LBNL-2001059

Lawrence Berkeley National Laboratory

The impact of Ancillary Services in optimal DER investment decisions

Gonçalo Cardoso[1], Michael Stadler[1,2], Salman Mashayekh[1], Elias Hartvigsson[3]

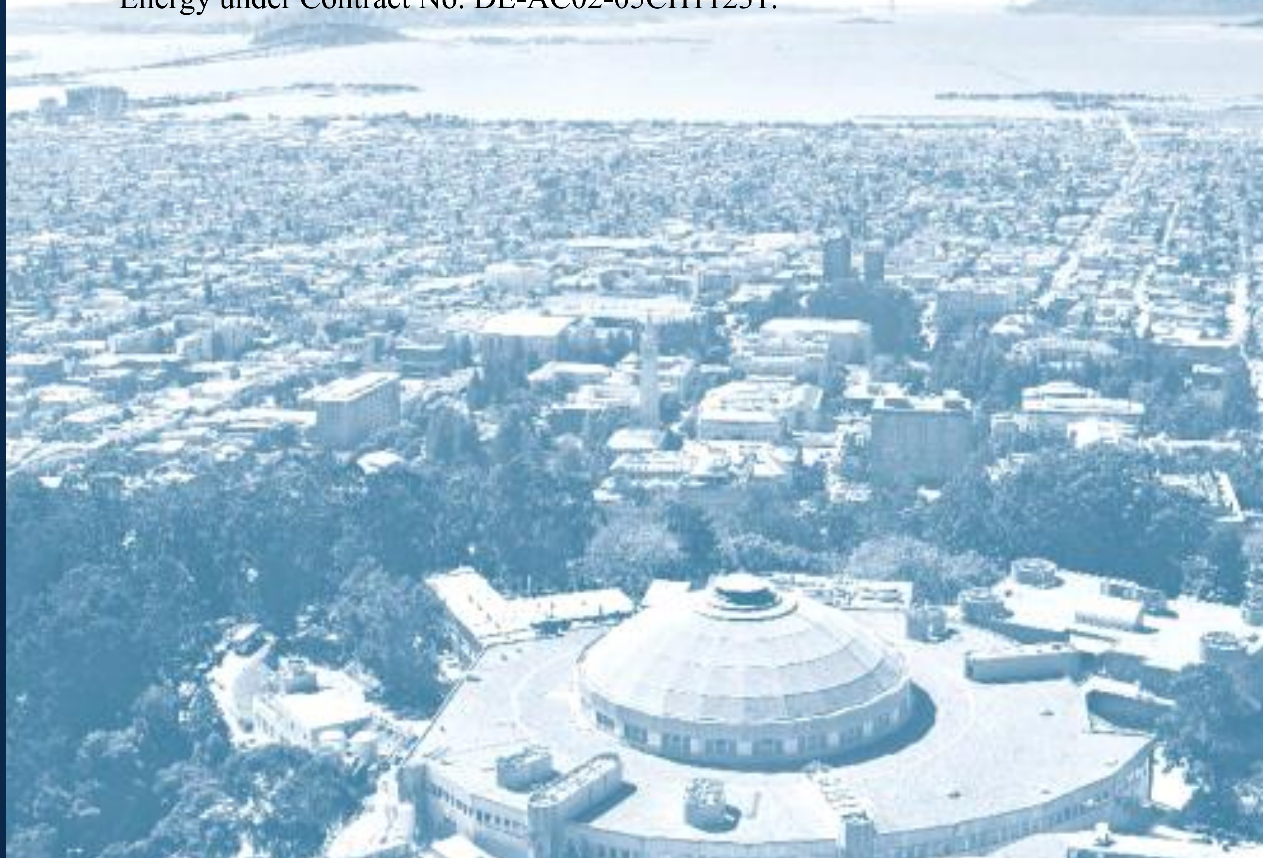
[1] Lawrence Berkeley National Laboratory, 1 Cyclotron Road, MS: 90-1121, Berkeley, California 94720, USA
[2] Center for Energy and innovative Technologies (CET), Doberggasse 9, 3681 Hofamt Priel, Austria

[3] Chalmers University of Technology, Maskingränd 2, 412 58 Göteborg, Sweden

To be published in Energy

April 2017

Partial funding for this work was provided by the Office of Electricity Delivery and Energy Reliability, Distributed Energy Program of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.



Disclaimer

The impact of Ancillary Services in optimal DER investment decisions

G. Cardoso[1,a], M. Stadler[1,b], S. Mashayekh[1,c], E. Hartvigsson[2,d]

[1]Lawrence Berkeley National Laboratory, USA
[2]Chalmers University of Technology, Sweden
[a]corresponding author, gfcardoso@lbl.gov
[b]mstadler@lbl.gov, [c]smashayekh@lbl.gov, [d]elias.hartvigsson@chalmers.se

Abstract

Microgrid resource sizing problems typically include the analysis of a combination of value streams such as peak shaving, load shifting, or load scheduling, which support the economic feasibility of the microgrid deployment. However, microgrid benefits can go beyond these, and the ability to provide ancillary grid services such as frequency regulation or spinning and non-spinning reserves is well known, despite typically not being considered in resource sizing problems. This paper proposes the expansion of the Distributed Energy Resources Customer Adoption Model (DER-CAM), a state-of-the-art microgrid resource sizing model, to include revenue streams resulting from the participation in ancillary service markets. Results suggest that participation in such markets may not only influence the optimum resource sizing, but also the operational dispatch, with results being strongly influenced by the exact market requirements and clearing prices.

Keywords

Microgrid, ancillary services, decision support tool, optimization, distributed energy resources, mixed integer linear programming

1. Introduction

Microgrids, defined as clusters of small sources, storage systems, and loads, which presents themselves to the main grid as single, flexible, and controllable entities [1,2], have recently been attracted considerable attention from both academia and industry due to their potential benefits. These include the ability to reduce costs of energy delivery as well as alleviate environmental burdens due to increased efficiency in supply, but also to increase system resiliency and reliability, particularly in the event of natural disasters and prolonged outages. By introducing dispatchable generation and storage assets, microgrids can be a valuable resource to the main grid and potentially contribute to issues such as hosting capacity or upgrade deferrals, while also being naturally more independent from it. While this creates settings for added flexibility in grid operation, microgrids are complex systems that require specific infrastructure, resource coordination, and information flows, as well as added layers of protection and power quality assurance. The added costs resulting form the need to meet these conditions can potentially jeopardize the economic viability of microgrids, and therefore it is fundamental to take into account all different revenue streams, both direct and indirect, that result from microgrid deployment [3].

Several methods are proposed in the literature to address the problem of sizing DER assets in microgrids. Simulation-based models are commonly found [4–8], but mathematical programing or optimization algorithms are equally available. In this domain, the most commonly used approaches are mixed integer linear programming (MILP) models [9–13], and mixed integer non-linear programming (MINLP) models [14,15].

Analyzing the fundamental differences between these approaches, simulation models generally have the advantage of being straightforward to develop, solve extremely fast, and allow non-linear behaviors can be easily modeled. Their main drawback is that they tend to rely heavily on user input and prior knowledge to build candidate solutions, and considering different objectives (e.g. changing from cost minimization, to CO_2 minimization) typically requires developing separate algorithms. In addition, simulation models do not guarantee that an optimal solution is found, which can be a key limitation in large problems where multiple technology options are available and defining candidate solutions can be extremely complex. Popular examples of commercial software belonging to this category includes HOMER [5,6] or RETSCREEN [7].

In contrast, optimization algorithms have the main advantage of guaranteeing optimality provided a convex feasible region is created, and typically do not require user intervention to define a feasible solution space. However, optimization models can become extremely large and require very significant computational power, potentially leading to intractable cases. Different approaches exist within the domain of optimization algorithms, with the main distinction regarding the nature of the objective function and constrains, particularly on linearity. Linear and mixed-integer linear models tend to have fast solution times, albeit at the cost of potentially losing accuracy in the representation of non-linear effects. An example of a publicly available MILP model used for microgrid resource sizing is the Distributed Energy Resources – Customer Adoption Model (DER-CAM) [9–11], although other similar models may be found in literature [16–18], with key differences being the number and type of technologies considered, the data granularity and time horizon, the exact definition of the objective function, and the number of energy carriers and end-uses being considered. Nonlinear and mixed-integer nonlinear (MINLP) models, on the other hand, add complexity and detail that MILP models may fail to capture, by explicitly including non-linearity in their formulation. While this may more accurately model the behavior of different technologies, it is often followed by the downside that finding a solution may not be possible due to the non-convexities occurring in the search space. Examples of such models can be found in [14,15,19].

More in-depth reviews of the different methodologies used for optimal microgrid resource sizing can be found in [20–22].

While microgrid resource sizing tools typically consider key revenue streams such as peak shaving, load shifting, or power exports, very little emphasis is given to revenues resulting from the participation in ancillary service (AS) markets, although their potential is known and has been widely identified [23–26].

The most common ancillary service markets include spinning and non-spinning reserve, as well as frequency up- and down-regulation, although other markets such as black start, reactive supply and voltage regulation also exist. These markets often operate using a bidding structure, where awarded bids are required to guarantee the service they have bid for, and while the exact rules depend on the different markets operated within each ISO, each market is typically characterized by different requirements including the time to react to a utility signal, the minimum asset size, or bid duration [27]. A detailed analysis of different AS markets currently operating in the United States can be found in [28].

Different studies have addressed operational strategies to use microgrid resources for AS provision, although they do not take into account potential revenues in the process of microgrid design. Namely, in [29] and [30] the participation of microgrids in ancillary service markets as an alternative to conventional generation and storage is discussed, covering both participation frequency regulation markets and voltage control. Specifically, the work presented in [29] introduces an adaptive hill climbing strategy to develop a central demand response (DR) algorithm, which the authors refer to as "Central Direct Load Control". The results presented in this work suggest that microgrid generation and storage assets can successfully be leveraged to regulate the system frequency and voltage while minimizing the amount of manipulated responsive loads needed to keep the frequency within the desired range. In a more recent work, authors [30] present a new framework for the coordination of distributed energy resources (DER) and DR, in order to support voltage and frequency in islanded microgrids. In this work that is formulated as a multi-objective problem and is solved by particle swarm optimization, the loads are classified into controllable and non-controllable categories. The results demonstrate that the proposed control strategy works effectively for different generation and consumption patterns. Another method that aims to improve a microgrid resilience following an unplanned islanding is presented in [31], where the microgrid is equipped with DERs, energy storage, and electric vehicles. A DR strategy is deployed that curtails pre-defined low-priority loads. The objective is to minimize the amount of load curtailed, while ensuring the microgrid stability in terms of energy balance and frequency control. This method was proven effective for short periods of islanding.

While surveying the existing literature suggests that both microgrid resource sizing problems and the potential benefits from ancillary service market participation are well-known, little work has been done regarding the inclusion of AS revenue streams in the process of finding optimal DER capacity for microgrids. This paper contributes to bridging this gap and builds on the state-of-the-art by introducing revenue streams from AS market participation in DER and microgrid sizing problems. Particularly, this is done by leveraging on DER-CAM, a state-of-the-art MILP optimization model used for microgrid sizing, and implementing support for the most common AS market products.

The remaining of this paper is organized as follows: In section 2, the mathematical formulation of DER-CAM is presented, along with changes introduced during this work. In section 3 a case study is introduced to demonstrate the inclusion of AS market revenues in microgrid sizing problems, including all key data used. Section 4 discusses the results obtained, and in Section 5 the key conclusions are presented.

2. DER-CAM

2.1. Overview, Objective, and Applications

The Distributed Energy Resources – Customer Adoption Model (DER-CAM) is a state-of-the-art decision support tool for decentralized energy systems, including buildings and microgrids, and has been developed by the Lawrence Berkeley National Laboratory. DER-CAM determines the optimal mix and capacity of the DERs, as well as the optimal dispatch of these resources, for a microgrid under different settings. DER-CAM is formulated as a Mixed Integer Linear Program (MILP), where the key inputs include customer loads broken into several end-uses; cost and performance characteristics of generation and storage technologies (e.g., investment cost, operation and maintenance costs, efficiency, heat-to-power ratio maximum operating hours, etc.); and electric and natural gas tariffs. The tool outputs optimal investment and operation decisions, including annual energy costs; optimal DER capacities; optimal dispatch of DERs; and load management measures. The objective of the model is to find the optimal combination of technology adoption and operation to supply all energy services required by the site under consideration, while optimizing the energy flows to minimize costs and / or CO_2 emissions.

The targeted user-groups of DER-CAM include microgrid owners and site operators, industry stakeholders including equipment manufacturers, and policy makers. Key applications for microgrid owners and site operators include optimized investment recommendations based on site-specific loads, tariffs, and objectives. Applications for Industry stakeholders include identifying cost and performance characteristics that will lead to adoption of their technologies in diverse segments of the market. For policy makers, key DER-CAM applications include determining high-level impacts on distributed energy resource penetration levels, and anticipating customer adoption behaviors given changes in electricity rates, demand-response programs, and different regulations.

