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Smart Meter Data to Optimize Combined Roof-Top Solar and Battery Systems Using a Stochastic Mixed Integer Programming Model

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ABSTRACT This paper presents the design and results of a model that uses household smart meter data, electric vehicle (EV) travel load and charging options, and multiple solar resource profiles, to make decisions on optimal combinations of photovoltaics (PV), battery energy storage systems (BESS) and EV charging strategies. The least-cost planning model is formulated as a stochastic mixed integer programming (MIP) problem that makes first stage decisions on PV/BESS investments, and recourse decisions on purchase/sell from/to the grid to minimize expected household electricity costs. The model undertakes a customer-centric optimization taking into consideration net metering policy, time-of-use grid pricing, and uncertainties around inter-annual variability of solar irradiance. The model adds to the existing literature in terms of stochastic representation of inter-annual variability of solar irradiance, together with BESS capacity optimization, and EV charging mode selection. Three case studies are presented: two for a residential house with and without EV load, and a third for a larger community facility. Results from the model for the first residential house case study are compared with commercially available software to show the impacts of an accurate load profile and different policy parameters. The stochastic feature of the model proves useful in understanding the impact of variability in solar resource profiles on PV sizing. Finally, simulations of alternative EV travel patterns and tariff policies that discourage charging during the evening peak show the efficacy of 'super off-peak' pricing being introduced in the state of Maryland.

INDEX TERMS Optimization model, battery storage, solar panel sizing, electric vehicle charging, smart meter data, TOU grid pricing.

I. INTRODUCTION

FALLING costs of solar PV systems have led to a rapid uptake of close to 600 GW of installed capacity worldwide in 2019 [1]. This includes a significant increase in solar roof-top (distributed), as well as ground-based utility-scale solar, in recent years. IEA's *Renewables 2019* projections suggested that by 2024, solar PV will grow globally by 1,200 GW, including 500-600 GW in distributed PV [2]. There is an even larger long term growth potential: e.g., the USA alone has more than 1,000 GW of potential according to NREL—roughly the size of the entire current power system of the country [3]. A key factor that heavily influences selection of roof-top solar (combined with battery storage) from a *customer* perspective is the savings on electricity bills it offers. There have been significant analyses done on the topic including a number of websites such as Google Sunroof that provide an assessment of roof-top panel size. There are also more generic tools such as Aurora, PVWatts, etc. that are gaining popularity.

There is, however, significant room for improvement in the existing software offerings. For instance, the commercially available tools typically do not consider the customer load shape in sufficient granularity, which could be an important factor in deciding system sizing. Additionally, many of the tools do not co-optimize battery size. There are also "new" types of loads that are controllable—most notably, electric vehicle (EV) charging that should be integrated in PV/battery optimizations. There is also a more arcane issue around the selection of a typical solar resource profile (e.g., a Typical Meteorological Year or TMY).

Figure 1 illustrates the issue of solar resource variability over the years that we have used for the case study in a later section of this paper. As the figure demonstrates, annual solar

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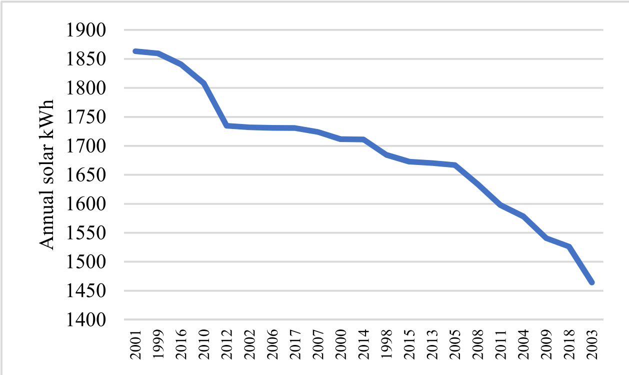

FIGURE 1. **Cumulative distribution of annual solar output per 1 kW installed (1998-2018) for a household.**

output (per kW) for the household over the last 21 years varies between 1464-1863 kWh. The levelized cost of solar electricity over this range falls on either side of the flat tariff the household pays, suggesting this inter-annual variability of solar is a reasonably important consideration that *should* be considered in any system sizing analysis.

Figure 2 casts some light on the issue of EV load for the same household before (2018) and after (2019) the EV load occurred. The household used only a fast charging option (220V) for the representative day in 2019 that caused the evening peak at 7 PM to increase sharply from 1.36 KW to over 13 kW. As the state regulation stipulates a limit on the amount of electricity that can be sold back to the grid, a joint consideration of solar and battery energy storage system (BESS) is important, even before considering the significant increase in evening peak from fast charging. These points are compelling motivation to improve the robustness of the modelling tools used to size home PV/BESS systems.

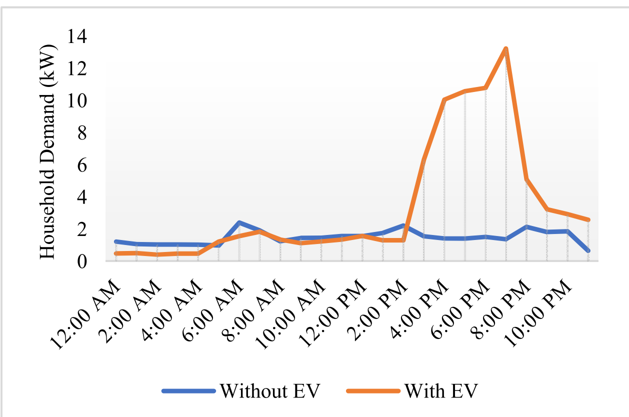

FIGURE 2. **Smart meter data for a household without EV (2018) and with EV (2019) for July 3 (a weekday in both years).**

The remainder of this paper is organized as follows: Section 2 provides a survey of the literature in this area; Section 3 presents a model that covers the stochastic representation of solar profiles and integrates EV charging in the analysis, followed by three case studies in Section 4. Section 5 concludes the paper.

