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***Abstract*—This paper proposes a new methodology to capture the impact of fast moving clouds on utility power demand charges observed in microgrids with photovoltaic (PV) arrays, generators, and electrochemical energy storage. It consists of a statistical approach to introduce sub-hourly events in the hourly economic accounting process. The methodology is implemented in the Distributed Energy Resources Customer Adoption Model (DER-CAM), a state of the art mixed integer linear model used to optimally size DER in decentralized energy systems. Results suggest that previous iterations of DER-CAM could undersize battery capacities. The improved model depicts more accurately the economic value of PV as well as the synergistic benefits of pairing PV with storage.**

***Index Terms*—Batteries, distributed generation, microgrids, mixed integer linear programming (MILP), photovoltaic cells**

I. Introduction

Growing energy demand, environmental concerns, and resiliency concerns driven by natural disasters are pushing forward the deployment of renewable energy technologies, causing the costs of these easily-scalable technologies to rapidly decrease. This is drawing attention to the concept of microgrids, defined as a group of interconnected loads and distributed energy resources (DERs) within clearly-defined electrical boundaries that acts as a single controllable entity with respect to the grid [1], where a potentially cheaper, more reliable, and environmentally friendly alternative to traditional centralized grids can be offered. DER solutions include conventional (heat and) power generation, energy storage, renewables, and load management strategies such as demand response and load shifting [2].

Generically, microgrids can be categorized in islanded and grid-connected, and several research questions arise in the context of microgrids, including optimal sizing, siting, and operation. This work focusses on the optimal sizing of grid-connected microgrids, although it should be noted that the boundaries between these categories are not strict [3]. Several approaches are proposed in the literature to tackle grid-connected microgrid sizing problems. Simulation models [3]–[7], mixed integer linear programming (MILP) models [8]–[12], and mixed integer non-linear programming (MINLP) models [13], [14] are amongst the most common approaches. Simulation models have the main advantage of being generally straightforward to develop and non-linear behaviors can be easily modelled. The main disadvantage is that user experience is usually required to build suitable candidate solutions, and that different objectives (e.g. cost minimization, battery cycling strategies, etc.) require building separate dispatch algorithms, where optimality is not guaranteed. Specifically, if the number of considered technologies is large enough, building the search space can become a critical issue and guaranteeing a good or near-optimal solution might not be possible. Another potential disadvantage is that the sizing relies in building robust dispatch algorithms, and if both storage technologies and monthly power demand charges are present, finding optimal dispatches with sequential simulation algorithms can be very challenging, and lead to errors in the final sizing decisions. Examples of commercial software belonging to this category are HOMER [5], [6] and RETSCREEN [7].

MILP models have the main advantage that an optimum solution can be guaranteed provided a convex feasible region is created, and that users are not required to manually define this region, as this is done by the constrains defined in the mathematical formulation. The use of such models is not limited by the presence of storage and demand charges, or different objectives. The main disadvantage of these models, however, is the difficulty to model non-linear effects without drastically increasing the computational time required by linearization techniques. An example of such type of MILP model is DER-CAM [8]–[10].

MILNP models bring an additional level of complexity and detail to MILP models, by explicitly considering non-linear effects. This has the advantage to more accurately modelling the behavior of different technologies, but is followed by the disadvantage that finding a solution may not be possible. Examples of such models can be found in [13]–[15] . More in-depth reviews of the different methodologies used for optimal microgrid sizing can be found in [16]–[18].

Several papers in the literature consider the stochastic nature of different elements in a microgrid, and take into account their impact on the optimal operation. For instance, uncertainty in solar or wind power generation is taken into account in [19]–[21], uncertainty in load is addressed in [22], the stochastic nature of electrical vehicle driving patterns is the focus of [23], and the reliability of storage technologies is

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addressed in [24]. In the aforementioned examples, a stochastic programming methodology is commonly employed.

However, these models typically assume that the capacities of different DER in the microgrid are known, and focus only on optimizing the dispatch of different technologies in the presence of uncertainty. This is due to the added complexity of simultaneously formulating capacity and dispatch as variables, in which case stochasticity may lead to extremely large problems where both solvability and runtime become critical. Some models found in literature do formulate DER capacity as a decision variable, but the majority of such cases address microgrid expansion problems, where only the capacity of a specific technology, e.g. energy storage systems (ESS), is unknown, while all other DER capacities are fixed. This is the case in [11], where the optimal size of an ESS is determined taking into account uncertainties in the output of PV and wind generation, both of known installed capacity.

In other work, the optimal size of an ESS in a microgrid is determined taking into account the intermittency of renewable units and the possible outage of conventional units [12]. The impact of uncertain EV driving schedules on optimal DER investments is presented in [10]. In [15], a model is presented to determine the optimal system design of a DC microgrid, where uncertainty in PV and wind output is taken into account using an optimization technique based on Multi-Objective Genetic Algorithm (MOGA). Multiple criteria are considered including size, cost, and availability, although the focus of this work is on the trade-off of the different objectives, and key microgrid economic drivers such as power demand charges are disregarded.

A survey of the existing literature shows that DER sizing formulations typically use hourly time steps to limit computational time. While this may be a significant benefit for usability that in most cases will not take a significant toll on the accuracy of the results, it must be noted that the use of hourly time steps can lead to inaccurate PV representation. Specifically, modeling PV output on an hourly basis may not consider short-term irradiance variability caused by fast moving clouds. This effect is non-negligible, and studies report deviations of more than 60-70% when comparing insulation values averaged over 1 min with 180 min averages of the same data on partly cloudy days [25], [26]. This loss of detail is particularly present in higher levels of data aggregation, such as when using a single 24h profile to represent irradiation for the entire month.