In previous iterations of DER-CAM, the most relevant revenue streams included in the process of microgrid sizing consisted of savings due to avoided utility purchase, peak shaving, load shifting, and power exports. Specifically, DER-CAM considers exporting power through the application of feed-in tariffs, and different demand-response programs are supported, including time-of-use rates, power demand charges, and direct load control, all of which are considered in the objective function.

2.2. DER-CAM formulation

A simplified version of the original DER-CAM formulation, i.e. the formulation prior to the modifications proposed in this paper is presented in this section, as introduced in [11,32,33]. In this deterministic model, customer loads are modeled with 3 typical day-types (week, peak, and weekend) per month with hourly time-steps. The objective is to minimize operational and investment costs over a typical year, where the investment costs are being annualized using an annuity rate that depends on the interest rate and technology lifetime. We model capacity of DER technologies using a continuous or discrete variable: If a technology is available in small enough modules (e.g. photovoltaic and storage), the optimal capacity is modeled as a continuous variable, significantly lowering the computation time. Discrete variables are used otherwise (e.g. micro-turbines).

Indices

c continuous generation technologies: photovoltaic panels (PV), and absorption chillers (AC)

g discrete generation technologies: internal combustion engines (ICE), micro-turbines (MT), gas turbines (GT), and fuel cells (FC)

i set of all technologies $(j \cup k)$

j set of all generation technologies $(g \cup c)$

k storage technologies: stationary storage (ES), and thermal storage (TH)

p tariff period {on-peak, mid-peak, off-peak}

s season {winter, summer}

u end-use: electricity only (eo), cooling (cl), refrigeration (rf), space heating (sh), water heating (wh), and natural gas only (ng)

m, d, h month {1, 2, ..., 12}, day type {1, 2, 3}, hour {1, 2, ..., 24}

Customer loads

$\mathrm{Load}_{m,d,h,u}$ customer load at time m, d, h for end-use u [kW]

Market data

$\mathrm{TP}_{s,p}$ regulated demand (power) charges under the default tariff for season s and period p [$/kW]

$\mathrm{TE}_{m,d,h}$ regulated tariff for electricity at time m, d, h [$/kWh]

TF_{m} regulated tariff fixed charge for electricity in month m [$]

$\mathrm{TEx}_{m,d,h}$ regulated tariff for electricity export at time m, d, h [$/kWh]

NGF_{m} regulated tariff fixed charge for natural gas in month m [$]

NGP_{m} regulated tariff for natural gas in month m [$/kWh]

Technology data

MaxP_{g} rated capacity of generation tech. g [kW]

MinL_{g} minimum acceptable load for generation tech. g [kW]

Lt_{i} expected lifetime of technology i [a]

CCD_{g} turnkey capital cost of generation technology g [$/kW]

$\mathrm{FCC}_{(c,k)}$ fixed capital cost of generation technology c or storage technology k [$]

$\mathrm{VCC}_{(c,k)}$ variable capital cost of generation tech. c or storage technology k [$/kW]

VCSC_{k} variable capital cost of storage technology k [$/kWh]

OMF_{i} fixed annual operation and maintenance costs of technology i [$/kW]

OMV_{i} variable operation and maintenance costs of technology i [$/kWh]

$\mathrm{MaxH_j}$ maximum number of hours technology j can operate during the year, [h]

$\mathrm{VC_{j,m}}$ generation cost of technology j during month m [$/kWh]

$\mathrm{S(j)}$ set of end-uses that can be met by technology j [-]

α_j heat to power ratio: units of useful heat that can be recovered from a unit of electricity generated by technology j [1]

$\mathrm{SCE_k}$ charging efficiency of storage technology k [%]

$\mathrm{SDE_k}$ discharging efficiency of storage technology k [%]

φ_k losses due to decay/self-discharge in storage technology k [%]

$\mathrm{MSC_k}$ minimum state of charge of storage technology k, [%]

COPu central microgrid chillers coefficient of performance [1]

COPa absorption chillers coefficient of performance [1]

$\mathrm{SPE_c}$ theoretical peak solar conversion efficiency of generation technology c [%]

$\mathrm{SRE_{c,m,h}}$ solar radiation conversion efficiency of generation technology c, in month m, and hour h [%]

Other parameters

IR interest rate on DER investments [%]

$\mathrm{An_i}$ annuity factor for investments in technologies i [1]

$\mathrm{SI_{m,d,h}}$ solar insolation at time m, d, h [kW/m²]

SA available area for solar technologies [m^2]

β_u units of heat energy generated from a unit of natural gas energy purchased for end-use u [1]

BAU total energy costs in the business-as-usual case, obtained by running the model with investments disabled [$]

PBP maximum payback period allowed on the integrated DER investment decision [a]

Decision Variables

IG_{g} number of units of generation technology g installed [1]

$RG_{\mathrm{g,m,d,h}}$ number of units of generation technology g operating at time m, d, h [1]

$GU_{\mathrm{j,m,d,h,u}}$ power generated by technology j, at time m, d, h for end-use u [kW]

$GS_{\mathrm{j,m,d,h}}$ power generated to export by technology j, at time m, d, h [kW]

$RH_{\mathrm{j,m,d,h}}$ useful heat recovered from technology j, at time m, d, h [kW]

$AL_{\mathrm{m,d,h}}$ heat used to drive absorption chillers at time m, d, h [kW]

$Cap_{(c,k)}$ rated output of generation technology c or storage technology k [kW]

$ECap_{k}$ energy capacity of storage tech. k [kWh]

$SOC_{k,m,d,h}$ state of charge of storage technology k at time m, d, h [kWh]

$SIn_{k,m,d,h}$ energy input to storage technology k, at time m, d, h [kW]

$SOut_{k,m,d,h,u}$ energy output from storage technology k, at time m, d, h for end use u [kW]

$sb_{k,m,d,h}$ binary charge/discharge decision of storage technology k at time m, d, h [b]

$psb_{m,d,h}$ binary decision of purchasing or selling electricity at time m, d, h [b]

$NGU_{m,d,h,u}$ natural gas purchase at time m, d, h for end-use u [kWh]

$UL_{m,d,h,u}$ electricity purchased from power utility at time m, d, h for end-use u [kW]

$Pur_{(c,k)}$ customer purchase binary decision of technology c or k [b]

Economic objective function

$$\begin{aligned}
\min \mathrm{C} = & \textstyle\sum_{\mathrm{m}} \mathrm{TF_m} \qquad [\$] \qquad (1)\\
& + \textstyle\sum_{\mathrm{m}}\sum_{\mathrm{d}}\sum_{\mathrm{h}}\sum_{\mathrm{u}} UL_{\mathrm{m,d,h,u}} \cdot \mathrm{TE_{m,d,h}}\\
& + \textstyle\sum_{\mathrm{s}}\sum_{\mathrm{m}\in\mathrm{s}}\sum_{\mathrm{p}} \mathrm{TP_{s,p}} \cdot \max\left(\sum_{\mathrm{u}\in \mathrm{eo,cl,rf}} UL_{\mathrm{m,(d,h)}\in\mathrm{p,u}}\right)\\
& + \textstyle\sum_{\mathrm{j}}\sum_{\mathrm{m}}\sum_{\mathrm{d}}\sum_{\mathrm{h}}\left(GS_{\mathrm{j,m,d,h}} + \sum_{\mathrm{u}} GU_{\mathrm{j,m,d,h,u}}\right)\cdot\left(\mathrm{VC_{j,m}} + \mathrm{OMV_j}\right)\\
& + \textstyle\sum_{\mathrm{g}} IG_{\mathrm{g}} \cdot \mathrm{MaxP_g} \cdot \left(\mathrm{CCD_g}\cdot\mathrm{An_g} + \mathrm{OMF_g}\right)\\
& + \textstyle\sum_{\mathrm{i}\in\mathrm{c,k}}((\mathrm{FCC_i}\cdot Pur_{\mathrm{i}} + \mathrm{VCC_i}\cdot Cap_{\mathrm{i}} + \mathrm{VCSC_k}\cdot ECap_{\mathrm{k}})\cdot\mathrm{An_i} + Cap_{\mathrm{i}}\cdot\mathrm{OMF_i})\\
& + \textstyle\sum_{\mathrm{m}} \mathrm{NGF_m}\\
& + \textstyle\sum_{\mathrm{m}}\sum_{\mathrm{d}}\sum_{\mathrm{h}}\sum_{\mathrm{u}} NGU_{\mathrm{m,d,h,u}}\cdot\mathrm{NGP_m}\\
& - \textstyle\sum_{\mathrm{j}}\sum_{\mathrm{m}}\sum_{\mathrm{d}}\sum_{\mathrm{h}} GS_{\mathrm{j,m,d,h}}\cdot\mathrm{TEx_{m,d,h}}
\end{aligned}$$

Microgrid constraints

$$\mathrm{Load_{m,d,h,u}} + \frac{SIn_{\mathrm{k,m,d,h}}}{\mathrm{SCE_k}} = SOut_{\mathrm{k,m,d,h,u}}\cdot\mathrm{SDE_k} + \textstyle\sum_{\mathrm{j}} GU_{\mathrm{j,m,d,h,u}} + UL_{\mathrm{m,d,h,u}}\ \forall\, \mathrm{m,d,h{:}\ k = \{ES\}} \wedge \mathrm{u = \{eo\}} \qquad [\mathrm{kW}] \qquad (2)$$

$$\mathrm{Load_{m,d,h,u}} + \frac{SIn_{\mathrm{k,m,d,h}}}{\mathrm{SCE_k}} + AL_{\mathrm{m,d,h}} = SOut_{\mathrm{k,m,d,h,u}}\cdot\mathrm{SDE_k} + \beta_{\mathrm{u}}\cdot NGU_{\mathrm{m,d,h,u}} + \textstyle\sum_{\mathrm{g}} RH_{\mathrm{g,m,d,h,u}}\ \forall\, \mathrm{m,d,h{:}\ k = \{TH\}} \wedge \mathrm{u} \in \mathrm{\{sh,wh\}} \qquad [\mathrm{kW}] \qquad (3)$$

$$\mathrm{Load_{m,d,h,u}} = \textstyle\sum_{\mathrm{j}} GU_{\mathrm{j,m,d,h,u}} + UL_{\mathrm{m,d,h,u}}\cdot\mathrm{COPu} \quad \forall \mathrm{m,d,h} : \mathrm{u} \in \mathrm{\{cl,rf\}} \qquad [\mathrm{kW}] \qquad (4)$$

$$\mathrm{Load_{m,d,h,u}} = NGU_{\mathrm{m,d,h,u}} \quad \forall\, \mathrm{m,d,h} : \mathrm{u = \{ng\}} \qquad [\mathrm{kW}] \qquad (5)$$

$$RG_{\mathrm{g,m,d,h}}\cdot\mathrm{MinL_g} \le \textstyle\sum_{\mathrm{u}} GU_{\mathrm{g,m,d,h,u}} + GS_{\mathrm{g,m,d,h}} \le RG_{\mathrm{g,m,d,h}}\cdot\mathrm{MaxP_g} \quad \forall\, \mathrm{g,m,d,h} \qquad [\mathrm{kW}] \qquad (6)$$

$$\sum_{m}\sum_{d}\sum_{h}\left(\sum_{u} GU_{g,m,d,h,u} + GS_{g,m,d,h}\right) \leq IG_{g} \cdot \mathrm{MaxP}_{g} \cdot \mathrm{MaxH}_{g} \quad \forall\, g, m, d, h \qquad [\mathrm{kW}] \tag{7}$$

$$\sum_{u} RH_{g,m,d,h,u} \leq \alpha_{g} \cdot \left(\sum_{u} GU_{g,m,d,h,u} + GS_{g,m,d,h}\right) \quad \forall\, g, m, d, h \qquad [\mathrm{kW}] \tag{8}$$

$$Cap_{i} \leq Pur_{i} \cdot \mathbf{M} \quad \forall\, i \in \{c, k\} \qquad [\mathrm{kW}] \tag{9}$$

$$\sum_{u} GU_{c,m,d,h,u} + GS_{c,m,d,h} \leq Cap_{c} \cdot \frac{\mathrm{SRE}_{c,m,h}}{\mathrm{SPE}_{c}} \cdot \mathrm{SI}_{m,d,h} \quad \forall m, d, h : c \in \{\mathrm{PV}\} \qquad [\mathrm{kW}] \tag{10}$$

$$\sum_{c} \frac{Cap_{c}}{\mathrm{SPE}_{c}} \leq \mathrm{SA} : c \in \{\mathrm{PV}\} \qquad [\mathrm{m}^2] \tag{11}$$