II. LITERATURE REVIEW

Research efforts on managing residential load using optimization tools date to the 1980s. Capehart *et al.* [4] introduced the concept of optimizing household electricity cost by reducing peak demand and usage time. Rahman and Bhatnagar [5], as well as Wacks [6] are other important examples of advancing the concept of home energy and utility load control through home automation. Khatib *et al.* [7] provides an overview of the methodologies available for PV capacity optimization at a *system* level. Given the scope of the current work, we have focused on four key aspects of the literature, namely: (a) operational simulation of a household level energy system; (b) capacity optimization of PV and BESS; (c) smart meter data that can inform both operational and capacity optimization aspects; and (d) commercially available models and tools.

The literature on Home Energy Management Systems (HEMS) has grown over the years to embrace developments on smart grid, roof-top PV and BESS. Beaudin and Zareipour [8] provide an account of the wider HEMS methodologies, including the ability of these systems to reduce household peak demand by almost 30%. Operational simulation of HEMS has added many critical nuances and sophistication over the years. Zhao *et al.* [9] uses a sophisticated Energy Management Controller (EMC) design including an optimal power scheduling scheme for each electric appliance. Zhou *et al.* [10] extends the concept of a smart HEMS to consider renewable options including solar, biomass, wind, etc. that may be available to the building. Additional operational capabilities of HEMS to include prioritization of appliances [11], demand response combined with storage [12], and electric vehicles [13], have been progressively added to the literature. Thomas *et al.* [13], for instance, developed a mixed integer linear programming model that considers the impact of PV uncertainty in scheduling of the HEMS. Hosseinnezhad *et al.* [14], [15] used artificial intelligence techniques in order to solve the HEMS scheduling problem. Shareef *et al.* [16] is a recent summary of the HEMS applications.

As battery storage costs drop, there is increasing attention on co-optimizing *investment decisions* on roof-top solar and storage for microgrids and households. There are papers that rely on linear/nonlinear mixed integer programming models to undertake the capacity optimization [17]–[22]. Zhao *et al.* [17] and Zhou *et al.* [18] consider co-optimization of battery storage together with PV systems for microgrids and households. The HEMS model in [18] uses a nonlinear MIP (MINLP) model to optimize battery storage and PV under alternative pricing mechanisms. It is a comprehensive model that includes an upper level capacity allocation problem solved in conjunction with a lower level operational problem using the DICOPT algorithm. Their analysis includes several pricing and subsidy scenarios to show how subsidies remain an essential component in some cases for PV to be selected in the optimal portfolio. Hemmati [19] and Hemmati and Saboori [20] adopt a similar approach to use variants of mixed integer programming to optimize selection of capacity. Hemmati and Saboori [20] also introduces uncertainty in PV output using a Monte Carlo simulation model to design Net Zero Energy (NZE) systems, which can reduce annual electricity bill of customers. Okoye and Solyal [21] also adopted an integer programming model for an application to a Nigerian system to determine PV and BESS capacity to reduce reliance on diesel that would otherwise be used. Erdinc *et al.* [22] used a mixed integer programming model to co-optimize distributed generation, storage and demand response.

Given the importance of load profile in deciding the optimal PV/BESS capacity and its operation, accurate load data from smart meters should play a major role. A review of smart meter data analytics [23], however, reveals surprisingly little application of it being used for solar panel sizing. Liang *et al.* [24] used smart meter data from 5,000 installations to analyze the number of solar panels needed to render systems as net zero emissions, but there was no optimization of solar panel sizing involved in the analysis. Dyson *et al.* [25] shows how smart meter data can be useful for identification of demand response options. They noted a high correlation between demand response (DR) resources identified and periods of high solar generation ramping. There appears to be no comprehensive analysis that uses: household-level smart meter data, regulations on excess solar that can be fed back to the grid, variability of solar including inter and *intra* year solar variability, tariff policy, and the role that batteries can play and changes in load pattern (e.g., EV charging).

Although the academic literature has explored many sophisticated models and algorithms, there remains a paucity of transparent and accurate customer-oriented tools that help inform investment and operational decisions on solar PV, storage systems, and EV charging strategies. There are simulation tools such as HOMER [26], which allows the user to define alternative configurations and simulate their performances mainly for off-grid systems, and commercial products such as Aurora Solar [27], AutoDesigner [28], and PVsyst [29], which are used for designing solar roof-top systems. Aurora Solar and AutoDesigner, use a mixed integer programming algorithm to determine the optimal location and wiring for solar panels taking into account shading, tilt, inverter sizing, etc. PVsyst is a popular tool that uses a simulation approach taking into consideration azimuth and tilt to decide alternative PV arrays. It then selects the optimal configuration using a heuristic approach considering a number of economic, technical, and financial attributes. PVWatts [30] is another popular tool—both in online and offline formats—from NREL that allows the user to simulate the impact of PV and BESS on electricity bills for a specific location down to one-minute resolution. It also contains multiple historic solar profiles and provides a range around the estimated solar output. Solar Estimates [31], Google's Project Sunroof [32], and WholesaleSolar [33] are more recent additions to the family of commercial tools that are extremely user-friendly, and backed up by detailed geospatial and solar resource data to provide a ready estimate of solar PV potential for a household. These online tools provide a customer-centric view on the solar capacity to be installed, payback period, and estimated savings. These tools mostly answer the questions around the amount and configuration of solar PV (and battery) once a target is specified (e.g., meet 100% of the household energy). However, they [31]–[33] do not seek to minimize household energy costs, and rely on high level estimate of load based on monthly electricity bill and do not use accurate load shape.

A household owner should be able to make an informed decision based on the exact load profile including EV travel load and charging options, on what combination of solar PV, BESS and tariff policy is best for the household. With the proliferation of smart meters, such design analysis can also take advantage of accurate high-resolution load data. There are elements of different operational simulation models and commercial tools that partially cover the intended objectives, but not a comprehensive model that covers them all.

III. METHODOLOGY

This paper presents a novel optimization tool that attempts to comprehensively analyze solar panel and battery sizing for household installations including:

(a) hourly/sub-hourly smart meter load data at the household level to represent load for one or more years;
(b) endogenous co-optimization of solar and battery capacity;
(c) consideration of solar irradiance data available in the public domain (e.g., NASA's MERRA-2) to represent hourly variability of solar within a year;
(d) representation of inter-annual variability of solar as a stochastic contingency-constrained model to assess if solar/battery needs to be oversized to cover for sustained cloudy periods;
(e) explicit consideration of net metering policy for the state/country, including restrictions on number of kWh that can be exported to the grid;
(f) analysis of changes to the load pattern such as load growth including addition of electric car and the optimal charging strategy (slow, fast, supercharger) given a travel load profile, and
(g) analysis of impact of alternative policies such as switching to time-of-use tariff, and/or tax mechanisms.

