedules to run with the two GTCCs at full load for all day offering all the generated energy in the DAM. By operating in this way, the COE is equal to 42.27 €/MWh$_{el}$ at any time, thus being always profitable (the minimum clearing price is 46.97 €/MWh$_{el}$). The reason why no quantities are bid in the ASM is the following: bidding on the DAM is a safe choice, since all the quantities offered will be remunerated at the clearing price, while the ASM profits are subject to the scenarios' probability (thus uncertain).

Given the results described above, it must be highlighted that the different operational decisions obtained by considering the two fuel costs appear to be mainly influenced by the plant net marginal operating profit (difference between electricity selling prices and specific operational cost to generate electricity, here defined as COE) and not by the energy and fuel prices alone. In fact, the optimal solution considers bidding in the DAM when the marginal operating profit on this market is positive (case with NG cost of 22 €/MWh$_{NG}$). On the contrary, with a high fuel price (30 €/MWh$_{NG}$), the net operating profit of the DAM is negative in most hours while positive on the ASM, thus explaining why no bids are made on the DAM.

6.2. *CHP with thermal storage and district heating*

The main characteristic of this plant is that it must run all day long to serve the heat demand linked to the district heating. The optimal solutions show that it participates in the DAM and ASM for both NG prices (Fig. 20).

By considering a NG price of 30 €/MWh$_{NG}$ the COE ranges between 57.89 and 60.06 €/MWh$_{el}$, with an average value across the scenarios of 59.34 €/MWh$_{el}$. With these values the plant is profitable just in some part of the day (e.g. in the morning and the evening). However, as can be seen in Fig. 20 (left), the power plant sells electricity in the DAM for every hour of the day, despite operating at loss (particularly in the first 4 h of the day). ASM bids tends to be maximized, since they are the main source of profit. Then, by looking at Fig. 21 (right), which depicts the operation of the GTCCs in one of the considered scenarios, it can be seen that the two GTCCs operate at full load for many hours of the day. This behavior is seen in most of the scenarios. When operating at full load, the fraction of the generated electricity that is sold to the ASM generates profit, while in some cases the fraction sold on the DAM generate loss. However, operating at full load has a higher efficiency and therefore a lower COE. As a consequence, losses are lower with respect to adopting a strategy based on minimizing the DAM quantities when the clearing price is lower than the COE.

When switching to a NG price of 22 €/MWh$_{NG}$, the COE ranges between 42.69 and 43.16 €/MWh$_{el}$, with an average value across the scenarios of 42.98 €/MWh$_{el}$. With these numbers, the power plant is always profitable in both markets. By looking at Fig. 20 (right), the bidding strategy is more oriented on selling energy in the DAM with respect to the ASM. This can be noted in Table 6, where the 22 €/MWh$_{NG}$ case features a + 31.7 % of DAM and a −38.6 % ASM quantities with respect to the other case. As for the previous case, offering more energy in the DAM is linked to the safer nature of such market with respect to the uncertain ASM one.

By considering the 485th scenario of the 30 €/MWh$_{NG}$ case as example, an insight on the CHP unit and storage operation is shown if Fig. 22 and Fig. 23. In Fig. 22 (left) it can be seen the heat balance of the system, with the district heating demand in dashed black line. At first, it can be noted that the heat output of both GTCC never gets to the

Table 6
Case 2 economic analysis.

[€/MWh] NG cost	Quantity sold [MWh]		COE [€/MWh]			Cost [€]	Revenue [€]			
	DAM	E(ASM)	min	mean	max	OPEX	DAM	ASM	Start-up	Total
30	3627.28	389.91	57.89	59.34	60.06	238,045	221,205	45,710	0	266,916
22	4777.19	239.86	42.69	42.98	43.16	215,568	285,967	28,240	0	314,208

