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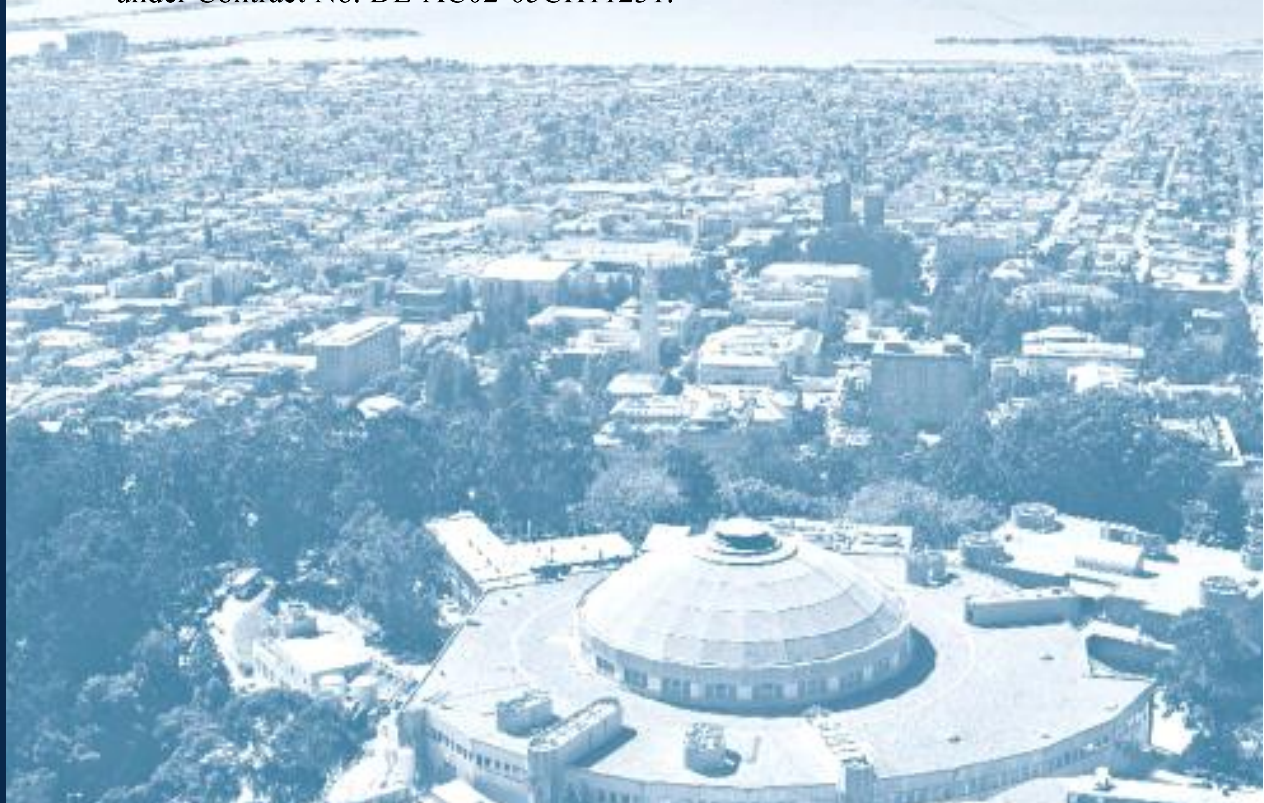

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Risk-Constrained Multi-Period Investment Model for Distributed Energy Resources Considering Technology Costs and Regulatory Uncertainties

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Abstract

One of the reasons for the emerging adoption of behind-the-meter distributed energy resources (DERs), particularly photovoltaic (PV) and storage, is the impressive decrease in technology costs over the last years together with favorable policy and regulatory environments that created early-stage incentives to the proliferation of these assets. However, when looking at the next decade, the evolution of the regulatory framework and the trajectory of technology costs are difficult to predict. This uncertainty poses a new challenge to prosumers and microgrid owners who are trying to find the best moment to invest in these DERs. In particular, unpredictable changes in the conditions of the investments may translate into economic risks to potential DER adopters, which raises the need for new risk-mitigation methods to support their investment decisions. To address this issue, this paper proposes a multi-period DER investment model with economic risk constraints, considering technology costs and regulatory uncertainties. A case study, involving a large building in California, is used to show that different types of economic risk constraints can affect not only the size, but also the optimal timing of these investments in a multi-year planning horizon with significant DER technology costs and regulatory uncertainties.

Keywords: Distributed Energy Resources, DER Planning, Risk Mitigation, Microgrids, Solar Compensation Mechanisms.

Nomenclature

Acronyms

CVaR Conditional Value-at-Risk

DER Distributed Energy Resource

PV Solar Photovoltaic

Sets

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$\mathcal{B}$ Set of electricity storage options, $\mathcal{B} \subseteq \mathcal{C}$, indexed by b

$\mathcal{C}$ Set of continuous DER options for investment, indexed by c

$\mathcal{D}$ Set of discrete DER options for investment, indexed by d

$\mathcal{I}$ Set of periods where investments are allowed, with size $\overline{\mathcal{I}}$, $\mathcal{I} \subseteq \mathcal{T}$, indexed by i

$\mathcal{K}$ Set of scenarios, with size $\overline{\mathcal{K}}$, indexed by k

$\mathcal{T}$ Set of periods in the planning horizon, with size $\overline{\mathcal{T}}$, indexed by t

$\mathcal{Y}$ Set of years in the planning horizon, with size $\overline{\mathcal{Y}}$, indexed by y

Variables

$b_{c,i}$ Yes/no decision whether to invest in continuous technology c in period i (binary)

$caa_{d,t}$ Available capacity of DER d at the end of period t (kW or kWh)

car_d Remaining capacity of DER d ($)

d_y Depreciation cost incurred in year y ($)

$fu_{d,t}$ Amount of fuel needed for generator d in period t (kWh)

$h, h_y, z_k, z_{k,y}$ Auxiliary variables needed for CVaR constraints

$i_{b,t}$ Power input to storage b in period t (kW)

$n_{d,i}$ Number of units of discrete generation technology d invested in period i (integer)

$o_{d,t}$ Power output of DER d in period t (kW)

$soc_{b,t}$ Energy amount stored in storage b in period t (kWh)

u_t Electricity demand imported from utility in period t (kW)

ux_t Power exported to utility in period t (kW)

$x_{c,i}$ Capacity to invest in continuous technology c in period i (kW or kWh)

Stochastic Parameters

$\xi = (CV, FU, TI, TE)$ Vector of uncertainty parameters

$CV_{c,i}$ Investment variable cost of continuous technology c in period i ($/kW or $/kWh)

FU_t Fuel cost in period t ($/kWh)

TE_t Export tariff in period t (\$/kWh)

TI_t Import tariff in period t (\$/kWh)

Deterministic Parameters

α Confidence level in the CVaR constraint for entire planning horizon

α_y Confidence level in the CVaR constraint for operating year y

Δ_t Length of period t (hours)

γ_d Salvage factor for technology d (portion of the investment in DER d salvaged at the end of its lifetime)

μ_d Fuel conversion efficiency of DER d

$\overline{\text{CCap}}_c$ Total investment capacity restriction for continuous DER c (kW, kWh)

$\overline{\text{DCap}}_d$ Total investment capacity restriction for discrete DER d (kW)

$\overline{\text{Risk}}$ Risk tolerance level for entire planning horizon

$\overline{\text{Risk}}_y$ Risk tolerance level for operating year y

ρ Annual discount rate for calculating the present value

CAP_d Capacity of discrete technology d (kW)

$\text{CD}_{d,i}$ Investment cost of 1 unit of discrete technology d in period i (\$)

CE_b Charging efficiency of storage b

$\text{CF}_{c,i}$ Fixed cost to install continuous technology c in period i (\$)

$\text{CMF}_{d,t}$ Fixed maintenance cost per unit of capacity of DER d in period t (\$/kW,\$/kWh)

$\text{CMV}_{d,t}$ Variable maintenance cost per unit of power output of DER d in period t (\$/kW)

DE_b Discharging efficiency of storage b

ED_t Electricity demand for period t (kW)

L_d Lifetime of technology d (hours)

MC_b Maximum power charged ratio at the defined Δ time step of storage b (kW/kWh)

MD_b Maximum power discharged ratio at the defined Δ time step of storage b (kW/kWh)

$\text{PCF}_{c,t}$ Power conversion factor for DER c in period t

Pr_k Probability of scenario k

R_d Ramping factor for discrete technology d

SD_b Self-discharged coefficient of storage b

$\mathrm{y}(i)$ The year containing period i

$\underline{\mathrm{SC}}_b$ Minimum state of charge of storage b

A note on the nomenclature: By "in period i," we mean "at the beginning of period i." By "technology/DER/storage d," we mean "technology/DER/storage of type d."