A. OVERVIEW OF THE MODEL

The model is cast as a least-cost planning problem to minimize household electricity cost. It is formulated as a stochastic mixed integer linear programming problem that considers historic smart meter load data for one or more years, and multiple historic solar profiles with their associated probability of occurrence. MIP is used for the model to select discrete PV/inverter size (for larger systems), and EV charging mode.

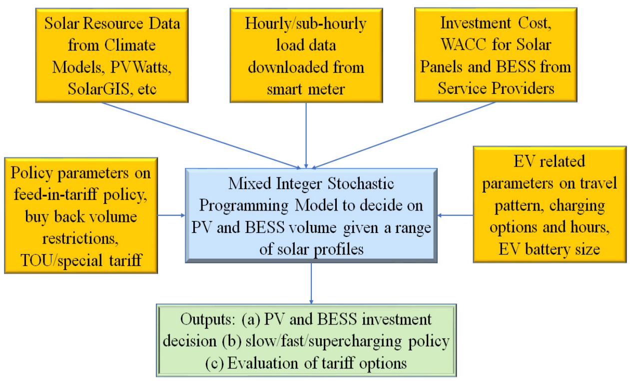

FIGURE 3. **Overview of the model.**

Stochastic modelling is introduced to account for the range of solar resource profiles shown in Figure 1. The model can be set up at hourly, or sub-hourly resolution with inputs on EV travel profile, available charging hours and options (i.e., slow, fast or supercharger at a higher cost outside the home). It optimizes the PV and BESS capacity as a first stage (“here and now”) decision variable, together with second stage resource decisions on hourly/sub-hourly buy/sell from/to the grid, and EV charge mode, subject to the uncertainties on solar availability. The capacity and operational decisions are also driven by policy parameters such as tax incentives for PVs, limits on energy that can be sold back to the utility, and tariffs (of which we consider three variants that are on offer in the state of Maryland: fixed/flat tariff, Time-of-Use and EV Special Tariff with low prices for super off-peak).[1] A schematic overview of the model is provided in Figure 3.

B. MATHEMATICAL DESCRIPTION

INDICES

t	Hours/sub-hours of the day
d	Days of the month
m	Months of the year
y	Solar profiles for years y=1, ... Y

INPUT PARAMETERS

$Demand_{y,m,d,t}$	Hourly/sub-hourly demand
$AvailableSolar_{y,m,d,t}$	Solar irradiance in kW/m^2 per 1 kW panels installed
$Tariff_{y,m,d,t}$	Cost of energy from the grid in c/kWh for day d and hour t
P_y	Probability of solar profile, y
E	Penalty on solar rejection which is kept very small in this analysis
PanelCost	Annualized cost in dollars of purchasing and installing 1 kW of solar panels
BuyBackRate	Price in c/kWh which can be earned by the household by selling 1 kWh of energy to the grid
TaxDiscount	Percent of the solar panel cost subsidized by the government
SolarEfficiency	Efficiency of the solar panel
BatteryCost	Annualized cost for purchasing and installing 1 kWh of BESS
BatteryEfficiency	BESS round-trip efficiency
ChargeRate	The rate in kW that the battery can charge
DischargeRate	The rate in kW at which the battery can discharge
EVBottomLimit	Minimum charge level of EV
EVUpperLimit	Maximum charge level of EV
EVDistance	EV travel load expressed as kWh lost during hours of travel

DECISION VARIABLES

Cost	Total cost of the energy in dollars
$Grid_{y,m,d,t}$	Supply of energy from the grid in kWh
SolarInstalled	Amount of solar panels installed by the model in kW – **first stage decision**
$Solar_{y,m,d,t}$	Available solar energy in kWh
$SolarInHouse_{y,m,d,t}$	Solar energy in kW being used in the household
$SolarExport_{y,m,d,t}$	Solar energy in kWh being sold to the grid
$SolarReject_{y,m,d,t}$	Solar energy in kWh being rejected (incurs a penalty)
BatterykW	Size of battery in kW to be installed – **first stage decision**
$BatteryIn_{y,m,d,t}$	Solar energy in kWh entering the battery
$BatteryOut_{y,m,d,t}$	Solar energy in kWh entering the household from the battery
$BatteryLevel_{y,m,d,t}$	Energy in kWh stored in the battery (household BESS)
$EVStored_{y,m,d,t}$	Energy in kWh stored in the EV's battery
$EVEntering_{y,m,d,t}$	Energy in kWh charging the EV from the household supply
$chargeMode_{y,m,d,t}$	Binary variable which defines whether the EV is being charged through slow (1.65 kW at 110V) or fast charging (6.6 kW at 220V) for the day.
$SuperCharge_{y,m,d,t}$	Energy in kWh charging the EV from the super charger (outside the home at a higher cost)

C. OPTIMIZATION MODEL

The model selects the optimal size of PV systems and battery size, coupled with grid-supply, to meet hourly/sub-hourly

[1] PEPCO rate, Schedule EV, www.pepco.com

household demand for one or more years. It takes into consideration multiple annual solar profiles (y) that embody inter-annual variability of the resource with associated probability for each profile (P_y). The model uses demand from a single year (2018) in its analysis. The optimization problem is formulated as a stochastic mixed integer linear programming problem (MILP). This model falls in the same category of the HEMS planning models [17]–[22], and especially [18], [20]. The incumbent model keeps the formulation as MILP as opposed to a MINLP in [18], to render it computationally tractable. This is particularly important given the consideration of uncertainties that may include up to 21 solar profiles in hourly resolution for our case studies. The stochastic formulation is different from a Monte Carlo simulation implementation in [20]. It should also be noted that the model integrates EV charging as an endogenous variable including selection of charging modes. Although there have been operational simulation models of HEMS (e.g., [13]) of EV, integrated treatment of EV related load together with PV and BESS capacity in a stochastic model has not been considered. The model formulation is presented in line with the implementation of the model for different case studies that use both deterministic and stochastic versions of the model.