$$SOC_{k,m,d,h} = SIn_{k,m,d,h} - \sum_{u} SOut_{k,m,d,h,u} + SOC_{k,m,d,h-1} \cdot (1 - \varphi_{k}) \quad \forall\, k, m, d, h \neq 1 \qquad [\mathrm{kWh}] \tag{12}$$

$$SOC_{k,m,d,1} = SOC_{k,m,d,24} \quad \forall\, k, m, d \qquad [\mathrm{kWh}] \tag{13}$$

$$SOC_{k,m,d,h} \geq ECap_{k} \cdot \mathrm{MSC}_{k} \quad \forall\, k, m, d, h \qquad [\mathrm{kWh}] \tag{14}$$

$$SOC_{k,m,d,h} \leq ECap_{k} \quad \forall\, k, m, d, h \qquad [\mathrm{kWh}] \tag{15}$$

$$SIn_{k,m,d,h} \leq Cap_{k} \quad \forall\, k, m, d, h \qquad [\mathrm{kW}] \tag{16}$$

$$\sum_{u} SOut_{k,m,d,h,u} \leq Cap_{k} \quad \forall\, k, m, d, h \qquad [\mathrm{kW}] \tag{17}$$

$$SIn_{k,m,d,h} \leq sb_{k,m,d,h} \cdot \mathbf{M} \quad \forall\, k, m, d, h \qquad [\mathrm{kW}] \tag{18}$$

$$\sum_{u} SOut_{k,m,d,h,u} \leq \left(1 - sb_{k,m,d,h}\right) \cdot \mathbf{M} \quad \forall\, k, m, d, h \qquad [\mathrm{kW}] \tag{19}$$

$$GU_{j,m,d,h,u} = AL_{m,d,h} \cdot \mathrm{COPa} \quad \forall\, m, d, h : j = \{\mathrm{AC}\} \wedge u = \{\mathrm{cl}, \mathrm{rf}\} \qquad [\mathrm{kW}] \tag{20}$$

$$\sum_{u} UL_{m,d,h,u} \leq psb_{m,d,h} \cdot \mathbf{M} \quad \forall\, m, d, h : u = \{\mathrm{eo}, \mathrm{cl}, \mathrm{rf}\} \qquad [\mathrm{kW}] \tag{21}$$

$$GS_{j,m,d,h} \leq \left(1 - psb_{m,d,h}\right) \cdot \mathbf{M} \quad \forall\, j, m, d, h \qquad [\mathrm{kW}] \tag{22}$$

$$\mathrm{An}_{i} = \frac{\mathrm{IR}}{\left(1 - \frac{1}{(1+\mathrm{IR})^{\mathrm{Lt}_{i}}}\right)} \quad \forall\, i \qquad [1] \tag{23}$$

$$\mathrm{C} \leq \mathrm{BAU} + \sum_{g} IG_{g} \cdot \mathrm{MaxP}_{g} \cdot \mathrm{CCD}_{g} \cdot \mathrm{An}_{g} + \sum_{i \in c,k} (\mathrm{FCC}_{i} \cdot Pur_{i} + \mathrm{VCC}_{i} \cdot Cap_{i} + \mathrm{VCSC}_{k} \cdot ECap_{k}) \cdot \mathrm{An}_{i} - \frac{\sum_{g} IG_{g} \cdot \mathrm{MaxP}_{g} \cdot \mathrm{CC}_{g} + \sum_{i \in c,k} (\mathrm{FCC}_{i} \cdot Pur_{i} + \mathrm{VCC}_{i} \cdot Cap_{i} + \mathrm{VCSC}_{k} \cdot ECap_{k})}{\mathrm{PBP}} \qquad [\$] \tag{24}$$

$$RH_{j,m,d,h,u} = 0 \quad \forall\, j, m, d, h : u \notin \mathrm{S}(j) \qquad [\mathrm{kW}] \tag{25}$$

$$UL_{m,d,h,u} = 0 \quad \forall\, m, d, h : u \in \{\mathrm{sh}, \mathrm{wh}, \mathrm{ng}\} \qquad [\mathrm{kW}] \tag{26}$$

The objective function (1) consists of all key cost components, including utility charges, annualized capital costs of DER investments, and operation and maintenance costs. The main optimization constraints are expressed in (2) - (26):

- Eq. (2) - (5) force the energy balances for the different end-uses.
- The boundaries for the operation of distributed generation and storage technologies are set in (6) - (11) and (12) - (19), respectively, where **M** is an arbitrarily large number.

- The absorption chiller operation is described in (20).
- Simultaneous import and export of power are prevented in (21) and (22).
- The annuity factors are calculated in (23).
- Eq. (24) presents the payback constraint, in which investments must be repaid in a period shorter than the payback period.
- Eq. (25) and (26) show the boundary conditions that ensure the proper links between different technologies and loads.

2.3. Changes to the formulation of DER-CAM

2.3.1. Overview

The following section describes the changes made to the mathematical formulation of DER-CAM to implement Ancillary Services (AS) market participation. It is important to keep in mind that AS markets are currently available in distinct ISO service territories, and each market may have specific requirements that differ from one another. Therefore, the formulation to support AS markets does not follow the rules of any specific market, but instead is designed in a flexible way to support all the relevant features.

As discussed in [28], the key AS markets can be grouped in three categories, including Frequency Regulation (Up and Down), Spinning Reserve, and Non-Spinning Reserve, all of which are considered in the enhanced DER-CAM formulation. These markets may have different requirements throughout different ISO territories, including how fast a unit must be able to respond to a service request upon a successful bid, the minimum size of the resource in order to participate in the market, or the minimum length of the bid duration. Typically, bids must hold for at least one hour in all AS markets, and response to requests may be required within seconds (or automatic) for frequency regulation markets, or within a few minutes, in the case of spinning and non-spinning reserve markets. For example, Non-Spinning Reserves in the CAISO territory, in California, must be able to respond within 10 minutes of being called, and must run for at least two hours, while the same service in the ERCOT territory, Texas, must respond within 30 min and run for at least one hour. All changes made to DER-CAM take such requirements into account.

2.3.2. Key Assumptions

Given the investment planning nature of DER-CAM, adding support to AS markets uses a deterministic approach. Historic information on market clearing prices for different AS markets is used as reference, under the general assumption that the microgrid under analysis is a price taker and the market clearing price is a good indicator for a successful bid. Under this premise, the capacity allocation determined by DER-CAM for participation in AS markets is always considered to be awarded.

The revenue resulting from each AS market bid is calculated based on the market clearing price and the bid duration as selected by the model, provided all market requirements are met. It should be noted that when successful, all bids in ISO markets are fully awarded, regardless of service requests.

Providing AS also creates an additional cost to the microgrid, as both additional fuel and O&M costs will be incurred whenever a service is requested. Additionally, costs due to increases in demand charges may also occur in the event of down-regulation requests, which can be severe if occurring during peak hours with high time-of-use rates. Other costs incurred by the microgrid as a result of AS provision include different opportunity costs, as the capacity allocation of a specific resource prevents its use for any other purpose. All of these are taken into account in the optimization.

Calculating the additional microgrid costs or benefits relies on the use of user-defined expectations on service provision. This is expressed in the formulation by an effective utilization ratio, α. In this initial implementation of AS products in DER-CAM all effective utilization ratios are assumed constant throughout the optimization window, although they can easily be expanded in future developments to model time-dependency of the service request expectation.

The addition of support to Spinning, Non-Spinning, and Regulation markets in DER-CAM led to several modifications to the existing formulation, including changes to operational constrains, and high-level balance equations. These changes are explained in detail below.

2.3.3. Operational constrains

Adding support for different AS markets requires, first and foremost, modifying the possible capacity allocations of each relevant resource. In prior formulations, all generation technologies could only provide power for either on-site consumption or export, and storage technologies could be used only for on-site arbitrage. After the modifications made to support Ancillary Services, both generator units and stationary storage can also provide spinning, non-spinning, up-regulation and down-regulation services.

In general, all dispatch equations for generators have been updated to include these services, as expressed below:

$$GU_{\mathrm{g,m,d,h,u}} + GS_{\mathrm{g,m,d,h,u}} + GRS_{\mathrm{g,m,d,h}} + GRSNS_{\mathrm{g,m,d,h}} + GRNS_{\mathrm{g,m,d,h}} + GRU_{\mathrm{g,m,d,h}} \leq \mathrm{MaxP_g} \quad \text{[kW]} \qquad (27)$$

Where:

$GRS_{\mathrm{g,m,d,h}}$ capacity allocated for spinning reserve by online technology g, at time m, d, h [kW]

$GRNS_{\mathrm{g,m,d,h}}$ capacity allocated for non-spinning reserve by offline technology g, at time m, d, h [kW]

$GRSNS_{\mathrm{g,m,d,h}}$ capacity allocated for non-spinning reserve by online technology g, at time m, d, h [kW]

$GRU_{\mathrm{g,m,d,h}}$ capacity allocated for up-regulation by online technology g, at time m, d, h [kW]

It should be noted that spinning units may typically also be used for non-spinning reserves, and for that reason the total reserve provided by spinning units was sub-divided into a component for spinning reserve and non-spinning reserve markets, as shown in Eq. (27). The resulting operational constraint now states that the overall capacity allocation, including on-site generation, power exports for traditional feed-in markets, and capacity allocated to ancillary service markets must not exceed the rated nameplate capacity of a given generation unit. Down-regulation is not included in this equation to prevent instances where call requests would lead to exceeding the unit capacity (for example symmetric up- and down-regulation hourly bids could keep the unit within operational boundaries, but requests occurring only to up-regulation would lead to an operational violation). Instead, the following additional constraints are added:

$$GU_{\mathrm{g,m,d,h}} + GS_{\mathrm{g,m,d,h}} - GRD_{\mathrm{g,m,d,h}} \geq \mathrm{MinL_g} \qquad [\mathrm{kW}] \qquad (28)$$

$$GRD_{\mathrm{g,m,d,h}} \leq \mathrm{MaxP_g} \cdot (1 - \mathrm{MinL_g}) \qquad [\mathrm{kW}] \qquad (29)$$

Where:

$GRD_{\mathrm{g,m,d,h}}$ capacity allocated for down-regulation by online technology g, at time m, d, h [kW]

Additionally, the following equations were added to ensure that Non-Spinning reserve bids respect minimum part-load requirements:

$$GRNS_{\mathrm{g,m,d,h}} \geq \mathrm{MinL_g} \cdot bAux_{\mathrm{g,m,d,h}}, \qquad bAux_{\mathrm{g,m,d,h}} \in \{0,1\} \qquad [\mathrm{kW}] \qquad (30)$$

$$GRNS_{\mathrm{b,m,d,h}} \leq bAux_{\mathrm{g,m,d,h}} \cdot \boldsymbol{M} \qquad [\mathrm{kW}] \qquad (31)$$

Other key elements relevant for determining market participation of DG units include the time requirements they must comply with in order to be eligible for bidding, either in its ability to start, TTSR, or to ramp, TTRR. For this purpose, additional parameters were introduced in the description of DG units, $\mathrm{TTS_g}$ and $\mathrm{TTR_g}$, where users can specify how fast each unit can go online or ramp from the minimum operating part-load to the rated nameplate capacity, respectively.

To understand this last parameter, it is important to keep in mind that DER-CAM is a mixed-integer linear program, where all variable relations are described using linear functions. This implies the use of several linearization procedures, which include fuel efficiency curves. In this particular case one of two methods can be applied – a linear step-wise approximation [34], or a constant efficiency associated with a minimum part-load requirement ($\mathrm{MinL_g}$ in equation 7). For most standard DG units this minimum part-load requirement is greater than or equal to 70% of the nameplate capacity, meaning that the $\mathrm{TTR_g}$ parameter is used to describe the time to ramp from this minimum part-load value up to the nameplate capacity.

The parameters described above are used to exclude DG units that do not meet market requirements, along with backup generators, which are equally excluded from bidding into AS markets, as shown in the operational constraints below.

$$GRS_{\mathrm{g,m,d,h}} = 0 : \mathrm{TTR_g} > \mathrm{TTRR} \cup \mathrm{BackUpOnly_g} = 1 \qquad [\mathrm{kW}] \qquad (32)$$

$$GRNS_{g,\mathrm{m,d,h}} = 0 : \mathrm{TTS_g} > \mathrm{TTSR} \cup \mathrm{BackUpOnly_g} = 1 \qquad [\mathrm{kW}] \qquad (33)$$

Further to these requirements, AS markets often define minimum length for bid durations, as well as minimum bid capacity. This is specific to each market, and requires the new set of operational constrains introduced below. To achieve this purpose while preserving linearity additional binary variables were added to track the change of status in the provision of ancillary services (enabled or disabled), and to force service duration for a minimum number of θ time steps. These equations were implemented separately for all four AS products.