1. Introduction

1.1. Motivation

The adoption of behind-the-meter Distributed Energy Resources (DERs) in power distribution grids has been fast increasing during the last decades, with potential impacts in terms of grid operational costs, loss reduction, reliability and security of supply, provision of ancillary services at the distribution level, emissions reduction, and deferral of transmission and distribution network upgrades [1]. This private adoption of DERs, namely PV and storage, has been motivated by a significant decrease in technology costs [2] combined with important changes in tariff policies and solar compensation mechanisms, such as net-metering schemes [3, 4, 5] or feed-in remunerations [6, 7], which made DER economically viable for medium size consumers and microgrid owners.

However, these two factors (technology costs and DER regulatory schemes) are constantly changing and there is a significant uncertainty about their evolution in the near future. For example, when planning behind-the-meter DER investments for the next 15 or 20 years, it is difficult to anticipate deterministic trends of evolution of PV and storage asset costs. In fact, there is a significant uncertainty about the future prices of these technologies, as they typically depend on multiple aspects, such as raw material costs, the level of maturity of underlying technologies, tax incentives, and rebates, etc. Even assuming that these prices tend to decline with time, the uncertainty about the "pace" of reduction is a challenge for prosumers and microgrid owners looking for the optimal time to invest in DERs.

Similarly, there is uncertainty from the side of the DER policies that determine the revenue streams associated with these technologies. As an example, the fast adoption of DERs has initiated a regulatory discussion around solar compensation mechanisms, such as the role of net-metering policies and time-of-use tariffs or the ability of utilities to recover fixed costs in distribution grids with high penetration of DERs [8, 9, 10]. Therefore, it is expected that this discussion may lead to sudden regulatory changes in DER interconnection and compensation policies, such as the transition from net-metering to net-billing schemes [11]. As shown in [12], even small variations in solar compensation mechanism significantly impact the adoption of PV and storage technologies.

It is clear that the evolving changes in DER technologies and policy will create a new uncertainty environment in which DER adopters will plan their investments. From their perspective, postponing the procurement and installation of DERs may allow taking advantage of the decreasing trajectories of technology costs. However, while waiting for "the best moment to invest", these potential investors might be losing important benefits and incentives coming from a favorable (DER friendly) regulatory framework. Thus, these long-term uncertainty in DER technology costs and policy trajectories introduce a new economic risk to potential DER adopters, which raises two main research questions: (i) how to plan DERs under this uncertainty environment? (ii) how to control the corresponding economic risk in the planning stage?

This paper aims to address these questions by proposing a multi-period DER investment model with economic risk constraints, considering technology costs and regulatory uncertainties.

1.2. Literature Review

This work expands on existing literature on behind-the-meter DER investment and planning models, traditionally used to determine the optimal portfolio and sizing of DERs assets in a building or a microgrid site, considering different costs and revenue streams [13]. Although there are some non-linear exceptions (e.g. [14]), these models are typically based on Mixed Integer Linear Programming (MILP) formulations [13, 15, 16] and have evolved over the last decade to address new challenges of DER planning and economics. Important additions to the original formulations of these investment models include the time resolution of the dispatch [17], the role of thermal loads in the optimal sizing [18], the optimal operation of multiple energy vectors [19], the security aspects of the design of electricity [20] and thermal [21] generation systems, the integration of electricity storage degradation models [22, 23], as well as the consideration of environmental objectives in the DER infrastructure planning [24].

Some of these models were also expanded to consider different types of uncertainty, such as the PV generation [25], the wind speed or the load demand [26], capturing the short-term uncertainty related to DER operations in the planning phase. The long-term aspects of planning are typically addressed through multi-period models, which determine not only the optimal portfolio and size of technologies, but also optimal timing of the investments within a planning horizon. In the context of DER investments, two multi-period planning models were presented in [27] and [28], considering deterministic evolution of load and prices throughout the horizon of investment. Stochastic models for DER planning were also proposed in the context of microgrid design, using a two-stage approach [29] and particle swarm optimization [30]. In both cases, these models focus on the long-term uncertainty exclusively associated with the load growth. The multi-period technology costs and regulatory uncertainties are not considered.

An additional objective of this paper is to approach uncertainty from the risk perspective. An approach to risk in multi-year investment problems, presented in several papers that show the economic benefits of deferring the investments/upgrades till a later time in the planning horizon, is known as the "real options approach". For example, in the DER investment case, the high volatility of fuel and electricity prices encourage the deferment of higher capacity assets [31, 32]. However, as pointed out in [32], the real options approach cannot analytically consider multiple risk factors, which may be a limitation in practical applications. Alternatively, another form of dealing with uncertainty in this context is quantifying multiple economic realizations using a risk measure, and guaranteeing that it falls below a specified threshold [33, 34]. Conditional Value-at-Risk (CVaR), due to its linear property, has been widely used to capture risk in various DER optimization problems. For example, on DER operations, [35] seeks to minimize a microgrid operational cost in addition to a corresponding CVaR component. In [36], CVaR is used to limit the risk associated with the operational cost of a scheduling problem for a wind-integrated smart multi-carrier energy hub, considering wind generation, electrical, and thermal demands as uncertainty parameters. In the context of power generation investment and planning, [37] uses a CVaR constraint to limit total investment and operational costs, considering fossil fuel prices and hydrological inflows as potential risk sources, while [38] employs CVaR to control the imbalance between energy generation and demand caused by uncertainty from wind and solar output and demand. Specifically in DER planning, CVaR has been used to capture risk where the uncertainty comes from electricity and gas prices [39]. The authors consider two different types of hedges: physical hedge (DER on-site investment) and financial hedge (gas/electricity futures). However, the model only captures investment at the beginning of the planning horizon, which does not allow the study of multi-year long-term uncertainties, such as the ones associated with DER technology costs and regulation.

1.3. Contribution

To the best of our knowledge, there is no multi-period planning model for behind-the-meter DERs which explicitly addresses technology costs and regulatory uncertainties. As discussed above, such model is key to help prosumers and microgrid owners plan their investment strategies in an increasing uncertainty environment around DER policy and regulation as well as around technology maturity and costs of DER assets, particularly PV and storage technologies. To fill this gap, this paper presents a muti-period investment and planning model with economic risk constraints that is able to generate consistent DER procurement strategies in this uncertainty environment. Specifically, the proposed model calculates the optimal investment in PV, batteries, and conventional distributed generation assets in each year of a planning horizon, taking into account the uncertainty in technology costs of solar and storage technologies, as well as in fuel pries and solar compensation policies. Finally, the model allows the investor to impose economic risk constraints to the problem, both in an annual basis and in the horizon of the investments. The paper uses a case study, comprising investments in a large building in California, to show how different types of economic risk constraints can affect the size of DER assets as well as the optimal schedule of the investments.

1.4. Structure

This paper is structured as follows. Section 2 presents the formulation of the model to determine an optimal portfolio for electricity generation subject to cost-risk balance. Section 3 presents a case study and discusses the numerical results. Section 4 concludes and proposes directions for future work.

2. Methodology

The optimization model considers 3 types of long-term uncertainty: (i) trajectories of electricity and fuel prices, describing the uncertainty associated with the evolution of the energy markets; (ii) scenarios of technology costs, representing the uncertainty around the maturation of PV and storage technologies; (iii) scenarios of evolution of the DER regulation policies, in particular the magnitude and structure of the solar compensation mechanisms. Considering the multiple combination of these scenarios together with deterministic technical parameters of DERs, the model outputs the optimal multi-period DER investment strategy that maximizes the expected revenue of the investor, while guaranteeing a maximum level of economic risk. Figure 1 provides an illustration of the methodology overview.