The deterministic objective function for the model which defines the cost of the household's electricity is defined as *Cost* for a pre-specified solar profile ($y = y^*$ and hence the index is dropped). Household electricity bill/cost comprises cost of purchasing electricity from the grid and the cost of the solar panel and its battery storage, along with any penalty associated with unused solar less the feed-in revenue:

$$\begin{aligned} Cost = \sum_{m,d,t} \big(&Grid_{m,d,t} * Tariff_{m,d,t} \\ &-SolarExport_{m,d,t} * BuyBackRate\big) \\ &+ SolarInstalled * PanelCost * TaxDiscount \\ &+ BatterykW * BatteryCost \\ &+ \sum_{m,d,t} SolarReject_{m,d,t} * \boldsymbol{\varepsilon} \end{aligned} \tag{1}$$

A modified version of this equation is used for the stochastic model. This modified equation in the stochastic version multiplies the annual costs by the relative probability, P_y of each solar profile:

$$\begin{aligned} Cost = \sum_{y} \Bigg(&P_y * \sum_{m,d,t} (Grid_{y,m,d,t} * Tariff_{y,m,d,t} \\ &-SolarExport_{y,m,d,t} * BuyBackRate)\Big) \\ &+ SolarInstalled * PanelCost * TaxDiscount \\ &+ BatteryCost * BatterykW \\ &+ \sum_{y,m,d,t} SolarReject_{y,m,d,t} * \boldsymbol{\varepsilon} \end{aligned} \tag{2}$$

The equation used by the model to balance the power injected from the grid along with the power coming from the solar panels and output from the battery in order to meet hourly demand is defined as follows:

$$\begin{aligned} &SolarInHouse_{y,m,d,t} + Grid_{y,m,d,t} + BatteryOut_{y,m,d,t} \\ &\quad * BatteryEfficiency = Demand_{y,m,d,t} \end{aligned} \tag{3}$$

The solar energy production is limited by availability of solar energy and the size of the solar panel system installed. Efficiency of the panel can also be represented as a piecewise linear function of production, but has not been considered here, keeping in view the marginal increase in accuracy vs significant increase in the size of the MIP model that this entails.

$$\begin{aligned} &Solar_{y,m,d,t} \leq AvailableSolar_{y,m,d,t} * SolarInstalled \\ &\quad * SolarEfficiency \end{aligned} \tag{4}$$

The solar energy which is generated can either be used in the household, sold to the grid, stored in the battery, or be rejected at a small penalty:

$$\begin{aligned} &SolarExport_{y,m,d,t} + BatteryIn_{y,m,d,t} + SolarReject_{y,m,d,t} \\ &\quad +SolarInHouse_{y,m,d,t} = Solar_{y,m,d,t} \end{aligned} \tag{5}$$

In order to reflect the net metering policy in the state that limits the amount of solar energy the household can sell to the grid, the model stipulates that export cannot exceed in-house consumption:

$$\sum_{m,d,t} SolarExport_{y,m,d,t} \leq \sum_{m,d,t} SolarInHouse_{y,m,d,t} \tag{6}$$

To simulate a high export scenario, the following equation is used:

$$\sum_{m,d,t} SolarExport_{y,m,d,t} \leq \sum_{m,d,t} Demand_{y,m,d,t} \tag{7}$$

The following equation represents the energy balance for the battery:

$$\begin{aligned} &BatteryLevel_{y,m,d,t} = BatteryLevel_{y,m,d,t-1} \\ &\quad +BatteryIn_{y,m,d,t} - BatteryOut_{y,m,d,t} \end{aligned} \tag{8}$$

The charging and discharging rates are predefined and incorporated into the model as follows:

$$BatteryIn_{y,m,d,t} \leq BatterykW * ChargeRate \tag{9}$$

$$BatteryOut_{y,m,d,t} \leq BatterykW * DischargeRate \tag{10}$$

The equations from (11) and onwards are used only in the EV Case Study. Equation (11) is identical to the objective function in Equation (1), however it includes a provision to account for the cost of the supercharging:

$$\begin{aligned} Cost = \sum_{y,m,d,t} \big(&Grid_{y,m,d,t} * Tariff_{y,m,d,t} \\ &-SolarExport_{y,m,d,t} * BuyBackRate\big) \\ &+ SolarInstalled * PanelCost * TaxDiscount \\ &+ BatterykW * BatteryCost \\ &+ \sum_{y,m,d,t} SolarReject_{y,m,d,t} * \boldsymbol{\varepsilon} + SuperCharge_{y,m,d,t} \\ &*SuperChargeCost \end{aligned} \tag{11}$$

Equation (12) is identical to Equation (3), except it includes a provision to account for the additional load from the EV:

$$SolarInHouse_{y,m,d,t} + Grid_{y,m,d,t} + BatteryOut_{y,m,d,t} * BatteryEfficiency = Demand_{y,m,d,t} + EVEntering_{y,m,d,t} \quad (12)$$

The following equations define the lower and upper limits of the EV's battery:

$$EVStored_{y,m,d,t} \geq EVBottomLimit \quad (13)$$

$$EVStored_{y,m,d,t} \leq EVUpperLimit \quad (14)$$

The EV can either charge using slow charging at a rate of 1.65 kW (110V), or fast charging at a rate of 6.6 kW (220V):

$$EVEntering_{y,m,d,t} \leq 1.65 \left(1 - ChargeMode_{y,m,d}\right) + 6.6 * ChargeMode_{y,m,d} \quad (15)$$

The following equation defines the balance for the EV's battery:

$$EVStored_{y,m,d,t} = EVStored_{y,m,d,t-1} + EVEntering_{y,m,d,t} + SuperCharge_{y,m,d,t} \quad (16)$$

Supercharging hours are restricted, e.g., excludes early midnight till 4 am.

$$Supercharge_{y,m,d,t}\big|_{t \neq \tau} = 0 \quad (16a)$$

For every hour the EV is out of the house, it loses charge at a predefined rate:

$$EVStored_{y,m,d,t} = EVStored_{y,m,d,t-1} - EVDistance \quad (17)$$

There must be continuity in the EV's battery from day to day, namely:

$$EVStored_{y,m,d,1} = EVStored_{y,m,d-1,24} \quad (18)$$

The model is implemented using GAMS (General Algebraic Modeling System [34]) and solved using the CPLEX Barrier algorithm.[2] The stochastic formulation of the model for a full-year in hourly steps with 21 solar resource profiles contains 1.5 million variables, 1.3 million constraints, and 4.6 million non-zeroes. It solves in 42 seconds on an i7-9750H (ninth generation) processor with 32 GB RAM. The deterministic version of the model for a single profile solves in 8 seconds.