When considering grid-connected microgrids with PV, the variability in insolation may not impact the net energy charges, since over- and underestimations in PV generation are typically compensated. However, the impact on power demand charges, typically paid on the highest average demand measured over 5 or 15 minute intervals, can be significant. This is confirmed by [4], where it is stated that behind-the-meter PV decreases energy costs, but the intermittency introduced by clouds may cause peak loads and demand charges to remain unaffected. Thus, using averaged solar data in the sizing process might lead to an overestimation of the economic benefit of PV.

Batteries and fast-ramping onsite generators can potentially be used to mitigate variability in PV generation, thus preventing high power demand charges in microgrids. However, both options represent additional investment and operational costs, creating a trade-off between adding more DER and avoiding utility demand costs. This will greatly be site-specific, and influenced by tariffs, electricity loads, and DER costs. This economic problem is addressed in this work by taking into account the solar insolation variability in the process of estimating power demand charges, and how either batteries or fast-ramping on-site generators may be used to mitigate this effect. Particularly, the novelty of this paper can be summarized by the introduction of a statistical component in a state-of-the-art MILP DER sizing model with hourly time steps, allowing sub-hourly variations in solar irradiance to be considered. By doing so, the gap between different modeling approaches is reduced, and the advantages and run-time of the linear formulation can be retained, while still incorporating relevant effects that would otherwise be ignored.

A statistical approach incorporated in a deterministic MILP is chosen over stochastic formulations, as deterministic models are the most common choice for DER sizing problems, positioning the work presented in this paper as a natural extension to the current state of the art, although the method suggested in this work can easily be extended to stochastic formulations.

This suggested methodology is implemented in DER-CAM, a state of the art MILP model developed by the Microgrid Team at the Lawrence Berkeley National Lab (LBNL) [8]–[10]. This choice is supported by the extremely comprehensive and modular design of DER-CAM, as it simultaneously considers electric, heating, and cooling loads, a wide array of DER options including reciprocating engines, micro-turbines, combustion turbines, fuel cells, heat-exchangers for CHP operation, renewable generation technologies including PV, wind turbines and solar thermal panels, energy storage technologies including heating storage, cooling storage, electric vehicles, and multiple stationary storage chemistries, as well as several load management strategies including load prioritization, peak shaving, load shifting, and demand response. Further, the applicability of DER-CAM has been demonstrated in a large number of peer-reviewed publications and real microgrid implementation projects [27], making it an ideal candidate for the purpose of this work.

The remainder of this paper is organized as follows: In section II a very compact formulation of DER-CAM is shown, and in section III the incorporation of sub-hourly cloud cover in the model is discussed. A case study is presented in section IV and in section V the case study results are discussed and conclusions are presented.

II. DER-CAM Formulation

This work builds on the deterministic version of DER-CAM where 3 typical days (week, peak, and weekend) of hourly loads per month are used to model energy loads. Operational and investment costs are included in the cost minimization objective function, with investments being annualized.

The optimal capacity of different technologies is modelled in DER-CAM using either a continuous or discrete variable, with the distinction being made if a technology is available in small enough modules and the investment costs can be approximated by a linear cost function, in which case a continuous variable will be used, significantly lowering the computational time. This distinction can be found in the formulation below, adopted from [10].

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]
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]
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]
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]
SCE_{k}	charging efficiency of storage technology k [%]
SDE_{k}	discharging efficiency of storage technology k [%]
φ_{k}	losses due to decay/self-discharge in storage technology k [%]
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]
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 [%]
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]
$GU_{j,m,d,h,u}$	power generated by technology j, at time m, d, h for end-use u [kW]
$GS_{j,m,d,h}$	power generated to export by technology j, at time m, d, h [kW]
$RH_{j,m,d,h}$	useful heat recovered from technology j, at time m, d, h [kW]
$AL_{m,d,h}$	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

$$\min \mathrm{C} = \sum_m \mathrm{TF}_m \tag{1}$$
$$+ \sum_m \sum_d \sum_h \sum_u UL_{m,d,h,u} \cdot \mathrm{TE}_{m,d,h}$$
$$+ \sum_s \sum_{m\in s} \sum_p \mathrm{TP}_{s,p} \cdot \max\left(\sum_{u\in eo,cl,rf} UL_{m,(d,h)\in p,u}\right)$$
$$+ \sum_j \sum_m \sum_d \sum_h \left(GS_{j,m,d,h} + \sum_u GU_{j,m,d,h,u}\right) \cdot \left(\mathrm{VC}_{j,m} + \mathrm{OMV}_j\right)$$
$$+ \sum_g IG_g \cdot \mathrm{MaxP}_g \cdot \left(\mathrm{CCD}_g \cdot \mathrm{An}_g + \mathrm{OMF}_g\right)$$
$$+ \sum_{i\in c,k}((\mathrm{FCC}_i \cdot Pur_i + \mathrm{VCC}_i \cdot Cap_i + \mathrm{VCSC}_k \cdot ECap_k) \cdot \mathrm{An}_i + Cap_i \cdot \mathrm{OMF}_i)$$
$$+ \sum_m \mathrm{NGF}_m$$
$$+ \sum_m \sum_d \sum_h \sum_u NGU_{m,d,h,u} \cdot \mathrm{NGP}_m$$
$$- \sum_j \sum_m \sum_d \sum_h GS_{j,m,d,h} \cdot \mathrm{TEx}_{m,d,h}$$