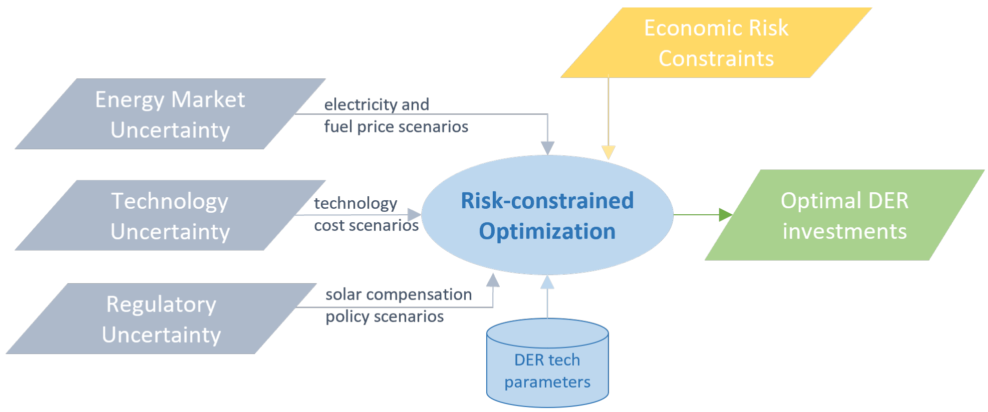


Figure 1: Methodology overview

It is important to stress that the optimization method presented in this paper is conceived to plan behind-the-meter DER assets and to support adoption decisions by medium and large-scale private consumers. In line with the literature on behind-the-meter DER economic planning [13]-[24], the model is designed to represent the investor interests, the objective function aims at maximizing their revenue, and the system-wide benefits and costs are assumed to be reflected in the prices, tariffs and solar compensation mechanisms. The impact of this adoption on the grid is out of the scope of this paper. Such analysis can be found in other works that study, for example, the impact of DER adoption on distribution grid reliability [40] and operational security [41], or that proposes environmental incentives to guide DER adoption [42].

This section presents a mathematical formulation for an investment and planning problem of DERs in a multi-period setting. We model the stochastic parameters with scenarios. Specifically, we use $|K|$ trajectories, each of which consists of realizations for each of the uncertainties: import tariff, export tariff, technology prices (PVs and batteries), and fuel prices for each operating and investment period.

2.1. Objective Function

The objective function aims to minimize net present cost of the DER investments and operations for the entire planning horizon. The detailed form of its components is given below.

1. Investment cost for continuous technology. Similar to [13] and [19], this represents the cost of technologies whose size of investments can be approximated by continuous variables, such as PV and storage assets. In this case, the size of the asset is represented by a quantity $x_{c,i}$ (in kW or kWh), while the decision of having it included in the portfolio is represented by the binary variable $b_{c,i}$.

$$\sum_{i\in\mathfrak{I}}\sum_{c\in\mathfrak{C}}\frac{\mathrm{CF}_{c,i}\cdot b_{c,i}+CV_{c,i}\cdot x_{c,i}}{(1+\rho)^{\mathrm{y}(i)-1}}. \tag{1}$$

The exponent in the denominator is $\mathrm{y}(i)-1$ instead of $\mathrm{y}(i)$ because the investment is made at the beginning of year i.

2. Investment cost for discrete technology. These costs are applied to DER technologies that are procured in integer quantities, $n_{d,i}$, such as thermal generators. The cost per unit invested is given by $\mathrm{CD}_{d,i}$.

$$\sum_{i\in\mathfrak{I}}\sum_{d\in\mathfrak{D}}\frac{\mathrm{CD}_{d,i}\cdot n_{d,i}}{(1+\rho)^{\mathrm{y}(i)-1}}. \tag{2}$$

3. Fuel costs of the generators:

$$\sum_{t\in\mathfrak{T}}\frac{FU_t\cdot\sum_{d\in\mathfrak{D}}fu_{d,t}}{(1+\rho)^{\mathrm{y}(t)-1}}. \tag{3}$$

4. Maintenance cost, which includes fixed and variable maintenance costs, for continuous and discrete technology:

$$\sum_{t\in\mathfrak{T}}\sum_{d\in\mathfrak{C}\cup\mathfrak{D}}\frac{\mathrm{CMF}_{d,t}\cdot caa_{d,t}+\mathrm{CMV}_{d,t}\cdot o_{d,t}}{(1+\rho)^{\mathrm{y}(t)-1}}. \tag{4}$$

5. Cost of energy purchases from utility:

$$\sum_{t\in\mathfrak{T}}\frac{u_t\cdot\Delta_t\cdot TI_t}{(1+\rho)^{\mathrm{y}(t)-1}}. \tag{5}$$

6. Revenue from the utility exports:

$$\sum_{t\in\mathfrak{T}}\frac{TE_t\cdot ux_t\cdot\Delta_t}{(1+\rho)^{\mathrm{y}(t)-1}}. \tag{6}$$

7. Remaining value of investment which has not expired at the end of the planning horizon:

$$\sum_{d\in\mathfrak{C}\cup\mathfrak{D}}car_d. \tag{7}$$

Some of the above components are functions of the stochastic parameters $CV_{c,i}$, FU_t, TI_t, and TE_t, which represent investment variable cost, fuel cost, import tariff, and export tariff, respectively. Regarding the notation, for a stochastic parameter W, W^k denotes a realization of W in scenario k. For example, FU_t^k denotes the fuel cost in period t and scenario k. We assume we know the values of these parameters in the first period, that is, $CV_{c,1}$, FU_1, TI_1, and TE_1 are known. The objective function minimizes the expectation of the sum of components (1)–(5) and the negative of components (6) and (7).

Let

$$
\begin{aligned}
f = \Bigg[& \sum_{i \in \mathcal{I}} \sum_{c \in \mathcal{C}} \frac{\mathrm{CF}_{c,i} \cdot b_{c,i}}{(1+\rho)^{\mathrm{y}(i)-1}} + \sum_{i \in \mathcal{I}} \sum_{d \in \mathcal{D}} \frac{\mathrm{CD}_{d,i} \cdot n_{d,i}}{(1+\rho)^{\mathrm{y}(i)-1}} + \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{C} \cup \mathcal{D}} \frac{\mathrm{CMF}_{d,t} \cdot caa_{d,t} + \mathrm{CMV}_{d,t} \cdot o_{d,t}}{(1+\rho)^{\mathrm{y}(t)-1}} \\
& - \sum_{d \in \mathcal{D}} \sum_{i=\max\{1, \overline{\mathcal{T}} - \mathrm{L}_d + 2\}}^{\overline{\mathcal{T}}+1} \left(\frac{\mathrm{CD}_{d,\overline{\mathcal{T}}+1} \cdot n_{d,i}}{(1+\rho)^{\mathrm{y}(\overline{\mathcal{T}}+1)-1}} \right) \cdot \left(1 - \frac{1-\gamma_d}{\mathrm{L}_d} (\overline{\mathcal{T}} + 1 - i) \right) \Bigg] \\
& + \Bigg[\sum_{i \in \mathcal{I}} \sum_{c \in \mathcal{C}} \frac{CV_{c,i} \cdot x_{c,i}}{(1+\rho)^{\mathrm{y}(i)-1}} + \sum_{t \in \mathcal{T}} \frac{FU_t \cdot \sum_{d \in \mathcal{D}} fu_{d,t}}{(1+\rho)^{\mathrm{y}(t)-1}} + \sum_{t \in \mathcal{T}} \frac{u_t \cdot \Delta_t \cdot TI_t}{(1+\rho)^{\mathrm{y}(t)-1}} \\
& - \sum_{t \in \mathcal{T}} \frac{TE_t \cdot ux_t \cdot \Delta_t}{(1+\rho)^{\mathrm{y}(t)-1}} - \sum_{c \in \mathcal{C}} \sum_{i=\max\{1, \overline{\mathcal{T}} - \mathrm{L}_c + 2\}}^{\overline{\mathcal{T}}+1} \left(\frac{CV_{c,\overline{\mathcal{T}}+1} \cdot x_{c,i}}{(1+\rho)^{\mathrm{y}(\overline{\mathcal{T}}+1)-1}} \right) \cdot \left(1 - \frac{1-\gamma_c}{\mathrm{L}_c} (\overline{\mathcal{T}} + 1 - i) \right) \Bigg].
\end{aligned}
$$

Considering uncertainty in technology costs of PV and storage assets, solar compensation policies as well as energy and fuel prices, the objective function is to minimize $\mathbb{E}[f]$.