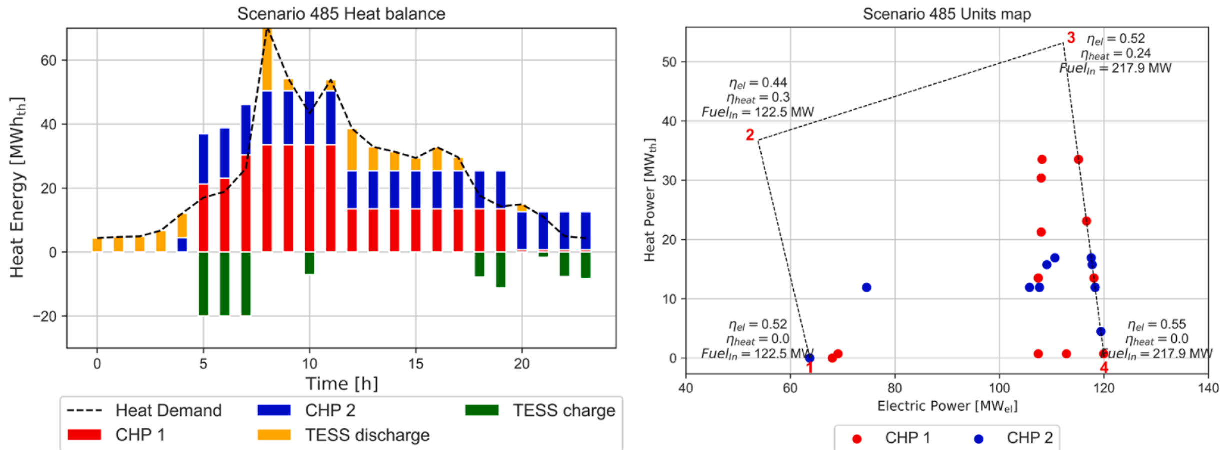


Fig. 22. Case 2 scenario 485, c_{NG} = 30€/MWh – Left: Heat balance; Right: CHPs operative points.

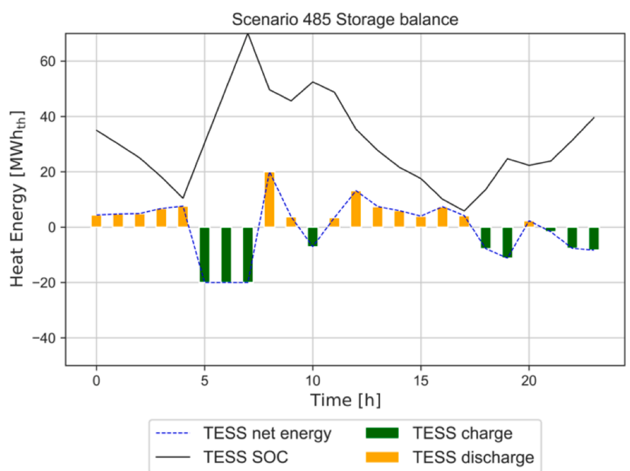


Fig. 23. Case 2 scenario 485, c_{NG} = 30€/MWh, storage opeartion.

maximum allowed value. Instead, most of the time both units have a low thermal output. This can be explained by looking at the Fig. 22 (right), noting that most of the operational points are on the left side of the performance map, where operational points characterized by a high electricity efficiency (and thus low COE) are present.

With reference to Fig. 22 (left) and Fig. 23, it is interesting to note how the TESS operates. The storage is used to meet the thermal demand in the first 4 h of the day, while it supports the GTCC both for serving the peak and the afternoon demand. By doing so, the GTCCs can operate with a lower heat output and higher efficiency. The TESS is charged in the morning and in the evening, to have enough energy for the two discharge phases. In particular, the charging phase happens when the DAM price is higher, thus avoiding losses due to the reduce efficiency (and higher COE). In general, it can be said that the TESS have a positive effect on the overall power plant performance.

As for the previous case, also here decisions are taken on the basis of the plant net marginal operating profit rather than just the DAM, ASM and NG prices alone. In addition, this case study is a clear example where a mathematical tool is needed in order to evaluate the optimal decision of such complex plant.

6.3. Virtual power plant

In the VPP case, the power plant features the same GTCC as the reference case, with the addition of PV and a battery (BESS).

By analyzing at first the case where a NG price of 30 €/MWh$_{NG}$ is considered, the power plant features a COE related to the dispatchable units between 70.63 and 141.39 €/MWh (Table 7), while the COE related to the PV field is basically null (having no variable O&M cost). Given the NG cost, participation in both the DAM and ASM is seen for this case. By referring to Fig. 24 (left) and Table 7, it can be seen that most of the quantities are offered in the ASM, while just a smaller fraction is bid in the DAM. This is similar to the results obtained for the first case study (featuring just two GTCCs) at the same NG cost. However, the addition of the PV field and a BESS increases the net revenues from 69,765 € to 98,779 € (+41.6 %) thanks to the additional quantities sold in the DAM.