IV. CASE STUDY RESULTS

This section presents results of the model for three cases using 2018 smart meter load data: (a) the ISKCON DC complex in Potomac, Maryland that includes a temple with relatively large annual peak load in excess of 25 kW; (b) a single family residential home with annual peak load below 10 kW; and (c) the same house with an added load from an EV. These case studies are chosen to illustrate how system sizing and selection is influenced by substantially different load shapes. ISKCON load generally occurs during day, while the household loads are concentrated during early evening hours, and the addition of the EV charging that can add substantially to it depending on the travel pattern.

The model uses a cost of \$3000/kW for fully installed solar systems, representing multiple quotes obtained from solar companies,[3] and a cost of \$300/kWh for BESS. We consider several different grid pricing scenarios, the most basic of which is a fixed/flat price of 15.65 c/kWh. The other two pricing scenarios consider two variants of Time of Use (TOU) schemes. The first maintains a 25 c/kWh peak from 6 PM to 10 PM, and an 8 cent off peak for the rest of the day. The second one is a more extreme variant, with a 30 c/kWh peak from 6 PM to 10 PM, an 8 c/kWh off-peak, and a 5 c/kWh super-off-peak from 11 PM to 5 AM. These pricing scenarios mimic the pricing schemes that are currently on offer from PEPCO—the major utility in Maryland—including the Special EV Tariff that encourages charging during late night.

A. CASE STUDY 1: ISKCON DC

The ISKCON DC case study illustrates the stochastic formulation, a key feature of the model. It uses solar profiles from the 21 years shown in Figure 1 and assigns a relative probability to each of these profiles. This probabilistic representation allows the model to account for interannual variability over a reasonably wide range of years that differ significantly in terms of insolation level and its timing during different parts of the year.

Peak hourly load for the ISKCON site in 2018 was 25.8 kW, and the daily consumption pattern remained relatively similar throughout the year including occurrence of the daily peak during the daytime. Figure 4 shows a typical day

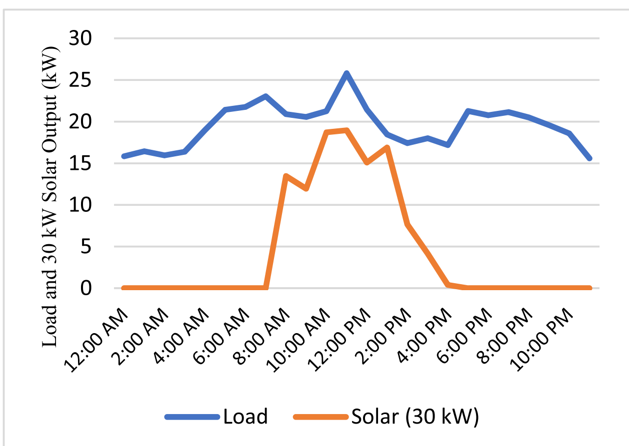

FIGURE 4. Typical load curve and solar output for a 30 kW panel.

[2]The model is implemented in GAMS with an Excel front-end The model will also be made available through IEEE Access.

[3]This cost is 2-3 times that of a utility-scale PV in the US (see for example Wiser *et al.* [35]). Cost for roof-top PV system included in this analysis represents commercial pricing for fully installed system.

TABLE 1. **Comparison of scenarios: ISKCON DC.**

	Annual Cost ($)	Solar PV Installed (in kW)
Base Case	11,423	38
Worst Solar Profile (2003)	12,641	25
Best solar profile (2001)	10,580	38
Conservative Scenario	12,618	31
No Solar Panels	12,773	0

Note: BESS selection is zero in all cases.

and shows how a 30kW panel could have met a substantial part of the load during peak.

Analysis for the ISKCON site is shown in Table 1:

1. The "Base Case" uses the stochastic model and includes all 21 solar profiles simultaneously. It results in selection of 38 kW of solar;
2. The "Worst Solar Profile" and "Best Solar Profile" scenarios use single year (2003 and 2001, respectively) deterministic scenarios. The former selects only 25 kW, while the latter matches the Base Case outcome of 38 kW;
3. The "Conservative Scenario" uses solar profiles of low irradiance years including 2003; and
4. The "No Solar Panel" case is included as a benchmark to calculate the savings.

As Figure 1 demonstrates, there is significant variation in solar irradiance throughout the years. The stochastic model helps to better analyze multiple profiles and yields a solution that reflects the resource risk. The base case in Table 1 recommends the installation of 38 kW of solar panels, saving nearly $1,350 in a single year (i.e., the difference between 'No Solar Panel' and Base Case in Table 1). This optimal capacity selection is identical to the single year scenario of 2001, which is the year with the highest irradiance of those included in the model. However, the model calculates that 25 kW of solar panel as the optimal choice if we were to consider the worst (2003) profile. This difference in outcomes underlines the importance of the stochastic formulation. The importance of considering inter-annual variability for system-wide planning has been discussed by Pfenninger [36] among others, but an issue that is largely ignored in the commercial applications. This effect is further demonstrated by the "Conservative Scenario," which shows the optimal capacity might be restricted to 31 kW by selecting a set of low-yield solar profiles—reflecting a more risk-averse investor.

Another significant result from this case study is that the model does not select any BESS. This is mostly because the load profile matches the solar irradiance profile well, and, in part because the additional cost in BESS is not justified given the fixed tariff in this instance is very close to the levelized cost (LCOE) of the PV system.