Microgrid constraints

$$\mathrm{Load}_{m,d,h,u} + \frac{SIn_{k,m,d,h}}{\mathrm{SCE}_k} = SOut_{k,m,d,h,u} \cdot \mathrm{SDE}_k + \sum_j GU_{j,m,d,h,u} + UL_{m,d,h,u} \ \forall\, m,d,h\!: k = \{\mathrm{ES}\} \wedge u = \{eo\} \tag{2}$$

$$\mathrm{Load}_{m,d,h,u} + \frac{SIn_{k,m,d,h}}{\mathrm{SCE}_k} + AL_{m,d,h} = SOut_{k,m,d,h,u} \cdot \mathrm{SDE}_k + \beta_u \cdot NGU_{m,d,h,u} + \sum_g RH_{g,m,d,h,u} \ \forall\, m,d,h\!: k = \{\mathrm{TH}\} \wedge u \in \{sh, wh\} \tag{3}$$

$$\mathrm{Load}_{m,d,h,u} = \sum_j GU_{j,m,d,h,u} + UL_{m,d,h,u} \cdot \mathrm{COPu} \quad \forall m,d,h : u \in \{cl, rf\} \tag{4}$$

$$\mathrm{Load}_{m,d,h,u} = NGU_{m,d,h,u} \quad \forall\, m,d,h : u = \{ng\} \tag{5}$$

$$\sum_u GU_{g,m,d,h,u} + GS_{g,m,d,h} \leq IG_g \cdot \mathrm{MaxP}_g \quad \forall\, g,m,d,h \tag{6}$$

$$\sum_m \sum_d \sum_h \left(\sum_u GU_{g,m,d,h,u} + GS_{g,m,d,h}\right) \leq IG_g \cdot \mathrm{MaxP}_g \cdot \mathrm{MaxH}_g \quad \forall\, g,m,d,h \tag{7}$$

$$\sum_u RH_{g,m,d,h,u} \leq \alpha_g \cdot \left(\sum_u GU_{g,m,d,h,u} + GS_{g,m,d,h}\right) \quad \forall\, g,m,d,h \tag{8}$$

$$Cap_i \leq Pur_i \cdot \mathbf{M} \quad \forall\, i \in \{c,k\} \tag{9}$$

$$\sum_u GU_{c,m,d,h,u} + GS_{c,m,d,h} \leq Cap_c \cdot \frac{\mathrm{SRE}_{c,m,h}}{\mathrm{SPE}_c} \cdot \mathrm{SI}_{m,d,h} \quad \forall m,d,h : c \in \{\mathrm{PV}\} \tag{10}$$

$$\sum_c \frac{Cap_c}{\mathrm{SPE}_c} \leq \mathrm{SA} : c \in \{\mathrm{PV}\} \tag{11}$$

$$SOC_{k,m,d,h} = SIn_{k,m,d,h} - \sum_u SOut_{k,m,d,h,u} + SOC_{k,m,d,h-1} \cdot (1 - \varphi_k) \quad \forall\, k,m,d,h \neq 1 \tag{12}$$

$$SOC_{k,m,d,1} = SOC_{k,m,d,24} \quad \forall\, k,m,d \tag{13}$$

$$SOC_{k,m,d,h} \geq ECap_k \cdot \mathrm{MSC}_k \quad \forall\, k,m,d,h \tag{14}$$

$$SOC_{k,m,d,h} \leq ECap_k \quad \forall\, k,m,d,h \tag{15}$$

$$SIn_{k,m,d,h} \leq Cap_k \quad \forall\, k,m,d,h \tag{16}$$

$$\sum_u SOut_{k,m,d,h,u} \leq Cap_k \quad \forall\, k,m,d,h \tag{17}$$

$$SIn_{k,m,d,h} \leq sb_{k,m,d,h} \cdot \mathbf{M} \quad \forall\, k,m,d,h \tag{18}$$

$$\sum_u SOut_{k,m,d,h,u} \leq \left(1 - sb_{k,m,d,h}\right) \cdot \mathbf{M} \quad \forall\, k,m,d,h \tag{19}$$

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

$$\sum_u UL_{m,d,h,u} \leq psb_{m,d,h} \cdot \mathbf{M} \quad \forall\, m,d,h : u = \{eo, cl, rf\} \tag{21}$$

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

$$\mathrm{An}_i = \frac{\mathrm{IR}}{\left(1 - \frac{1}{(1+\mathrm{IR})^{\mathrm{Lt}_i}}\right)} \ \forall\, i \tag{23}$$

$$\mathrm{C} \leq \mathrm{BAU} + \sum_g IG_g \cdot \mathrm{MaxP}_g \cdot \mathrm{CCD}_g \cdot \mathrm{An}_g + \sum_{i\in c,k}(\mathrm{FCC}_i \cdot Pur_i + \mathrm{VCC}_i \cdot Cap_i + \mathrm{VCSC}_k \cdot ECap_k) \cdot \mathrm{An}_i - \frac{\sum_g IG_g \cdot \mathrm{MaxP}_g \cdot \mathrm{CC}_g + \sum_{i\in c,k}(\mathrm{FCC}_i \cdot Pur_i + \mathrm{VCC}_i \cdot Cap_i + \mathrm{VCSC}_k \cdot ECap_k)}{\mathrm{PBP}} \tag{24}$$

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

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

Eq. (1) shows the objective function, consisting of all key cost components. This includes all utility charges, annualized capital costs of DER investments, as well as all related operation and maintenance costs.

The key microgrid constraints are expressed by (2) - (26). Eq. (2) - (5) force the energy balances for the different end-uses. The operation of DER on-site generation is constrained by (6) - (11), where **M** is an arbitrarily large number. The operation of the storage technologies is constrained by (12)-(19). Eq. (20) describes the operation of the absorption chiller. Eq. (21) and (22) ensure no simultaneous import and export of power can occur. Eq. (23) shows the calculation of annuity factors. The payback constraint in (24) states that investments must be repaid in a period shorter than the payback period. Lastly (25) and (26) are boundary conditions that ensure the proper links between different technologies and loads.