Spinning Reserve

$$S_{\mathrm{m,d,h}} \leq bS_{\mathrm{m,d,h}} \cdot \mathbf{M}, \qquad bS_{\mathrm{m,d,h}} \in \{0,1\} \qquad [\mathrm{kW}] \qquad (34)$$

$$SwS_{\mathrm{m,d,h}} = bS_{\mathrm{m,d,h}} - bS_{\mathrm{m,d,h-1}} \qquad [1] \qquad (35)$$

$$\sum\nolimits_{\hat{\mathrm{h}}} bS_{\mathrm{m,d},\hat{\mathrm{h}}} \geq SwS_{\mathrm{m,d,h}} \cdot \theta, \qquad \dot{\hat{\mathrm{h}}} = \{\mathrm{h}, \mathrm{h}+1, .., \mathrm{h}+\theta\} \qquad [1] \qquad (36)$$

$$S_{\mathrm{m,d,h}} \geq bS_{\mathrm{m,d,h}} \cdot \mathrm{SMinBid} \qquad [\mathrm{kW}] \qquad (37)$$

Non-Spinning Reserve

$$NS_{\mathrm{m,d,h}} \leq bNS_{\mathrm{m,d,h}} \cdot \mathbf{M}, \qquad bNS_{\mathrm{j,m,d,h}} \in \{0,1\} \qquad [\mathrm{kW}] \qquad (38)$$

$$SwNS_{\mathrm{m,d,h}} = bNS_{\mathrm{j,m,d,h}} - bNS_{\mathrm{j,m,d,h-1}} \qquad [1] \qquad (39)$$

$$\sum\nolimits_{\hat{\mathrm{h}}} bNS_{\mathrm{m,d},\hat{\mathrm{h}}} \geq SwNS_{\mathrm{m,d,h}} \cdot \theta, \qquad \dot{\hat{\mathrm{h}}} = \{\mathrm{h}, \mathrm{h}+1, .., \mathrm{h}+\theta\} \qquad [1] \qquad (40)$$

$$NS_{\mathrm{m,d,h}} \geq bNS_{\mathrm{j,m,d,h}} \cdot \mathrm{NSMinBid} \qquad [\mathrm{kW}] \qquad (41)$$

Up-Regulation

$$RUp_{\mathrm{m,d,h}} \leq bRUp_{\mathrm{m,d,h}} \cdot \mathbf{M}, \qquad bRUp_{\mathrm{m,d,h}} \in \{0,1\} \qquad [\mathrm{kW}] \qquad (42)$$

$$SwRUp_{\mathrm{m,d,h}} = bRUp_{\mathrm{m,d,h}} - bRUp_{\mathrm{m,d,h-1}} \qquad [1] \qquad (43)$$

$$\sum\nolimits_{\hat{h}} bRUp_{m,d,\hat{h}} \geq SwRUp_{m,d,h} \cdot \theta, \qquad \dot{\hat{h}} = \{h, h+1, .., h+\theta\} \qquad [1] \qquad (44)$$

$$RUp_{m,d,h} \geq bRUp_{m,d,h} \cdot \mathrm{RUpMinBid} \qquad [\mathrm{kW}] \qquad (45)$$

Down Regulation

$$RDn_{m,d,h} \leq bRDn_{m,d,h} \cdot \mathbf{M}, \qquad bRDn_{m,d,h} \in \{0,1\} \qquad [\mathrm{kW}] \qquad (46)$$

$$SwRDn_{m,d,h} = bRDn_{m,d,h} - bRDn_{m,d,h-1} \qquad [1] \qquad (47)$$

$$\sum\nolimits_{\hat{h}} bRDn_{m,d,\hat{h}} \geq SwRDn_{m,d,h} \cdot \theta, \qquad \dot{\hat{h}} = \{h, h+1, .., h+\theta\} \qquad [1] \qquad (48)$$

$$RDn_{m,d,h} \geq bRDn_{m,d,h} \cdot \mathrm{RDnMinBid} \qquad [\mathrm{kW}] \qquad (49)$$

Where:

$S_{\mathrm{m,d,h}}$ total spinning reserve bid, including generation and storage components, in time m, d, h [kW]

$bS_{\mathrm{m,d,h}}$ binary spinning market participation decision [b]

$SwS_{\mathrm{m,d,h}}$ change on the spinning reserve market participation decision [1]

SMinBid minimum bid for spinning reserve market [kW]

$NS_{\mathrm{m,d,h}}$ total non-spinning reserve bid, including generation and storage components, in time m, d, h [kW]

$bNS_{\mathrm{m,d,h}}$ binary non-spinning market participation decision [b]

$SwNS_{\mathrm{m,d,h}}$ change on the non-spinning reserve market participation decision [1]

NSMinBid minimum bid for non-spinning reserve market [kW]

$RUp_{\mathrm{m,d,h}}$ total up-regulation bid, including generation and storage components, in time m, d, h [kW]

$bRUp_{\mathrm{m,d,h}}$ binary up-regulation market participation decision [b]

$SwRUp_{\mathrm{m,d,h}}$ change on the up-regulation market participation decision [1]

RUpMinBid minimum bid for up-regulation market [kW]

$RDn_{\mathrm{m,d,h}}$ total up-regulation bid, including generation and storage components, in time m, d, h [kW]

$bRDn_{\mathrm{m,d,h}}$ binary up-regulation market participation decision [b]

$SwRDn_{\mathrm{m,d,h}}$ change on the up-regulation market participation decision [1]

RDnMinBid minimum bid for up-regulation market [kW]

Regarding storage, the power input and output from conventional technologies has also been divided into multiple components, including power for onsite consumption, but also for spinning and non-spinning reserve, as well as up and down frequency regulation, as shown below.

$$SOut_{\mathrm{k,m,d,h}} = \sum_{u} SOutSite_{\mathrm{k,m,d,h,u}} + SOutRUp_{\mathrm{k,m,d,h}} + SOutS_{\mathrm{k,m,d,h}} + SOutNS_{\mathrm{k,m,d,h}}, \quad k = \{ES\} \qquad \text{[kW]} \qquad (50)$$

$$SIn_{k,m,d,h} = SInSite_{k,m,d,h} + SInRDn_{k.m,d,h}, \quad k = \{ES\} \qquad \text{[kW]} \qquad (51)$$

$SOut_{\mathrm{k,m,d,h}}$ total output of storage technology k, at time m, d, h [kW]

$SOutSite_{\mathrm{k,m,d,h}}$ output of storage technology k, at time m, d, h, for end-use u [kW]

$SOutS_{\mathrm{k,m,d,h}}$ capacity allocated for spinning reserve by storage technology k, at time m, d, h [kW]

$SOutNS_{\mathrm{k,m,d,h}}$ capacity allocated for non-spinning reserve by storage technology k, at time m, d, h [kW]

$SInSite_{\mathrm{k,m,d,h}}$ input from on-site to storage technology k, at time m, d, h [kW]

$SInRDn_{\mathrm{k,m,d,h}}$ input to storage technology k, at time m, d, h, due to down-regulation [kW]

2.3.4. High level balance equations

The extension of DER-CAM to support AS products requires high-level power balance equations to guarantee each service is provided by the adequate technologies. Namely, spinning reserves can be provided by any spinning on-site generator and stationary batteries, non-spinning reserve can be provided both by spinning and non-spinning on-site generators and stationary batteries, and both up and down regulation can be provided by spinning on-site generators and stationary batteries, as shown in the equations below.

$$S_{\mathrm{m,d,h}} = \sum_{\mathrm{g}} GRS_{\mathrm{g,m,d,h}} + SOutS_{\mathrm{m,d,h}} \qquad \text{[kW]} \qquad (52)$$

$$NS_{\mathrm{m,d,h}} = \sum_{\mathrm{g}} \left(GRNS_{\mathrm{g,m,d,h}} + GRSNS_{\mathrm{g,m,d,h}} \right) + SOutNS_{\mathrm{m,d,h}} \qquad \text{[kW]} \qquad (53)$$

$$RUp_{\mathrm{m,d,h}} = \sum_{\mathrm{g}} GRUp_{\mathrm{g,m,d,h}} + SOutRUp_{\mathrm{m,d,h}} \qquad \text{[kW]} \qquad (54)$$

$$RDn_{\mathrm{m,d,h}} = \sum_{g} GRDn_{\mathrm{g,m,d,h}} + SInRDn_{\mathrm{m,d,h}} \qquad \text{[kW]} \qquad (55)$$

It should be noted that in this first implementation all discrete generation technologies are allowed to provide ancillary services, as well as stationary storage. Renewable technologies are currently not directly included, due to the greater uncertainty in their output. However, renewable generation technologies can still be used to charge stationary storage, and in that way participate indirectly in AS markets.

2.3.5. AS Market revenues

The expected revenue from spinning reserve provision is calculated assuming the market clearing price is applicable.

$$SRev = \sum_{\mathrm{m,d,h}} S_{\mathrm{m,d,h}} \cdot \mathrm{SMktP}_{\mathrm{m,d,h}} \qquad \text{[\$]} \qquad (56)$$

$$NSRev = \sum_{\mathrm{m,d,h}} NSn_{\mathrm{m,d,h}} \cdot \mathrm{NSMktP}_{\mathrm{m,d,h}} \qquad \text{[\$]} \qquad (57)$$

$$RUpRev = RUp_{\mathrm{m,d,h}} \cdot \mathrm{RUpMktP}_{\mathrm{m,d,h}} \qquad \text{[\$]} \qquad (58)$$

$$RDnRev = RDn_{\mathrm{m,d,h}} \cdot \mathrm{RDnMktP}_{\mathrm{m,d,h}} \qquad \text{[\$]} \qquad (59)$$

$\mathrm{SMktP}_{\mathrm{m,d,h}}$	market clearing price for spinning reserve ancillary service in time m, d, h [$/kW]
$\mathrm{NSMktP}_{\mathrm{m,d,h}}$	market clearing price for non-spinning reserve ancillary service in time m, d, h [$/kW]
$\mathrm{RUpMktP}_{\mathrm{m,d,h}}$	market clearing price for up-regulation ancillary service in time m, d, h [$/kW]
$\mathrm{RDnMktP}_{\mathrm{m,d,h}}$	market clearing price for down-regulation ancillary service in time m, d, h [$/kW]

2.3.6. Added Costs

The additional costs incurred by the microgrid include four different components: added capital cost from additional DER investment, added fuel consumption for generator units, added O&M costs for generator units, and opportunity costs due to capacity allocation for AS provision.

The added capital costs resulting from additional investments are taken into account by the existing formulation without requiring any changes, as the current objective function already considers all investments and the financial constrains ensure that any additional investments are only made if proven to be cost-effective.

Similarly, all opportunity costs are considered in the existing formulation. By finding the cost-optimal solution, the trade-off between on-site resource utilization and allocation for AS markets is determined endogenously, and no additional changes are necessary.

Additional fuel costs and O&M costs require updating the formulation, to reflect both the added fuel and use of the generation resource. These are then used to replace the fuel and O&M components of the objective function.

$$FCn_{\mathrm{m,d,h}} = \sum_{\mathrm{g}} \Big(GU_{\mathrm{g,m,d,h}} + GS_{\mathrm{g,m,d,h}} + GRS_{\mathrm{g,m,d,h}} \cdot \alpha_S + \left(GRSNS_{\mathrm{g,m,d,h}} + GRNS_{\mathrm{g,m,d,h}} \right) \cdot \alpha_{NS} + GRUp_{\mathrm{g,m,d,h}} \cdot \alpha_{RUp} - GRDn_{\mathrm{g,m,d,h}} \cdot \alpha_{RDn} \Big) / \eta_g \qquad [\$] \qquad (60)$$

$$OMVC_{\mathrm{g,m}} = \sum_{\mathrm{d,h}} \Big(GU_{\mathrm{g,m,d,h}} + GS_{\mathrm{g,m,d,h}} + GRS_{\mathrm{g,m,d,h}} \cdot \alpha_S + \left(GRSNS_{\mathrm{g,m,d,h}} + GRNS_{\mathrm{g,m,d,h}} \right) \cdot \alpha_{NS} + GRUp_{\mathrm{g,m,d,h}} \cdot \alpha_{RUp} - GRDn_{\mathrm{g,m,d,h}} \cdot \alpha_{RDn} \Big) \cdot OMV_g \qquad [\$] \qquad (61)$$

3. Case Study

3.1. General Remarks

The following section presents an analysis of selected cases to illustrate the potential impact of considering the revenue of AS market participation in the optimal sizing of DER. These cases focus on sample microgrid configurations, including both single-building and multi-building microgrids.

The selected cases include residential buildings, office buildings, hospitals, and hypothetical microgrids where residential, office, and hospital buildings are aggregated. Two separate models were created for each of these cases, so that two distinct ISO territories could be analyzed. The selected territories include the California Independent System Operator (CAISO) and PJM (East Coast), as both these locations depict distinct weather conditions, energy loads, tariffs, and AS market prices.