2.2. Energy Balance Constraints

Energy balance constraints ensure that the amount of produced energy is equal to the amount of consumed energy. Energy balance for the system is presented in (8), which enforces that energy flow equality is satisfied for each operating period $t \in \mathcal{T}$.

$$
u_t + \sum_{d \in \mathcal{C} \cup \mathcal{D}} o_{d,t} = ux_t + \mathrm{ED}_t + \sum_{b \in \mathcal{B}} i_{b,t} \tag{8}
$$

Note that $o_{d,t}$, where d is a storage device, indicates the amount of energy discharged from the battery.

2.3. Investment Restriction Constraints

To comply with regulations or physical limits to the DERs investment capacity, we enforce constraints (9) and (10) to restrict the capacity installations of each technology.

$$
\sum_{i \in I} x_{c,i} \leqslant \overline{\mathrm{CCap}}_c, \text{for } c \in \mathcal{C}, \tag{9}
$$

$$
\sum_{i \in I} \mathrm{CAP}_d \cdot n_{d,i} \leqslant \overline{\mathrm{DCap}}_d, \text{for } d \in \mathcal{D}. \tag{10}
$$

In addition, we need constraints (11) to relate capacity investment decision $x_{i,c}$ and binary investment decision $b_{i,c}$. If an investment in technology c is made in period i, that is, $x_{i,c} > 0$, then the corresponding binary decision variable $b_{i,c}$ will be equal to 1, and hence a fixed cost has to be paid, otherwise it is 0:

$$
x_{c,i} \leqslant M \cdot b_{c,i}, \text{for } c \in \mathcal{C}, i \in \mathcal{I}, \tag{11}
$$

where M is a large number.

2.4. Generation Constraints

For each continuous generation technology c, its output in each operating period t is restricted by its available capacity times its power conversion factor in that period. For example, in the case of solar, $PCF_{c,t}$ would represent the hourly productivity profile.

$$o_{c,t} \leqslant caa_{c,t} \cdot \mathrm{PCF}_{c,t}. \tag{12}$$

Discrete generation constraints are imposed on diesel/gas generators and are based on the amount of fuel used by each generator d as in (13).

$$fu_{d,t} = o_{d,t} \cdot \Delta_t \cdot \frac{1}{\mu_d}, \text{ for } t \in \mathcal{T}. \tag{13}$$

Additionally, a generator's output is constrained to not exceed its available capacity:

$$o_{d,t} \leqslant caa_{d,t}, \text{ for } t \in \mathcal{T}. \tag{14}$$

It is also important to take into account the ramping rate for generators using constraints (15) and (16).

$$o_{d,t} - o_{d,t-1} \leqslant \mathrm{R}_d \cdot o_{d,t-1}, \text{ for } d \in \mathcal{D}, t \in \mathcal{T}\backslash\{1\}. \tag{15}$$

$$o_{d,t-1} - o_{d,t} \leqslant \mathrm{R}_d \cdot o_{d,t-1}, \text{ for } d \in \mathcal{D}, t \in \mathcal{T}\backslash\{1\}. \tag{16}$$

Constraint (17) ensures that the energy exported to the utility only comes from renewable generators:

$$\sum_{d \in \mathcal{D}} o_{d,t} \leqslant \mathrm{ED}_t, \text{ for } t \in \mathcal{T}. \tag{17}$$

2.5. Battery Storage Constraints

For each storage technology $b \in \mathcal{B}$ and each operating period $t \in \mathcal{T}$, we enforce the following set of constraints. This represents well-known first-order storage reservoir model with technical limit constraints, used in several DER investment models, e.g., [41]. For the sake of simplicity, and to keep the focus on the specific contribution of this paper, the storage degradation factors were not considered. It is important to stress that such expansion is straightforward, using the linearized model presented in [22].

$$soc_{b,t} = i_{b,t} \cdot \Delta_t \cdot \mathrm{CE}_b - o_{b,t} \cdot \Delta_t \cdot \frac{1}{\mathrm{DE}_b} + soc_{b,t-1} \cdot (1 - \mathrm{SD}_b), \tag{18}$$

$$o_{b,t} \leqslant \mathrm{MD}_b \cdot caa_{b,t}, \tag{19}$$

$$i_{b,t} \leqslant \mathrm{MC}_b \cdot caa_{b,t}, \tag{20}$$

$$soc_{b,t} \geqslant \underline{\mathrm{SC}}_b \cdot caa_{b,t}, \tag{21}$$

$$soc_{b,t} \leqslant caa_{b,t}, \tag{22}$$

$$soc_{b,1} = 0, \tag{23}$$

$$o_{b,1} = 0. \tag{24}$$

2.6. Available and Remaining Capacity Constraints

Variables *available capacity* and *remaining capacity* are functions of the investment decision variables $b_{d,i}, x_{d,i}$, and $n_{d,i}$. *Available capacity* of each type of DER indicates the capacity of that DER available for use at the beginning of period t. For continuous technology c, it is defined as

$$caa_{c,t} = \sum_{i=\max\{1,t-\mathrm{L}_c+1\}}^{t} x_{c,i}, \tag{25}$$

For discrete technology d, its available capacity is defined as

$$caa_{d,t} = \sum_{i=\max\{1,t-\mathrm{L}_d+1\}}^{t} \mathrm{CAP}_d \cdot n_{d,i}. \tag{26}$$

Remaining capacity of each type of DER indicates the amount which would have not expired by the end of the analysis, i.e., period $\overline{\mathcal{T}}$. For continuous technology c:

$$car_c = \sum_{i=\max\{1,\overline{\mathcal{T}}-\mathrm{L}_c+2\}}^{\overline{\mathcal{T}}+1} \left(\frac{CV_{c,\overline{\mathcal{T}}+1} \cdot x_{c,i}}{(1+\rho)^{\mathrm{y}(\overline{\mathcal{T}}+1)}}\right) \cdot \left(1 - \frac{1-\gamma_c}{\mathrm{L}_c}(\overline{\mathcal{T}}+1-i)\right), \tag{27}$$

Similarly, for discrete technology d:

$$car_d = \sum_{i=\max\{1,\overline{\mathcal{T}}-\mathrm{L}_d+2\}}^{\overline{\mathcal{T}}+1} \left(\frac{\mathrm{CD}_{d,\overline{\mathcal{T}}+1} \cdot n_{d,i}}{(1+\rho)^{\mathrm{y}(\overline{\mathcal{T}}+1)}}\right) \cdot \left(1 - \frac{1-\gamma_d}{\mathrm{L}_d}(\overline{\mathcal{T}}+1-i)\right). \tag{28}$$

We assume all technology lifetimes, L_d, are whole numbers of hours and $L_d \geqslant 1$. For all DER d, we set $b_{d,i}, x_{d,i}$, and $n_{d,i}$ to 0 when $i = \overline{\mathcal{T}}+1$. We need this condition to enforce the definition for remaining capacity of technology whose lifetime is $L_d = 1$ (so they will have a remaining value of 0).

In (27), the first term of the product inside the summation is the evaluation made right after the end of the analysis of the period-i investment in DER c. In the second term of the product, γ_c represents the portion of the investment in DER c salvaged at the end of its lifetime, so $\frac{1-\gamma_c}{L_c}$ represents the portion of c used in each of its operating years. $\overline{\mathcal{T}}+1-i$ is the number of years the DER would have been in use by the end of the analysis. Therefore, the second term of the product represents the remaining portion which would have not been used by the end of the analysis. A similar rationale is used in (28) for discrete technologies.