Figure 5 shows the supply to ISKCON DC for 3 days (Jan 1-3, 2018) from grid and in-house usage of solar to meet

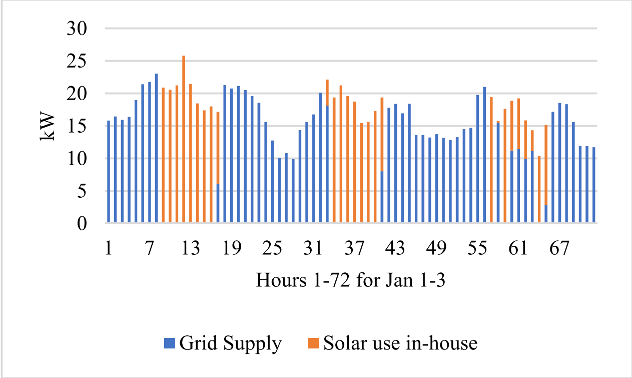

FIGURE 5. **Grid and in-house solar usage for ISKCON: Base Case.**

its demand. It shows how the daytime peak demand is met through use of solar, although the mix of grid and solar may vary significantly over the days. The selection of 38 kW of solar is driven by the high demand during the day, and also the fact that part of it can make a small profit (i.e., the difference between buy-back tariff and LCOE of the PV system). The volume of export back to the grid varies across the years: it is 33% for the worst solar profile (2003), and 39% for the best solar profile (2001).

B. CASE STUDY 2: RESIDENTIAL HOME (WITHOUT EV)

1) BASE CASE AND COMPARISON WITH OTHER MODELS

This section describes the findings from a residential home in Maryland. Smart meter data at hourly resolution for 2018 is obtained for the household together with an average PV system price based on quotes from multiple providers. The model is used in a relaxed mixed integer programming (RMIP) mode allowing for fractions of kilowatts, in order to make it comparable with the quotes received.

The Base Case of the model using the stochastic formulation yields an optimal solar panel size of 3 kW. Figure 6 shows the hourly use from the grid and solar for the first three days of the year. It shows that the low selection of solar panels is ultimately due to the low daytime demand, which mostly stays under 1 kW.

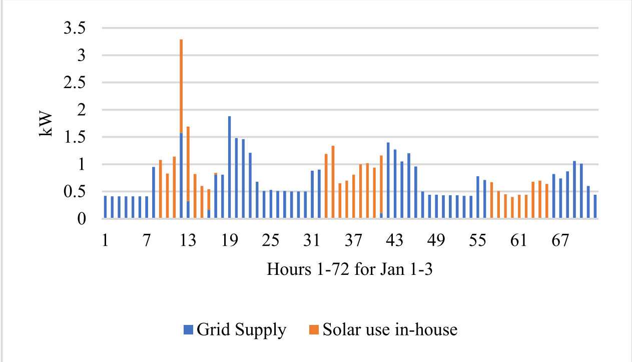

FIGURE 6. **Grid and in-house solar usage for the household: Base Case.**

Next, we present the findings from our model vis-à-vis alternative estimates obtained using other tools (Figure 7).

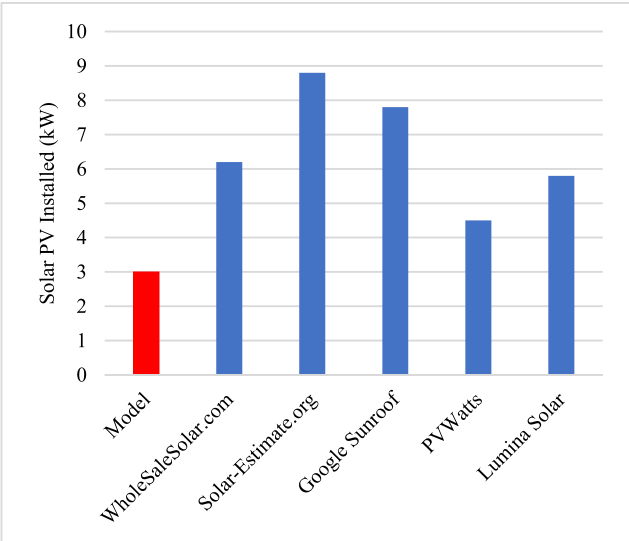

FIGURE 7. Comparison of PV sizing across different models. ***Note: Lumina Solar uses LIDAR together with Aurora [27]. Google Sunroof estimate represents an average for the postcode and not available for the precise location. The estimate from PVWatts is obtained by running the model repeatedly to meet the household demand.***

The model's estimate is markedly lower than the other appraisals. Although we do not present the findings of other household case studies, it is likely the case that the commercially available tools tend to overestimate system size. Detailed load profiles are not used in most commercial tools. The online tools and the solar company recommended the installation of solar PV well in excess of the peak hourly load, which was 4.7 kW for 2018, and occurs in the evening. As several of the online tools use a combination of monthly bills and synthetic load profiles, their estimations overlooked the fact that the household's average demand during daylight hours is only 0.635 kW. The household in this instance could overinvest anywhere between \$5,000 and \$18,000. That said, there are several other factors that would also determine the PV/BESS as we discuss next.

2) NO EV SCENARIO: OTHER CASES

Table 2 shows a comparison of PV and BESS selection for the following scenarios:

1. The "**Base Case**," which implements fixed pricing and the stochastic model;
2. "**Best Solar Year**" and the "**Worst Solar Year**," which use single-year solar profiles of 2001 and 2003, respectively and fixed pricing;
3. "**TOU**," which implements a Time of Use pricing scenario (25 c/kWh peak from 6 PM to 10 PM and an 8 cent off peak for the rest of the day);
4. A "**Special (EV) Tariff**" scenario (30 c/kWh peak from 6 PM to 10 PM, an 8 c/kWh off-peak, and a 5 c/kWh super-off-peak from 11 PM to 5 AM);

TABLE 2. Comparison of model scenarios.

	Annual Bill ($) (and Savings*)	PV Installed (kW)	Battery Installed (kWh)
Base Case	1,314 (7%)	3.0	0.0
Worst Solar Year	1,409 (1%)	2.5	0.0
Best Solar Year	1,250 (12%)	3.0	0.0
TOU	1,100 (22%)	1.3	1.3
Special (EV) Tariff	1,165 (18%)	2.1	2.0
High Export	1,040 (27%)	7.0	0.0
No Export	1,387 (2%)	1.0	0.4
Cost of Solar Reduced 50%	867 (39%)	4.0	1.2
Cost of Solar Reduced 50% + No Export	1,199 (16%)	3.0	2.0
No Solar*	1,419 (0%)	0.0	0.0

Note: Electricity Bill savings (in parenthesis) relative to the No Solar case.