III. Incorporation of Fast Cloud Cover

A. Sub-hourly variability in irradiance

This work focusses on the variability of PV generation on a sub-hourly scale. The most important parameter related to the PV output in DER-CAM is $\mathrm{SI}_{m,d,h}$, expressing the solar insolation received during hour h of day-type t in month m.

The PV output is modeled to be proportional to the solar irradiance as can be seen in (10). For this reason, PV variability can be estimated using solar irradiance data, similarly to what was done in [26], [28].

Fig. 1 shows typical solar irradiance profiles, with the average solar irradiance for each hour of each month over a 5 year period, for a selected site in Moab, Utah [29]. Fig. 2 displays the distribution of 15-minute solar irradiation data at 12 pm in April, for the same site, illustrating how valuable information is lost when only average values are used.

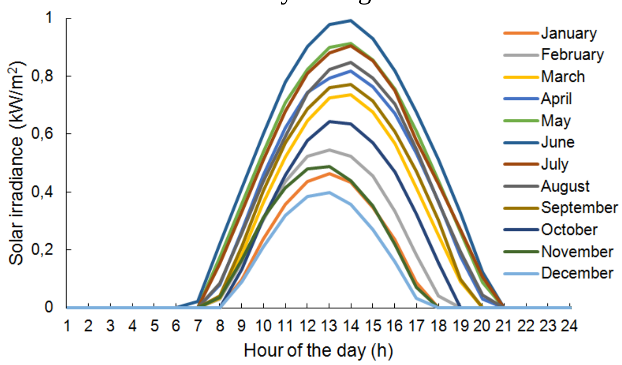

Fig. 1 Example of solar irradiance profiles used in DER-CAM

The variability in irradiance shown in Fig. 2 is essentially caused by two components: changes in irradiance levels occurring at the same hour in different days of a specific month, and changes occurring within different 15-min intervals of the same hour due to fast moving clouds. Since these issues occur on different time scales, they are handled separately.

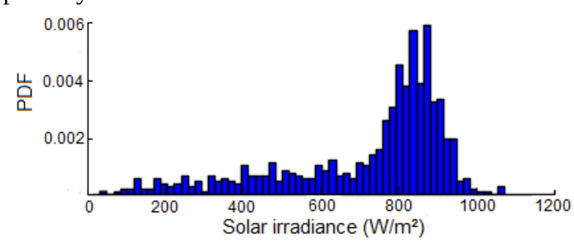

Fig. 2 Empirical probability density function of solar irradiance in April during 11 am to 12 pm using 15-min data (average irradiance: 745 kW/m^2)

The variability reflecting differences in average hourly irradiance in different days of the month, can be expressed by making solar insolation dependent of the day-types, i.e. establish different solar insolation profiles for different day-types. This may not have a relevant physical meaning, but creating different average-hourly profiles for different day-types allows capturing different solar irradiance scenarios, such as critical conditions where a cloudy day is coupled with the peak load day-type profile, as will be shown in the case study.

It is assumed in DER-CAM that the irradiance is constant during an hour, leading to identical numeric hourly values for both insolation and irradiance. As shown in [3], this may lead to errors in the sizing of storage systems, as it is stated that any microgrid modeling package will overestimate the capabilities of energy storage in the presence of fluctuating photovoltaics, and underestimate the amount of storage required.

In addition to the variability observed in solar irradiance, other key sources of uncertainty will come into play when determining energy costs in a microgrid, such as the variability in energy loads. However, this is not addressed in this work as it typically exhibits better predictability and smaller magnitude, as discussed in [28]. Finally, it is also important to mention that the sub-hourly variability in PV output will only have a significant influence on the total energy costs if demand charges are calculated using periods shorter than one hour, and if they represent a significant portion of the electricity bill. This is typically the case with utilities such as Pacific Gas & Electric, one of the largest Californian utilities, where demand charges are calculated over 15-min intervals, and it is not uncommon for larger customers that roughly 30-40% of the electricity bill consists of demand charges.

B. Formulation in DER-CAM

The proposed formulation to incorporate sub-hourly variability of solar irradiance in hourly-based DER sizing models has a probabilistic nature. The proposed approach consists of incorporating an expected percentual drop in irradiance of magnitude $\Delta^{M}_{\mathrm{m,d,h}}$ and duration $\Delta^{D}_{\mathrm{m,d,h}}$ relative to the average irradiance, $\mathrm{SI}_{\mathrm{m,d,h}}$, thus reflecting potential changes in utility imports that could negatively impact the demand charge. By incorporating this effect in the calculations, a trade-off can be established between the cost of offsetting PV drops with batteries or online fast-ramping generators, and the cost of an increase in the demand charges. The financial impact of fast moving clouds is then modeled as a positive continuous variable to reflect the expected increase in power demand, $\delta_{\mathrm{m,d,h}}$, shown in Equation (27) below:

$$\min \mathrm{C} = \ldots \tag{27}$$
$$+ \sum_{\mathrm{s}} \sum_{\mathrm{m}\in\mathrm{s}} \sum_{\mathrm{p}} \mathrm{TP}_{\mathrm{s,p}} \cdot \max\left(\sum_{\mathrm{u}\in\{\mathrm{eo,cl,rf}\}}\left(UL_{\mathrm{m,(d,h)\in p,u}} + \boldsymbol{\delta}_{\mathbf{m,(d,h)\in p,u}}\right)\right) + ..$$