2.7. Risk Constraints

The purpose of risk constraints is to limit undesirable consequences of the uncertainty realization. Roughly speaking, a CVaR risk measure quantifies the right tail of the risk distribution, which constitutes the worst case scenarios. The risk distribution is induced by the underlying distribution of the stochastic parameters. The size of this right tail is determined by the corresponding VaR. One of the earliest papers on the use of CVaR in portfolio optimization is [43], which shows how CVaR can be used in either the objective function or constraints, and gives conditions under which the corresponding formulations yield the same efficient frontier. Specifically, for all convex risk measures, which includes CVaR, and convex cost f of decision $\boldsymbol{x}$, if the decision set $\boldsymbol{X}$ is convex and the constraints $f(\boldsymbol{x}) \leqslant \upsilon$ and $\mathrm{CVaR}^{\alpha}(\boldsymbol{x}) \leqslant \rho$ have internal points, the following three formulations yield the same efficient frontier as we vary their parameters μ, υ, and ρ:

$$
\begin{array}{lrr}
(P1) & \underset{\boldsymbol{x}}{\text{minimize}} & \mathrm{CVaR}^{\alpha}(\boldsymbol{x}) + \mu f(\boldsymbol{x}) \\
 & \text{subject to} & \boldsymbol{x} \in \boldsymbol{X}, \mu \geqslant 0. \\
(P2) & \underset{\boldsymbol{x}}{\text{minimize}} & \mathrm{CVaR}^{\alpha}(\boldsymbol{x}) \\
 & \text{subject to} & \boldsymbol{x} \in \boldsymbol{X}, f(\boldsymbol{x}) \leqslant \upsilon. \\
(P3) & \underset{\boldsymbol{x}}{\text{minimize}} & f(\boldsymbol{x}) \\
 & \text{subject to} & \boldsymbol{x} \in \boldsymbol{X}, \mathrm{CVaR}^{\alpha}(\boldsymbol{x}) \leqslant \rho.
\end{array}
$$

One major difference between having a CVaR term in the objective function (as in $(P1)$) and enforcing a CVaR constraint (as in $(P3)$) is that the former would have the same feasible set as in the risk neutral case (i.e., without adding the CVaR term). The meanings, however, are interpreted differently, given the choice of parameters μ in the objective function of $(P1)$ and υ in the risk constraint of $(P3)$. In this paper, we impose two types of CVaR constraint: one for the entire planning horizon, and the other for each operating year within the planning horizon.

For the entire planning horizon, we enforce one CVaR constraint to restrict the total investment and operation cost f of the worst $1-\alpha$ cases:

$$\Phi_{\alpha}\big(f\big) = h + \frac{1}{1-\alpha} \sum_{k \in \mathcal{K}} \mathrm{Pr}_k \cdot [f(\xi^k) - h]^+ \leqslant \overline{\mathrm{Risk}}, \tag{29}$$

where $[\cdot]^+ = \max\{\cdot, 0\}$, h is an auxiliary variable, and $\xi = (CV, FU, TI, TE)$ represents the vector of stochastic parameters.

We can relax (29) by the following set of linear constraints:

$$h + \frac{1}{1-\alpha} \sum_{k \in \mathcal{K}} \mathrm{Pr}_k \cdot z_k \leqslant \overline{\mathrm{Risk}}, \tag{30}$$

$$z_k \geqslant f(\xi^k) - h, \qquad \text{for } k \in \mathcal{K}, \tag{31}$$

$$z_k \geqslant 0, \qquad \text{for } k \in \mathcal{K}, \tag{32}$$

where z_k are auxiliary variables, and

$$
\begin{aligned}
f(\xi^k) = & \sum_{i \in \mathcal{I}} \sum_{c \in \mathcal{C}} \frac{\mathrm{CF}_{c,i} \cdot b_{c,i} + CV_{c,i}^k \cdot x_{c,i}}{(1+\rho)^{\mathrm{y}(i)-1}} + \sum_{i \in \mathcal{I}} \sum_{d \in \mathcal{D}} \frac{\mathrm{CD}_{d,i} \cdot n_{d,i}}{(1+\rho)^{\mathrm{y}(i)-1}} + \sum_{t \in \mathcal{T}} \frac{FU_t^k \cdot \sum_{d \in \mathcal{D}} fu_{d,t}}{(1+\rho)^{\mathrm{y}(t)-1}} \\
& + \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{C} \cup \mathcal{D}} \frac{\mathrm{CMF}_{d,t} \cdot caa_{d,t} + \mathrm{CMV}_{d,t} \cdot o_{d,t}}{(1+\rho)^{\mathrm{y}(t)-1}} + \sum_{t \in \mathcal{T}} \frac{u_t \cdot \Delta_t \cdot TI_t^k}{(1+\rho)^{\mathrm{y}(t)-1}} \\
& - \sum_{t \in \mathcal{T}} \frac{TE_t^k \cdot ux_t \cdot \Delta_t}{(1+\rho)^{\mathrm{y}(t)-1}} - \sum_{d \in \mathcal{C} \cup \mathcal{D}} car_d.
\end{aligned}
$$

$\overline{\text{Risk}}$ and α, specified by the planner, together determine the trade-off between risk and cost. Investors typically have a predetermined investment budget so it is natural that they want to make sure even in the $1-\alpha$ worst case scenarios the total cost still falls under this budget. Note that we can shape the distribution of f by enforcing multiple CVaR constraints. They would have the same form as (29) but with different values of α and $\overline{\text{Risk}}$.

For each operating year in the planning horizon, we impose one CVaR constraint. The "risk" considered is the running stream for that year. A year's running stream is defined as the difference between its running cost and its export revenue. Let us first define the *depreciation cost* for each operating year y:

$$d_y = \sum_{t \in \mathcal{T}_y} \sum_{i=\max\{1, t-L_d+1\}}^{t} \frac{1}{(1+\rho)^{\mathrm{y}(i)-1}} \left[\sum_{c \in \mathcal{C}} \frac{\mathrm{CF}_{c,i} \cdot b_{c,i} + CV_{c,i} \cdot x_{c,i}}{L_c} + \sum_{d \in \mathcal{D}} \frac{\mathrm{CD}_{d,i} \cdot n_{d,i}}{L_d} \right]. \tag{33}$$

The inner summation of (33) sums up all investments which have been invested and not expired by the end of operating period t. Note that we assume the investments have a salvage value of 0 at the end of their lifetime, i.e., salvage factor $\gamma_d = 0$ for all d. The lifetime parameters Lc and L_d have the same units as the length of each operating period t. We define the *running stream* f_y, which is the sum of fuel cost, maintenance cost, utility cost, depreciation cost, and the negation of export revenue, for each year as:

$$\begin{aligned} f_y(\xi) = & \sum_{t \in \mathcal{T}_y} \frac{FU_t \cdot \sum_{d \in \mathcal{D}} fu_{d,t}}{(1+\rho)^{\mathrm{y}(t)-1}} && (34) \\ & + \sum_{t \in \mathcal{T}_y} \sum_{d \in \mathcal{C} \cup \mathcal{D}} \frac{\mathrm{CMF}_{d,t} \cdot caa_{d,t} + \mathrm{CMV}_{d,t} \cdot o_{d,t}}{(1+\rho)^{\mathrm{y}(t)-1}} && (35) \\ & + \sum_{t \in \mathcal{T}_y} \frac{u_t \cdot \Delta_t \cdot TI_t}{(1+\rho)^{\mathrm{y}(t)-1}} && (36) \\ & + d_y && (37) \\ & - \sum_{t \in \mathcal{T}_y} \frac{TE_t \cdot ux_t \cdot \Delta_t}{(1+\rho)^{\mathrm{y}(t)-1}}, && (38) \end{aligned}$$

where $\mathcal{T}_y$ is the set of operating periods in year y and for $y = 1, 2, ..., \overline{\mathcal{Y}}$.

For each year $y \in \mathcal{Y}$ in the planning horizon, we impose one CVaR constraint to restrict the running stream of the worst $1 - \alpha_y$ cases:

$$\Phi_{\alpha_y}(f_y) = h_y + \frac{1}{1-\alpha_y} \sum_{k \in \mathcal{K}} \mathrm{Pr}_k \cdot [f_y(\xi^k) - h_y]^+ \leqslant \overline{\mathrm{Risk}_y}, \tag{39}$$

where h_y are auxiliary variables. We can relax (39) by the following set of linear constraints:

$$h_y + \frac{1}{1-\alpha_y} \sum_{k \in \mathcal{K}} \mathrm{Pr}_k \cdot z_{y,k} \leqslant \overline{\mathrm{Risk}_y}, \tag{40}$$

$$z_{y,k} \geqslant f_y(\xi^k) - h_y, \qquad \text{for } k \in \mathcal{K}, \tag{41}$$

$$z_{y,k} \geqslant 0, \qquad \text{for } k \in \mathcal{K}, \tag{42}$$

where $z_{y,k}$ are auxiliary variables.