The procedure consisted of conducting three sets of runs per model, creating a total of 24 cases:

- Set one, base case: The initial set consists of reference runs to establish the business as usual scenario, i.e., determining the site-wide energy costs prior to any investment analysis.
- Set two, investment analysis without AS market: The second set consists of an investment optimization run, however, it does not consider participation in the AS market.
- Set three, investment analysis with AS market: The third set consists of an investment optimization run with the consideration of participation in the AS market.

3.2. Data collection

3.2.1. Energy Loads

The building energy load data used to create the DER-CAM models consisted of information found in building load databases made available by the U.S. Department of Energy (DOE). These datasets contain load profiles for commercial and residential buildings and are based on the DOE's commercial reference building model and the Residential Energy Consumption Survey (RECS) [35].

The load profiles are based on meteorological data using the Typical Meteorological Year (TMY3) dataset, and the buildings selected include two commercial buildings (a hospital and a medium sized office building) and one standard residential building. Load data was collected for two locations in the United States, namely San Francisco and Washington/Baltimore, as they are located in the CAISO and PJM territory, respectively.

The summary of the electric loads (electricity-only plus cooling plus refrigeration) used in the DER-CAM models created is presented below.

Table 1 - Summary of the electric loads used in the DER-CAM runs

3.2.2. Market Information

Utility Tariffs

The tariff information used in the creation of DER-CAM models relied on the built-in tariff database available in DER-CAM. This database contains tariffs for multiple locations across the U.S, and in this case study, two tariffs were selected from both Pacific Gas & Electric (PG&E) and Baltimore Gas & Electric (BG&E), as presented below.

Table 2- Summary of the PG&E tariff information used in the DER-CAM runs, less than 200kW peak

Table 3- Summary of the PG&E tariff information used in the DER-CAM runs, more than 500kW peak

Table 4- Summary of the BG&E tariff information used in the DER-CAM runs, less than 2 GWh consumption

Table 5- Summary of the BG&E tariff information used in the DER-CAM runs, large commercial customers

AS Market Information

All Ancillary Service market prices used in the case study were based on hourly historic data from 2014, and summarized below.

Figure 1- CAISO average weekday spinning reserve market clearing prices [28]

Figure 2- CAISO average weekday non-spinning reserve market clearing prices [28]

Figure 3- CAISO average Up-Regulation market clearing prices [28]

Figure 4- CAISO average Down-Regulation market clearing prices [28]

Figure 5- PJM average weekday spinning reserve market clearing prices [28]

Figure 6- PJM average weekday non-spinning reserve market clearing prices [28]

Figure 7- PJM average weekday regulation market clearing prices [28]

Analyzing the data presented in these figures, AS market clearing prices tend to be highly volatile, with large variability being observed not only from hour to hour, but also throughout different months of the year. Nonetheless, it can be observed that non-spinning reserve is consistently the lowest priced product, and that PJM clearing prices tend to be higher than those observed in the same product for CAISO markets. Additionally, prices found in CAISO tend to observe peak values around 16:00, suggesting system wide peaks occur around that period.

3.2.3. DER Information

The set of DER technologies considered in the case study includes both conventional and renewable generation technologies, as well as stationary storage.

Provided below are the techno-economic data used to describe all DER options considered in the DER-CAM runs.

Table 6 - Photovoltaic modules

Table 7- Stationary Storage Characteristics

Table 8 - Conventional generation units

3.3. Key Results

3.3.1. Results in the CAISO territory

The key results obtained in the CAISO territory are summarized in Table and Table , where San Francisco data was used. Table summarizes the results for both residential and office building models.

Analyzing the results shows that investments in PV generation is advised, with a small 19 kW PV system being suggested in the residential building and a larger 157 kW system being advised in the Office building. Each of these cases leads to a reduction in both costs and CO_2 emissions, with a cost reduction of roughly 15% in the residential building case and a more significant reduction of roughly 33% in the office building case. However, it should be noted that the investment suggestions do not include any technology with the ability to provide AS.

When analyzing the runs where AS was enabled, it is observed that the optimal solution did not change. In other words, given the problem size and economics, adding DG units and / or storage with the ability to provide AS was not economically feasible, resulting in no impact from the expansion of the DER-CAM capabilities.Table summarizes the results obtained for both a hospital microgrid, and the hypothetical microgrid resulting from the aggregation of the residential, office and hospital buildings.

In this case, both models show once again cost reductions when analyzing potential DER investments prior to the introduction of potential revenue from AS markets. Results obtained for the Hospital building suggest a 1075 kW PV system as well as a combined 900 kW generation capacity, of which 750 kW consist of CHP-enabled generation, leading to an overall cost reduction of approximately 16% in total energy costs. In the aggregate case, the cost-optimal system configuration is similar, although 1343 kW of PV are suggested, and conventional generation capacity is slightly higher, with a combined 1MW installed capacity, of which 750 consist of CHP. In this case, the cost reduction is roughly 17%.

Table 9 – CAISO: Costs, emissions and investments for a residential building and a medium sized office

Table 10 – CAISO: Costs, emissions and investments for a hospital and aggregated for all buildings.

When analyzing the results obtained in the expanded DER-CAM model it can be observed that introducing the ability to participate in AS markets had an impact on optimal results both for the Hospital and Aggregated model. In this case, cost reductions were of roughly 17% in the hospital case and 18% in the aggregated model, suggesting a slightly better economic performance due to the participation in AS markets. Specifically, AS market participation led to annual revenues of roughly $3,600 in the hospital model and of $4,500 in the aggregated model. While these revenues have little impact in the overall energy cost, it should be noted that the optimal DER capacity portfolio is changed due to the possibility to participate in AS markets. Namely, both cases see a reduction in total installed capacity, with the Hospital case showing an optimal PV capacity of roughly 1MW and 750 kW of CHP, and the Aggregated model showing a suggested PV capacity of roughly 1.1MW and an identical 750 kW CHP system.

While the ability to participate in AS markets could lead to the belief that additional capacity would be installed, it must be noted that the ability to participate in AS markets has an influence on capacity factors. Specifically, and given the minimum load constrains, the results obtained with prior DER-CAM formulations suggest that larger generation units are often not used as it is not economically feasible to run them below the minimum load requirement, potentially leading to the investment in smaller and more flexible units. By adding the ability to participate in AS markets, cases where running generation at load levels above the minimum requirements where not cost effective may now become attractive, as this is a requirement to participate in Spinning markets, i.e., the additional revenue obtained from successful AS bids makes it economically viable to run larger units at load levels that were previously not economic, resulting in a lower need to install additional capacity for load following. This can be observed when analyzing Figure and Figure , where the same dispatch period is shown both for the simple investment case and the investment case where AS are considered. The comparison of these dispatch profiles indicates a higher utilization and capacity factor for DG units when participation in AS markets is enabled.

Figure 8 – CAISO Aggregate Model, Simple Investment Case

Figure 9 – CAISO Aggregate Model, Investment Case with AS

3.3.2. Results for the PJM territory

The key results obtained for the PJM territory are summarized in Table and Table 1, where Baltimore data has been used. Table summarizes the results in the residential building microgrid model, and the office building model. Unlike the results obtained in the CAISO runs, no DER investments were suggested in either the simple investment or AS-enabled investment runs. These results are justified by the different utility tariffs in these different territories, which make DER investments for smaller sized systems not cost-effective.

Table 1 summarizes the results obtained for both the hospital microgrid model, and the hypothetical microgrid resulting from the aggregation of the residential, office and hospital buildings.

Table 11 - Costs, emissions and investments for a residential building and a medium sized office.

In this case, both models show cost reductions when analyzing potential DER investments prior to the introduction of potential revenue from AS markets. Results obtained for the Hospital building suggest a combined 1250 kW generation capacity from conventional units, of which 750 kW consist of CHP-enabled generation, leading to an overall cost reduction of approximately 16% in total energy costs. In the aggregate case, the cost-optimal system configuration is similar, although a very small amount of PV is suggested, and conventional generation capacity is slightly higher, with a combined 1325 kW installed capacity, of which 750 consist of CHP. In this case, the cost reduction is roughly 32%.

Table 1 - Costs, emissions and investments for a hospital and aggregated for all buildings.

When analyzing the results obtained in the expanded DER-CAM model it can be observed that introducing the ability to participate in AS markets had a significant impact in optimal results both for the Hospital and Aggregated model. In this case, cost reductions were of roughly 22% in the hospital case and 36% in the aggregated model, suggesting a more significant increase in the economic performance due to the participation in AS markets when compared with the results obtained in CAISO. Specifically, AS market participation led to an annual revenue of roughly $108,000 in the Hospital model and of $102,000 in the aggregated model, two orders of magnitude above the revenues estimated in CAISO.

Figure 10 – PJM Hospital Model, Simple Investment Case

Similarly to the results obtained in the CA region, these revenues also had an impact in the optimal DER capacity portfolio. In this case, however, the Hospital model showed the same overall installed capacity but lower CHP. This result is a direct reflection of the participation in AS markets, as part of the testing setup included disabling participation of CHP units in AS markets. As results show, the additional revenue from AS justifies replacing a CHP unit with a conventional generator, even considering the additional utility purchase to meet on-site heating requirements.

In the Aggregate model, a similar occurrence was observed, although the overall installed capacity was increased to 1565 kW, suggesting that in this case the economic returns have improved following the participation in AS markets.

It should be noted that the PJM regulation market requires up- and down- regulation markets to be made symmetrically, i.e., both bids must be of equal magnitude in opposite directions.

Figure 11 – PJM Hospital Model, Investment Case with AS

3.4. Final Remarks

The analysis of overall results indicates that participation in AS markets has little impact on the optimal DER portfolio, i.e., in all runs performed with AS the set of technologies was unchanged when compared to the results obtained without AS participation.

It was further observed that participation in AS markets may influence the overall installed capacity, although the exact behavior is dependent on the market economics. In the runs performed in the CAISO territory the added revenue from AS markets led to a slightly lower installed capacity as a result of increased capacity factor, while in the PJM territory the opposite behavior was observed, highlighting the strong differences in utility tariffs in both territories.

4. Conclusion

This paper contributes to the state-of-the-art in DER sizing models by expanding upon DER-CAM and implementing support for different ancillary service products. This includes Spinning, Non-Spinning, Up-Regulation, and Down-Regulation AS products, and all changes to the formulation were implemented in a flexible way and allow support to different AS markets throughout different ISO territories.

Further to the description of the revised mathematical formulation, a case study was conducted highlighting the impact of potential revenues from AS market participation in optimal DER selection for microgrids. The demonstration case consisted of four potential microgrid configurations, including a residential building, an office building, a hospital, and a hypothetical microgrid consisting of the aggregation of a residential building, and office building, and a hospital. The analysis was made assuming these microgrids were located both in San Francisco and Baltimore, and PG&E and BG&E tariffs were used, as well as CAISO and PJM market clearing prices for all four AS products introduced.

Results suggest that revenues from AS markets have a variable impact in the overall site-wide energy costs, with results depending widely on the site-specific tariffs and AS market prices, although even in cases where little overall cost impact was observed results suggest that the optimal investment portfolio may change in a disproportional way, as a result of higher capacity factors being observed in DER where market participation is enabled. In such cases as the added revenue from AS participation enables operation in load levels that would otherwise not be cost-effective.

From a broader perspective, the results obtained in this work suggest that, provided the appropriate regulatory conditions are created, DER participation in AS markets may be a viable revenue stream to influence both microgrid sizing and dispatch, and more importantly provide valuable services to support grid operations. Some initial policy efforts to enable DER participation in AS markets are already underway, namely in the CAISO territory, through the establishment of DER Providers (owner or operator of a DER aggregation) as new market participants [36].

5. Acknowledgment

The authors gratefully thank Rima Oueid and Dan Ton, the Smart Grid R&D Program Manager at the US Department of Energy, for their continuous support of DER-CAM. Furthermore, we want to thank Argonne National Laboratory, especially Guenter Conzelmann for providing the historical AS data needed for our work. James T. Reilly played an instrumental role in our AS DER-CAM work and we are very grateful for his support advancing DER-CAM into the latest DER-CAM$^+$ version which considers also AS features.

The Distributed Energy Resources Customer Adoption Model (DER-CAM) has been designed at Lawrence Berkeley National Laboratory (LBNL). DER-CAM has been funded partly by the Office of Electricity Delivery and Energy Reliability, Distributed Energy Program of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

6. References

[1] Lasseter B. Microgrids [distributed power generation]. Power Eng Soc Winter Meet 2001 IEEE 2001;1:146–9. doi:http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=917020&tag=1.

[2] Marnay C, Robio FJ, Siddiqui a S. Shape of the microgrid. Power Eng Soc Winter Meet 2001 IEEE 2001;1:150–3 vol.1. doi:10.1109/PESW.2001.917022.

[3] Stadler M, Cardoso G, Mashayekh S, Forget T, DeForest N, Agarwal A, et al. Value streams in microgrids: A literature review. Appl Energy 2016;162:980–9. doi:10.1016/j.apenergy.2015.10.081.