This additional term is a function of the expected PV output, $PVOut_{\mathrm{m,d,h}}$, the expected potential for batteries to offset PV drops, $BPot_{\mathrm{m,d,h}}$, and the potential for online fast-ramping generators to offset PV drops, $GPot_{\mathrm{g,m,d,h}}$. Please note that $PVOut_{\mathrm{m,d,h}}$ is the sum of PV generation for on-site consumption, exports, and eventual curtailments. The estimation of $\delta_{\mathrm{m,d,h}}$ is thus given by:

$$\delta_{\mathrm{m,d,h}} \geq \Delta^{M}_{\mathrm{m,d,h}} \cdot \mathrm{PVOut}_{\mathrm{m,d,h}} - \left(\mathrm{PVOut}_{\mathrm{m,d,h}} - GU_{\mathrm{c,m,d,h,u}}\right) - BPot_{\mathrm{m,d,h}} \cdot \mathrm{SDE}_{\mathrm{k}} - \sum_{g} GPot_{\mathrm{g,m,d,h}} \quad \forall\, \mathrm{m,d,h} : \mathrm{c} = \{\mathrm{PV}\} \wedge \mathrm{k} = \{\mathrm{ES}\} \wedge \mathrm{u} = \{\mathrm{eo}\} \tag{28}$$

It should be noted that this equation establishes that both batteries and online fast ramping generators can be used to offset PV drops, but depending on the relation between the potential PV output and the expected drop this may not be necessary – e.g. the PV output may drop to a level that is still enough to cover on-site loads.

Further, it should be noted that the proposed methodology only addresses the potential financial implications of PV drops, and does not consider changes in the energy balance equations – only the availability of both batteries and online fast ramping generators to provide buffering to PV drops is considered. In the case of batteries, this is a function of maximum power output and state of charge in each time-step:

$$BPot_{\mathrm{m,d,h}} \leq Cap_{\mathrm{k}} - SOut_{\mathrm{k,m,d,h,u}} \quad \forall \, \mathrm{m,d,h}: \mathrm{k} = \{\mathrm{ES}\} \wedge \mathrm{u} = \{\mathrm{eo}\} \tag{29}$$

$$BPot_{\mathrm{m,d,h}} \leq \frac{1}{\Delta^{D}_{\mathrm{m,d,h}}} \left(SOC_{\mathrm{k,m,d,h}} - ECap_{\mathrm{k}} \cdot \mathrm{MSC_k} \right) \quad \forall \, \mathrm{m,d,h}: \mathrm{k} = \{\mathrm{ES}\} \tag{30}$$

In the case of generators, this potential is determined as a function of their available capacity – although it is required that they are already online – and on their ability to do fast-ramping, set by a user-defined binary parameter ($\gamma_{\mathrm{g}} = 1$). This is translated into the following equations:

$$GPot_{\mathrm{g,m,d,h}} \leq IG_g \cdot \mathrm{MaxP_g} - GU_{\mathrm{g,m,d,h,u}} \quad \forall \, \mathrm{g,m,d,h}: \mathrm{u} = \{\mathrm{eo}\} \tag{31}$$

$$GPot_{\mathrm{g,m,d,h}} \leq GU_{\mathrm{g,m,d,h,u}} \cdot \gamma_{\mathrm{g}} \cdot \mathbf{M} \quad \forall \, \mathrm{g,m,d,h}: \mathrm{u} = \{\mathrm{eo}\} \tag{32}$$

C. *Magnitude and duration of the drops in PV output*

Obtaining values for both the magnitude and duration of drops in solar irradiance, $\Delta^{M}_{\mathrm{m,d,h}}$ and $\Delta^{D}_{\mathrm{m,d,h}}$, requires statistical analysis. The drop magnitude is estimated by finding the lowest average irradiance values over 15-min periods in each hour, as this is the time interval typically used in demand charge calculations. Repeating the process over the entire data set allows establishing representative distributions of the irradiance drop magnitude on a 24-hour basis for every month, and define confidence levels. Namely, a confidence level of 70% corresponds to the 70$^{\text{th}}$ percentile of drop magnitude, or drops in irradiance occurring in an hour that are exceeded only 30% of all identical hours in the same month. The results presented in this case study use confidence levels ranging from 70% to 95%, and the resulting distributions are illustrated in Fig 3.

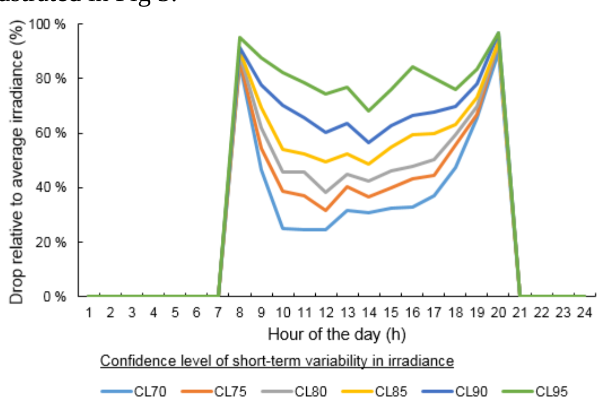

Fig. 3 Short term drop in irradiance relative to the average irradiance in April for confidence levels ranging from 70% to 95%

After obtaining the distributions for the magnitude of solar irradiation drops, $\Delta^{M}_{\mathrm{m,d,h}}$, information on duration, $\Delta^{D}_{\mathrm{m,d,h}}$, can also be obtained. This is done for any given magnitude level by calculating the median duration of events where the irradiance drop is equal to or greater than the magnitude selected. However, given the process of calculating power demand charges, only durations in multiples of 15-min intervals are considered within each hour. The general observed behavior is that higher confidence levels lead to higher drops in magnitude and shorter durations.