With the aim of providing a more detailed description of the operational decisions, the plant schedule is presented for Scenario 323 (Fig. 25, upper-left and upper-right). At first, the DAM quantities are bid just for the sixth and seventh hour of the day. In particular, these quantities are supplied by the BESS and PV, with the BESS storing the electricity provided by the solar source. This behavior can be seen for all the 729 scenarios.

Then, the BESS operation can be seen in Fig. 25 (bottom). By also looking at the other two upper figures, it can be noted how the BESS is also used for ancillary service purposes. This happens at hour 4:00 and 20:00 when it discharges electricity to sell it in the ASM. In this way, low cost, renewable energy is sold to the grid at high selling prices (ASM) by shifting the PV production thanks to the BESS. In this scenario the BESS operation is characterized by 0.78 daily equivalent cycles (ratio between total charged electricity and total storage capacity), while across all other scenarios this value ranges between 2.84 and 0.62 with an average value of 0.91.

Regarding the GTCCs, their only role is to generate electricity to sell on the ASM and to award the start-up revenue. This can be seen in

Table 7
Case 3 economic analysis.

NG cost [€/MWh]	Quantity sold [MWh]		COE [€/MWh]			Cost [€]	Revenue [€]			
	DAM	E(ASM)	min	mean	max	OPEX	DAM	ASM	Start-up	Total
30	108.47	433.13	70.63	115.39	141.39	36,840	6840	39,186	89,593	135,619
22	5797.36	0.00	42.27	42.40	42.49	223,605	349,287	0.00	0.00	349,287

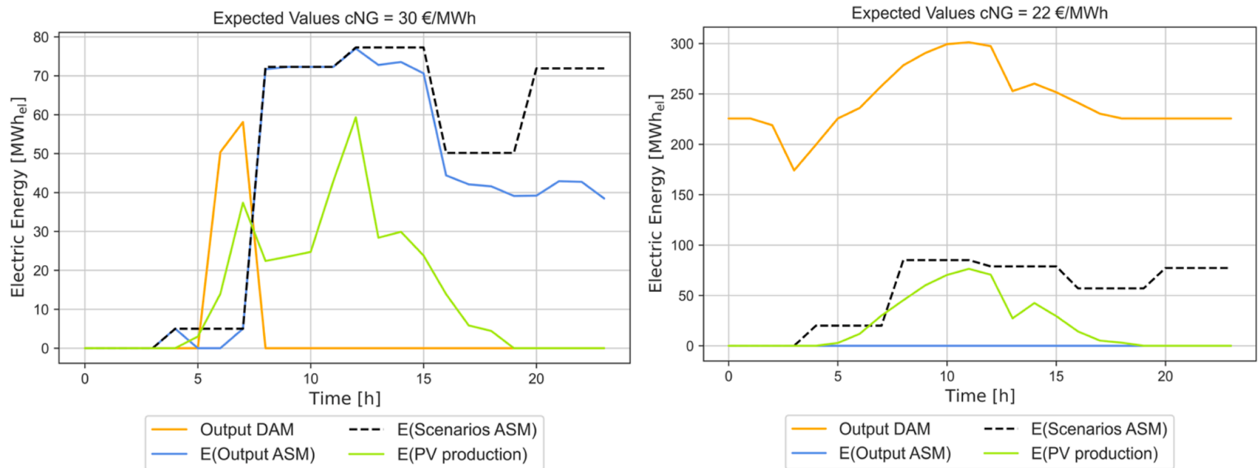


Fig. 24. Case 3 – Left: Expected Scheduling c_{NG} = 30€/MWh; Right: Expected Scheduling c_{NG} = 22€/MWh.