[4] Neubauer J, Simpson M. Deployment of Behind-The-Meter Energy Storage for Demand Charge Reduction. NREL/TP-5400-63162 2015:30. doi:NREL/TP-5400-63162.

[5] Hafez O, Bhattacharya K. Optimal planning and design of a renewable energy based supply system for microgrids. Renew Energy 2012;45:7–15. doi:10.1016/j.renene.2012.01.087.

[6] HOMER. Hybrid Optimization of Multiple Energy Resources n.d.

[7] RETScreen. Energy Management Software n.d.

[8] Hittinger E, Wiley T, Kluza J, Whitacre J. Evaluating the value of batteries in microgrid electricity systems using an improved Energy Systems Model. Energy Convers Manag 2015;89:458–72. doi:10.1016/j.enconman.2014.10.011.

[9] Stadler M, Kloess M, Groissböck M, Cardoso G, Sharma R, Bozchalui MC, et al. Electric storage in California’s commercial buildings. Appl Energy 2013;104:711–22. doi:10.1016/j.apenergy.2012.11.033.

[10] Marnay C, Venkataramanan G, Stadler M, Siddiqui AS, Firestone R. Optimal Technology Selection and Operation of Commercial-Building Microgrids. IEEE Trans Power Syst 2008;23:975–82.

[11] Cardoso G, Stadler M, Bozchalui MC, Sharma R, Marnay C, Barbosa-Póvoa a., et al. Optimal investment and scheduling of distributed energy resources with uncertainty in electric vehicle driving schedules. Energy 2014;64:17–30. doi:10.1016/j.energy.2013.10.092.

[12] Chen SX, Gooi HB, Wang MQ. Sizing of energy storage for microgrids. IEEE Trans Smart Grid 2012;3:142–51. doi:10.1109/TSG.2011.2160745.

[13] Bahramirad S, Reder W, Khodaei A. Reliability-constrained optimal sizing of energy storage system in a microgrid. IEEE Trans Smart Grid 2012;3:2056–62. doi:10.1109/TSG.2012.2217991.

[14] Chen C, Duan S, Cai T, Liu B, Hu G. Optimal allocation and economic analysis of energy storage system in microgrids. IEEE Trans Power Electron 2011;26:2762–73. doi:10.1109/TPEL.2011.2116808.

[15] Logenthiran T, Srinivasan D, Khambadkone a. M, Sundar Raj T. Optimal sizing of Distributed Energy Resources for integrated microgrids using Evolutionary Strategy. 2012 IEEE Congr Evol Comput 2012:1–8. doi:10.1109/CEC.2012.6256143.

[16] Simpkins T, Cutler D, Anderson K, Olis D, Elgqvist E, Callahan M, et al. REopt: A Platform for Energy System Integration and Optimization. Proc. ASME 2014 8th Int. Conf. Energy Sustain., 2014. doi:10.1115/ES2014-6570.

[17] Ren H, Gao W. A MILP model for integrated plan and evaluation of distributed energy systems. Appl Energy 2010;87:1001–14. doi:10.1016/j.apenergy.2009.09.023.

[18] Naraharisetti PK, Karimi I a., Anand A, Lee D-Y. A linear diversity constraint – Application to scheduling in microgrids. Energy 2011;36:4235–43. doi:10.1016/j.energy.2011.04.020.

[19] Shadmand MB, Balog RS. Multi-objective optimization and design of photovoltaic-wind hybrid system for community smart DC microgrid. IEEE Trans Smart Grid 2014;5:2635–43. doi:10.1109/TSG.2014.2315043.

[20] Mendes G, Ioakimidis C, Ferrão P. On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools. Renew Sustain Energy Rev 2011;15:4836–54. doi:10.1016/j.rser.2011.07.067.

[21] Gamarra C, Guerrero JM. Computational optimization techniques applied to microgrids planning: A review. Renew Sustain Energy Rev 2015;48:413–24. doi:10.1016/j.rser.2015.04.025.

[22] Fathima a. H, Palanisamy K. Optimization in microgrids with hybrid energy systems – A review. Renew Sustain Energy Rev 2015;45:431–46. doi:10.1016/j.rser.2015.01.059.

[23] Joos G, Ooi BT, McGillis D, Galiana FD, Marceau R. The potential of distributed generation to provide ancillary\nservices. 2000 Power Eng Soc Summer Meet (Cat No00CH37134) 2000;3:1762–7. doi:10.1109/PESS.2000.868792.

[24] Pepermans G, Driesen J, Haeseldonckx D, Belmans R, D'haeseleer W. Distributed generation: Definition, benefits and issues. Energy Policy 2005;33:787–98. doi:10.1016/j.enpol.2003.10.004.

[25] Prodanović M, De Brabandere K, Van den Keybus J, Green T, Driesen J. Harmonic and reactive power compensation as ancillary services in inverter-based distributed generation. IET Gener Transm Distrib 2007;1:432–8. doi:10.1049/iet-gtd:20060064.

[26] Madureira a. G, Peças Lopes J a. Ancillary services market framework for voltage control in distribution networks with microgrids. Electr Power Syst Res 2012;86:1–7. doi:10.1016/j.epsr.2011.12.016.

[27] Cappers P, MacDonald J, Goldman C, Ma O. An assessment of market and policy barriers for demand response providing ancillary services in U.S. electricity markets. Energy Policy 2013;62:1031–9. doi:10.1016/j.enpol.2013.08.003.

[28] Zhou Z, Levin T, Conzelmann G. Survey of U.S. Ancillary Services Markets 2016. doi:Technical Report ANL/ESD-16/1.

[29] Pourmousavi S a, Nehrir MH. Real-Time Central Demand Response for Primary Frequency Regulation in Microgrids. IEEE Trans Smart Grid 2012;3:1988–96. doi:10.1109/tsg.2012.2201964.

[30] Bayat M, Sheshyekani K, Member S, Hamzeh M. Coordination of Distributed Energy Resources and Demand Response for Voltage and Frequency Support of MV Microgrids 2015:1–11.

[31] Gouveia C, Moreira J, Moreira CL, Pecas Lopes J a. Coordinating storage and demand response for

microgrid emergency operation. IEEE Trans Smart Grid 2013;4:1898–908. doi:10.1109/TSG.2013.2257895.

[32] Schittekatte T, Stadler M, Cardoso G, Mashayekh S, Sankar N. The impact of short-term stochastic variability in solar irradiance on optimal microgrid design. IEEE Trans Smart Grid 2016;3053:1–9. doi:10.1109/TSG.2016.2596709.

[33] Mashayekh S, Stadler M, Cardoso G, Heleno M. A mixed integer linear programming approach for optimal DER portfolio, sizing, and placement in multi-energy microgrids. Appl Energy 2017;187:154–68. doi:10.1016/j.apenergy.2016.11.020.

[34] Milan C, Stadler M, Cardoso G, Mashayekh S. Modeling of non-linear CHP efficiency curves in distributed energy systems. Appl Energy 2015;148:334–47. doi:10.1016/j.apenergy.2015.03.053.

[35] U.S Energy Information Administration. Residential Energy Consumption Survey n.d. http://www.eia.gov/consumption/residential/.

[36] CAISO. Order Accepting Proposed Tariff Revisions - Distributed Energy Resource Provider 2016:ER16-1085-000. http://www.caiso.com/Documents/Jun2_2016_OrderAcceptingProposedTariffRevisions_DistributedEnergyResourceProvider_ER16-1085.pdf.

Table 2- Summary of the electric loads used in the DER-CAM runs

Case	San Francisco		Baltimore	
	Peak load (kW)	Total annual load (MWh)	Peak load (kW)	Total annual load (MWh)
Residential	45	180	30	120
Office	125	548	123	547
Hospital	1027	5646	986	5270
Aggregated	1147	6374	1101	5937

Table 3- Summary of the PG&E tariff information used in the DER-CAM runs, less than 200kW peak

PG&E - less than 200kW peak	Summer (June-September)		Winter (October-May)	
	electricity (US$/kWh)	demand (US$/kW)	electricity (US$/kWh)	demand (US$/kW)
non-coincident	-	-	-	-
on-peak	0.60974	-	-	-
mid-peak	0.28352	-	0.17883	-
off-peak	0.15605	-	0.14605	-
fixed (US$/month)	9.8			

summer on-peak: 11:00 to 18:00 on weekdays

summer mid-peak: 08:00 to 11:00 and 18:00 to 22:00 on weekdays

summer off-peak: 00:00 to 08:00 and 22:00 to 24:00 on weekdays, 00:00 to 24:00 on weekends

winter on-peak: N/A

winter mid-peak: 08:00 to 22:00 on weekdays

winter off-peak: 00:00 to 08:00 and 22:00 to 24:00 on weekdays and 00:00 to 24:00 on weekends

Table 4- Summary of the PG&E tariff information used in the DER-CAM runs, more than 500kW peak

PG&E - greater than 500kW peak	Summer (June-September)		Winter (October-May)	
	electricity (US$/kWh)	demand (US$/kW)	electricity (US$/kWh)	demand (US$/kW)
non-coincident	-	14.38	-	14.38
on-peak	0.16233	19.04		-
mid-peak	0.10893	4.42	0.10185	0.24
off-peak	0.07397	-	0.07797	-
fixed (US$/month)	591.45			

summer on-peak: 11:00 to 18:00 on weekdays

summer mid-peak: 08:00 to 11:00 and 18:00 to 22:00 on weekdays

summer off-peak: 00:00 to 08:00 and 22:00 to 24:00 on weekdays, 00:00 to 24:00 on weekends

winter on-peak: N/A

winter mid-peak: 08:00 to 22:00 on weekdays

winter off-peak: 00:00 to 08:00 and 22:00 to 24:00 on weekdays and 00:00 to 24:00 on weekends

Table 5- Summary of the BG&E tariff information used in the DER-CAM runs, less than 2 GWh consumption

BG&E - Less than 2GWh	Summer (June-September)		Winter (October-May)	
	electricity (US$/kWh)	demand (US$/kW)	electricity (US$/kWh)	demand (US$/kW)
non-coincident	-	-	-	-
on-peak	0.13546	-	0.13546	-
mid-peak	0.11874	-	0.11874	-
off-peak	0.09859	-	0.09859	-
fixed (US$/month)	17.5			

summer on-peak: 09:00 to 22:00 on weekdays

summer mid-peak: 06:00 to 10:00 and 21:00 to 23:00 on weekdays

summer off-peak: 00:00 to 06:00 and 23:00 to 24:00 on weekdays, 00:00 to 24:00 on weekends

winter on-peak: 07:00 to 12:00 and 16:00 to 21:00 on weekdays

winter mid-peak: 12:00 to 16:00 on weekdays winter off-peak: 00:00 to 06:00 and 21:00 to 24:00 on weekdays and 00:00 to 24:00 on weekends

Table 6- Summary of the BG&E tariff information used in the DER-CAM runs, large commercial customers

BG&E – Large Commercial	Summer (June-September)		Winter (October-May)	
	electricity (US$/kWh)	demand (US$/kW)	electricity (US$/kWh)	demand (US$/kW)
non-coincident	-	3.54	-	3.54
on-peak	0.12170	2.46	0.08149	2.46
mid-peak	0.08696	-	-	-
off-peak	0.08149	-	0.08149	-
fixed (US$/month)	88			

summer on-peak: 09:00 to 22:00 on weekdays

summer mid-peak: 06:00 to 10:00 and 21:00 to 23:00 on weekdays

summer off-peak: 00:00 to 06:00 and 23:00 to 24:00 on weekdays, 00:00 to 24:00 on weekends

winter on-peak: 07:00 to 12:00 and 16:00 to 21:00 on weekdays

winter mid-peak: 12:00 to 16:00 on weekdays

winter off-peak: 00:00 to 06:00 and 21:00 to 24:00 on weekdays and 00:00 to 24:00 on weekends

Table 7 - Photovoltaic modules

PV technology	Bifacial HIT-Si
Installation cost ($/kW)	3237
Lifetime (years)	30
Peak efficiency	15.29%

Table 8- Stationary Storage Characteristics

Battery technology	Li-ion
Battery cost ($/kWh)	560

Lifetime (years)	5
Maximum charge rate	C/4
Maximum discharge rate	C/4
Charging efficiency	0.95
Discharging efficiency	0.95
Max. depth of discharge	80%