IV. Case Study

A. *Case study setup*

The proposed methodology to address the impact of short-term variability in solar radiation in DER sizing is tested by conducting the case study presented below. A large hotel is selected from the DER-CAM database, containing all load data for a typical year. This hotel exhibits a yearly peak demand of 736 kW and an average daily electricity demand of 10.6 MWh. The E-19 tariff from PG&E is applied [30]. In a business as usual (BAU) case, with no DER investments, the annual energy cost is estimated to be approximately $745,000. In this case, the power demand charges account for roughly 35% of annual electricity costs. Solar data from a selected site in Moab, Utah, made available by the Solar Radiation Monitoring Laboratory at the University of Oregon [29] is used, as no freely accessible high quality short-term irradiance data spanning several years could be found in the area of San Francisco, although this does not impact demonstrating the method presented in this work. The average daily insolation measured in the entire data set is 5.189 kWh/m^2. One peak day with high energy loads is defined for every month, and it is conservatively assumed that this peak day of loads is also a cloudy day, i.e. the 10$^{\%}$ lowest values of hourly solar irradiance data are used. All other days in each month are considered to be either typical weekdays or weekend days, and the average monthly solar irradiance profile is assumed.

The default DER-CAM settings are used to define the techno-economic parameters of different DER, and only lithium-ion batteries are used for stationary storage. In this case, the investment cost is assumed to be the same for both energy content ($/kWh) and power output ($/kW), as suggested in [4], and different values ranging from $250 to $500 are considered to perform a sensitivity analysis on battery costs. This approach is intended to represent the cost of both the battery and inverter, where the cost of the battery scales largely with energy and the inverter costs scale with power. The settings for other key parameters are shown in Table I. The possible DER investment options considered in this case study consist of PV, batteries, and on-site generators.

TABLE I:
KEY MODEL PARAMETERS

Parameter	Value
Investment cost PV	$3,000 per kWp
Life time PV	30 years
Efficiency PV	Variable: 15-18 %
(Dis)charge efficiency battery	90%
Min. state of charge battery	30%
Lifetime battery	5 years
Interest rate	5%
Maximum payback period	10 year

Table II highlights the key data for the on-site generators, where three technologies are considered: internal combustion engines (ICE), micro turbines (MT), and phosphoric acid fuel cells (PAFC). All generators use natural gas as fuel and only ICE are considered as fast ramping. The lifetime of ICE, MT, and PAFC is assumed to be 15, 15, and 20 years, respectively. Electricity exports are allowed for PV (using net metering), but capped at half of the yearly peak demand (368 kW). The sensitivity towards short-term variability in irradiance is investigated by varying confidence levels in the magnitude of irradiance drops between 70 and 95%.

TABLE II:
IMPORTANT PARAMETERS OF THE GENERATORS

Tech.	MaxP (kW)	Capital cost ($/kW) [no CHP/ CHP]	Electric Eff. (%)	Heat to Power Ratio
ICE	75	2,360/3,011	26	1
ICE	250	2,163/2,704	27	1
MT	65	2,737/3,220	23.8	1.5
MT	250	2,311/2,719	26.1	1
PAFC	400	7,000/7,300	38.2	0.5

B. Results

The results obtained for the total energy cost, taking into account the sensitivity to the capital cost of batteries and confidence levels in irradiance drops are shown in Fig. 4.

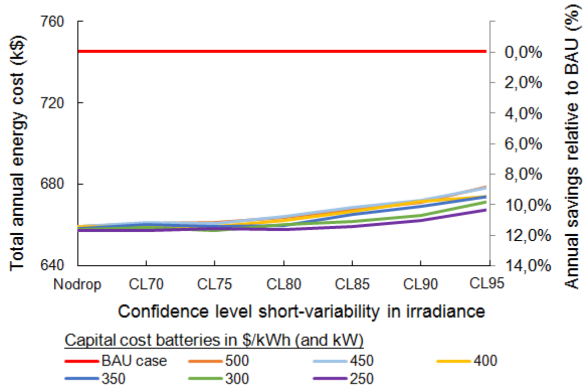

Fig. 4 Total annual energy costs and savings relative to the business-as-usual-case as a function of stationary storage capital cost[1] and confidence level of short-term irradiance variability

It can be seen that relative to the BAU case, where no DER investments are allowed, annual savings between 9 and 12% are realized. The estimated savings are sensitive to both the capital costs of the batteries and the confidence level of short-term variability in irradiance. It should be noted, however, that the total annual energy cost only increases on average by roughly 2% when comparing to the 'no drop' case, with the case with highest confidence levels (highest drops).

Although changes in total annual energy costs are seemingly low, a further analysis of results is required in order to capture the effect of short-term solar irradiance variability. Specifically, Fig. 5 shows the results obtained for the rated output of installed battery systems. In this case, a clear trend can be observed, with higher confidence levels leading to average rated output values up to twice as high as those where no variability is considered. Looking into battery energy capacity, a similar trend can be observed, as higher confidence levels lead to higher values of energy content. However, as shown in Fig. 6, the increase in energy content is not as significant as in rated output.

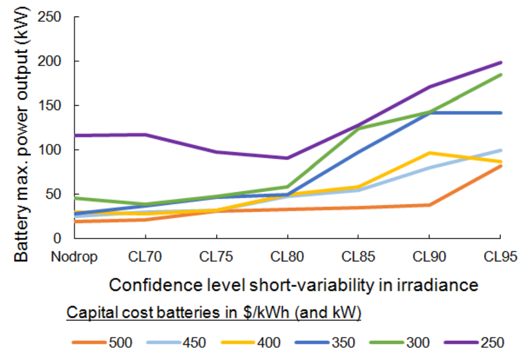

Fig. 5 Rated output of installed batteries

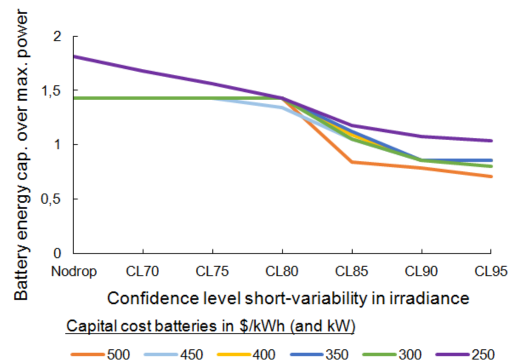

Fig. 6 Energy capacity over rated output of installed batteries

The installed capacity of PV is shown on Fig. 7, suggesting a slight overestimation when short-term variability in irradiance is not taken into account. However, it should be noted that an increase of PV capacity is observed with lower battery investment costs, highlighting the complementarity between these technologies. Of all on-site generators analyzed, only CHP enabled MTs were included in investment decisions (Table III). These were modelled as non-fast-ramping, thus without the ability to offset short-term irradiance variability. It can be seen that the installed capacity is sensitive to both battery capital costs and short-term variability in irradiance, as it affects the overall economic analysis. Once again, results suggest that the generator capacity might be underestimated if short-term irradiance is not taken into account.