5. A "**High Export**" scenario which allows the model to sell higher amount of energy to the grid up to the household demand (i.e., Eq (6) is relaxed);
6. There is also a "**No Export**" scenario which prohibits net-metering reflecting a situation where the Maryland state cap of 1,500 MW for roof-top solar is reached;
7. "**Cost of Solar Reduced 50%**," with panel price dropping to \$1,500/kW;
8. The "**Cost of Solar Reduced 50% + No Export**," which halves the cost of solar panels, but no net-metering is in place which reduces profitability of solar;
9. The "No Solar" scenario, which serves as a benchmark for all scenarios to calculate the benefit of PV/BESS system.

Several observations arise. First, the Base Case shows 3 kW of solar can save 7.4% net of all costs including the capital costs for a year, relative to the No Solar counterpart. This savings is not insignificant, and we note that there are many environmental and other benefits that are not counted in an electricity bill reduction. However, it is typically a small fraction of the savings reported by the commercially available models. SolarEstimate [31], for instance reports an average annual electric bill savings of \$2,566 pa (or \$64,171 over a 25-year period), using a panel size of 8.8 kW (Figure 7). Even if we adjust for the panel size, these benefits are 8.3 times higher than what we have estimated using an accurate load profile. Secondly, the difference in optimal PV between the "Best Solar Year" and the "Worst Solar" is small unlike the ISKCON DC case study. The savings associated with the latter case is only \$10 relative to the No Solar case, making solar potentially a marginal investment in low insolation years.

The grid pricing scenarios are especially interesting because they include the installation of BESS even though they recommend installing fewer solar panels. This makes sense, because in the TOU scenario, the peak hours where the cost of energy from the grid is the highest comes in the evening. The TOU scenario provides the desired incentive to optimize PV/BESS and lower the electricity bill by \$319 or 22% of the No Solar scenario. The Special (EV) Tariff which is geared towards an EV off-peak charging brings in more BESS to take advantage of the very low prices during super off-peak hours, but absent an EV load in this case, is not as effective, although it also results in 18% savings.

The net metering scenarios with High and No Export provide good insights into the significant impact of this policy. In our Base Case as well as other scenarios, the model [Eq (6)] restricts net-metering to the amount of solar energy used in the household. When the model can sell energy back to the grid up to the year's demand, it recommends installing 7 kW, i.e., more than double of the Base Case outcome. However, when net-metering is restricted which is a policy risk that homeowners and investors have to consider over the longer term, the model recommends installing only 1 kW of solar panels. This indicates that for this residential home, solar panels are not well suited for the load profile. The household cannot reap significant benefits from solar energy (as indicated by the \$31 difference between the "No Solar" case and the "No Export" case) without being able to sell excess energy back to the grid. The results from the "No Export" scenarios in particular demonstrate that solar panels have little impact on the household's utility bill without net-metering.

As the last two cases with 50% drop in solar cost demonstrates, there is a much greater prospect for solar if the current costs in the US falls in line with those observed internationally (especially in India and China) where roof-top solar can be installed for \$1,500/kW. With the current net-metering policy in place ("Cost of Solar Reduced 50%"), there is room to oversize the panel to 4 kW and include 1.2 kWh of BESS to generate 39% savings. Even absent any export to the grid, the model selects 3 kW with 2 kWh BESS to provide a 16% reduction in electricity bill.

As a more general observation on BESS at its current costs, the model rarely finds it attractive. BESS selection is influenced mostly by the other factors, such as the grid pricing scenarios or the cost of solar panels. It is certainly striking that the model recommends installing BESS when the cost of solar panels is halved, even when net-metering is restricted.

In this case study, the only factor which was not altered was the demand. The following case study analyzes the impact of an EV on the sizing of solar PV and BESS.

C. CASE STUDY 3: RESIDENTIAL HOME WITH EV

This section details the findings for the same residential household, but with an EV. This uses the same 1-year smart-meter data used in the previous case study for 2018. The EV travels every day: on weekdays, the EV is outside of the home from 7 AM to 6 PM, and on weekends, the EV is out of the home from 8 AM to 12 PM, and again from 6 PM to 8 PM. These hours are meant to reflect a typical working family's weekly travel pattern. The model provides complete flexibility in setting any pattern and vary the travel distance.

TABLE 3. Comparison of model scenarios.

	Cost (\$)	PV (kW)	Battery (kWh)	Super-charge hours	Fast Charge kWh
Base Case	1,856	3.4	0.10	0	65
2*Distance	2,574	3.5	0.10	0	3,600
3*Distance	3,297	3.5	0.10	1	8,550
TOU	1,382	2.5	1.60	0	40
Special Tariff	1,307	4.0	2.30	0	1,380
Special Tariff + 2*Distance	1,553	4.0	2.30	0	7,007
Special Tariff + 3*Distance	2,055	5.0	4.30	1	13,067

When out of the house, the EV loses 1 kWh of its battery for every hour that it remains out of the house. This means that on weekdays, by the time it returns to the household, it will lose 14 kWh of its battery to travel ~42 miles. The EV cannot be charged when it is outside of the household, except for a supercharger.

The EV's battery has a capacity of 60 kWh and its state of charge cannot go below 20% or 12 kWh. In most EV's, going below a certain limit of the battery reduces the lifespan of the battery, and hence this lower limit is enforced as a hard constraint.

The EV has three charging options:

1. Slow charging at a rate of 110 Volts/1.65 kW
2. Fast charging at a rate of 220 Volts/6.6 kW
3. Supercharging outside of the household at a rate of 480 Volts/72 kW, but at a high cost of \$0.6/kWh

An additional constraint on the supercharging is that it cannot be done between 11 PM and 5 AM – this is again a constraint that is customized for each application. The model has been run for a single-year solar profile with the following scenarios (Table 3):

1. The "Base Case," which implements fixed pricing;
2. Two scenarios, "2*Distance" and "3*Distance" which double/triple travel distance and hence the amount of battery the EV loses every day (28 kWh per weekday in "2*Distance" and 42 kWh per weekday in "3*Distance");
3. Two scenarios, "TOU" and "Special (EV) Tariff" which alter the grid pricing schemes as discussed earlier;
4. Two scenarios, "Special Tariff + 2*Distance" and "Special Tariff + 3*Distance" which combine the special tariff with higher travel load scenarios.