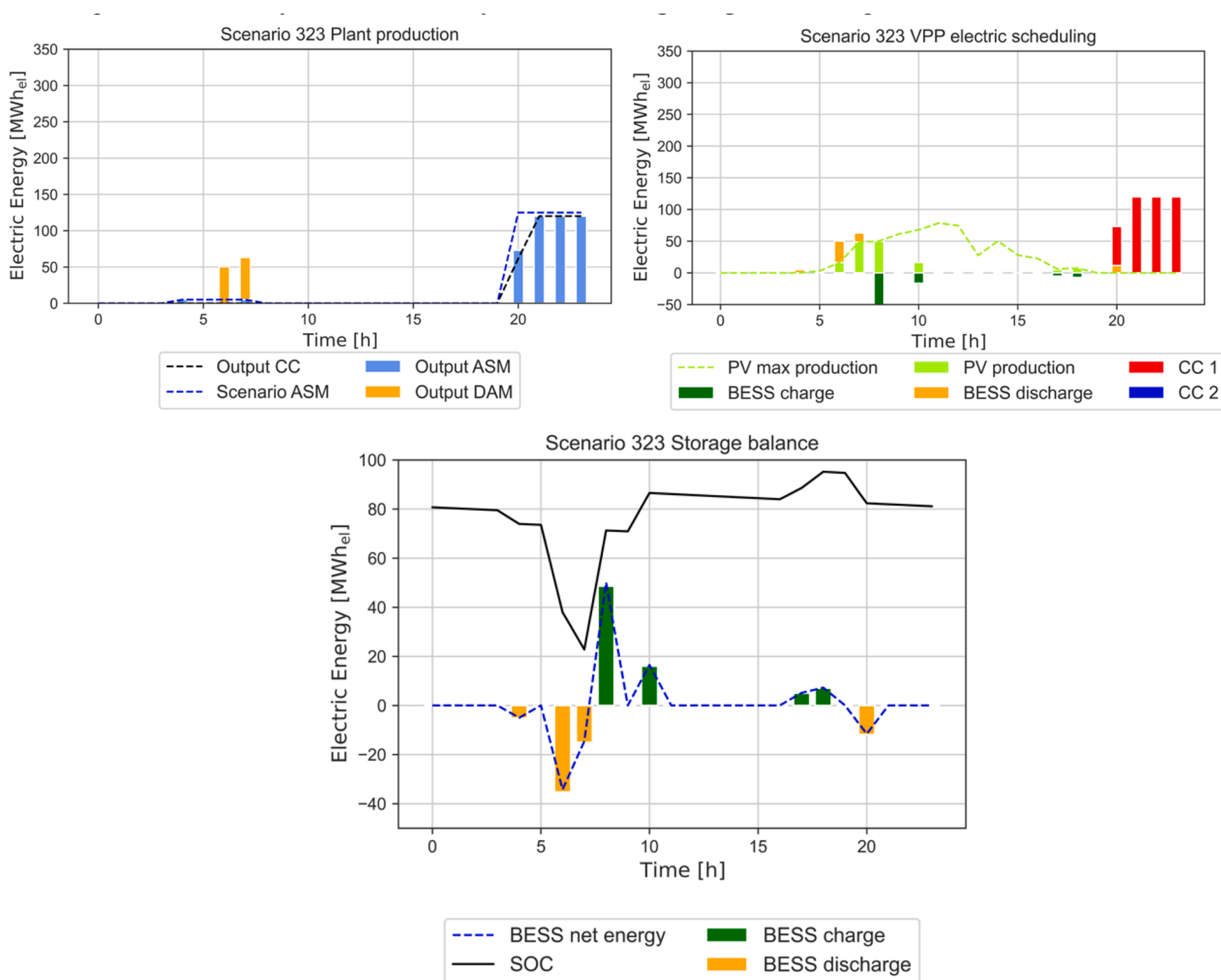


Fig. 25. Case 3 scenario 485, c_{NG} = 30€/MWh, Upper left: power plant electricity export; Upper right: power plant electricity scheduling; Bottom: Storage operation.

Fig. 25 (upper-left and upper-right) where the ASM quantities bid are generated by the first Combined Cycle, that switches on just for this purpose. This is in line with what seen in the first case study: given the GTCCs' COE and market prices, the net marginal operating profit is positive just for the ASM.

Profits from the ASM and the start-up revenue are the reasons behind the limited quantities bid in the DAM (despite the PV null specific operational cost would make it profitable at whichever hour of the day). By looking at the black dashed line in Fig. 24 (left), it can be noted how most of the ASM quantities are expected to be awarder after 8:00 (very common among the different scenarios). Since selling on both ASM and DAM is a condition that does not allow to get the start-up revenue (a

Table 8
Model characteristics.