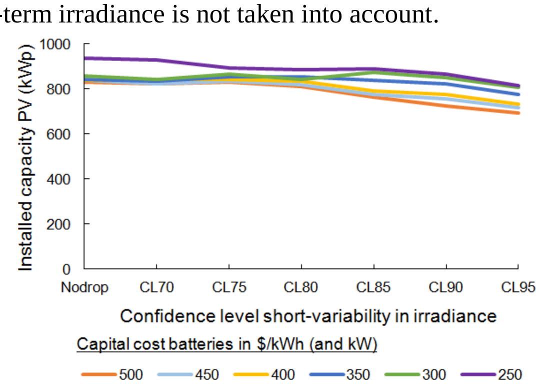

Fig. 7 Capacity of PV installed

[1] Battery cost is calculated based on energy capacity (kWh) and rated output (kW). The same price value is used in both ($/kWh = $/kW).

It should be noted that the confidence level for the short-term drops in solar irradiance is an input to the model. While this allows different users to express their individual preference, running the model with different confidence levels also provides an insight on the trade-off between investments and expected utility costs. Namely, for higher confidence levels the final sizing solution will be more conservative to offset the variability of PV output and minimize its implications on the power demand costs.

TABLE III:
OPTIMAL CAPACITY OF CHP MICROTURBINES (kW)

Battery cost $/kWh (and $/kW)	No drop	CL70	CL75	CL80	CL85	CL90	CL95
500	250	250	250	250	250	315	315
450	250	250	250	250	250	315	315
400	250	250	250	250	250	250	315
350	250	250	250	250	250	250	250
300	250	250	250	250	250	250	250
250	130	130	195	250	250	250	250

Additional calculations show that if variability in solar irradiance is not taken into account for the case study, the annual demand charges can be underestimated by 15 to 35%. The exact underestimation depends on the assumed investment cost of the batteries and the confidence level of the sub-hourly drops in irradiance applied in the calculations. The lowest underestimation is observed when the lowest investment cost for the batteries (250$/kW and 250$/kWh) is assumed, given the higher overall investment in this technology. The underestimation of the demand charges can lead to an increase of the annual energy costs up to 2-7 %, or a reduction of the anticipated savings using the default DER-CAM settings from around 11-12% to 9-5%, demonstrating the added value of the proposed methodology. Additionally, it should be noted that the effective payback period will be longer than anticipated if the sub-hourly variability in irradiance is not taken into account when making the investment decision.

Analyzing similar models found in literature corroborates the results found in this work. Particularly, the work presented in [3] has found that switching from 1-min to 1-h time step increased the levelized cost of energy by only 3%, which is comparable with the variation in the cost objective function found in this work. Further, the work presented in [3] has found that the optimal amount of batteries in this system at a 1-min resolution is more than double (236%) the optimal amount at a 1-h resolution, which emphasizes the relevance of sub-hourly variability of irradiance when sizing DER, in accordance to our findings. However, the work presented in [3] assumed a diesel/PV/battery system with a large amount of solar, and the analysis was conducted using a simulation model. That approach is not directly comparable with the optimization model now being presented, and this remark extends to other models found in literature, although the overall conclusions are in line with each other.

Regarding the model performance, the methodology proposed in this paper led to a negligible increase in the run time, with all runs being concluded within 5-10 min. In contrast, stochastic formulations of the same problem led to a runtime increase of at least one order of magnitude using only three solar irradiance scenarios.

V. Conclusion

This paper presents a statistical approach to incorporate stochastic sub-hourly variability in solar irradiance caused by fast moving clouds in MILP DER sizing problems where hourly time steps are used. The proposed formulation was incorporated in DER-CAM, a state-of-the art MILP model used in DER and microgrid sizing and scheduling, and a case study was performed.

Results show that total annual energy costs obtained are slightly underestimated when short-term fluctuations in PV output is not considered. This is influenced by the dynamic solutions found by DER-CAM, where the inclusion of solar irradiance variability is compensated by changes in the optimal capacity of DER investments.

It has been observed that the ratio of energy and power was previously overestimated when designing storage systems, and the inclusion of short-term variability in irradiance led to rated output values up to twice as high as those observed when no variability was considered. Similarly, it has been found that the capacity of on-site generators is underestimated when not considering short-term irradiance variability. Lastly, the value of PV has been found to be overestimated, as the inclusion of short-term variability leads to capacity values decreasing by 6 to 15%.

Additional case studies (not reported in the paper) were performed and the impact of fast moving clouds has been found to be dependent on a wide spectrum of variables, the most important ones being the solar data, tariffs, load data, and DER investment options. Specifically, in cases where only PV and battery investments are considered, the overestimation of optimal PV capacity reaches 50% if high storage prices prevent its adoption and therefore the ability to offset drops in PV output.

In future developments this method will be expanded to incorporate electrical vehicles and demand response as additional alternatives to offset variability in PV output due to fast moving clouds. Similarly, the implications of short-term variability in loads will be investigated in future research.