Table 1: Specifications of Discrete Technology

Type	Capacity [kW]	Investment Cost [$/unit]	Lifetime [year]	Fuel Conversion Efficiency	Ramping Factor
NG_125	125	18000	20	0.32	0.5
NG_40	40	12000	20	0.29	0.5

Table 2: Specifications of Battery Technology

Minimum State of Charge	0.05
Max Power Discharged Ratio	0.3
Max Power Charged Ratio	0.3
Charging Efficiency	0.95
Discharging Efficiency	0.95
Self-discharged Coefficient	0.01
Lifetime [year]	10

Investors might also have a predetermined investment and operating budget for each year depending on their cash flow, so it is natural that they want to make sure even in the $1 - \alpha_y$ worst case scenarios of year y the running stream still falls under this budget.

3. Case Study

This section presents a case study to illustrate how the proposed model can find the optimal multi-year DER investment strategy, considering PV, storage and two types of natural gas generators. The program is solved by CPLEX using a computer with 8 GB of RAM and a 2.3 GHz Quad-Core processor.

3.1. Data

The case study considers the annual electric load profile of the reference mid rise apartment building in the climate zone of San Francisco, California, obtained from the US Department of Energy Reference buildings database [44]. When constructing the profile, the reference cooling and space heating loads were assumed to be electric. The annual PV productivity profile was built based on the radiation data from Typical Meteorological Year data set [45] for the same climate zone.

As mentioned above, the set of DER investments considered in this case study include PVs, batteries, and generators. Two types of natural gas generators, with different nameplate capacity sizes, listed in Table 1, were taken into account. The storage parameters used in this simulation are presented in Table 2.

Regarding the technology costs, we assume the reference *energy storage price* in period 1 to be 563 $/kWh. This price is based on a 13.5 kWh Tesla Powerwall, which is quoted $7,600 [46]. According to

Table 3: Hourly Import Tariff for the First Year of the Planning Horizon [$/kWh]

Time	Summer (May – September)	Winter (October – April)
10:00 AM – 1:00 PM	0.2653	0.1896
1:00 PM – 5:00 PM	0.3773	0.1896
5:00 PM – 7:00 PM	0.3773	0.2064
7:00 PM – 9:00 PM	0.2653	0.2064
All other times	0.1852	0.1896

different estimates, the energy storage technology costs are projected to decrease around 6.5% annually for the 2019–2028 period [47], or decrease 8% annually for the 2018–2022 period [48]. We set the *PV price* in period 1 to 2400 $/kW. This price is projected to decrease by 5–7 % annually for the 2019–2028 period [49].

The reference *natural gas price* used in this study was obtained from the Pacific Gas and Electric (PG&E) residential gas rate in December 2019, which was 1.36907 $ per therm (approximately equivalent to 0.0467259 $/kWh) [50]. According to [51], this price is projected to increase by approximately 3.64% annually for the 2019–2030 period.

A time-of-use residential rate from PG&E was also assumed to define the reference import tariff in different hours of the day, as presented in Table 3. The remuneration of PV exports was abstractly defined in relation to the import tariff: $TE_t = a \cdot TI_t$. Here a expresses the solar compensation policy. For example, when $a = 1$, the exports are remunerated at the same rate of the imports, replicating similar conditions of a net-metering scheme. Conversely, when $a < 1$, the PV injections lose value in relation to the energy costs, replicating a net-billing scheme, which typically favours PV self-consumption and the utilization of storage resources.

To model the uncertainty of the technology costs, we assume 3 decreasing trajectories for PV and battery costs with different probabilities (Figure 3). The objective is to represent pessimistic, realistic and optimistic projections for the maturity of each technology. Similarly, we generate 5 trajectories projecting natural gas prices until the end of the investment horizon (Figure 2) as well as 5 scenarios of annual increase of electricity costs (table 5). Additionally, we model the regulatory uncertainty around solar compensation policies by generating 5 scenarios for the parameter a. These scenarios (Table 4) represent sudden changes in the regulatory framework around solar compensation, specifically the transition from net-metering to net-billing schemes (with exports remunerated at 30% of the electricity rate) at any point in time, during the investment horizon. Thus, the combined trajectories associated with the uncertainty of technology costs, fuel and electricity prices, and solar compensation policy, result in a total of 1,125 scenarios k in the proposed model.

Table 4: Scenarios of a

Scenario	1	2	3	4	5
Probability	6.5%	24.8%	38.1%	24.6%	5.9%
Year					
1	1	1	1	1	1
2	1	1	1	1	1
3	0.3	1	1	1	1
4	0.3	1	1	1	1
5	0.3	0.3	1	1	1
6	0.3	0.3	1	1	1
7	0.3	0.3	0.3	1	1
8	0	0.3	0.3	1	1
9	0	0.3	0.3	0.3	1
10	0	0	0.3	0.3	1

Table 5: Increase Rate of Import Tariff

Scenario	1	2	3	4	5
Annual rate	0.5%	1.0%	1.5%	2.0%	2.5%
Probability	6.51%	24.82%	38.09%	24.64%	5.94%

Figure 2: Trajectories for Natural Gas Price.

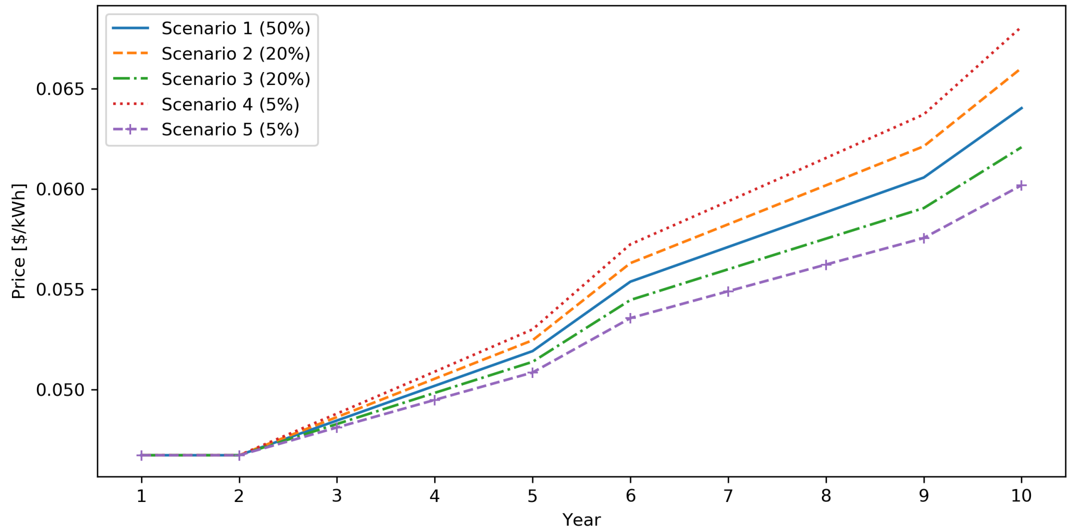
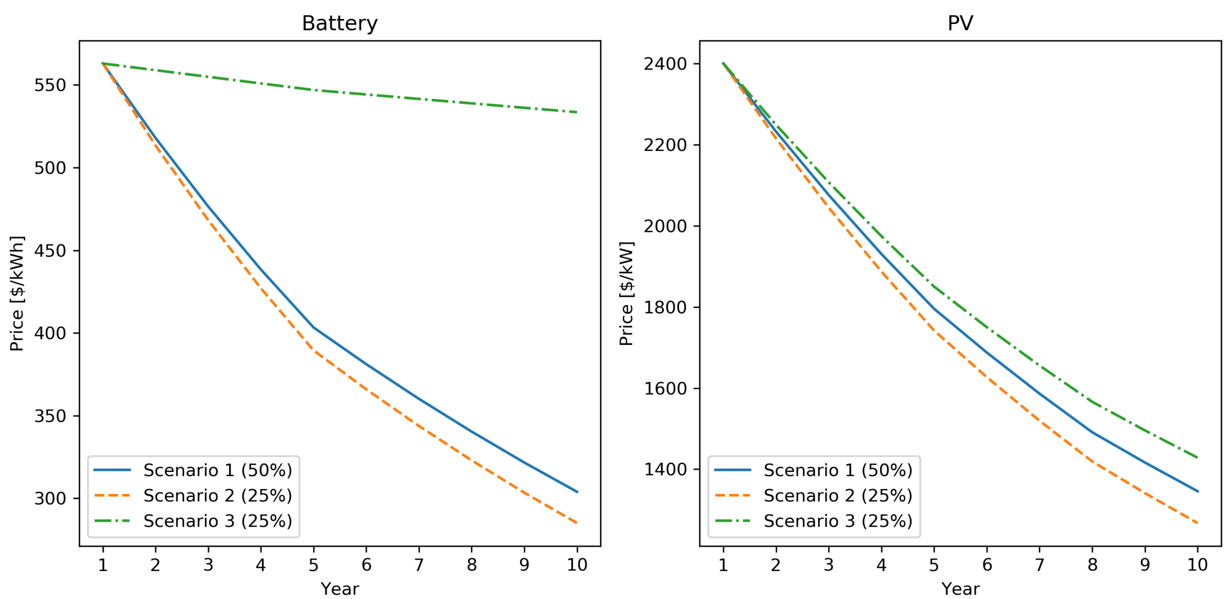


Figure 3: Trajectories for PV and Battery Price.