Table 9 - Conventional generation units

DG Units	maxp kW	lifetime yr	capcost $/kW	OMVar $/kWh	electr. eff. -	HPR -	NoX g/kWh	UpTime -	MinLoad -
ICE_RB_75	75	15	2230	0.024	0.26	0	0.0068	93%	70%
ICE_RB_250	250	15	2073	0.024	0.27	0	0.0068	93%	70%
ICE_LB_500	500	15	1814	0.021	0.33	0	0.0008	93%	70%
MT_65	65	15	2737	0.013	0.24	0	0.0001	95%	75%
MT_200	200	15	2678	0.016	0.27	0	0.0001	95%	75%
MT_250	250	15	2311	0.011	0.26	0	0.0001	95%	75%
MCFC_300	300	20	10000	0.045	0.43	0	0.0000	98%	100%
PAFC_400	400	20	7000	0.036	0.38	0	0.0000	98%	100%
ICE_RB_CHP-HW_75	75	15	2881	0.0255	0.26	2.00	0.0068	93%	70%
ICE_RB_CHP-HW_250	250	15	2614	0.025	0.27	1.83	0.0068	93%	70%
ICE_LB_CHP-HW_500	500	15	2309	0.0215	0.33	1.22	0.0008	93%	70%
ICE_LB_CHP-HW_750	750	20	2200	0.0215	0.35	1.16	0.0008	93%	70%
MT_CHP-HW_65	65	15	3220	0.0145	0.24	1.57	0.0001	95%	75%
MT_CHP-HW_200	200	15	3150	0.017	0.27	1.10	0.0001	95%	75%

DG Units	maxp kW	lifetime yr	capcost $/kW	OMVar $/kWh	electr. eff. -	HPR -	NoX g/kWh	UpTime -	MinLoad -
MT_CHP-HW_250	250	15	2719	0.012	0.26	1.20	0.0001	95%	75%
MCFC_CHP-HW_300	300	20	10300	0.046	0.43	0.47	0.0000	98%	100%
PAFC _HP-HW_400	400	20	7300	0.037	0.38	0.57	0.0000	98%	100%

ICE - Internal Combustion Engine, MT - Micro Turbine, MCFC - Molten Carbonate Fuel Cell

PAFC - Phosphoric Acid Fuel Cell

RB - Rich Burn, LB – Lean Burn, CHP - Combined Heat and Power, HW - Hot Water Applications

HPR – Heat-Power Ratio

Table 10 – CAISO: Costs, emissions and investments for a residential building and a medium sized office

Costs in US$	Residential building			Medium sized office		
	Base case	Simple investment	With AS	Base case	Simple investment	With AS
Total Costs	37,429	32,320	32,320	143,679	96,724	96,724
Electricity Costs	27,322	18,200	18,200	139,013	58,536	58,536
Fuel costs	10,107	10,107	10,107	4,666	4,666	4,666
Ann. Cap. cost	0	3,956	3,956	0	33,050	33,050
O&M cost	0	56	56	0	471	471
AS Revenue	-	-	0	-	-	0
CO_2 (kg)	115,614	98,656	98,656	324,263	175,606	175,606
PV (kW)	-	19	19	-	157	157
Total DG (kW)	-	-	-	-	-	-
CHP (kW)	-	-	-	-	-	-

Table 11 – CAISO: Costs, emissions and investments for a hospital and aggregated for all buildings.

Costs in US$	Hospital	Aggregated system

	Base case	Simple investment	With AS	Base case	Simple investment	With AS
Total Costs	1,385,310	1,164,147	1,157,303	1,517,047	1,264,577	1,249,716
Electricity Costs	1,239,299	255,314	323,248	1,360,328	264,103	278,942
Fuel costs	146,011	379,486	363,445	156,719	391,958	410,706
Ann. Cap. cost	0	424,787	374,744	0	502,786	450,362
O&M cost	0	104,560	100,325	0	105,729	113,324
AS Revenue	-	-	3,618	-	-	4460
CO_2 (kg)	5,533,957	3,668,595	3,712,145	5,973,834	2,175,789	3,986,516
PV (kW)	-	1075	999	-	1343	1111
Total DG (kW)	-	900	750	-	1000	1000
CHP (kW)	-	750	750	-	750	750

Table 12 - Costs, emissions and investments for a residential building and a medium sized office.

Costs in US$	Residential building			Medium sized office		
	Base case	Simple investment	With AS	Base case	Simple investment	With AS
Total Costs	31,357	31,357	31,357	73,215	73,215	73,215
Electricity Costs	25,451	25,451	25,451	69,573	69,573	69,573
Fuel costs	5,906	5,906	5,906	3,642	3,642	3,642
Ann. Cap. cost	0	0	0	0	0	0
O&M cost	0	0	0	0	0	0
AS Revenue	-	-	0	-	-	-
CO_2 (kg)	223,946	223,946	223,946	534,395	534,395	534,395
PV	-	-	-	-	-	-
Total DG	-	-	-	-	-	-
CHP	-	-	-	-	-	-

Table 13 - Costs, emissions and investments for a hospital and aggregated for all buildings.

Costs in US$	Hospital			Aggregated system		
	Base case	Simple investment	With AS	Base case	Simple investment	With AS
Total Costs	1,001,780	837,859	782,605	1,343,417	919,607	856,020
Electricity Costs	9,45,984	73,175	130,433	1,281,700	23,308	34,380
Fuel costs	55,795	328,331	329,119	61,716	385,584	432,678
Ann. Cap. cost	0	275,645	301,883	0	331,310	370,779
O&M cost	0	159,433	129,760	0	170,051	120,892
AS Revenue	-	-	108,381	-	-	102,350
CO_2 (kg)	8,492,950	6,199,267	6,703,209	9,251,291	6,876,192	7,768,291
PV	-	-	-	-	9	-
Total DG	-	1250	1250	-	1325	1565
CHP	-	750	500	-	750	500

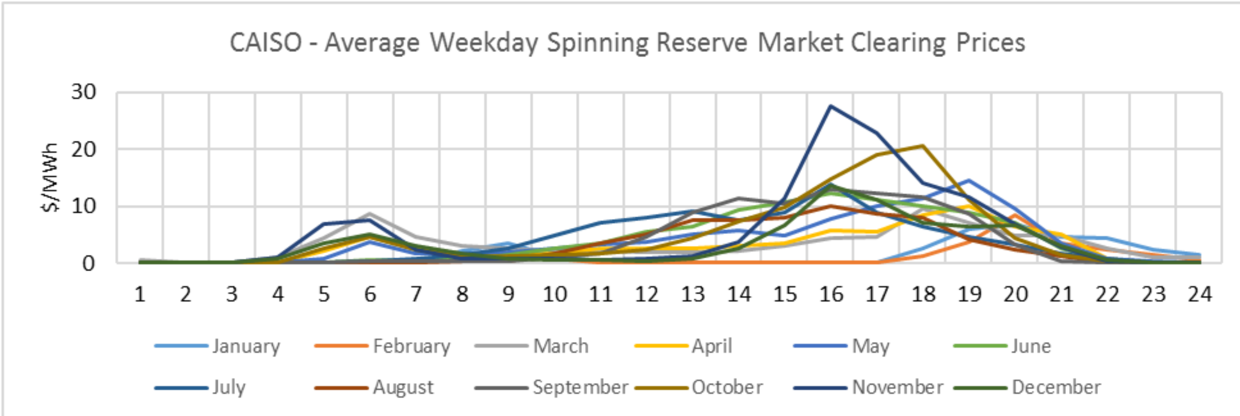


Figure 1- CAISO average weekday spinning reserve market clearing prices [28]

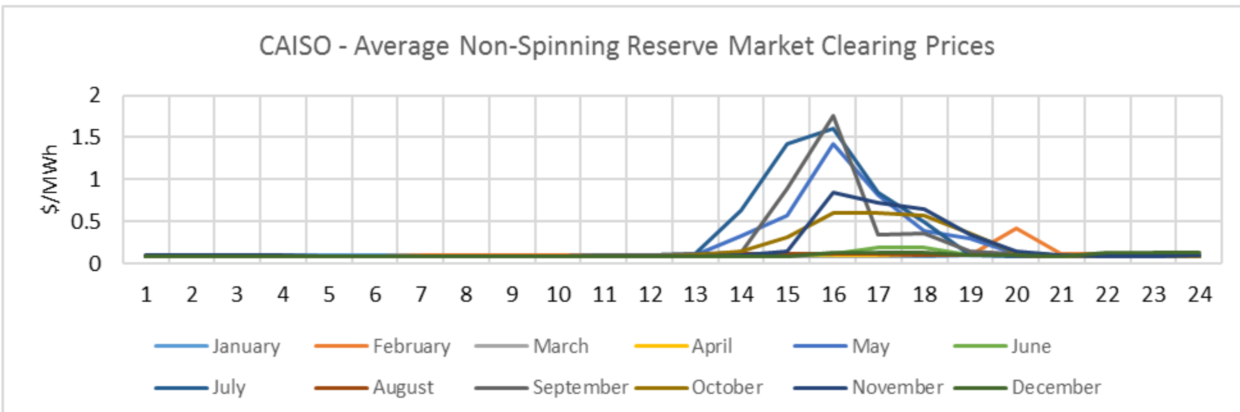


Figure 2- CAISO average weekday non-spinning reserve market clearing prices [28]

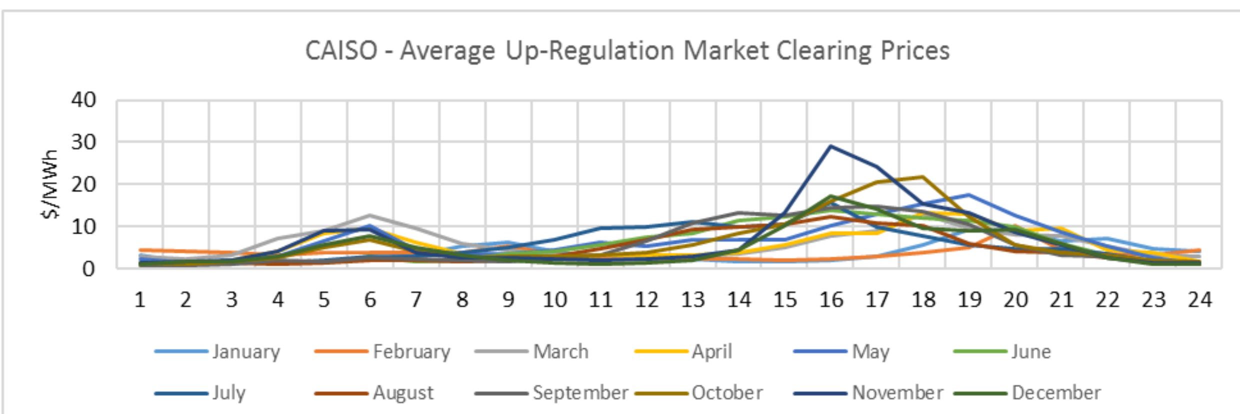


Figure 3- CAISO average Up-Regulation market clearing prices [28]

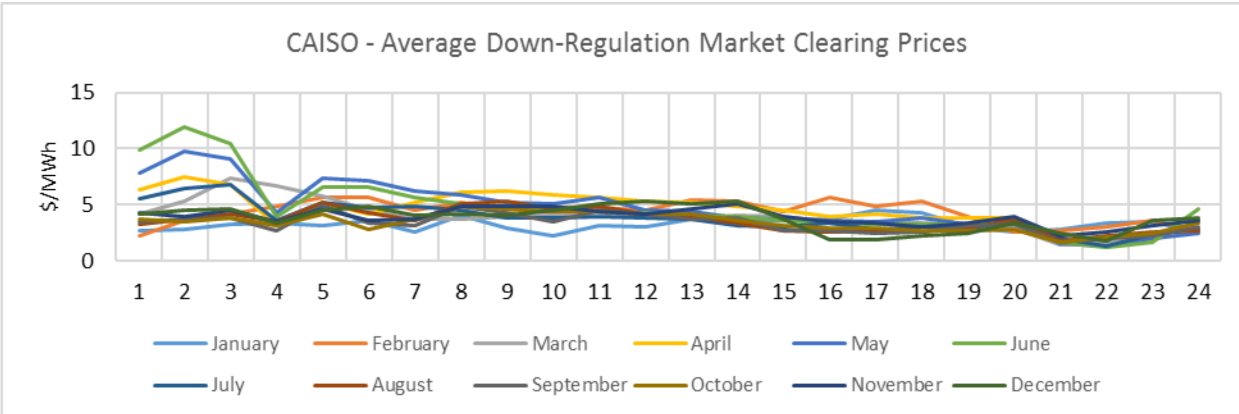


Figure 4- CAISO average Down-Regulation market clearing prices [28]