Case	Scenarios	Binary variables	Continuous variables	Constraints	Root Relaxation
CC	3ˆ6 = 729	192,456	139,968	948,489	−1.26E+05
CHP	3ˆ6 = 729	122,472	384,912	1,030,921	−9.90E+04
VPP	3ˆ6 = 729	192,456	227,448	1,105,977	−1.90e + 05

GTCC must be switched on such that the VPP sells only in the ASM), DAM quantities are bid just for those hours where it is less likely to sell on the ASM. In this way the GTCCs are let free to switch on at any time after 8:00, generating power that the plant would only sell for ancillary services and getting the start-up revenue.

Taking about the case with NG price of 22 €/MWh$_{NG}$, the description is very similar to the one regarding the first case study featuring the same fuel cost. The COE related to the dispatchable units is always lower than the DAM clearing price, ranging between 42.27 and 42.49 €/MWh (Table 7). This makes convenient to sell all the available generation in this market (see Fig. 24, right). As a consequence, no start-up revenue is awarded since the two GTCCs run for 24 h, the BESS barely operates (among all considered scenarios the resulting number of daily equivalent cycles ranges between 0.01 and 1), and all the available PV generation is directly sold in the DAM.

Also in this case, the plant net marginal operating profit is the main driver in the decision process. Also in this case the advantage of using a stochastic optimization model to tackle the problem can be seen: given the complexity and the presence of two uncertain parameters, the optimal solution would have been extremely challenging to find with conventional approaches.

6.4. Computational results and assessments.

In Table 8 and Table 9, the main features of the models (i.e., variables, constraints, etc.) and a summary of the solutions are reported. As it is possible to see, the performance of the models developed for the above-mentioned test cases are quite heterogeneous.

In terms of EVPI, this value varies from up to 31 % of the overall objective function for the GTCC configuration, to nearly 50 % for the CHP and up to 30 % for the Virtual Power Plant. This means that for the problem investigated the value related to the uncertainty increased with the complexity of the power plant and the number of uncertain parameters. In fact, the EVPI quantifies the expected objective function gain from having perfect information of the uncertain parameters. Therefore, the higher the EVPI, the higher the cost related to the uncertainty.

Talking about the VSS, the CC case with a NG cost of 30 €/MWh$_{NG}$ and CHP cases (both with NG price of 22 and 30 €/MWh$_{NG}$) were the only cases for that it could be evaluated. The decrease in the objective function (corresponding to an increase in revenues) obtained by solving the problem with a stochastic model instead of a deterministic one with average scenarios is just −0.39 % for the CC case (NG cost 30 €/MWh$_{NG}$), and −1.8 % and −13.58 % for the CHP case with NG cost of 22 and 30 €/MWh$_{NG}$ respectively. For all the other cases, the VSS was not computable since the solution found by the deterministic model with average scenarios was not feasible in some of the stochastic ones. For the CC case with 22 €/MWh$_{NG}$, the infeasibility lies in the DAM and ASM decisions that force the CCs to shut down and subsequently start up in a time interval lower than the minimum allowed. For the VPP cases, the DAM decisions overcommit the plant generation in some stochastic scenarios (not enough PV generation). This can be explained by the fact that average scenarios cannot be representative of every stochastic one, thus resulting in over- or underestimation.

The evaluation of the VSS also underline how it is impossible to decide a priori whether a deterministic approach with average scenarios should be used over a stochastic one. The analysis on the conditional distribution used for the creation of the ASM scenarios (that is the only thing in common among the three case studies) cannot provide any significant information, also given the fact that in half of the considered cases a deterministic approach produced an infeasible solution. Then, the decision about which approach to adopt cannot be taken just by looking at plant layout: results show that by changing only one parameter (fuel price) either a deterministic approach can result in an unfeasible solution (CC case with NG at 22 €/MWh$_{NG}$), or the VSS can significantly change (from −1.8 % to −13.58 % for the CHP cases). The impossibility of defining a priori which approach to adopt is further underlined by the results about the VSS for the VPP cases: the assessment can only be done a posteriori, by testing the solution obtained with

Table 9
Solution outcomes.