VI. Acknowledgment

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VII. BIBLIOGRAPHY

[1] Department of Energy Office of Electricity Delivery and Reliability, “Summary Report: 2012 DOE Microgrid Workshop,” 2012. .

[2] M. T. Miller, M. B. Johns, E. Sortomme, and S. S. Venkata, “Advanced integration of distributed energy resources,” *2012 IEEE Power Energy Soc. Gen. Meet.*, pp. 1–2, 2012.

[3] E. Hittinger, T. Wiley, J. Kluza, and J. Whitacre, “Evaluating the value of batteries in microgrid electricity systems using an improved Energy Systems Model,” *Energy Convers. Manag.*, vol. 89, pp. 458–472, 2015.

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

[5] O. Hafez and K. Bhattacharya, “Optimal planning and design of a renewable energy based supply system for microgrids,” *Renew. Energy*, vol. 45, pp. 7–15, 2012.

[6] HOMER, “Hybrid Optimization of Multiple Energy Resources.” .

[7] RETScreen, “Energy Management Software.” .

[8] M. Stadler, M. Kloess, M. Groissböck, G. Cardoso, R. Sharma, M. C. Bozchalui, and C. Marnay, “Electric storage in California’s commercial buildings,” *Appl. Energy*, vol. 104, pp. 711–722, 2013.

[9] C. Marnay, G. Venkataramanan, M. Stadler, A. S. Siddiqui, and R. Firestone, “Optimal Technology Selection and Operation of Commercial-Building Microgrids,” *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 975–982, 2008.

[10] G. Cardoso, M. Stadler, M. C. Bozchalui, R. Sharma, C. Marnay, a. Barbosa-Póvoa, and P. Ferrão, “Optimal investment and scheduling of distributed energy resources with uncertainty in electric vehicle driving schedules,” *Energy*, vol. 64, pp. 17–30, 2014.

[11] S. X. Chen, H. B. Gooi, and M. Q. Wang, “Sizing of energy storage for microgrids,” *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 142–151, 2012.

[12] S. Bahramirad, W. Reder, and A. Khodaei, “Reliability-constrained optimal sizing of energy storage system in a microgrid,” *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2056–2062, 2012.

[13] C. Chen, S. Duan, T. Cai, B. Liu, and G. Hu, “Optimal allocation and economic analysis of energy storage system in microgrids,” *IEEE Trans. Power Electron.*, vol. 26, no. 10, pp. 2762–2773, 2011.

[14] T. Logenthiran, D. Srinivasan, a. M. Khambadkone, and T. Sundar Raj, “Optimal sizing of Distributed Energy Resources for integrated microgrids using Evolutionary Strategy,” *2012 IEEE Congr. Evol. Comput.*, pp. 1–8, 2012.

[15] M. B. Shadmand and R. S. Balog, “Multi-objective optimization and design of photovoltaic-wind hybrid system for community smart DC microgrid,” *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2635–2643, 2014.

[16] G. Mendes, C. Ioakimidis, and P. Ferrão, “On the planning and analysis of Integrated Community Energy Systems: A review and survey of available tools,” *Renew. Sustain. Energy Rev.*, vol. 15, no. 9, pp. 4836–4854, 2011.

[17] C. Gamarra and J. M. Guerrero, “Computational optimization techniques applied to microgrids planning: A review,” *Renew. Sustain. Energy Rev.*, vol. 48, pp. 413–424, 2015.

[18] A. H. Fathima and K. Palanisamy, “Optimization in microgrids with hybrid energy systems – A review,” *Renew. Sustain. Energy Rev.*, vol. 45, pp. 431–446, 2015.

[19] W. Su, J. Wang, and J. Roh, “Stochastic energy scheduling in microgrids with intermittent renewable energy resources,” *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1876–1883, 2014.

[20] Y. Zhang, N. Gatsis, and G. B. Giannakis, “Robust energy management for microgrids with high-penetration renewables,” *IEEE Trans. Sustain. Energy*, vol. 4, no. 4, pp. 944–953, 2013.

[21] M. Hossain, K. Tushar, C. Assi, S. Member, M. Maier, and S. Member, “Smart Microgrids : Optimal Joint Scheduling for Electric Vehicles and Home Appliances,” *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 239–250, 2014.

[22] A. Zakariazadeh, S. Jadid, and P. Siano, “Stochastic operational scheduling of smart distribution system considering wind generation and demand response programs,” *Int. J. Electr. Power Energy Syst.*, vol. 63, no. February 2016, pp. 218–225, 2014.

[23] L. Zhu, F. R. Yu, B. Ning, and T. Tang, “Stochastic charging management for plug-in electric vehicles in smart microgrids fueled by renewable energy sources,” *2011 IEEE Online Conf. Green Commun. GreenCom’11*, pp. 7–12, 2011.

[24] G. Cardoso, M. Stadler, a. Siddiqui, C. Marnay, N. Deforest, a. Barbosa-Póvoa, and P. Ferrão, “Microgrid reliability modeling and battery scheduling using stochastic linear programming,” *Electr. Power Syst. Res.*, vol. 103, pp. 61–69, 2013.

[25] North American Electric Reliability Corporation, “Accommodating High Levels of Variable Generation,” 2009.

[26] A. Mills and R. Wiser, “Implications of Wide-Area Geographic Diversity for Short-Term Variability of Solar Power,” 2010.

[27] “DER-CAM Website.” Available: http://der.lbl.gov/der-cam.

[28] R. Marquez, B. Davis, A. Kaur, and C. Coimbra, “Characterization and Cost Analysis for the UC Merced Campus,” in *Proceedings of the ASME 2012 6th International Conference on Energy Sustainability*, 2012.

[29] Solar Radiation Monitoring Laboratory, “Solar Radiation Database,” *University of Oregon*. .

[30] PG&E, “E-19 Tariff information,” 2015.

VIII. Biographies

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