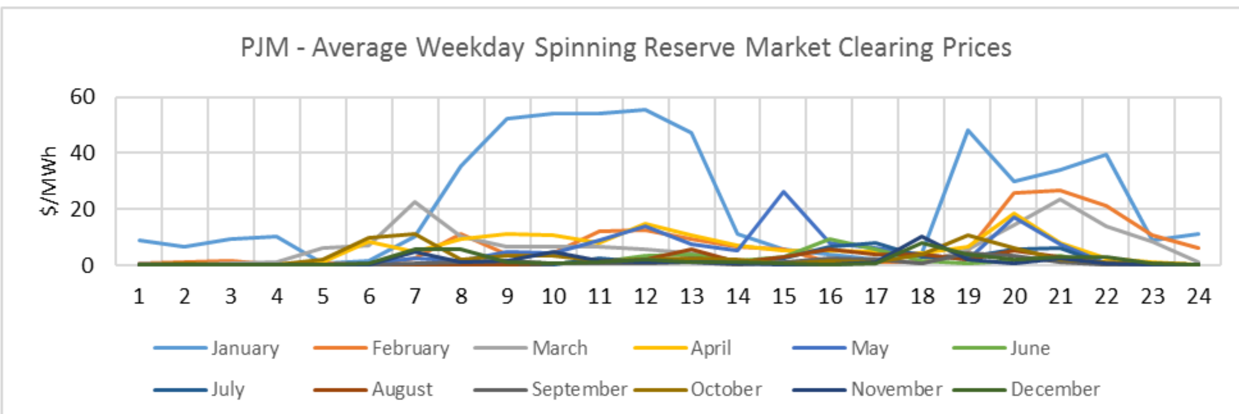


Figure 5- PJM average weekday spinning reserve market clearing prices [28]

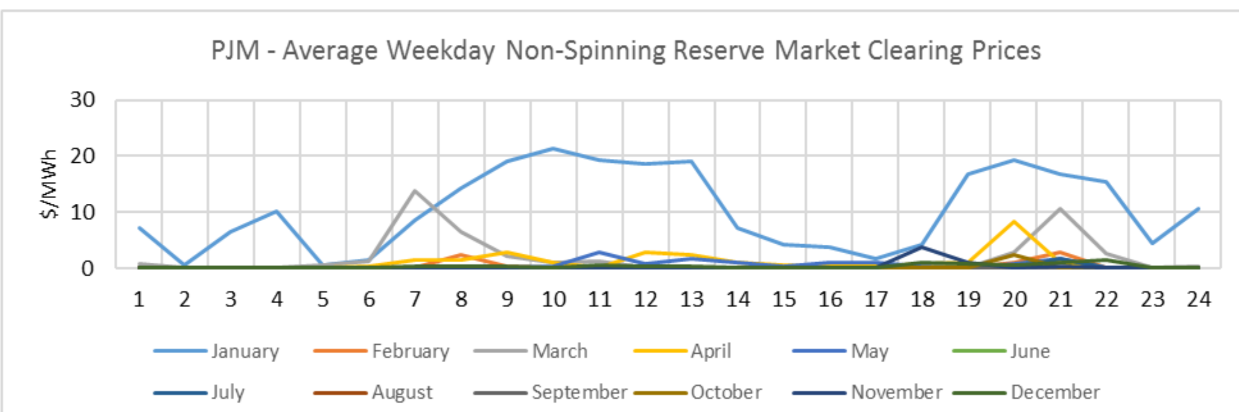


Figure 6- PJM average weekday non-spinning reserve market clearing prices [28]

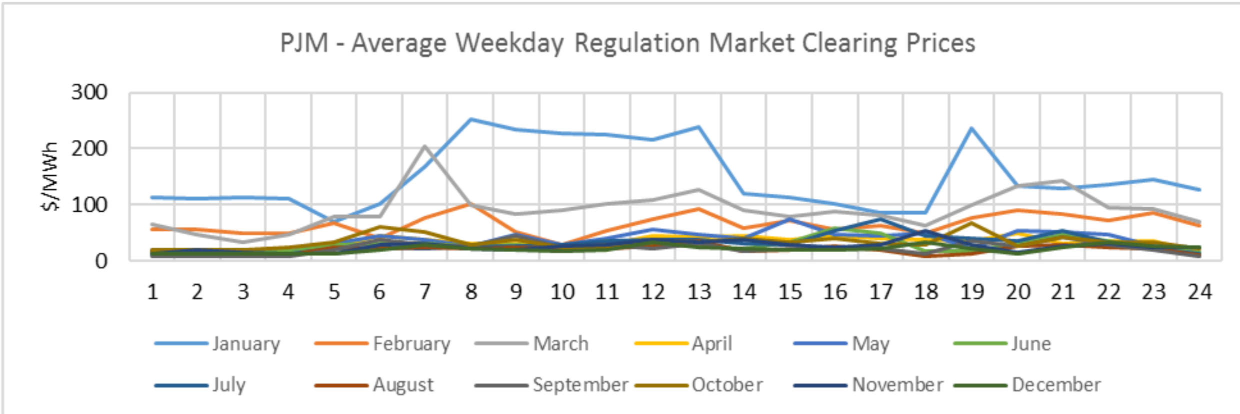


Figure 7- PJM average weekday regulation market clearing prices [28]

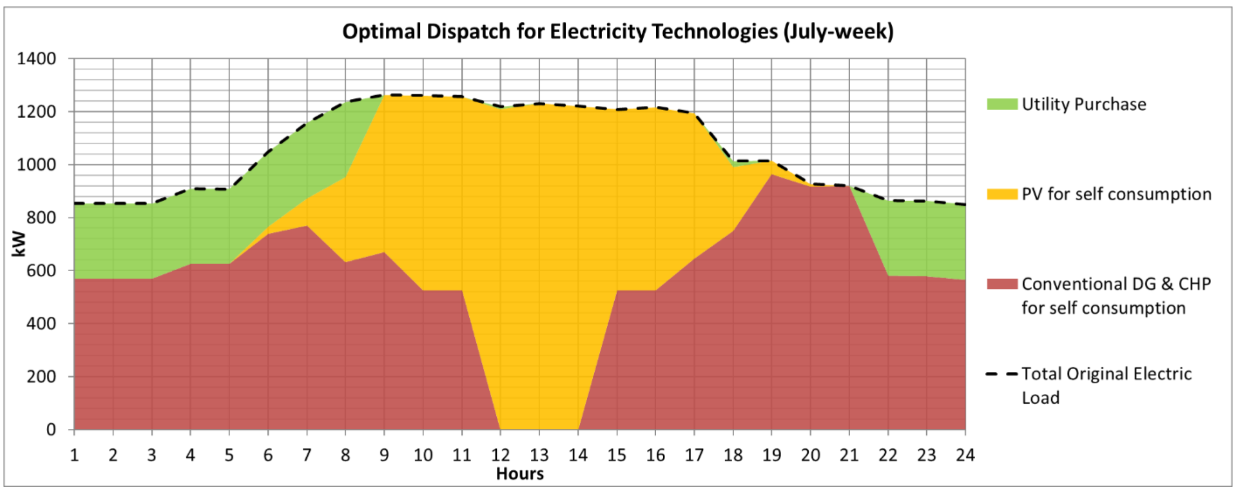


Figure 8 – CAISO Aggregate Model, Simple Investment Case

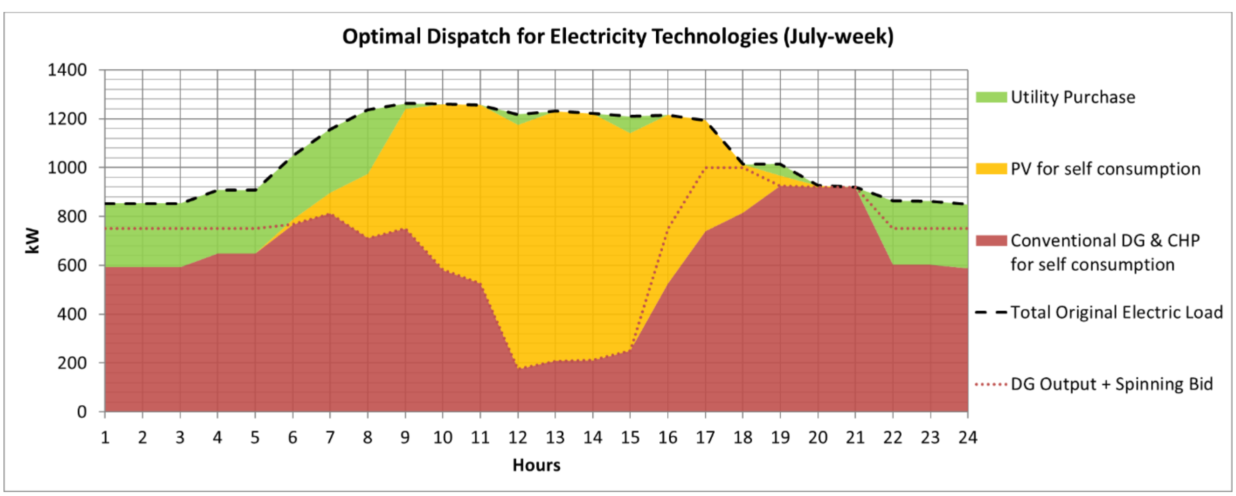


Figure 9 – CAISO Aggregate Model, Investment Case with AS

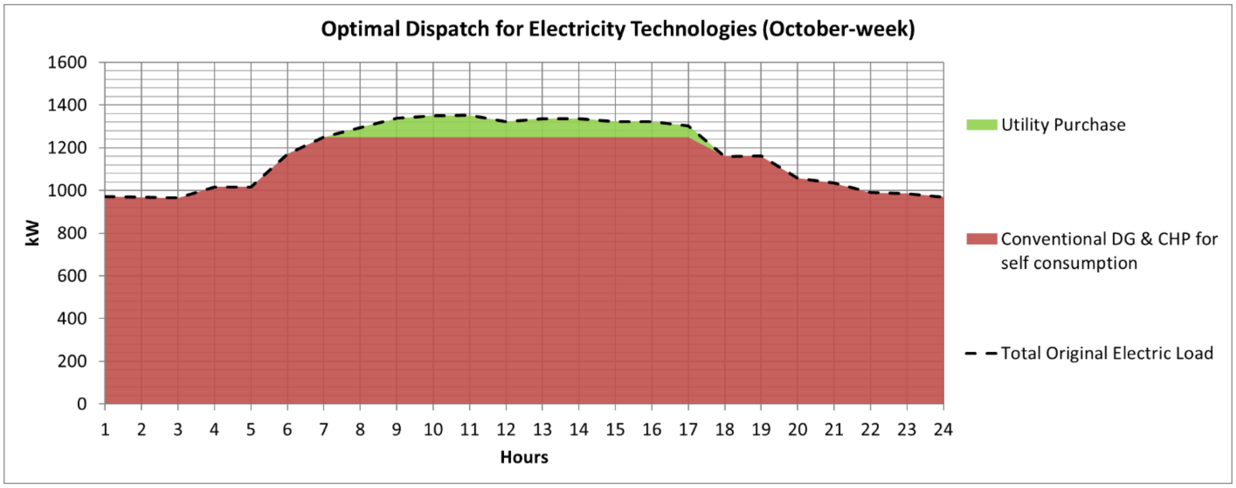


Figure 10 – PJM Hospital Model, Simple Investment Case

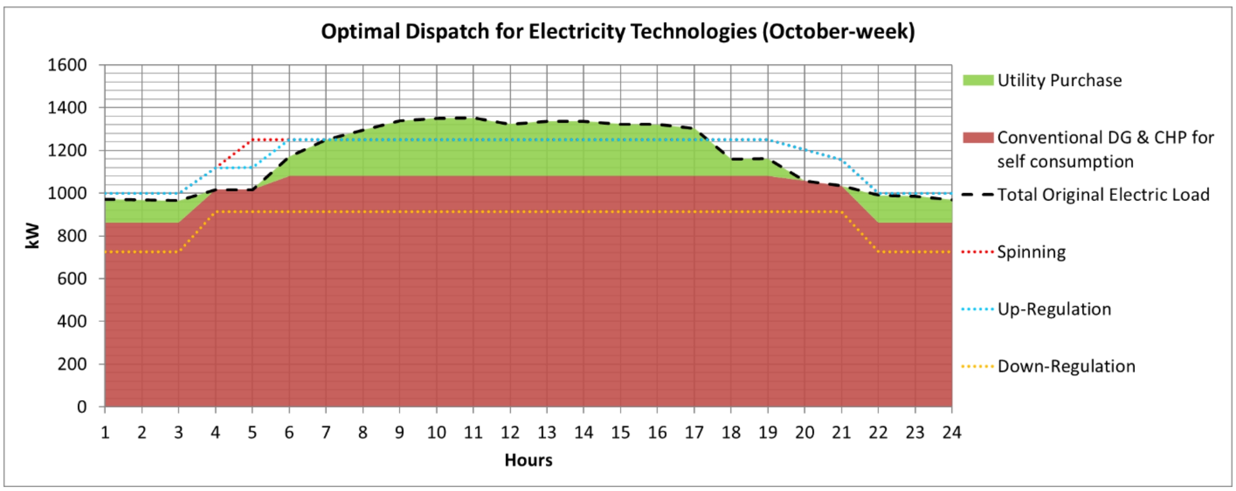


Figure 11 – PJM Hospital Model, Investment Case with AS