Case	Computational Time	22 €/MWh$_{NG}$			30 €/MWh$_{NG}$		
		Objective	EVPI	VSS	Objective	EVPI	VSS
CC	25 h	−9.60E+04	2.99E+04	n.c.**	−6.98E+04	9.06E+03	2.71E+02
CHP	7.56 h	−9.84E+04	2.19E+04	1.76E+03	−2.81E+04	1.39E+04	3.35E+03
VPP*	greater than3 d	−1.25E+05*	3.41E+04	n.c.**	−9.88E+04*	3.05E+04	n.c.**

*: Best solution found after three days of run (optimality not proven, MIP gap = 26 %).
**: VSS could not be computed ("not computable") since the operational solution found by the deterministic model considering average scenarios is not feasible in some of the stochastic scenarios.

Table 10
Combined cycles case solution outcomes.

		22 €/MWh$_{NG}$		30 €/MWh$_{NG}$	
		Complete model	Decomposed model	Complete model	Decomposed model
CC case	Scenarios	729	729	729	729
	Computational Time	25 h	2.5 min	24 h	1 min
	Objective	−9.60E+04	−9.60E+04 (+0.0 %)	−6.98E+04	−6.95E+04 (+0.3 %)
CHP case	Scenarios	729	729	729	729
	Computational Time	7.5 h	4 min	7 h	18 min
	Objective	−9.84E+04	−9.53E+04 (+3.2 %)	−2.81E+04	−2.36E+04 (+15.9 %)
VPP case	Scenarios	729	729	729	729
	Computational Time	greater than3 days	18 min	greater than 3 days	13 min
	Objective	−1.25E+05*	−1.25E+05 (+0.3 %)	−9.88E+04*	−9.82E+04 (+0.6 %)

*: Best solution found after three days of run (optimality not proven, MIP gap = 26 %).

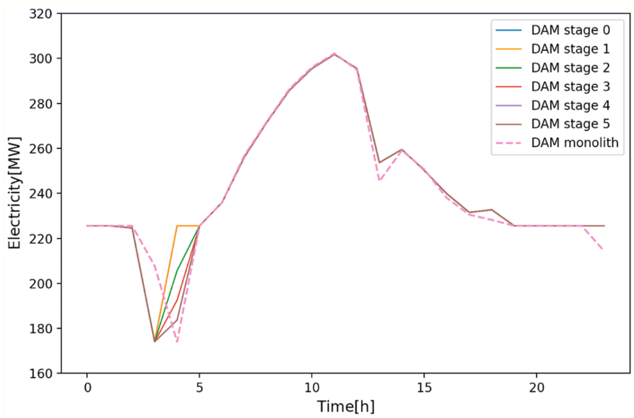


Fig. 26. DAM adjustment through the adaptive procedure for the VVP case with NG price of NG price 22 €/MWh$_{NG.}$

average values over all the stochastic scenarios. These results show that to avoid any unfeasible operational schedule (which might result in substantial penalties), a stochastic approach is suggested when day-ahead decision are strongly influenced by uncertain parameters.

Regarding the computational time needed to solve the three different case studies as a monolithic stochastic model, they are show in Table 9. The reference case with just two GTCC and the VPP case took more than 24 h, making this methodology useless from a practical point of view. In particular, by referring to Table 8, for the VPP cases the complete model solved with Gurobi was not able to provide a solution with an MIP gap lower than 26 % after 3 days of computation. For this reason, the decomposition approach introduced in Section 4.3 was developed and applied to the mentioned cases. As it can be seen in Table 10, the reduction in computational time is significant, going from more than 24 h to less than 3 min for the CC case, from about 7 h to less than 20 min for the CHP case, and from more than 3 days to less than 20 min for the VPP case.

In reference with the case featuring the two CCs, the solution obtained by the complete model by applying the decomposition leads to the same objective function when NG cost is 22 €/MWh$_{NG}$, while a minimal difference of + 0.3 % is present if a price of 30 €/MWh$_{NG}$ is considered.