The major difference between this case and the previous one is that the load profile has a sharp peak in the evening, when the EV returns to the household. A cursory glance at these results reveals that the model avoids using supercharging, meaning the immediate benefit of filling the battery is outweighed by its high cost, albeit a larger EV and/or travel load can increase the need for supercharging. Nevertheless, it should be noted that supercharging and the associated sharp increase in peak load could be avoided in this instance with an optimized charging strategy.

A closer look at the first three scenarios indicates how the model switches between slow-charging and fast-charging. In the "Base Case," the model charges only 65 kWh through fast charging, even though the EV required 4,015 kWh throughout the entire year, i.e., only 2% of the charging needed through fast charging. This is a significant point from a utility perspective as most daily commuting need using EV (up to 42 miles per day) can be accommodated through slow charging without causing a sharp increase in evening peak. For the other two scenarios with heavy EV travel loads, the model must charge more energy between each day to meet the more stringent travel load. Doubling (84 miles per working day) and tripling (126 miles per working day) EV travel requires 45% and 70% of the energy through fast charging. It is also worth noting that the PV/BESS size remains almost identical throughout all these cases. This is because the cost of PV is relatively high which in turn reduces the need for BESS, and the fact that the household is on a fixed price that gives no incentive to alter its consumption pattern.

In the "TOU" scenario, energy costs more in the evening. It follows logically, then that the model would recommend the installation of more batteries to use cheap energy to charge the EV rather than use grid energy at 25 c/kWh. The model's findings suggest using more solar energy than grid energy compared to the Base Case even though it is using fewer panels, because of the presence of BESS.

The "Special Tariff" scenario sees the installation of more PV/BESS than any of the previous scenarios, as it is cheaper to use energy from the PV//BESS than the expensive evening peak rate. However, doubling, or even tripling, the distance the EV travels every day has no effect on PV/BESS is because it gets the additional energy from the grid at 5 c/kWh and use fast charging. In other words, the super off-peak rate is lower than the levelized cost of PV/BESS. The model recommends using 1,380 kWh for the year which is almost 20 times the amount of fast charging than the Base Case for 14 kWh (42 miles) of daily EV load. If EV load doubles, fast charging rises over 7,000 kWh annually, or nearly double that of the Base Case 2∗Distance scenario. When tripling the distance under Special Tariff, the model recommends installing 5 kW of solar panels and 4.3 kWh of battery, as the fast charging requirements include some of the evening peak. The value of the model lies in the fact that it can look at PV/BESS/EV options in order to maximize the value of PV/BESS for the household and it can also help policy makers to design tariff that avoids adding expensive peaking generation capacity. TOU/EV pricing in this instance can create the necessary incentive to install solar panels and batteries for households with EVs.

Figure 8 shows the difference in hourly EV load for a day across the three pricing scenarios averaged across the year for the 3*Distance sensitivity. In the fixed price scenario, the EV demand remains almost entirely constant, including the household peak in the evening. In the other two pricing scenarios, however, the added demand is shifted away from the evening peak. This is a serious issue because a fixed price regime would *on average* lead to EV load that is four times that of TOU/Special Tariff regime. The Special Tariff can be particularly effective in moving part of this load to late night and early AM hours. During the super-off-peak period (11 PM to 5 AM), the Special Tariff leads to an average consumption of 30 kWh which is higher than that for the TOU (27 kWh), and fixed price scenario (20 kWh).

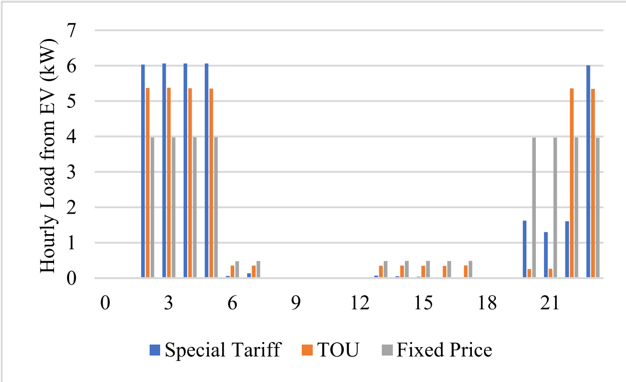

FIGURE 8. **Comparison of added EV load for an average day across pricing scenarios for 3*Distance sensitivity case.** ***Note: Daytime EV loads in the plot between 6 AM-6PM reflect the charging that take place during weekends (averaged across all 365 days).***

V. CONCLUDING REMARKS

Although there has been significant research and development of commercial tools to design roof-top solar systems, there is relatively less analysis of combined PV/BESS/EV systems that employs smart meter data. Estimations for solar panels in households often come from online solar company resources that are opaque and use limited load information. The proposed model addresses these gaps by using hourly/sub-hourly smart meter data to accurately estimate solar panel and battery size with the integration of the consumption pattern (including EV load), and policies, which both have a significant influence on purchase and sizing.

The model's results vary significantly depending upon the customer load shape and solar resource availability. Analysis conducted for households suggests the commercial software estimates are significantly higher (in estimating installed solar PV capacity needed)—on average by a factor of two. This may mean sub-optimal investment, e.g., up to $18,000 in the example presented in the second case study for a single household. The analysis also demonstrates how detailed smart meter load data can be useful in determining the precise volume of solar PV and battery combination that may differ a great deal from one case to another. In contrast, the first case study conducted for a larger multi-house complex shows that solar PV can be highly profitable because its consumption pattern aligns quite well with solar availability. The analysis, however, also points to the role uncertainty of solar resource availability may play in shaping the decision. A stochastic programming model is demonstrated to be a useful tool in gaining insights on this issue.

The addition of EV load is materially significant for PV/BESS, and it should be analyzed together with PV/BESS sizing. The model allows a user to help optimize the EV charging load by observing practical constraints around timing and available charging options, as well as pricing options. These considerations are critical as excessive additions to the household (and system) evening peak load can be avoided through a proper optimization of the charging regime, even for very high travel load, by choosing the right tariff scheme.

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