We consider a horizon of 10 years of investment and aggregate the hourly load profile into 2 design days per month, representing a weekday and weekend. Considering the 120 months of the horizon, this results in 5,760 hourly operating periods. In this case study, DERs can be purchased at the beginning of each year. Given that all technologies lifetimes are greater than or equal to the study horizon of 10 years, and investments take place only at the beginning of the first period of each year, we can simplify the depreciation cost expression (33) as:

$$d_y^k = A \times \sum_{i=1}^{\text{first operating period of year } y} \frac{1}{(1+\rho)^{\mathrm{y}(i)-1}} \left[\sum_{c \in \mathcal{C}} \frac{\mathrm{CF}_{c,i} \cdot b_{c,i} + CV_{c,i}^k \cdot x_{c,i}}{L_c} + \sum_{d \in \mathcal{D}} \frac{\mathrm{CD}_{d,i} \cdot n_{d,i}}{L_d} \right]. \quad (43)$$

For example, if $y = 1$, the upper bound of the summation is 1; if $y = 2$, the upper bound of the summation is 577; if $y = 3$, the upper bound of the summation is 1153. In addition, A is the number of operating periods in a year, which is the product of number of profile days, number of hours per day, and number of months in a year. In this case, $A = 2 \times 24 \times 12 = 576$.

We assume an annual discount rate ρ of 2% and consider $\alpha = \alpha_y = 95\%$ for the CVaR constraints.

3.2. Numerical Results

Here we examine the impact of CVaR constraint (29). First without, and then with CVaR constraints for the yearly running stream (39).

3.2.1. Including investment horizon risk constraints

In this subsection, we present the results when adding risk constraints related to the overall investment strategy. In other words, we exclude the CVaR constraints for the yearly running stream. These will be discussed later, in the next section.

Table 6: Comparison of Methods

	No DERs Investment	DERs Investment with No CVaR Constraints	DERs Investment with $\overline{\text{Risk}} = 450,000$
Objective Function	\$631,682	\$365,048	\$377,479
95%–CVaR	\$660,181	\$484,992	\$449,856

As shown in Table 6 the expected cost of the system without investments is \$631,682 and the 95%–CVaR value is \$660,181 (this means that only the worst 5% of cases' costs exceed \$660,181). When investments are allowed and no risk constraint is enforced, the expected cost decreases to \$365,048 and the 95%–CVaR to \$484,992. When imposing a constraint of \$450,000 in the 95%–CVaR, the expected cost increases by 3.4% to \$377,479 but 95%–CVaR decreases by 7.2% to \$449,856 comparing to the previous case. In other words, this 3.4% can be seen as an additional cost paid to reduce the risk of the investor, mitigating the exposure to the technology and regulatory uncertainties. Thus, the choice of $\overline{\text{Risk}} = 450,000$ is only illustrative of the trade-off between cost and risk. In practice, decision makers would choose $\overline{\text{Risk}}$ among a set of solutions, according to their risk tolerance and/or their budget constraints. Figure 4 presents the cost–risk Pareto frontier to further illustrate how this trade-off relationship could be presented to decision makers.

Figure 4: Cost-Risk Pareto Frontier (without CVaR constraints for yearly running stream).

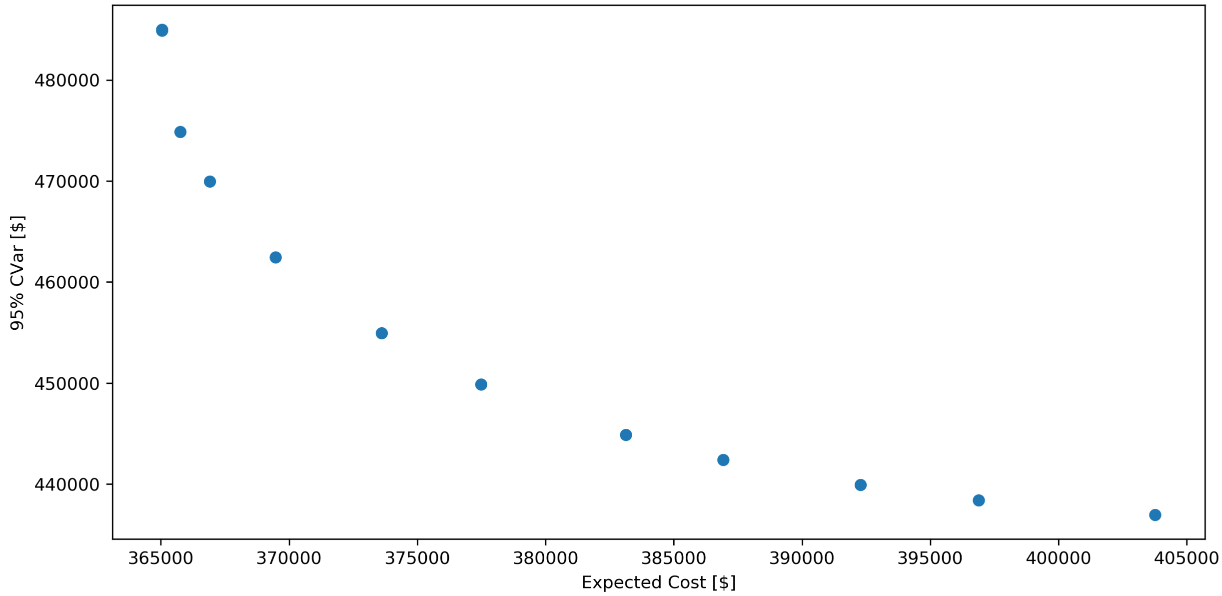


Table 7 presents the corresponding DER portfolios for various choices of $\overline{\text{Risk}}$, where case A1 is the least risk averse (no CVaR constraints) and case D1 is the most risk averse (lowest possible $\overline{\text{Risk}}$ at which there is still a solution). For all values of $\overline{\text{Risk}}$ that we run, a gas generator of 40 kW is installed in the first year, regardless of the level of risk averse assumed in the solution. As we decrease the risk exposure by reducing the value of $\overline{\text{Risk}}$, solar investment decreases, while battery investment increases. In addition, a common trend in all scenarios (including when no risk constraint is imposed) is that battery investments occur later in the planning horizon due to the distribution of a (see Table 4). In fact, as time progresses, a transition from net-metering to net-billing scheme is more likely to happen, which creates an incentive for the utilization of storage resources at the end of the investment horizon.

To further illustrate the advantage of our model in accounting for the economic risk associated with technology and regulatory uncertainties, we compare three approaches to DER planning (deterministic, stochastic and risk-constrained) in a situation where the worst case scenario happens. From a DER investor's perspective, the worst case scenario corresponds to the highest import tariff, the lowest export tariff, the highest natural gas price and the slowest decreasing rate in DER prices, *i.e.*, a combination of the following: Scenario 1 of a, Scenario 5 of Import Tariff, Scenario 4 of Natural Gas Price, Scenario 3 of Battery and PV prices. Assuming this worst case combination of scenarios, we compare the costs of the planning solutions obtained by the simple stochastic and risk-constrained approaches (solutions A1 and D1 in Table 7) with a deterministic planning solution obtained for a central scenario (Scenario 3 of a and Import Tariff, Scenario 1 of Natural Gas, PV and Battery prices). The economic evaluation in Table 8 shows that the approach with CVaR leads to significantly better costs when the technology and regulatory conditions are unfavorable to DER investments.