For the CHP case, the solutions found when using the decomposition are + 3.2 % and + 15.9 % higher (lower revenues) than the ones found in the complete model for a gas price of 22 and 30 €/MWh$_{NG}$ respectively. In particular, when the NG price is set to 30 €/MWh$_{NG}$, the solution obtained by means of the decomposition features 243575€ of OPEX (+2.32 %) and total expected revenues of 267476€ (+0.21 %), with 232,836 € in the DAM (+5.26 %) and 34,639 € in the ASM (-24.22 %). As it can be seen, the 15.9 % difference in revenues for the solution obtained with the decomposition comes mainly from the lower ASM quantities. The overall units' scheduling is very similar among the two approaches, but the reduced set of scenarios considered in the first step of the decomposition (10 profiles evaluated with k-medoids) limits the information related to the potential revenues on the ASM. In addition, since the CHP units operate at a loss in some part of the day, the DAM quantities are maximized in the first stage decision (hence explaining the + 5.26 %), leaving less room to ASM offers in the subsequent decision stages.

For the VPP case, the decomposition provides solutions featuring a + 0.3 % and + 0.6 % increase for the 22 and 30 €/MWh$_{NG}$ cases respectively, being very close to the best one found in with complete model.

In general, for those cases where operation is not constrained by an energy demand, the decomposition shows remarkable performance, with a great reduction in computational time, a small sensitivity with respect to the NG price and providing solutions very close to the optimal ones. For the CHP case, the solution found showed a higher degree of sub-optimality (30 €/MWh$_{NG}$ case). However, the significant reduction in computational time allows the user to consider this tool for the evaluation of a first, feasible and close-to-optimal solution that can be further refined with ad-hoc heuristics or used as solver warm start.

Finally, Fig. 26 shows how the DAM profile changes iteration after iteration for the VPP case as the number of scenarios are added in the model. The dashed pink line is the DAM solution for the 729-scenario complete model.

7. Conclusion and further developments

In this work a methodology for the optimal operation of a power plant participating to both the DAM and ASM was developed. This consists in a multi-period multi-stage stochastic optimization model, an ad-hoc algorithm for the generation of ASM and PV scenarios, and a clustering-based sequential two-stage decomposition method.

A complete statistical analysis of the electricity markets has been performed, looking for correlation between parameters. Then, conditional probability distributions were evaluated for generating the scenarios needed by the stochastic model. This one is composed by seven decision stages, comprising all the different DAM and ASM sessions that the power plant must undergo while deciding its operational schedule. In addition, the conditions under which the start-up revenue is awarded was carefully modelled.

The gain in revenues obtained by considering a multi-stage stochastic model over a deterministic one with average scenarios is up to 13.58 %, but for other cases is limited to less than one percentage point. However, for half of the considered test instances (CC with NG at 22 €/MWh$_{NG}$ and the two VPP cases) the solution obtained with a deterministic approach based on averaged values resulted infeasible with respect to the stochastic scenarios. This underlines how a stochastic approach must be considered over a deterministic one for the considered case studies.

The computational time associated with solving the complete model directly with a commercial solver makes the proposed methodology unpractical. For this reason, a new decomposition algorithm was developed with the aim of reducing the run time still retaining a solution close to optimal. This algorithm is based on the concept of the shrinking horizon and solves a sequence of two-stage stochastic models whose scenarios are selected by means of k-medoids clustering. The decomposition leads to a significant reduction of time (the greatest going from more than 3 days to 13 min) while finding close-to-optimal solutions. In particular, for the CC and VPP cases the solution found with the decomposition was at most 0.6 % worse, while the CHP case showed a solution with revenues up to 15.9 % lower than the optimal solution. Nevertheless, the significant amount of time saved justifies the adoption of this decomposition approach.

Finally, the results show that the proposed methodology is an effective tool for optimizing the scheduling of power plants and virtual power plants operating on the day ahead and ancillary service markets. Since the presented methodology can be easily adapted to other market frameworks, future development should focus on assessing its computational tractability over those ones characterized by a higher number of sessions (e.g. every hour) and/or higher price volatility (e.g. considering DAM price scenarios).

CRediT authorship contribution statement

Andrea Fusco: Methodology, Software, Validation, Formal analysis, Visualization, Writing – original draft, Data curation. **Domenico Gioffrè:** Methodology, Software, Validation, Formal analysis, Visualization, Writing – original draft, Data curation. **Alessandro Francesco**

Castelli: Methodology, Software, Validation, Visualization, Data curation, Supervision, Writing – review & editing. **Cristian Bovo:** Conceptualization, Methodology, Supervision. **Emanuele Martelli:** Conceptualization, Methodology, Supervision, Writing – review & editing, Resources.

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

Data will be made available on request.

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