Table 7: Comparison of Generation Portfolios (without CVaR constraints for yearly running stream)

Case	A1	B1	C1	D1
	No CVaR	$\overline{\text{Risk}}$		
		450,000	442,500	437,000
Installed Capacity [kW]				
Solar	153.78	152.97	152.55	147.99
Gas Generator	40	40	40	40
Battery	262.55	273.63	278.85	282.92
Expected Generated Energy [kWh]				
Solar	82%	72%	66%	58%
Gas Generator	18%	28%	34%	42%
Expected Cost [$]	$365,028	$377,185	$386,442	$402,551
Expected Cost [%, compared to case A1]	100%	103%	106%	110%
95%–CVaR [$]	$485,205	$449,930	$442,401	$436,958
95%–CVaR [%, compared to case A1]	100%	93%	91%	90%
Installed Capacity [kW] [solar/battery/gas]				
Year 1	124.6/0/40	118.19/0/40	104.31/0/40	79.47/0/40
Year 2	29.19/0/0	0/0/0	0/0/0	0/0/0
Year 3	0/0/0	0/0/0	0/0/0	0/25.16/0
Year 4	0/0/0	0/0/0	0/0/0	0/0/0
Year 5	0/0/0	0/62.99/0	0/67.65/0	0/0/0
Year 6	0/0/0	0/0/0	0/0/0	20.37/79.87/0
Year 7	0/186.89/0	0/52.18/0	0/0/0	0/0/0
Year 8	0/0/0	0/74.35/0	0/120.3/0	0/86.55/0
Year 9	0/0/0	0/0/0	0/0/0	0/0/0
Year 10	0/75.67/0	34.78/84.11/0	48.24/90.89/0	48.15/91.34/0

Table 8: Comparison of Different Approaches for the Worst Case Scenario

Case	Deterministic Planning	Stochastic Planning	Stochastic Planning with CVaR
Cost [$]	$483,842	$482,354	$447,538
Installed Capacity [kW] [solar/battery/gas]			
Year 1	136.03/0/40	124.6/0/40	79.47/0/40
Year 2	0/0/0/	29.19/0/0	0/0/0
Year 3	29.07/0/0	0/0/0	0/25.16/0
Year 4	0/0/0	0/0/0	0/0/0
Year 5	0/203.15/0	0/0/0	0/0/0
Year 6	0/0/0	0/0/0	20.37/79.87/0
Year 7	0/0/0	0/186.89/0	0/0/0
Year 8	0/0/0	0/0/0	0/86.55/0
Year 9	0/0/0	0/0/0	0/0/0
Year 10	0/59.43/0	0/75.67/0	48.15/91.34/0

3.2.2. Including CVaR Constraints for the Yearly Running Stream

This subsection presents the investment results when risk constraints are added to the yearly running stream. The addition of such CVaR constraints (39) makes sense when investors want to limit their risk of exceeding the annual budget for the yearly running stream. To illustrate the impact of those constraints, we fix $\overline{\text{Risk}}$ to 450,000 and set the same $\overline{\text{Risk}}_y$ for all years y. However, it is important to stress that each year can have a different value of $\overline{\text{Risk}}_y$ depending, for example, on the investors' cash flow restrictions. Similar to the previous subsection, Table 9 presents different risk policy solutions: from A2 to G2, where G2 is the most constrained investment solution.

As shown in the table, the introduction of annual risk constraints has an impact on the objective function. For example, when reducing the yearly CVaR limit from $42,500 to $40,000, the overall costs increase 2.36%. On the other hand, despite a small decrease in battery investments, there is no major modifications to the optimal portfolio of DERs. However, it is possible to observe a significant change in the multi-period strategy of investments. In other words, the annual risk constraints have a significant impact on the way investments are made throughout the years. For example, when looking at the lower risk solution (G2), one can notice that some PV investments are delayed while some storage investments are anticipated. In fact, this behavior decreases the risk in two ways: first, it spreads out the investments across the time; second, it makes the PV and storage assets coincide earlier in the horizon, which provides more flexibility to deal with sudden changes in solar compensation policies. Thus, this result highlights the importance of a multi-period investment model when facing significant uncertainties in DER technology costs and regulatory policies.

Table 9: Comparison of Generation Portfolios, $\overline{\text{Risk}} = 450,000$

Case	A2	B2	C2	D2	E2	F2	G2
	No CVaR_y	$\overline{\text{Risk}}_y$					
		42,500	42,000	41,500	41,250	41,000	40,000
Installed Capacity [kW]							
Solar	152.97	152.97	152.97	153.02	152.97	152.61	152.34
Gas Generator	40	40	40	40	40	40	40
Battery	273.63	273.63	273.63	273.09	271.35	272.51	271.68
Expected Generated Energy [kWh]							
Solar	72%	72%	72%	72%	72%	71%	65%
Gas Generator	28%	28%	28%	28%	28%	29%	35%
Expected Cost [$]	$377,185	$377,185	$377,186	$377,436	$377,822	$378,644	$386,077
Expected Cost [%, compared to case A2]	100.00%	100.00%	100.00%	100.07%	100.17%	100.39%	102.36%
Installed Capacity [kW] [solar/battery/gas]							
Year 1	118.19/0/40	118.19/0/40	118.24/0/40	113.87/0/40	110.76/0/40	105.99/0/40	71.96/0/40
Year 2	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0
Year 3	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	25.53/17.93/0
Year 4	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	0/31.19/0	0/0/0/
Year 5	0/62.99/0	0/62.99/0	0/62.21/0	0/54.91/0	0/47.37/0	0/0/0	20.14/0/0
Year 6	0/0/0	0/0/0	0/0/0	10.88/0/0	16.97/0/0	22.35/0/0	0/42.82/0
Year 7	0/52.18/0	0/52.18/0	0/52.96/0	0/82.75/0	0/94.95/0	0/99.53/0	0/0/0
Year 8	0/74.35/0	0/74.35/0	0/74.48/0	0/57.05/0	0/53.99/0	0/64.1/0	0/123.89/0
Year 9	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0	0/0/0
Year 10	34.78/84.11/0	34.78/84.11/0	34.73/83.98/0	28.27/78.37/0	25.23/75.04/0	24.27/77.7/0	34.71/87.05/0

4. Conclusion and Future Works

This paper presents a stochastic muti-period investment and planning model with economic risk constraints facing an uncertainty environment around DER technology costs and regulatory policies. The model is capable of generating consistent risk-constrained optimal DER investment strategies for a multi-year horizon.

As shown in the results, such strategies can be translated into "cost vs risk" solutions to support the decisions of prosumers and microgrids owners, who are interested in investing in DERs. In particular, the new modeling characteristics introduced in this paper allow investors make decisions that are robust to long-term variations of the regulatory and energy market conditions, such as variation in natural gas prices or electricity rates.

We showed that risk-controlled solutions entail additional expected investment costs. From the investor's perspective, this can be seen as price to pay to be less exposed to the uncertainty in DER regulation and technology prices.

The results also demonstrated that different types of risk constraints can impact not only the size, but also the timing of these investments. In particular, when imposing higher risk-aversion constraints to the problem, the optimal solutions tend to spread out the procurement of the DER assets throughout the planning horizon. Additionally, in the presence of uncertainty about solar compensation schemes (e.g., transition from net-metering to net-billing), lower risk strategies tend to articulate PV and storage investments, allowing them to coincide for longer periods, and providing more flexibility to adapt to sudden variations in solar exports remuneration.

Thus, accounting for the economic risks associated with technology regulatory conditions of DER investments is key, particularly for medium and large size prosumers and microgrid owners. It is important that risk-based methodologies, such as the one developed in this paper, can be adopted by the industry and incorporated into a new generation of DERs and microgrid planning tools to support the deployment of economically robust portfolios of DER investments.

Finally, potential future works may include the combination of the economic risk framework presented in this paper with other forms of risk relevant to DER planning, such as the security risk in the context of resilience investment applications.

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